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Performance Estimation for Complex Manufacturing Environments

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*“All our knowledge has its origins
in our perceptions”*

Leonardo da Vinci

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ABSTRACT

To cope with today's market challenges and guarantee adequate competitive performances, companies have been decreasing their products life cycles, as well as increasing the number of product varieties and respective services available on their portfolio. As result, an increasing of complexity in all domains has been observed, from product and process development, factory and production planning to factory operation and management.

The capacity to continuously react to the changes imposed by this complex market demand, implies that organizations should be able to generate knowledge, compiling and analysing, in a more agile way, the immense quantity of performance data generated within their manufacturing environments. Based on this generated knowledge, stakeholders should apply the suitable tools that will support them to make decisions, envisioning future performance behaviours. Consequently, decision makers have been showing an increasingly interest in developing innovative approaches that will empower them to control their production systems in a more proactive way.

Indeed, from a research perspective, developing the foundations capable of supporting companies on applying a proactive performance management approach within their decision making processes, raises an interesting set of opportunities and challenges. Indeed, in the context of complex manufacturing systems, interpreting the performance data to make the suitable decisions, is not neither a trivial nor a straightforward issue to be performed in an ad-hoc way. To handle this complexity, new approaches capable to model organizational processes using engineering systems techniques, capable to represent and manage the flow of information through a system, are strongly required. Based on this premise, systems dynamics approach should be explored as a solution to support decision makers to enhance their knowledge on dynamic, non-linear and closed boundary systems behaviours, as well as converting real-life situations into enhanced and formal models.

Inspired by this theoretical approach, the main objective of this research is to design a proactive performance management framework, composed by two key stages: (i) the collection of reliable performance data, also known as evidence of the system behaviour; and (ii) analysis and interpretation of the evidence, for a suitable decision making process. Thus, as result of this performance data interpretation, decision makers become capable to bring their mental model about the system behaviour closer to the reality. This enhancement will empower them to foresee the future behaviour of their manufacturing systems, based on the assumption that the degree of belief in the prediction strictly depends on the quality of the evidence obtained.

Aiming to pursuing this vision, a performance management methodology was developed to support decision makers to identify endogenous and exogenous variables, able to hinder the achievement of their strategic objectives, by enhancing their understanding about the dynamic behaviour of their manufacturing systems. Moreover, both performance measurement and estimation engines, responsible for measuring reliable lagging indicators as well as estimate future performance behaviours, based on an estimation horizon comprised by a set of leading indicators, were fully developed. The entire framework was successfully tested and validated within three different scenarios, all of them related with complex manufacturing environments.

RESUMO

Para lidar com os desafios atuais impostos pelo mercado, assim como garantir um elevado nível de competitividade, as empresas têm vindo a diminuir o tempo e ciclo de vida dos seus produtos, bem como aumentar a variedades de produtos e respectivos serviços disponibilizados. Como resultado desta mudança de paradigma, tem-se observado um aumento de complexidade a todos os domínios, desde o desenvolvimento do produto e respectivos processos de produção, passando pelo planeamento das fábricas e processos logísticos até à gestão e manutenção das operações fabris.

A capacidade de reagir, continuamente, às mudanças impostas por este comportamento complexo por parte do mercado, implica que as organizações devam ser capazes de gerar conhecimento, compilando e analisando, de uma forma mais ágil, a imensa quantidade de dados de desempenho gerados dentro de seus ambientes de produção. Consequentemente, e com base no conhecimento gerado, devem aplicar as ferramentas adequadas que lhes permitam prever os comportamentos de desempenho futuros dos seus sistemas de produção, de forma a ajudar os gestores a tomar as decisões mais acertadas. Com base nesta realidade, os tomadores de decisão têm vindo a mostrar um maior interesse no desenvolvimento de métodos e ferramentas quantitativas que lhes permitam controlar os seus sistemas de produção de uma forma mais pró-ativa.

De um ponto de vista científico, o desenvolvimento das bases que irão apoiar as empresas a aplicar uma abordagem de gestão de desempenho pró-ativa, levanta um conjunto significativo de oportunidades e desafios. De facto, no contexto dos sistemas de produção complexos, a interpretação dos dados de desempenho não é um processo trivial, capaz de ser realizado de uma forma *ad-hoc*. Para lidar com esta complexidade, novas abordagens de modelação de processos organizacionais, baseadas em técnicas de sistemas de engenharia, capazes de representar e gerir o fluxo de informações através de um sistema complexo, são estritamente necessárias. Com base nessa premissa, uma abordagem de analise dinâmica de sistemas (*Systems Dynamics*) deve ser explorada, como uma solução capaz de apoiar os tomadores de decisão a melhorar os seus conhecimentos sobre os comportamentos dinâmico e não-linear de sistemas fechados, assim como converter situações da vida real em modelos formais.

Inspirado por esta abordagem teórica, o objetivo principal deste trabalho de investigação baseia-se na necessidade de projetar um sistema de gestão de desempenho pró-ativo, composto por duas etapas principais: (i) aquisição de dados de desempenho com elevada precisão, também conhecidos como a evidência sobre o comportamento do sistema, e (ii) uma abordagem de análise e interpretação da evidência, para se obter um processo de tomada de decisão mais eficaz. Assim, como resultado desta interpretação dos dados de desempenho, os tomadores de decisão aproximam o seu *mind-set,* relativo ao comportamento dos sistemas, à realidade, o que lhes permitirá prever o comportamento futuro dos seus sistemas de produção.

Com o objetivo de materializar este objectivo, foi desenvolvida uma metodologia de gestão de desempenho, que acompanha os gestores durante todo o processo de identificação das variáveis endógenas e exógenas, capazes de afetar a concretização dos objetivos estratégicos traçados. Além disso, tanto o mecanismo de medição de desempenho, bem como o motor de estimação, foram integralmente desenvolvidos, testados e validados com sucesso em três cenários diferentes, todos eles relacionados com ambientes de produção complexos.

ZUSAMMENFASSUNG

Um die heutigen Herausforderungen des Marktes zu bewältigen und ausreichende Wettbewerbsaufführungen zu garantieren, haben die Unternehmen die Lebenszyklen ihrer Produkte gekürzt, sowie die Anzahl der Produktvarianten und die jeweiligen Dienste in ihrem Portfolio erhöht. Als Ergebnis wurde eine zunehmende Komplexität in allen Bereichen festgestellt, von der Produkt- und Prozessentwicklung, Fabrik- und Produktionsplanung bis zum Fabrikbetrieb und -management.

Die Fähigkeit, ständig auf die Veränderungen durch diese komplexe Marktnachfrage zu reagieren, bedeutet, dass Organisationen in der Lage sein müssen, die immense Menge der in ihren Produktionsumgebungen erzeugten Performance-Daten in einer flexiblen Weise zusammenzustellen und zu analysieren, als auch die Anwendung der geeigneten Werkzeuge, die auf der Grundlage dieses Wissens erzeugt wurden, die die Beteiligten bei der Entscheidung, mit der Vorstellung der zukünftigen Verhaltensweise der Performance, unterstützen sollen. Folglich haben Entscheidungsträger ein zunehmendes Interesse daran gezeigt, Methoden und Werkzeuge herzustellen, die es ihnen ermöglichen quantitative Systeme zu aufzuschließen, die sie befähigt ihre Produktionssysteme in einer proaktiven Weise zu steuern.

In der Tat, aus Sicht der Forschung, steigert die Entwicklung von Grundlagen, die die Fähigkeit haben, Gesellschaften im Rahmen ihrer Entscheidungsprozesse auf einen proaktiven Performance-Management-Ansatz zu unterstützen, die Möglichkeit auf eine Reihe von interessanten Chancen und Herausforderungen. Tatsächlich ist im Rahmen von komplexen Fertigungssystemen, die Interpretation der Messdaten, um die geeigneten Entscheidungen zu treffen, nicht trivial weder noch eine einfache Frage, die in einer Ad-hoc-Weise gestellt werden sollte. Um mit dieser Komplexität umzugehen, sind neue Ansätze, die in der Lage sind, Organisationsprozesse durch Engineering-System-Techniken zu modellieren, wie diese die für Steuerungssysteme verwendet werden, die in der Lage sind den Informationsfluss durch ein System zu vertreten und zu verwalten, stark erforderlich. Basierend auf diese Prämisse sollten Systemdynamik Ansätze als Lösung für die Unterstützung von Entscheidungsträger erkundet werden, um so ihr Wissen auf dynamische, nicht-lineare, geschlossene Verhaltensweisen der Randsysteme zu verbessern und reale Situationen in formale und verbesserte Modelle umzuwandeln.

Inspiriert von diesem theoretischen Ansatz, ist das Hauptziel dieser Forschung das Entwerfen einer proaktiven Leistungsmanagement-Struktur, die aus zwei Hauptphasen zusammengestellt wird: (i) die Erfassung von zuverlässigen Leistungsdaten, die auch als Beweis für das Systemverhalten bekannt sind, und (ii) Analyse und Interpretation der Beweise für ein geeignetes Entscheidungsprozess. So, als Ergebnis der Interpretation dieser zuverlässigen Leistungsdaten, werden Entscheidungsträger ermächtigt das zukünftige Verhalten ihrer Fertigungssysteme vorzusehen, basierend auf der Annahme, dass der Grad an Glaube an die Prognose von der Qualität der erhaltenen Beweise abhängt.

Mit dem Ziel diese Vision zu verfolgen, wurde eine Leistungsmanagement-Methodik entwickelt, die Entscheidungsträger bei der Identifizierung endogener und exogener Variablen, die die Erreichung ihrer strategischen Ziele hindern könnten, durch die Verbesserung ihres Verständnis über das Verhalten ihrer Fertigungssysteme, unterstützt.

Darüber hinaus wurden sowohl die Leistungsmessungen wie die Schätzungsverfahren, zuständig für die Messung von Spätindikatoren sowie Schätzung zukünftiger Verhaltensweisen von Performances, basierend auf Frühindikatoren, vollständig entwickelt. Die gesamte Struktur wurde erfolgreich getestet und innerhalb von drei verschiedenen Szenarien, die alle mit komplexen Fertigungsumgebungen zusammenhängten, validiert.

PREFACE

This thesis represents a culmination of work and learning that has taken place over a period of almost three years and a half (2010 - 2014). During this time period, I have met amazing people, with who I have been exploring and developing not only hard but also soft skills. From this group of people I would like to highlight my colleague Álvaro Caldas. Together, and joining our computer and management skills, we are proud to say that we have successfully developed a management tool, strictly focus on performance measurement and management, which is currently installed in the larger Portuguese industrial company, and since 2014 is supporting decision makers to enhance the competitiveness of this automotive plant from the Volkswagen group.

On the other hand, I would like to emphasize the importance of my supervisor Dr. Américo Azevedo during these first years of my professional and scientific career. Due to its guidance I had been involved in the larger European project performed under the umbrella of the 7th Framework Program from the European Commission, to date. In this cross-Europe project more than 25 institutions, from the industrial and scientific areas, had been working aiming to research and implement the underlying models and ideas at the foundation of a new conceptual framework designed to implement the next generation Virtual Factory, constantly synchronized with the real one. Due to my involvement in this project, I had the chance to travel to different European countries and meet people from some of the best institutes such as: ETH Zurich, ITIA from the Polytechnic of Milano and Fraunhofer IPA. In the same line, I had the chance to share knowledge and experience with people working in some of the best industrial organizations such as Volkswagen, Audi, Compa and Homag, and thus know a little bit about the reality of their industrial organizations, not only but also concerning their performance measurement and management methodologies and tools.

Moreover, with the INESC Porto support, I had the chance to participate in a series of international conferences where I disseminated my research work on performance measurement and management disciplines with some of the best in the area. For instance I would like to highlight my participation on the IEEE IEEM 2012 conferences in Hong Kong, as well as on the PRO-VE 2011 conference in S. Paulo. Also, with the support of my supervisor I was Organizing Chair of the FAIM 2013 conference that was held in Porto, Portugal. This was an amazing and pleasant experience, since during almost one year I was responsible by preparing and managing this international conference from both the scientific and logistic perspectives. Moreover, this gave me the opportunity to be guest-editor of one international journal from Elsevier titled Robotics and Computer Integrated-Manufacturing Journal (RCIM).

In sum, I strongly believe that the entire path that was followed during this doctoral program gave me not only the enough knowledge and experiences to develop the work reported in this document, but also to prepare myself for successfully dealing with the challenges that will arise during my life after finishing my PhD.

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List of Abbreviations and Acronyms

AE: Autoeuropa

AI: Artificial Intelligence

BP: Backpropagation algorithm

BPMN: Business Process Modelling Notation

BSC: Balance Scorecard

CLD: Causal Loop Diagram

CN: Collaborative Network

CPPR: Customer – Product – Process – Resource

DDT: Delivers with Delay

EKF: Extended Kalman Filter

EPV: Electricity per Vehicle

ETL: Extract Transform and Load

FOPD: Function Oriented Product Descriptions

GMRAE: Geometrical Mean of Relative Absolute Errors

GPV: Gas per Vehicle

GRV: Gaussian Random Variables

GUI: Graphic User Interface

HPV: Hours per Vehicle

IT: Information Technology

KPI: Key Performance Indicator

MPC: Model Predictive Control

NN: Neural Network

NON: Number of Nonconformities

NRMSD: Normalized Root-Mean-Square Deviation

OWL: Web Ontology Language

PDCA: Plan – Do – Check – Act

PEE: Performance Estimation Engine

PI: Performance Indicator

PME: Performance Measurement Engine

PMM: Performance Measurement & Management

PTM: Performance Thinking Methodology

RBFN: Radial basis Function Network

RDFS: Resource Description Framework Schema

RMP: Requirement Management Planning

RMS: Root-Mean-Square

SPARQL: SPARQL Protocol and RDF Query Language

SPDM: Strategic Performance Data Model

SPM: Strategic Performance Management

SPMS: strategic Performance Management System

UKF: Unscented Kalman Filter

VFDM: Virtual Factory Data Model

VFF: Virtual Factory Framework

VW: Volkswagen

XML: eXtensible Markup Language

XSD: XML Schema Definition

Chapter One

INTRODUCTION

More and more industrial companies are performing in competitive markets, forcing them to become more proactive than reactive. This way, ad-hoc approaches based on the calculation of lagging indicators is no longer suitable for this type of companies. Indeed, organizations must become able to analyse their leading indicators, understand their meaning and the feedback loops that affect them. Only this way, decision makers can look into the future, and act even before these causes affect the systems efficiency and effectiveness.

In line with this context, chapter one of this document is mainly responsible by the presentation, in a succinct way, of the scope of this research project as well as the enhancements that are expected to be introduced in the performance management domain. In addition to the topics previously described, from the research perspective, it will be presented the research questions defined and the research strategy used to successfully conduct this investigation.

1.1. Context

Nowadays, manufacturing is being shaped by the paradigm shift from mass production to on demand dictated, customer-driven and knowledge-based proactive production (Jovane, Westkämper, & Williams, 2009). Consequently, shorter product life cycles, an increased number of product varieties, high performance processes and flexible machines and production systems result in an increased complexity in all domains, from product design, process development, factory and production planning to factory operations (Aitken, Childerhouse, & Towill, 2003). To handle this complexity, new knowledge-based processes, technologies and tools to model, simulate, optimize and monitor planned and existing manufacturing systems behaviours are required (Constantinescu, Hummel, & Westkämper, 2005; Tolio et al., 2010; Westkämper, 2007). Such new approaches, models and tools should allow adaptations and changes to be made in advance, following a feed-forwarding strategy, in order to maximize the system efficiency and effectiveness. Also, at operational level, these tools must be smooth in their interaction with human stakeholders as well as working in an integrated way on different organizational levels along the whole engineering and management life cycle (Gunasekaran, 2001).

Furthermore, from an operations performance point-of-view companies need to be more assertive, in order to decrease the ramp-up time when they are introducing new products or modifying the existing ones, and thus decrease the time-to-market, aiming at monetizing the product development as quickly as possible (Hendricks & Singhal, 1997). They also need to implement continuous improvement approaches over the management and manufacturing processes in order to reduce costs and consequently increase profit.

In line with this, managers are continuously designing and conceiving new efficient production processes, aligned with the company's strategy and market needs (Braz, Scavarda, & Martins, 2011) (F. Williams, D'Souza, Rosenfeldt, & Kassaee, 1995). However, still managers of complex manufacturing systems are dependent of their own experience and knowledge about the system to take important strategic decisions and implement initiatives, due the lack of tools and methodologies that assist them with real-time and leading performance information. In that context, the performance measurement and management of complex manufacturing systems must have a crucial role in the decision-making process as well as in the evaluation of the effectiveness of operational initiatives and actions plans (de Leeuw & van den Berg, 2011).

Therefore, industrial organizations are more and more interested in developing strategies designed to provide decision makers with the resources and capabilities that will allow them to implement quantitative systems to identify, quantify and evaluate risks, uncertainties and variability for all stages of the manufacturing system life cycle, and thus controlling them in a more proactive way (Haimes, 2001). Indeed, many decision makers are now realizing the importance of having tools capable of gathering and manipulating data in order to support the continuous process of monitoring and assessing performance. As a consequence, companies are increasing their ability to build understanding of their manufacturing system's nature, its functional behaviour and respective interactions with the environment (Vaneman, 2002).

In terms of research, developing the foundations to support companies applying a proactive performance management approach, within their management processes, raises an interesting set of opportunities and challenges. Indeed, if we revisit Shewhart[1] proposal (Shewhart, 1930) it is possible to understand that performance measurement, system's behaviour prediction and control are three areas of research that should be combined if it is expected to manage industrial processes in a more efficient way. Based on this premise, Shewhart showed that in order to predict future behaviours, decision makers must interpret the present using as driver the performance information extracted from the past. Moreover, according to Shewhart's research, if the historical data collection process is performed under statistical control, i.e. the production system has already achieved a suitable level of stability in which only common and known causes of variation remain, then it becomes possible to make reasonably accurate predictions based on this historical information (Shewhart, 1930; Wilcox & Bourne, 2003).

Nevertheless, within complex manufacturing systems, it can be challenging when the technology infrastructure makes it difficult to obtain or extract the right information to calculate the correct performance metrics. In order to overcome this challenge, companies have sophisticated enterprise systems or extensive legacy systems that can support the operational performance measurements. However, due to the complex and sophisticated nature of these systems, the technology available may make it either too expensive and time-consuming to access the raw data required for effectively measure this performance. Furthermore, professionals who feel confortable enough with the technology infrastructure, normally, do not have clear access to the organisation's strategic plan and the business process that supports it. Therefore, it can be observed a critical misalignment between the strategic and operational layers (Kleingeld & de Haas, 1999).

Despite the impact and relevance of Shewhart's research work, it is important to underline that it is scarce the number of research papers that focus on the necessity to explore the concept around the predictive performance management approach. Even if this topic has been considered essential by different entities such as SAP, Oracle, SAS and other IT companies, due to the necessity to actively respond to current industrial context and market demands (Cokins, 2009). Moreover, from the reduced literature available on this topic, it is not visible that these research works have given rise to suitable frameworks, capable to be successfully implemented within industrial scenarios.

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[1] Walter Shewhart was one of the creators of the original notions of Total Quality Management and continuous improvement paradigms. One of W. Edwards Deming's teachers, he preached the importance of adapting management processes to create profitable situations for both business and consumers, promoting the utilization of his own creation, the SPC control chart. He also developed the Shewhart cycle learning and improvement cycle, combining both creative management thinking with statistical analysis, currently known as PDCA cycle.

On the other hand, the study around complexity management is already mature and can be seen as a strong pillar to the development of research around complex manufacturing systems analysis, envisioning the development of a suitable knowledge-driven predictive performance management framework (Forrester, 1958). Indeed, from the different studies performed within the complexity management scope, it has been observed that, in opposition to algorithmic complexity, which is strictly related with the difficulty to solve a well-defined problem, on the specific case of contextual complexity a very different phenomenon is entailed (Vrabic & Butala, 2012). Indeed, when dealing with complex manufacturing systems, the complexity concept is mainly a measure of absence of information. In other words, complexity represents the degree of the decision makers' ignorance about the reality's behaviour principles (Vasconcelos & Ramirez, 2011).

Thus, the complexity concept is particularly critical in manufacturing systems management, mainly due to its structural and behavioural reality (Calinescu, 2002). In the scope of this research work, we look at a complex manufacturing system as one whose processes are difficult to analyse, understand or explain due to the fact that the degree and nature of the relationship between them is imperfectly known. Inherent structural complexity increases when multiple products compete for shared resource(s), creating logistics dependencies on production sequencing and cycle time decisions. Fluctuations in process execution and different process instances, with cross-functional interaction of subject matter experts and different time frames (process instances in concurrency), also create dynamic complexity that hinders system analysis and prediction of behaviour (Löffler, Westkämper, & Unger, 2011). As an example, Figure 1 depicts a complex manufacturing system where different families of products compete for shared processes, managed by different stakeholders and using/sharing resources (i.e. raw material, machines and people).

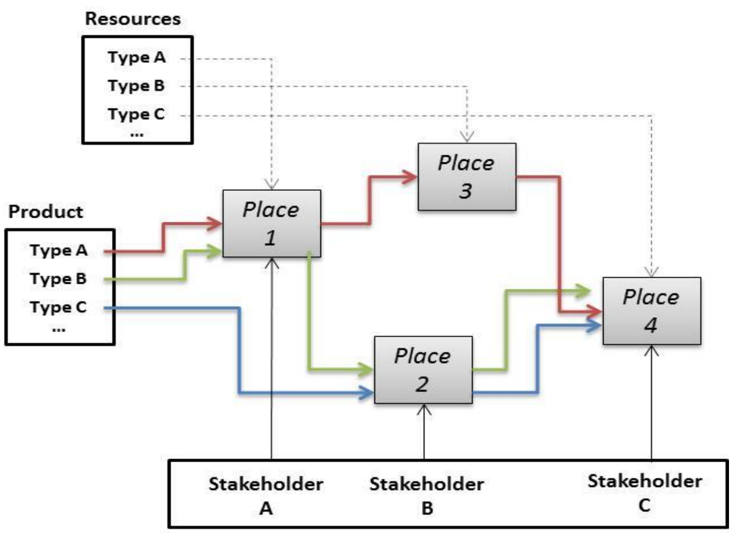

Figure 1 - Complex Manufacturing Systems

But how can one overcome manufacturing system's complexity, aiming to understand the system as a whole and thus take more effective decisions? For many, the solution lies in systems thinking approaches, through the ability to see the world as a complex system where everything is connected to everything else.

Aiming to support industrial companies studying about the structure and dynamics of their complex systems, and thus design effective strategies for sustained improvement actions, the field of system dynamics was created at MIT in the 1950s by Jay Forrester[2]. Drawing on engineering control theory and the modern theory of nonlinear dynamical systems, system dynamics discipline enables the development of formal models to capture and represent complex dynamics and thus create a user-friendly environment for learning and policy design.

Taking into account this context, a proactive performance approach, based not only on knowledge and expertise available in the stakeholders' minds, but also regarding information on manufacturing performance, generated along the plant, can sustain the development of a multi-perspective performance estimation approach for complex manufacturing systems. What we want to explore is the potential of combining dynamic performance measures with a reliable, dynamic and formal representation of the reality, in order to cope with the complex behaviours of contemporary manufacturing systems (Maisel, 2013).

However, in order to achieve this vision, it is necessary to overcome the limitations of existing approaches, currently based on reactive paradigms. Indeed, reactive approaches are not capable of anticipating and avoiding bottlenecks or malfunctions, neither to explore the capability to understand the intra- and inter- processes synergies in order to support managers to make decisions that can really enhance their production system behaviour (Busi & Bititci, 2006a). Thus, this research project proposes the development of a new concept based on a prediction approach that intends to use performance information as an enabler to support companies to implement a more proactive management strategy.

1.2. Problem Statement and Research Questions

Due to the levels of complexity previously described, it is observed that industrial organizations are forced to base their management strategy on functional approaches, using the principle of specialization based on function or role. If it is true that this type of structure makes it possible to delegate issues to specialized persons or units, leaving them the responsibility of implementing, evaluating and controlling a given set of procedures or goals, on the other hand this departmentalization is also responsible by creating distributed architectures for data storage, through different data sources. This reality doesn't only hinders data interoperability but also hampers data standardization. Thus, within complex systems, analyse the efficiency and effectiveness of cross-functional processes to the entire organization, can result in an extremely challenging task.

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[2] Jay Forrester, educated at the MIT in electrical engineer, is the founder of System Dynamics. Industrial Dynamics was the first book Forrester wrote using Systems Dynamics to analyse industrial business cycles. In 1982 he received the IEEE Computer Pioneer award and in 2006 he was inducted into the Operational Research Hall of Fame.

On the other hand, the traditional gap between the strategic and operational layers also represents a critical bottleneck in what concerns the detection and resolution of problems arising from the implementation of a non-effective strategy. (Richtermeyer & Webb, 2010; M. W. Meyer, 2002). Since the strategy is defined at the higher level of an organization but its materialization is performed at the operational layer, the way how performance information flows within the organization and is available at all points of decision, represent a serious problem when it is aimed to shift from a reactive to a proactive management approach.

Although industrial companies have a set of information systems that generate huge quantities of data, their capability to use it to build performance information in a short time and with low effort is still weak or inexistent. Indeed, if in the past this issue was not a problem of pivotal importance, currently, due to the volatile market conditions and short life cycle of products, this constraint has proven to be a strong restriction concerning the success performance management solutions implementation. Indeed, the lower the frequency of KPIs calculation, the bigger is the time interval between the moment that a bottleneck/problem arises until some corrective actions are performed (Neely, 2005). This means that during this time interval companies are losing money and competitive advantage. A critical example of this reality is the Nokia and Ericsson case study[3], which showed how a purely reactive management strategy from Ericsson, concerning their supply chain management, was capable to alter the entire mobile phone market (Yossi Sheffi & Sheffi, 2007).

In addition to the gaps previously described, it is observed that current performance management solutions are only capable of supporting decision makers with regard to decision taken and implemented in the past. This means that, due to weak and inappropriate performance analytics tools, decision makers only are capable to realize what is happening in the present, as response to decisions taken in the past, and after a specific feedback time. Indeed, this reality has a direct consequence on the effectiveness of the decisions taken, since without the support of a proper global vision of the system behaviour, organizations deeply rely on the individual expertise of stakeholders involved, when analysing the causes, risks, trade-offs and impacts of current decisions into the future behaviour (Cokins, 2009). In sum, following such reactive approach, decision makers simply react to effect, instead of managing their causes (Wilcox & Bourne, 2003).

To successfully overcome the gaps previously identified, two research questions were formulated since they were used as a plumb line that defined the strategy and path to be followed during the entire research program. Following, each of these research questions will be presented and detailed:

[3] Nearly a decade ago, lighting struck a Philips microchip plant causing a fire that contaminated millions of mobile phone chips. Among Philips' biggest customers were Nokia and Ericsson that reacted differently to the disaster. While Nokia's strategy allowed it to quickly identify the problem and switch suppliers in a short period of time, on the other hand, Ericsson took a lot of time to identify this problem, allowing its competitors to acquire all the remaining microchips from the Philips plant as well as the stock available on other plants around the world. This reactive approach leads Ericsson to lose its position as one of the market leaders.

RQ1. How can we use raw data to generate performance information?

Recognizing the fact that KPIs metrics can be defined at the upper layers but calculated at the operational one, it is important to overcome both the technological and conceptual gaps that can hinder decision maker to deploy the calculation process of a new/existing KPI. Thus, the first objective of this research question is to study effective mechanisms that supports decision makers gathering and fusing the raw data existing in the different data sources within a single but aggregated KPI, and thus extract in real time the most meaningful information that should rule the management of trade-offs, characteristic from complex systems, envisioning the strategic goals achievement.

Nevertheless, the performance management is a multidisciplinary domain, combining different areas of study and analysis. Therefore, if it is true that it is important to increase the level of granularity when calculating a specific KPI, in order to empower stakeholders' decisions, on the other hand, due to limitations imposed by the human condition, analyse a significant number of indicators, in concurrency, can be a very complex task (Parmenter, 2009). Thus, it is critical explore how to decrease the number of KPIs but, keeping the capacity to assess a manufacturing system based on a multi-perspective approach, taking into account its static complexity (Sikdar, Sengupta, & Harten, 2012).

In sum, we strongly believe that the success of the overall project is strongly dependent from the achievements obtained at this stage of the research, since this outcome will provide decision makes with the foundations to explore in detail the dynamic complexity of the system, and thus build a more reliable mental model about its behaviour.

RQ2. How should the performance information and the system's knowledge be used to project future performance behaviours?

The main focus of this research question is to understand how to provide stakeholders with a methodology that allows them to better understand the complexity that characterizes their manufacturing systems, and thus bring their mental model about the system's behaviour closer to reality, always envisioning the achievement of the strategic objectives of their organization. Then, based on the expected outcomes of the methodology implementation, explore how to combine the knowledge generated about the different feedback loops that comprise the system, and give it a specific personality, with the variables that can be foreseen for the predictive time horizon defined, in order to estimate with the highest reliability and confidence possible the present and future manufacturing system's behaviour.

In sum, it is expected to break the paradigm that performance indicators simply replicate information related with past. In fact, these variables should be seen as estimators' variables, capable to provide insights about future systems' behaviours. If properly measured and used, then it becomes possible to estimate with high levels of confidence the future behaviour of a manufacturing system. Finally, it should be explored how this information can be used in order to support decision makers shifting from a reactive to a proactive approach.

1.3. Outcomes

Envisioning the development of knowledge and insights on the performance measurement and management areas, mainly in the scope of process-based complex manufacturing environments, it was developed an innovative proactive performance management framework, based on a feed-forwarding strategy[4]. In line with this vision, it is proposed the implementation of methods and tools normally used in specific disciplines from technological areas, such as robotics or automation and control, capable to be not only shaped to the production system characteristics and complexity but also easily implemented, configured and maintained.

Therefore, two main outcomes were established as an objective to be accomplished by the end of this research project:

I. **Performance Information Assessment Solution**: envisioning a more proactive performance management approach, the first objective of this research project is to bridge the gap between the strategic and operational layers of an industrial organization, not only facilitating both processes of KPIs specification and calculation but also easing its linkage. In other words, guarantee that in a user-friendly and flexible way, any stakeholder is capable to design the metric of a specific KPI and, without any IT support, launch its calculation in order to obtain measures of the system's performance aligned with the strategic vision of the company. In sum, as a first milestone a performance measurement engine and a performance data model were developed. From the combination of these two components it is expected to obtain not only a semantic performance repository for performance information exchange, but also a real time performance measurement tool.

II. **Framework for Performance Estimation**: As the most relevant result, this research intends to establish a new framework for a predictive assessment of performance in complex manufacturing systems, based on leading performance indicators analysis. By framework it is meant the combination of a well-structured methodology, responsible for guiding decision makers to enhance their mental model concerning manufacturing systems operations, with a mathematical algorithm, normally used in automation and control areas, capable of estimating future performance behaviour. Through the combination of lagging and leading indicators, selected according to the expertise and knowledge developed with the methodology implementation, it is expected to project in the future, with high levels of confidence, the values of a specific KPI.

[4] A feed-forward management strategy is an approach focused not only lagging indicators, strictly related with past actions, but also in leading indicators that support decision makers to project the behaviour of a specific manufacturing system into the future.

1.4. Research Development

Aiming at responding to the challenges and, more concretely, the research questions previously proposed this research project was conducted using an action research approach as reference. Indeed, the action research method was selected since this approach supports both the production of practical outcomes as well as the production of research theory through a cyclic process. According to Meyer's (2000) point of view action research's strength lies not only in its focus on generating solutions to practical problems but also in its ability to empower practitioners by getting them to engage not only with the research project planning but also with the subsequent development or implementation activities. One important reason that leads to this reality based on the fact that throughout the research process the findings are continually feedback to practitioners for validation, aiming to make the research process and outcomes more meaningful to practitioners, as well as aligned with the reality of day-to-day practice.

Therefore, and as is characteristic of this research strategy, for the successful development of this research project, not only data gathered from a literature review was used. On contrary, others techniques such as formal and informal interviews, focus groups, participant observation, and a review of industrial partner's documentation were used to approximate as much as possible the researcher's mind-set from the reality characteristic from the performance management domain.

The setting selected for the development of this research project was an automotive plant from the Volkswagen group, located at south of Portugal. This factory represents the largest foreign investment project ever done in Portugal, and this ambitious project was designed with the main goal of producing niche products, suitable to be exported to the entire world, especially China and North America markets. Therefore, this automotive plant presents a highly positive impact on the Portuguese economy, especially concerning exports.

Aiming to synthesize the research work done during the entire doctoral programme, following (Figure 2) it is presented and described the main stages of the research project life cycle.

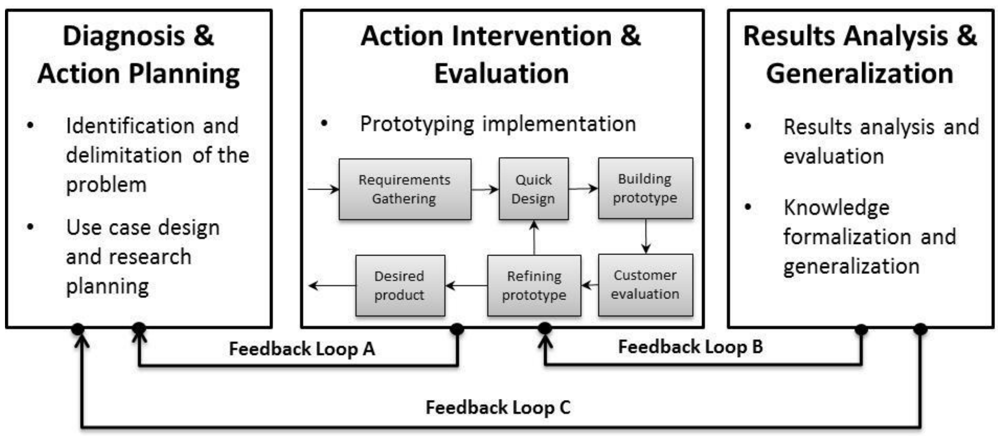

Figure 2 - Action Research Diagram

Diagnose & Action Planning – Initially, the problem to be considered was identified and bounded. Due to the fact that the issue here explored is very broad and requires a multi-disciplinary approach, during this initial stage it was critical to find an industrial partner, holder of a complex manufacturing system, that not only recognized the importance of the issue explored in this research project, but was also receptive enough to enhance their internal processes by implementing the solutions here developed. As previously explained, guarantee high levels of collaboration and participation of all actors involved in the research is fundamental for a successful implementation of an action research strategy, since this is an approach that requires for participants to play an active part in the entire research process, from its design until its validation and implementation.

Therefore, envisioning the successful research development, well-defined groups of work were established with people belonging to three main departments of this automotive plant: the Industrial Engineering and Lean Management department, the Painting area and Body area. During the entire research project, each intervention performed within the industrial partner facility was strictly focused on a specific group of work, aiming to avoid conflicts of visions and interests that could increase the level of complexity of this project, and consequently affect the project's results. Indeed, at a first stage, the main objective was to collect, in a separated way, the different perspectives and realities of each group, being the responsibility of the researcher to analyse, filter and merge all of them. It is important to underline that during this initial stage of the research project it was vital to obtain practitioners trust, reaching a consensus on the rules and terms about how data could be extracted, used and published.

Therefore, during this action planning stage, in-depth interviews were carried out with departments' managers in order to successfully capture the stakeholders' vision about the issue and the solution to be developed. On the other hand, operational and tactical data were also gathered via focus group meetings with the technicians responsible for the manufacturing system maintenance and operation, selected according to their level of expertise and knowledge about the system behaviour. Moreover, informal meetings with unstructured interviews with administrative staff were performed aiming to better understand the auxiliary processes normally performed by these actors as well as the IT solutions used.

Another tool used to collect information from the industrial case were the practice meetings, including guided visits through the different manufacturing system's areas, performed during the entire research project, backed up by field notes and research dairies. Moreover, reviews of relevant documentation – such as annual reports, excel files, strategy maps, and others – also provided important data input for the research development. In addition, due to the level of trust and transparency created between researcher and practitioners, it was possible to have access to critical data sources, available along the plant, in order to collect historical data about the system's performance. The variables selected to be collected, from these data sources, were identified according to the interviews and fieldwork previously described

Due to the complexity and size of this research project, simultaneously to the data collection process (field notes, interview transcripts, reflective diaries, and documents) this information was continuously analysed using a simplified comparative approach. This way, it was possible to identify emerging themes, from practitioners' discussions, which were explored and interpreted in an interactive way with the project participants and were then triangulated between the different groups of work. Due to this exhaustive research work, it was possible to combine both scientific and industrial perspectives, envisioning the enhancement and enrichment of the final solution.

Identified the problem and bounded the use cases to be explored, following it was deployed the process of creating and formalizing a robust and reliable mental model of the industrial case, acceptable by all stakeholders involved.

Action & Evaluation – From the mental model carefully developed during the diagnosis and action planning stages, it was possible to not only define the details concerning the research execution, but also the architecture and necessary components of the framework to be implemented, aiming to overcome the gaps identified. Aiming to fulfil all the requirements proposed by the industrial partner, as well as provide the scientific universe with an innovative solution, a prototyping approach was followed.

As depicted in Figure 2, it is possible to understand that this is an iterative process where after receiving the functional requirements, desired for the final solution, a prototype of the system should be designed and developed. Following, both researchers and practitioners must perform an evaluation process, in order to understand if the solution developed is capable of answering the requirements imposed at the diagnose and planning stages. If not, a refining process should be performed aimed at enhancing the solution developed. This loop should be iteratively performed until a suitable version is achieved, both from researcher and practitioners' perspectives.

Indeed, due to its iterative approach, prototyping can be seen as an attractive solution for complicated and fuzzy systems, for which there is no trivial solution to determine the suitable functional requirements. By using this prototype approach, industrial partner's stakeholders were continually involved during the solution development, in order to provide them an "actual feel" of the system and thus enable final users to refine and better understand the expected functional requirements for the system.

Results Analysis & Generalization – Finally, an important effort of knowledge structuring and formalization was performed. In fact, this report materializes the necessity to compile all the knowledge generated, through a well-structured research project performed at a complex manufacturing environment, into an innovative theory capable to be shared within the scientific community and, be seen as a pillar and reference for future researches in the performance measurement and management areas.

Indeed, this stage of the research project gains a special importance since one of the main gaps of the action research methodology is based on its focus on a specific context and set of requirements. Therefore, aiming to overcome this bottleneck, the author not only participated in other smaller projects (i.e. satellite projects), aiming to apply the theory developed within other contexts and scopes, but also submitted several scientific publications within national and international conferences and journals, aiming to continuously validate the research work done with the scientific community.

1.5. Document Structure

In sum, the document here presented is structured in six main chapters, and it was designed in order to provide readers not only with a clear view about the current state-of-art, concerning performance measurement and management disciplines as well as complex manufacturing systems management and control, but also present the proactive performance management concept and framework developed.

After presenting the scope and relevance of the research project here presented, as well as the research strategy used, chapter two is dedicated to the state of the art. Indeed, this chapter should then be seen as the driver of the entire research project, since this is the moment where gaps, challenges and researches performed until now, as well as respective scientific contributions, will be presented.

Thus, this chapter is divided in five main sections. While section one is dedicated to the analysis of the complexity concept for manufacturing systems, being explored different theories and perspectives, on the other hand, section two details the system dynamics approach, as this is the method selected to be used in this research project in order to model and materialize the level of complexity of current manufacturing systems. Following, it is presented the importance of reliable performance information gathering and analysis for complex manufacturing systems control. In this scope, important characteristics of a suitable performance measurement system will be enumerated. Finally, a special attention will be provided to the predictive relevance for a proactive management approach implementation. In line with this, a predictive control approach called Model Predictive Control (MPC), for industrial processes, will be explored. Although the fact that MPC has been applied as an advanced method of industrial processes control, its fundamentals and premises are strictly aligned with the vision that supports the predictive performance management solution presented in following chapters.

After understanding the state of the art that supports this research project, chapter three specifies in detail the proactive performance management approach here proposed. Therefore, not only the main concepts and foundations used as pillars of this innovative concept will be presented, but also the main vision that supports the entire research development will be depicted.

Chapter four is mainly related with the necessity to design and develop a proactive performance management framework, in order to materialize the concept presented in the previous chapter. Thus, after presenting the main requirements to be fulfilled, as well as the architecture designed for this framework, each of its components will be deeply analysed and described. In sum, both Performance Estimation and Performance Measurement Engines will be described, as well as the Performance Thinking Methodology and the Performance Data Model.

Chapter five, on the other hand, intends to combine all the information explored in chapters three and four within a series of application cases. It is important to underline that these pilot cases are distributed along the chapter taking into account the normal evolution of this research project. Therefore, the first example is a pilot case strictly related with the application of the Performance Thinking Methodology and the Performance Estimation Engine (PEE) within a Brazilian supply chain. It is important to underline that, despite the success of this application case, this was mainly a proof of concept, where some theoretical data was used to emulate the real behaviour of the system. The second application case, on the other hand, describes the implementation of the Performance Measurement Engine within an automotive plant, envisioning the enhancement of the performance management system, both in terms of timing, quality and richness of the information retrieved. Finally, within this same industrial partner, it was implemented again the Performance Thinking Methodology and the Performance Estimation Engine (PEE). However, at this case it was performed a full implementation of the solution, within a real industrial scenario.

Finally, chapter six presents the main conclusion about the proactive performance management concept and framework developed, as well as the main contribution of this research work for industrial companies. Moreover, it will be enumerated some further work and future lines of investigation that should be performed after the finishing of this doctoral program, in order to not only enhance the research work done until now, but also guarantee the successful transfer of the knowledge, expertise and technology developed to industry.

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Chapter Two

STATE OF THE ART

Defined the scope, context and relevance of this research *project, during chapter two it will be presented the state-of-the-art related with the main topics that leveraged and supported the achievement of the research objectives defined. Therefore, at a first stage, it won't only be presented the main characteristics of a complex manufacturing system but also it will be explored the main factors responsible by hindering the system's predictability. Then, it will be enumerated and described some modelling techniques that have been used as support tools for complex manufacturing systems analysis. From this list, an important attention will be provided to the System Dynamics approach, since this is the technique selected to be the pillar of the proactive performance management framework here developed.*

Moreover, it won't only be explored the main advantages that can be obtained from a competent performance information management approach, envisioning the enhancement of complex manufacturing systems comprehension, but also it will be underlined the main functional requirements that should be considered when designing and developing a suitable performance measurement system. Finally, a special attention will be given to the estimation paradigm, due to its importance for the implementation of a successful proactive management strategy.

2.1. Manufacturing Complexity and Modelling

More and more it has been observed that in almost all market segments innovation, globalisation and increasing demanding customers are critical trends that companies are forced to follow, aiming to guarantee high levels of competitiveness. Consequently, companies not only are continuously looking for enhancing their mix of products but also to develop products with features more tailored to customers' individual needs. This relentless effort has caused a ballooning in the complexity of manufacturing systems: wider product variety, smaller production lot sizes, more tiers and different actors to co-ordinate within the manufacturing system (Randall & Ulrich, 2001).

An interesting example of this evolution can be found in the automotive industry. While in the mid-1960s the Chevrolet Impala was the bestselling car in the USA with a selling rate of 1.5 million vehicles per year, in the year of 1991 the bestselling car was the Honda Accord with a selling rate of 400.000 vehicles per year. Indeed, within this interval of time, the selling rate decreases by a factor of four despite the increase of the market size.

Consequently, manufacturing companies are becoming more and more complex not only in terms of their strategies, materialised by a business model (Smith, Binns, & Tushman, 2010), but also in how they put into action the planning and objectives defined to improve the quality of products, guarantee sustainable issues, remain at the forefront of innovation, improve yield and process efficiency and to minimise production costs. In line with this, it is possible to infer that more and more paradoxical strategies such as exploring and exploiting (Smith et al., 2010), low cost and high quality (Williamson, 2010), stability and agility (Doz & Kosonen, 2010), learning and performance (Itami & Nishino, 2010), as well as profitable and social/environmental outcomes (Thompson & MacMillan, 2010) thrive within contemporary industrial business models.

This way, manufacturing systems have developed the ability to learn and adapt to a new environment, presenting a self-organising behaviour that supports organisations so that they can dynamically update their strategies for the future. The main problem allied to this situation is that, since uncertainty represents one of the main factors responsible for the increasing of complexity within manufacturing systems, a higher level of complexity at the business layer propagates this complexity until the operational level (Koren, 2010). This fact not only increases the management complexity but also introduces incremental difficulties during the manufacturing system monitoring stage and its behavioural understanding.

Before beginning to analyse the causes of complexity as well as its consequences and methods of management, it is important to clearly define the boundaries of this concept. In fact, complexity is not only the opposite of simplicity, nor the same as complicacy. Aiming to understand complicated systems, the best approach is to divide these entities into single elements and, from the analysis and clear understanding of their linear behaviours, it is then possible to manage and control the system as a whole. As an example of this approach, it is possible to underline the strategy for designing algorithms called "divide and conquer". This top-down approach consists on dividing the problem into smaller sub-problems hoping that the solutions of the sub-problems are easier to find, and then composing the partial solutions into the solution of the original problem.

Contrariwise, complex systems are composed by single elements which have intimate connections with counterintuitive and non-linear links: as a consequence, complex systems present self-emerging and often chaotic behaviours (Forrester, 1961). Thus, understanding the functioning of each single part does not imply to understand the whole system (Perona & Miragliotta, 2004), neither to improve systems predictability. Therefore, one of the goals of control is to make the outputs behaviour more deterministic. This, however, is countered by the nature of the inputs and possible internal and external disturbances, as well as by the control and manufacturing processes themselves. The more complex these influences, the harder it is to predict the output.

When we start analysing a normal manufacturing system, it is possible to understand that complexity is strictly related with the amount of information that needs to be processed in order to keep the system under control. In a manufacturing scope, under control represents the capability to operate the system at a desired level of performance, for some measures of interest. Therefore, the "degree of difficulty" of controlling manufacturing systems can be measured in terms of the number of parameters that need to be controlled, simultaneously, to make the system predictable.

Taking into account that a manufacturing system is mainly composed by a significant number of machines, tools, logistics, information systems as well as human operators and managers, a high dimensionality approach is needed to represent such extended space of possibilities. Thus, it is easily understandable that small increases on the variety of products, and their complexity, directly generates over the manufacturing system more information that need to be managed, in order to control the chances of happening unexpected or unknown behaviours of products, processes or systems (H. A. ElMaraghy, 2006).

Aiming to understand the impact of increasing product complexity as well as uncertainty created by product variety and market fluctuations, on the entire manufacturing systems life cycles, different research projects have been conducted in order to explore complexity as a key constraint for manufacturing systems. The state of the art and the research literature about complexity can be reviewed from three main perspectives (W. ElMaraghy, ElMaraghy, Tomiyama, & Monostori, 2012):

(i) Complexity of engineering design and the product development process;
(ii) Complexity of manufacturing processes and systems;
(iii) Complexity of the global supply chain and managing the entire business.

For each of the different perspectives enumerated before, it is possible to identify a series of factors responsible for the enhancement of the level of complexity typical from a certain manufacturing system. Figure 3 shows how these perspectives interact with each other and also itemizes, for each of them, the factors responsible for the increase of complexity. Some of the factors here presented, will be analysed in detail during this chapter due to its impact on the overall system complexity.

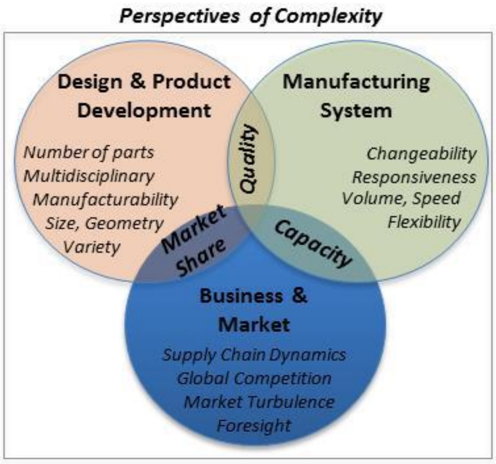

Figure 3 - Complexity of the design, manufacturing and business (W. ElMaraghy et al., 2012)

If it is true that each of these perspectives present its own boundaries, more and more it is being recognized the necessity to integrate them not only during the planning stage of a new manufacturing system but also during its entire life cycle (Westkämper et al., 2006). To this approach, Engelbert Westkämper called Unified and Sustainable Life Cycle Management, where it is represented, in a simplified view, the complexity of manufacturing engineering as a whole (Figure 4). More information about this approach will be explored in following chapter.

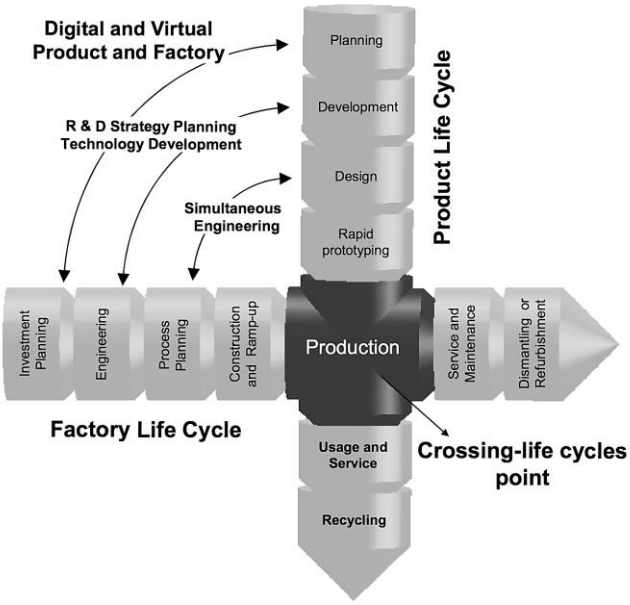

Figure 4 - The harmonization of Product and Factory Life Cycle (Pedrazzoli et al., 2007)

Presently, there are several definitions of complexity. Some authors propose that manufacturing complexity is a system characteristic that integrates several key dimensions of the manufacturing environment including *size*, *variety*, *concurrency*, *objectives*, *information*, *variability*, *uncertainty*, *control*, *cost* and *value* (Hon, 2005). Others understand the necessity to structure this information. For instance, Rok Vrabic (2012) states that manufacturing companies must deal with two kinds of complexity, strictly related with the structure and operational perspectives of an organisation. While the formed one is linked with the organization of departments, shop floors, and supply chains, on the other hand the operational perspective is more connected with the temporal aspects of coordination and control.

On the other hand, Suh (2005) states that dependent upon the domain complexity can be divided into two types, namely the functional and the physical domains. In the functional domain, complexity is defined as a measure of uncertainty in achieving the functional requirements defined (Suh, 2005). This type of complexity is close to the manufacturing systems design and can be further divided into time independent and time dependent (Figure 5), in order to assess if complexity can change over time. Time-independent complexity is the result of not satisfying the functional requirements of a system at all times, including the uncertainty that arises because of the designer lacking in knowledge or understanding of the system and its components. Time-dependent complexity, on the other hand, may be either combinatorial, increasing as a function of time, due to the continuous expansion of possible combinations of states with time, or periodic complexity, which exists in a finite time period, with a limited number of possible combinations of states.

- **Time-independent real complexity**: Measure of uncertainty when the probability of achieving the functional requirements is less than 1.0;
- **Time-independent imaginary complexity**: Uncertainty that arises because of the designer's lack of knowledge and understanding of a specific design itself;
- **Time-dependent combinatorial complexity**: Complexity that arises because future events cannot be predicted a priori;
- **Time-dependent periodic complexity**: Complexity that arises due to the periodicity of a system.

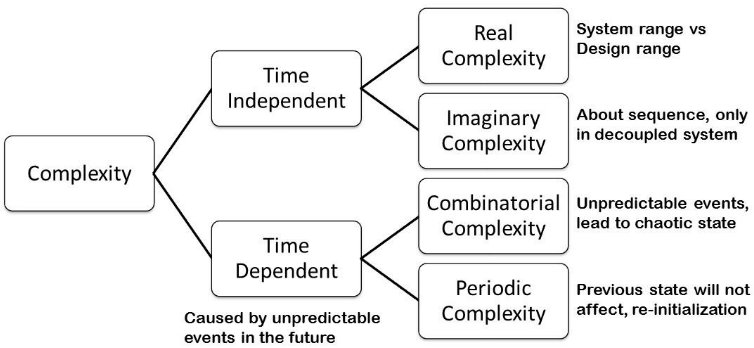

Figure 5 – Classification of Manufacturing Complexity in Functional Domain (W. ElMaraghy et al., 2012)

In the physical domain, manufacturing complexity is also further classified into two types (Deshmukh, Talavage, & Barash, 1998):

Static Complexity, also termed as structural due to its objective of describing the state of an engineered system, is concerned with the system's structure and configuration, the number and the variety of the products, the system's variety of components (e.g. labours, machines, buffers, transportation mechanisms), as well as their interconnections and interdependencies.

Dynamic complexity is related to the uncertainty of the system's behaviour for a specific time period and deals with the probability of the system to be in control. In opposition to the static complexity, the dynamic complexity of a manufacturing system is time-dependent and relates to its real-time operation, material flow patterns, modules reliability and failures. Other factors related to the system operational aspects over a time period including deviation from the norm/steady-state, uncertainty of events, unpredictable behaviour and adaptive responses also influence the system dynamic complexity (Kuzgunkaya & ElMaraghy, 2006). The drivers of dynamic complexity may be internal (e.g., machines reliability, breakdown and maintenance and scheduling policies) or external (e.g., suppliers reliability causing variation in the quantity and timing of materials and tools). This classification of complexity in the physical domain is illustrated in Figure 6.

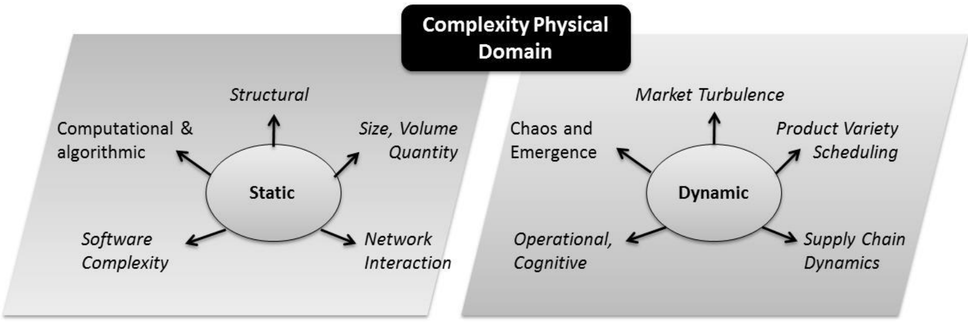

Figure 6 - Classification of engineering design and manufacturing complexity in the physical domain (W. ElMaraghy et al., 2012)

Complex Systems Modelling

By definition, a modelling of a system should be developed in order to imitate the normal behaviour of this system and thus enable the study or simulation of its behaviour, even before creating or implementing some changes within the real system. In other words, the value of a model arises from its ability to improve understanding of obscure behaviour characteristic from the system (Deshmukh, 1993). Once the problem has been identified, model development involves many stages, such as choosing a particular type of representation that is consistent with the issues being investigated, making assumptions on what information is available, understanding which information should be aggregated and which should be excluded. Of course, due to the complexity allied to the manufacturing system, it is not possible to select the ideal modelling paradigm for each type of problem, since each modelling technique has its own advantages and drawbacks. Therefore, the objective should be optimizing the combination between a specific problem and modelling technique (Morrison, 1991).

It is important to underline that, irrespective of the modelling methodology chosen, results of all abstract models are expressed and evaluated in terms of system parameters and variables. Performance measures are functions of these two sets of quantities. Hence, in order to represent and control a system efficiently using models, it is essential to identify these quantities very carefully. In manufacturing context, deciding which quantities fall in these two categories is a difficult task, since it involves identifying boundaries of the modelling paradigm, which are not precisely defined.

Several models, dealing with different aspects and specifications from manufacturing, following specific strategies and characteristics of modelling principle used, have been developed. In line with this, Figure 7 presents a diagram built by Deshmukh (1993) where it is presented, in a structured way, the different types and characteristics of manufacturing systems models.

In this schema, abstract models are firstly defined in terms of analytical and simulation models. While analytical models represent a formal mathematical description of the systems that must be subject to rigorous testing using well-known mathematical principles, on the other hand simulation models are based on the logical description of the system. Within both these classes, models could be descriptive or evaluative, which means they can be used to estimate the performance of a system for a selected set of parameters, or the models could be prescriptive or generative, which implies that they suggest the best set of parameters for a system based on certain operating constraints. Further grouping is based on the nature of variables and their interrelation, for example, deterministic and stochastic, or linear and nonlinear, or static and dynamic. Following, it is presented a brief description of some of the modelling methods shown in Figure 7.

Aggregate Capacity Allocation Models: this is a modelling technique used in making rough-cut planning decisions. These models give estimates based on the deterministic evaluation of capacity of a system as a whole. Due to their inherent simplicity, this type of models are normally used in material requirement planning (MRP) systems or capacity requirements planning (CRP).

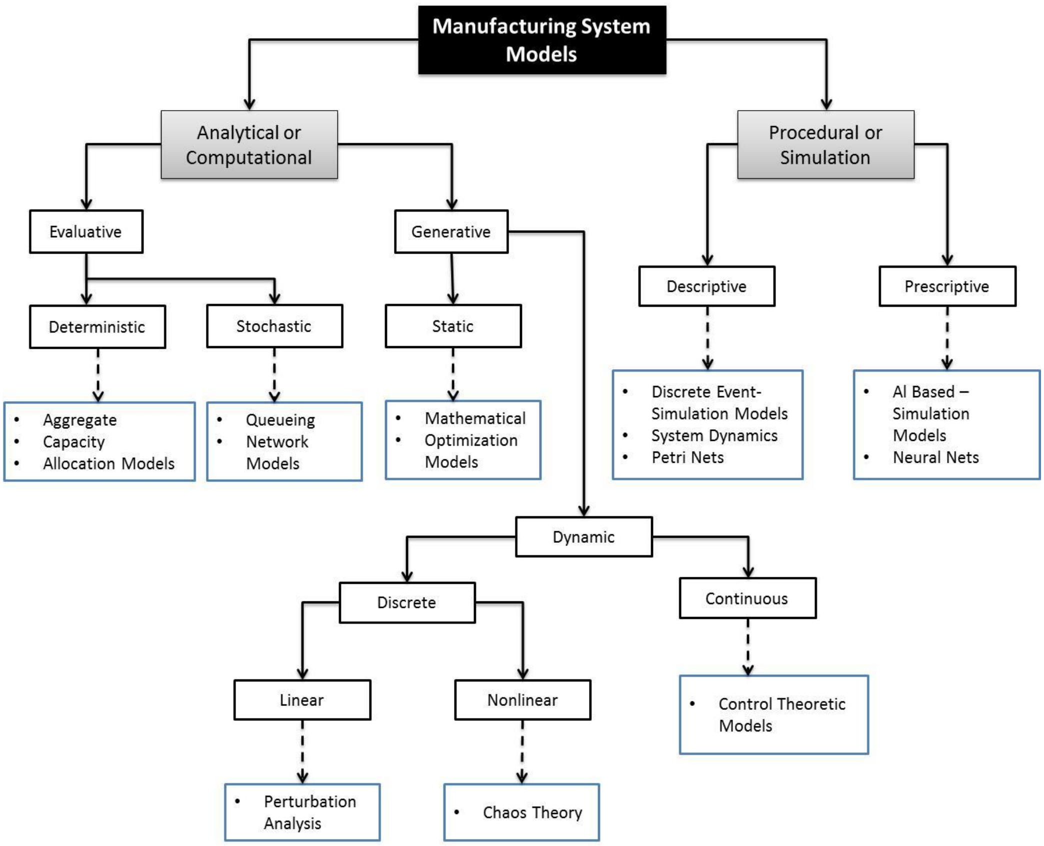

Figure 7 - Classification of Manufacturing Models on the characteristics of modelling techniques (Deshmukh, 1993)

Queuing Network Models: this is maybe one the most used types of analytical modelling to study behaviour of contemporary manufacturing systems. Queueing network models support decision making in the design and capacity planning of these systems. The manufacturing network consists of interconnected individual queueing systems, with users moving among them to receive service. While these users can be jobs, items, product parts or assemblies, on the other hand the nodes of the network are shops, machines or workstations and the network arcs connecting the nodes define the product routings in the stations (Negri da Silva & Morabito, 2009). In line with this, queue analysis is capable of determining production rates, average queue lengths, and utilization of machines. Most queueing models estimate steady state performance of the system.

Mathematical Programming Models: mathematical models have been used to solve many traditional production planning and scheduling problems. These models generate optimal values for decision variables based on certain objective function and constraints. These models are best suited for low variability environments, since they fail to capture the dynamic nature of manufacturing systems, for example the often observed phenomenon of queuing or blocking cannot be explicitly modelled (Deshmukh, 1993).

Perturbation Analysis: the Perturbation Analysis method was defined as a technique for the performance evaluation of discrete event systems through information obtained in a single simulation run (Ho & Cao, 1991). Indeed, from this approach decision makers can very efficiently, and not intrusively, extract sensitivities of various performance metrics with respect to at least certain types of design or control parameters (Turki, Hennequin, & Sauer, 2013). In other words, this modelling approach is normally used for estimating the gradient of performance measures of discrete event dynamical systems with respect to its parameters.

The basic idea behind this technique is simple, since it tries to infer knowledge about average performance measure, $\Upsilon(\theta + \Delta\theta, \xi)$, by observing $x(t; \theta, \xi)$, where $\Upsilon(\theta + \Delta\theta, \xi)$ is the performance of the system when the parameter under consideration has values $\theta + \Delta\theta$, $x(t; \theta, \xi)$ is time history of the system when parameter value is θ, and ξ is a set of random variables affecting the system. In order to use this technique, the dynamical system under consideration has to satisfy conditions of unbiasedness and consistency (Ho & Cao, 1991). However, due to the limitation imposed by current performance measurement systems, it is possible to state that many manufacturing performance measures shows discontinuous behaviour and hence will not satisfy these conditions globally (Deshmukh, 1993). Also, as $\Delta\theta$ increases, information that can be gathered about $\Upsilon(\theta + \Delta\theta, \xi)$ from $x(t; \theta, \xi)$ reduces, and hence one can only predict behaviour in small ranges, and this gradient is assumed to be linear at that range. In spite of the limitation presented, this modelling technique is still a very interesting approach for analysing discrete dynamical systems.

Control Theoretic Models: control theory has been a useful framework for theoretical development in many fields. According to this theory, a feedback loop should be considered as a fundamental building block of action. In its simple form, the feedback loop consists of four elements: a referent standard or goal, a sensor or input function, a comparator and an effector or output function (Klein, 1989). As depicted in Figure 8, when the sensor sends the signal to the comparator, this will test the received signal against the standard. In case that this comparison reveals a discrepancy, an error signal is generated and the system takes some action through the effector in order to minimize this discrepancy.

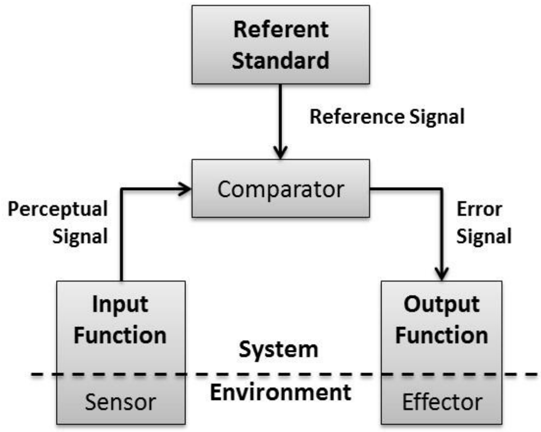

Figure 8 - The Simple Feedback Loop Schema (Klein, 1989)

Although in manufacturing systems management feedback involves much more that physical variables, goals are not predetermined in flexible standards and there are a series of alternatives to minimize discrepancies. The fact is that, in many ways, an automated manufacturing system appears to embody the key concepts of classical control theory. For instance, it can be viewed as multiple-input/output closed loop system, with raw materials, energy and resources as inputs, and the finished products as outputs of the system.

The primary objective of these models is to devise a strategy that will direct the system behaviour along a desired trajectory in time. Shop floor control strategy corresponds to the transfer function of the controller. However, within complex and large manufacturing systems it is not trivial to build this layer of control. Therefore, Howard Klein proposes that hierarchies of feedback loops may be seen as a strong strategy, capable of explaining complex behaviours in manufacturing system environments (Klein, 1989). In such hierarchy, the means of reduction of discrepancies in higher order feedback loops become the standards of lower order loops. In other words, the output function of a certain feedback loop might consist on a string to another loop, and each of those, in turn, might contain other strings of loops, and so on.

Nevertheless, even when it is possible to model the manufacturing system, then another problem can arise, mainly linked with the difficulty to represent the top-level production characteristics and control strategies as differential or finite-difference equations. This issue, aligned with the fact that manufacturing systems are, by nature, discrete event driven, contributes to the exploitation of a hybrid control methodology, capable of unifying formal control theory and knowledge-based engineering aiming to overcome some of the above mentioned shortcomings (Deshmukh, 1993).

Simulation Models: due to the aforementioned limitation of analytical modelling techniques, simulation has been a dominant modelling and decision-making tool for manufacturing systems. As already stated, manufacturing systems are discrete dynamical stochastic systems, and since simulation is capable of dealing with such systems, it has been widely accepted. Simulation can be distinguished from analysis as it generates historical data as determined by the operative procedures of the real system that the simulation model is trying to mimic. Evaluation by simulation provides a step-by-step description of a system as it evolves through various states. This approach allows for the construction of fairly complex and realistic models. Continuous simulation languages have been developed (Forrester, 1961), however discrete event simulators are most commonly used for manufacturing applications (Castilla, Garcia, Aguilar, 2009). Petri nets (Aalst, 1998) and neural network based approaches have also been developed for simulating systems.

Unlike analytical models, simulations models are not limited to tractable formulation, but by the available computational resources, time needed for constructions and verification of detailed models, and the cost involved in data preparation and model generation. But simulation models do not define the underlying physical relationships between interacting components in the system. They are based on empirical or observed functioning of each component. Thus simulation models rarely provide the kind of insight into the system behaviour that is provided by analytical models, since simulation models are primarily descriptive "what-if" situations and it is practically impossible to theorize any general system behaviour based on these results. Hence, the quality and consistence of decisions taken on these models depend heavily on the decision maker's personal expertise. Attempts have been made to develop generative/prescriptive simulation models using artificial intelligence tools. (Deshmukh, 1993).

System Dynamics: Aiming to provide an important contribution in the scope of the industrial dynamics, Jay Forrester, at the MIT Institute, developed a systems dynamics approach as a solution to support decision makers to enhance their knowledge about varying (or dynamic), non-linear, closed boundary systems behaviours and converting real-life situations into enhanced simulation models (Almeida & Azevedo, 2013). His insight was that the processes of organizations could be modelled using engineering systems techniques, such as those used for control systems, capable to represent the flow of information through a system, based on their internal policies (Middleton, 2005).

In its initial application, the system dynamics methodology was used to study the behaviour of industrial systems where the short-term dynamics of production rates and inventory levels could be analysed (Forrester, 1961). Nevertheless, during the past forty years system dynamics models have been used in order to solve problems in many diverse disciplines including sociology, economics, and engineering since the strength of system dynamics modelling is that it allows system policies and laws to be evaluated by studying the structure of the system through a series of causal relationships.

The fundamental premise of system dynamics is that system behaviour is a consequence of factors endogenous to the system structure (Richardson and Pugh, 1981). This premise is based on the belief that decision–makers should focus on systemic problems within their purview. If the problem is not within their purview, then they should not expend energy trying to control the problem, as it is uncontrollable from their perspective. Thus, the main paradigm imposed by this approach is based on the idea that each system's structure relies on a series of cause and effect relationships that determine the underlying flows within a system. If well managed, these flows can then be used to bring the system elements together in a holistic manner instead of treating each element independently (Roberts, 1978). Consequently, from the interaction between these variables, it is not only possible to represent the synergies within the system, but also understand how the manufacturing system will behave in the future, based on a series of leading factors that can be measured from the operational level, captured from the strategic level or estimated based on the external environment analysis (e.g. market, economic, social analysis) (Sterman, 2000).

While system dynamics modelling is a powerful tool for predicting and evaluating systems, as well as to select the "right" system structure and policies, it falls short of optimizing the system. To optimize the system, an optimization heuristic must be added to the system dynamics framework. By including optimization within system dynamics, it is possible not only to have the power to evaluate system behaviour, but also to select policies that will ensure that the system is operating at its optimum. Therefore, the idea of combining performance management with system dynamics is almost natural, since their main concepts are strictly together. For instance, while performance management intends to improve the systems performance based on feedback analysis, on the other hand the system dynamics support decision makers to understand and fully explore the existing feedback connections.

2.2. System Dynamics

Roberts (1978), founding member of the MIT System Dynamics Group under the supervision and direction of Professor Jay Forrester, defined system dynamics approach as following presented:

> *"The system dynamics philosophy rests on a belief that the behavior (or time history) of an organization is principally caused by the organization's structure. The structure includes the physical aspects of plant and production process but, more importantly, the policies and traditions, both tangible and intangible, which dominate decision-making in the organization. Such a structural framework contains sources of amplification, time lags, and information feedback similar to those found in complex engineering systems. Engineering and management systems containing these characteristics display complicated response patterns to relatively simple system or input changes. The subtleties and complexities in the management area make these problems even more severe. Here the structural orientation of system dynamics provides a beginning for replacing confusion with order."*

Indeed, the system dynamics modelling approach is a powerful tool capable to represent the flow of information through a system based on the policies that govern them. Typically, system dynamics models have two attributes in common: (1) they involve quantities that change over time; and (2) the systems have control or feedback loops. Thus, the main paradigm behind system dynamics approach is based on the necessity to study the system's feedback structures in parallel with the decisions taken at a certain moment in time, since this combination always influences or affects actions taken in subsequent time periods. However, these effects may be readily apparent for a system with a short (with respect to time and space) feedback structure, or may be manifested with a long time delay for a system with many elements in the control loop.

In order to drill-down a system's behaviour, these feedback structures can be broken down into a hierarchy of feedback elements called variables, linkage, feedback loop, and feedback system. In terms of variables, these can be defined as a quantity that changes over time. Typical variables found in a system dynamics model include levels, rates, and auxiliaries. The rate variables flow from one area of the system to another and control the changes to the stocks. In other words, rate variables model the system's policies imposed by endogenous and exogenous factors, in order to represent the system dynamics as reliable as possible. While endogenous variables can be easily managed since they are strictly connected with the decision taken by the different stakeholders of the process in analysis, on the other hand, exogenous factors cannot be controlled due to the fact that they are mainly linked with the external environment that surround the system and, directly or indirectly, affects the normal behaviour of the system.

A rate equation recognizes the goal towards which the system strives, compares the goal to the current system condition (level variables) and makes adjustments to correct the discrepancy (Forrester, 1961; 1968). The relationship expressed in equation 2.1 is the mathematical statement for a rate variable:

$$Rate(t) = f(levels(t), auxillaries(t), data(t), constants) \qquad \text{Eq.2.1}$$

where f is an arbitrary, non-linear, time varying, vector function.

Levels (also known as stocks, state variables, or integrations) are the accumulations of inflows and outflows within a system, describing the state of the system over time. Examples of these accumulations include inventory levels, number of employees, and bank balances (Forrester, 1961; 1968; Richardson & Pugh, 1981). Since the variable level aims at integrating the results of actions (rates) within a system, then these variables cannot be changed instantaneously, being dependent on the system nature.

As previously stated, levels should be represented by an integral equation, as depicted in equation 2.2 (Sterman, 2000):

$$Level(t) = Level(t_0) + \int_{t_0}^{t} (Inflow - Outflow)dt \qquad \text{Eq.2.2}$$

where $Inflow$ represents the value of the quantity that has flowed into the level; $Outflow$ represents the value of the quantity that has flowed out of the level and $Level(t_0)$ is the initial value of the levels, and is governed by the relationship:

$$Level(t_0) = f(levels(t_0), auxillaries(t_0), data(t_0), constants) \qquad \text{Eq.2.3}$$

Also, equation 2.2 represents the accumulation of level variables within a system. Equivalently, levels can be described by their net rate of change. This relationship can be defined by the differential equation (Sterman, 2000):

$$\frac{d}{dt} level = Inflow(t) - Outflow(t) \qquad \text{Eq.2.4}$$

A rule of thumb is helpful to distinguish between level and rate variables. Since the rates are action variables and the levels are accumulations of past actions, rate variables become zero when action in the system stops, and levels would continue to exist at their current accumulation (Forrester, 1968).

After analysing the importance of rate and level variables within a system dynamics models, it is now important to explore the others elements of this modelling approach. If it is true that any feedback loop can adequately be represented by a series of rates and levels (Forrester, 1968), it has been proved that auxiliary equations should be used to enhance the information in the feedback loop. By definition, these variables should be seen as "a computation representing information in a feedback system" (Richardson & Pugh, 1981) that can be used to support in the formulation of rate equation and to assist with system decisions.

On the other hand, a linkage represents a cause-and-effect relationship between two variables (Roberts, 1978). This element of the system dynamics approach aims to establish a positive or negative relationship between the causal variable and the effect variable. As an example, Figure 9 shows a positive and negative linkage, represented by an arrow linking the cause and effect variables.

A plus sign indicates that there is a direct variation between the two variables (i.e. both variables tend to move in the same direction). A negative sign indicates that the variables have an inverse relationship (i.e. the variables move in different directions) (Richardson & Pugh, 1981).

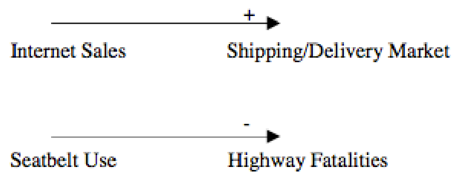

Figure 9 - Positive and Negative Linkage in System Dynamics

Going up in the system dynamics hierarchical model, it is possible to identify a feedback loop (also known as causal loop diagrams, or directed graphs) as a grouping of two or more linkages, which are properly connected so that one can begin with any variable, and follow the loop through the diagram and back to the original variable.

In fact, feedback loops form the basic structures of system dynamics problems, being the pillars of every decision or actions occurring within the system. Similarly to individual linkages, feedback loops can be categorized as being positive or negative. As a rule of thumb, a feedback loop is positive if it contains an even number of negative linkages and, a feedback loop is negative if it contains an odd number of negative linkages (Richardson & Pugh, 1981).

To see this concept mathematically, consider the feedback loop on the left side of Figure 10 (Sterman, 2000). To determine its polarity, the loop should be broken at any point, as depicted on the right hand side of Figure 10. Now that an open loop exists, the mathematical concepts from control theory can be applied to determine its polarity.

Equation 2.5 shows that the polarity of the open loop is determined by a series of partial derivatives.

$$polarity\ of\ loop = \partial x_1(e)/\partial x_1(b) \qquad \text{Eq.2.5}$$

where:

$$\frac{\partial x1(e)}{\partial x1(b)} = \left[\left(\frac{\partial x1(e)}{\partial x4}\right)\left(\frac{\partial x4}{\partial x3}\right)\left(\frac{\partial x3}{\partial x2}\right)\left(\frac{\partial x2}{\partial x1(b)}\right)\right] \qquad \text{Eq.2.6}$$

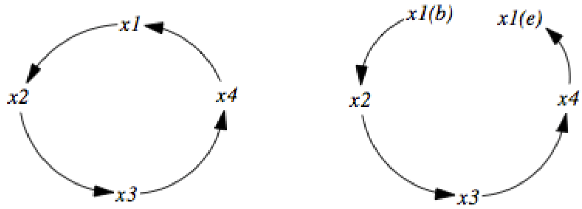

Figure 10 - Polarity Analysis in a Feedback Loop (Sterman, 2000)

Since the polarity of the loop is a product of all of the partial derivatives of that loop, it can easily be seen from equation 2.6 that an even number of negative signs would result in a positive loop polarity, and an odd number would result in a negative loop polarity.

By definition, positive feedback loops are known as self-reinforcing feedback loops which, if not controlled, can eventually lead to self-destruction. For instance, in Figure 11 Sterman[5] (2000) shows how automobile emissions contribute to greenhouse gases and eventually lead to coastal devastation. If closed conditions can be assumed, and this system is undisturbed, coastal devastation will increase to a point where property losses will devastate the economies of many seashore municipalities. One intervention to stop the self-reinforcing cycle is to develop programs that would reduce the greenhouse gases. In the scope of the system dynamics approach, this means to explore a negative feedback capable of opposing to the self-reinforcement behaviour of the system.

These negative feedback loops, also known as self-balancing feedback loops, tend to stabilize the system. For example the thermostat in a home is a self-reinforcing feedback system. When the room temperature drops to the desired setting, the thermostat sends a signal to the furnace to turn on. After the furnace heats the room to the desired temperature, the thermostat sends a signal to cease heating.

[5] John David Sterman, director of the MIT System Dynamics group at the MIT Sloan School of Management is mostly considered as the current leader of the System Dynamics school of thought. He is author of "*Business Dynamics: Systems Thinking and Modeling for a Complex World*". Professor Sterman has twice been awarded the Jay Forrester Prize for the best published work in system dynamics and was names one of the MIT Sloan School's "Outstanding Faculty" by the Business Week Guide to the Best Business Schools.

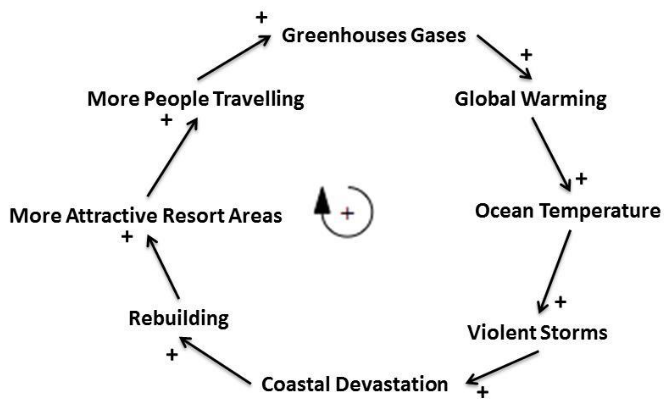

Figure 11 - Self-Reinforcement loop (Sterman, 2000)

Finally, with the purpose of illustrating how rate, level and auxiliary variables interact together within a feedback loop, please consider Figure 12. As it is possible to see, the rate variable uses the rules established by the policy to determine the flow within the system. Based on this variable, the integration is performed to determine the value of the level variable. In parallel, an auxiliary variable compares the level variable to the desired value, defined by a constant variable, and sends the discrepancy to the rate variable. The rate variable uses this information to determine the flow for the next system iteration.

In sum, it is possible to state that typical organizational and industrial problems are generally described by a feedback system, composed by a series of two or more feedback loops. Since system dynamics models derive the most information from areas where multiple feedback loops converge, this can be seen as an optimal approach if it is expected to manage and control a complex manufacturing system, where different factors impose their own synergies within the system. Following, are presented patterns of behaviour normally observed in manufacturing systems, using the system dynamics approach as reference model.

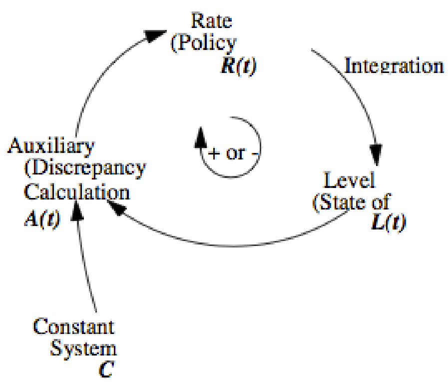

Figure 12 - System Dynamics Feedback System (Sterman, 2000)

As previously stated, system dynamics can be used to not only model the manufacturing system behaviour, but also to better understand the synergies within a complex manufacturing environment. According to this modelling approach, a system behaviour can be categorized by eight distinct behaviour patterns: *static equilibrium*, *exponential* *growth, goal seeking, exponential decay, oscillation, S-shaped growth, S-shaped growth with o*vershoot, and overshoot and collapse (Sterman, 2000).

Static Equilibrium Behaviour: The most basic system behaviour is equilibrium. When a system is in equilibrium, the net rate of change of the system is equal to zero. This can be achieved in two ways: First, static equilibrium is defined when there is no flow of inputs x_t affecting the outputs y_t from the system at time period t. Second, when a system has achieved a state of dynamic equilibrium, the net flow of inputs equals the net flow of outputs. In this case, although the state of the system is unchanged, the system is not in an idle mode.

Exponential Growth Behaviour: A system presents exponential growth (Figure 13) the larger the state of the system, the larger the system´s growth, leading to an even larger system state (Sterman, 2000). This behaviour is governed by a single positive (or self-reinforcing) feedback loop. Therefore the growth of the system remains unchecked such that $\lim_{t\to\infty} y_t = \infty$, where y_t is the system output at time t.

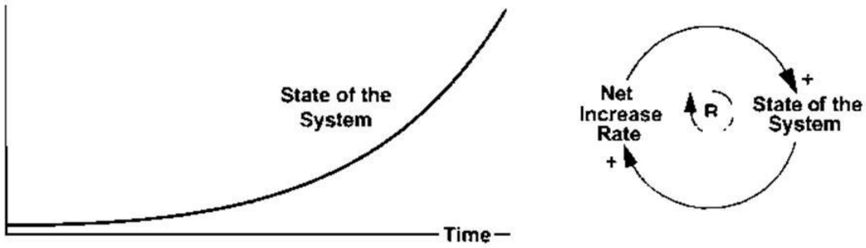

Figure 13 - Exponential Growth Structure and Behaviour (Sterman, 2000)

Goal seeking Behaviour: Goal seeking behaviour strives to bring the state of the system in line with its goal. This is accomplished by a single negative (or goal seeking) feedback loop, which counteracts any disturbance that moves the system away from its desired goal (Figure 14). As the system approaches its desired goal $\hat{L}$, the inputs x_{t-d} are transformed into outputs such that $\lim_{t\to\infty} y_t = \hat{y}$, where $\hat{y}$ is the system requirement. In most cases, the system's desired goal $\hat{L}$ is equal to the system's requirement $\hat{y}$.

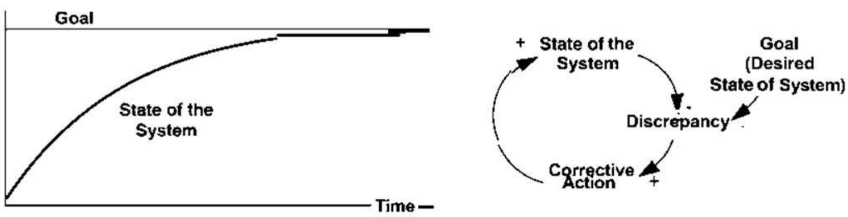

Figure 14 - Goal Seeking Structure and Behaviour (Sterman, 2000)

Exponential Decay Behaviour: A special single negative feedback structure is the source of the exponential decay behaviour (Figure 15). Exponential decay occurs when the relationship between the net input x_{t-d} and the system discrepancy Δ is linear (Sterman, 2000). The system discrepancy is defined as the difference between the desired state and the current state of the system, $\Delta = L_t - \hat{L}$. As the discrepancy Δ decreases, so does the net inflow rate x_{t-d}. Being the discrepancy $\Delta \to 0$, and the inflow rate $x_{t-d} \to 0$, then the $\lim_{t\to\infty} y_t = 0$.

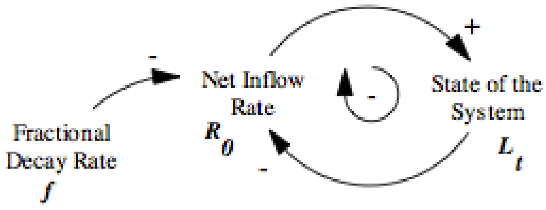

Figure 15 - Exponential Decay Structure and Behaviour (Sterman, 2000)

Oscillatory behaviour: Oscillatory behaviour is perhaps the most common behaviour found in dynamic systems. This behaviour can assume many forms, including damped oscillation, chaos or expanding oscillation. Oscillation is caused by a single negative feedback loop (Figure 16) that has a significant delay within at least one of its causal linkages. The negative feedback loop structure compares the state of the system to the goal, and makes adjustments accordingly. However, given the delay, the system continues to take corrective action even after the system achieves its goal. Thus, the system is constantly overshooting and undershooting the desired system state (Sterman, 2000).

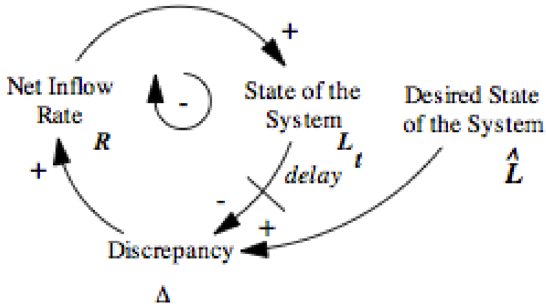

Figure 16 – Oscillator Structure and Behaviour (Sterman, 2000)

S-shaped Behaviour: The S-shaped growth behaviour presents an exponential growth at first, but then shows goal-seeking behaviour as the system approaches its equilibrium. This behaviour is governed by two feedback loops: a positive feedback loop which leads to the exponential growth behaviour; and a negative feedback loop which leads to the goal-seeking behaviour (Figure 17). For this behaviour to exist, two conditions must be satisfied: (1) the system production capacity must be fixed; and (2) the system must not contain any significant time delays (Sterman, 2000). The feedback loop that is dominant at time t, determines which behaviour the system is currently exhibiting.

To further explain the concept of S-shaped growth, assume that a system has a fixed production capacity. As the production process begins, the resources available appear to be infinite, thus exponential behaviour is experienced. As the system approaches its production capacity, system resources become scarce. As a result the system continues to increase towards the production capacity, but at a slower growth rate. Thus, goal-seeking behaviour is experienced (Sterman, 2000).

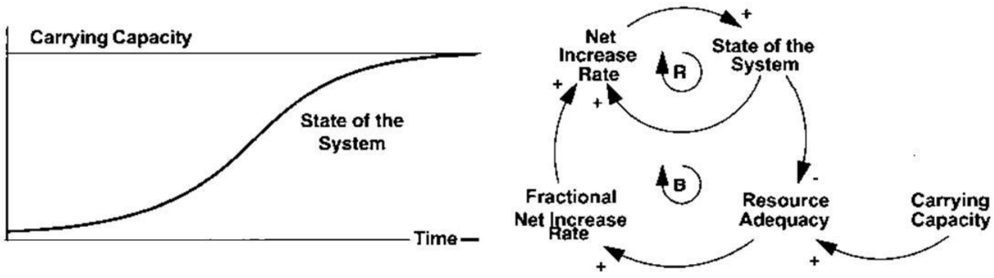

Figure 17 - S-shaped Growth Structure and Behaviour (Sterman, 2000)

S-shaped growth with Overshooting Behaviour: S-shaped growth characterizes a perfect system behaviour whose single positive and negative feedback loops are combined into a single system structure. However, real production systems are not perfect as demonstrated by the oscillatory behaviour discussion. When a negative feedback loop with a significant delay is coupled with a positive feedback loop, S-shaped growth with overshoot occurs (Figure 18).

S-shaped growth with overshoot behaviour initially behaves like exponential growth due to the dominant positive feedback structure. As the system approaches its production capacity, the system presents oscillatory behaviour around that capacity. This oscillation occurs because of the presence of significant delays embedded in the negative feedback loop. Thus, the system continues to take corrective action even after the system achieves its production capacity (Sterman, 2000).

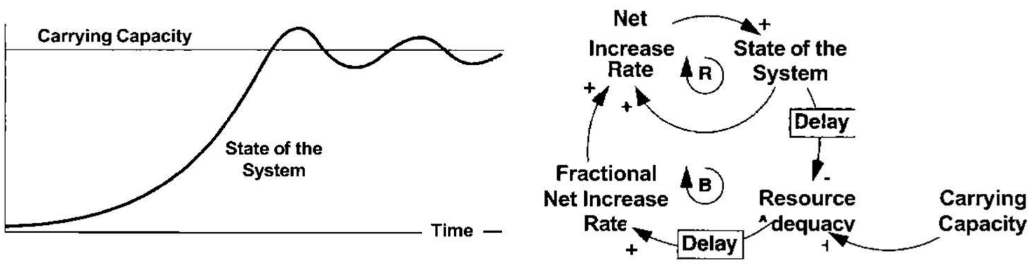

Figure 18 - S-shaped with Overshoot Structure and Behaviour (Sterman, 2000)

S-shaped growth with Overshoot and Collapse Behaviour: A structure that contains a positive feedback loop coupled with two negative feedback loops produces the S-shaped growth with overshoot and collapse behaviour (Figure 19). Unlike the S-shaped growth behaviour, the production capacity is not fixed, but is consumed as the ability of the system to support the system requirements erodes (e.g. the erosion of a non-renewable resource within the system). When the positive feedback loop is dominant, the system displays exponential growth. As the system matures, the discrepancy Δ begins to fall and the negative feedback loops gain in strength. When Δ→0, the inputs x_{t-d} are transformed into outputs such that $\lim_{t \to t_m} y_t = \hat{y}$, where $0 < t_m < \infty$, but the system does not achieve dynamic equilibrium. When $\lim_{t \to t_m} y_t = \hat{y}$, production is at its maximum, but the production capacity drops because resources are being consumed to sustain the system requirement. If the production capacity is not regenerated (e.g. a non-renewable resource), the state of the system declines until static equilibrium is achieved (i.e. $\lim_{t \to \infty} y_t = 0$) (Sterman, 2000).

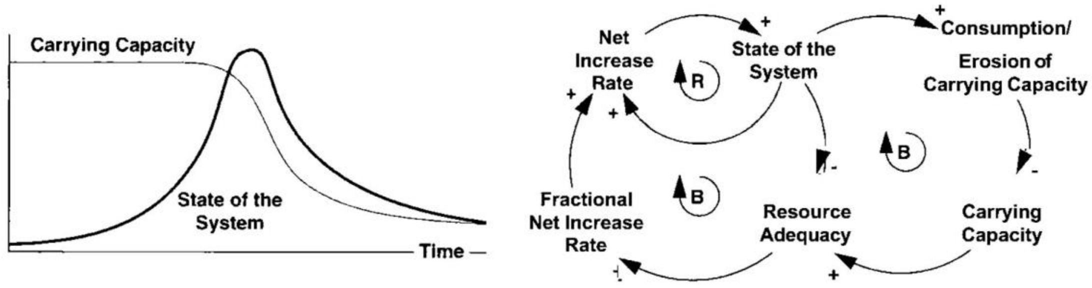

Figure 19 - S-shaped Growth with Overshoot and Collapse (Sterman, 2000)

In his book, John Sterman (2000) not only highlighted the main advantages of using system dynamics approach in the scope of complex systems, but also identified the main patterns of behaviour normally observed within the real world. Therefore, based on this research work, during this section eight distinct types of behaviours were enumerated and described, based on the system dynamic modelling approach: *static equilibrium, exponential growth, goal seeking, exponential decay, oscillation, S-shaped growth, S-shaped growth with overshoot, and overshoot and collapse.*

Indeed, if this perception is applied to the scope of manufacturing, then it is possible to extract important conclusions about how an industrial process should be managed, not only from the operational but also from the strategic perspectives. For instance, the main objective of a decision maker is to design a proper manufacturing system performing under a static equilibrium paradigm. If this stage of maturity could be achieved, then the endogenous and exogenous factors would be completely controlled, and the system behaviour would be completely predictable (Henry Ford paradigm).

However, as previously stated, industrial organizations present volatile and complex characteristics. This means that they are not only continuously affected by exogenous and unpredictable variables, but also they need to continuously define new strategic trends and objectives, as well as redefining their product and services portfolio and respective operational processes and technological solutions. That is the reason why simple behaviours, such as goal seeking behaviour, are not the nature of these world-class manufacturing firms. Since this kind of manufacturing systems are environments that are continuously subject to external disturbances, internal constraints and imposed limitation, then, more complex system's behaviours such as S-shaped growth with overshoot and collapse can be observed. Thus, it becomes critical to explore performance measurement systems capable of reducing or, if possible, anticipate the delay between the moment when an exogenous factor has occurred, or is expected to occur, and the moment that a corrective action is taken and, consequently, decrease the chances of overshooting or collapse. In sum, the main objective should be to assure that decision makers become capable to control their manufacturing systems as smooth as possible, in one hand, and decrease the systems delays effects, on the other, envisioning a more responsive behaviour for the system.

Aligned with this vision, the following section is mainly related with the necessity to explore the performance measurement and management discipline as a key driver of competitiveness.

2.3. Performance Information

Identified the main characteristics of a complex manufacturing system, as well as the main sources of complexity, in terms of static and dynamic perspectives, it is critical to understand how manufacturing complexity can be managed and the respective non-linear behaviours can be controlled in order to make these manufacturing systems more controllable and predictive (Efthymiou, Pagoropoulos, Papakostas, Mourtzis, & Chryssolouris, 2012).

In 1958, Forrester stated that management was on the verge of a major breakthrough in understanding how industrial company success depends on the interaction between the flows of information, materials, money, manpower, and capital equipment (Forrester, 1958). At his point of view, the capability to understand how these five elements interact with each other as well as understand how these variables are susceptible to external factors would be an important competitive advantage since it would form a basis for anticipating the effects of decisions, polities, organizational forms and investments choices.

However, in order to achieve this level of excellence in terms of management control depends upon what information executives use and for what they use it, as well as on their skills as administrators (Forrester, 1958). However, within complex manufacturing system this is not a simple and straightforward task to be accomplished. In fact, due to the increased intricate relationships and interrelations among the system's elements, characteristic from complex manufacturing systems, along with the stochastic and non-linear nature of the system, characterized by unpredictability, make the system management more and more complex. In line with this, its management critically dependents from the decision makers capability to model the system comportment, extract the correct information from the real system and, from the merge between model and data, build its own mind-set about present and future behaviours (McCarthy, Rakotobe-Joel, & Frizelle, 2000). Moreover, this should be seen as a continuous activity, with which decision-makers are capable to maintain their knowledge on the manufacturing system, even when the system's behaviour continually changes

Nevertheless, aiming to build and maintain the correct mathematical model, responsible by formalizing the relationships between all factor characteristics from a complex manufacturing system, is quite challenging as well as time and cost demanding. In particular, it has not yet been possible to establish relations, in a set of closed form analytical equations, which could describe the dynamic behaviour of a manufacturing system (Chryssolouris, 2006). For instance, the queuing theory, mathematical programming and optimization techniques have been used extensively, over the past years, for the purpose of modelling and analysing production systems, however, understanding and controlling complexity by conventional methods, is becoming more and more difficult.

Thus, it is becoming clear that, in order to setup the right measures and the correct analysing methods aiming to study the manufacturing complexity, it is no longer feasible to simply rely only on the existing traditional approaches. Therefore, during the last years, the complexity theory, including approaches such as the information and chaos theories, system dynamics as well as the non-linear theory have been explored aiming to provide methods that seem to be useful for the analysis of a manufacturing system's complexity (Efthymiou et al., 2012).

In the scope of these approaches, the information continuously obtained through feedback loops from the system, represents a critical advantage, being seen as a key driver for the complexity analysis of a manufacturing system. In fact, as systems become more and more sophisticated in terms of information processing, also the capability to link one form of feedback with future events will be enhanced. From this advantage, it is possible to accumulate experience about the types of feedback that compose a certain manufacturing system and, based on this knowledge, support decision makers to foresee and make decisions in a proactive way.

Currently, performance analysis in complex manufacturing systems is performed in an ad-hoc way since the main objective is to verify if the strategy designed has been helping companies achieve their targets following a reactive approach. Thus, simply calculating lagging indicators using an excel tool is normally enough to achieve this objective. However, more and more companies are performing in competitive markets forcing them to become more proactive than reactive (Almeida, Politze, Azevedo, & Caldas, 2012). This way, a simple approach as described before is no longer suitable for this type of companies and, therefore, it is essential to have an effective approach that allows them to accelerate the learning process of their complex systems (Garengo, Biazzo, & Bititci, 2005). Companies should be able to analyse their leading indicators, and to understand their meaning and the feedback loops that affect them. Only this way can decision-makers look to the future and act even before these consequences affect the systems' efficiency and effectiveness (Hoek, Harrison, & Christopher, 2001).

However, the way that data should be collected from the system is strictly linked with its complexity, since the information generated from this data must be aligned with the type of decisions that are going to be made based on this knowledge. As such, the impact of the same information will be different depending on the decision-makers who will use this information. For instance, at the strategic level, return on invest or profit are the main challenges, whereas at the shop floor level utilization of resources and idle-time must be the utmost importance (Deshmukh, 1993). In other words, the definition and prioritization of performance measures depends on the stakeholders that will use this information. Therefore, the amount and characteristics of the information needed to make good decisions is directly linked with the complexity of the system in analysis. Similarly to the complex systems theory, the performance management discipline for complex systems is not about the study of complexity. On the contrary, it means understanding the behaviour of systems that evolve, learn and adapt according to the different environment characteristics.

Since 1990s, there has been an increasing interest of research in performance measurement, mainly in issues related with the proposal of the Balanced Scorecard presented by Kaplan and Norton. However, most of such performance systems were developed from a business perspective which gives full coverage on management and financial performance (Hon, 2005). However, aiming to achieve the highest performance behaviour in the shortest time possible (performance Ramp-up), decision makers have been showing interest on the development of effective methods of measuring and evaluating the performance of their manufacturing processes.

In other words, explore dynamic approaches that allow them to focus on a small number of indicators, nevertheless taking into account multiple facets and perspectives of complex manufacturing systems (Dekkers, 2003). Following this approach, they become capable to reflect the current state of manufacturing situation, monitor and control operational efficiency, drive improvement programmes and gauge the effectiveness of manufacturing decisions. In sum, for contemporary organizations, performance measures are indispensable for management to understand the state of the manufacturing system and to take appropriate action for maintaining competitiveness as shown in Figure 20.

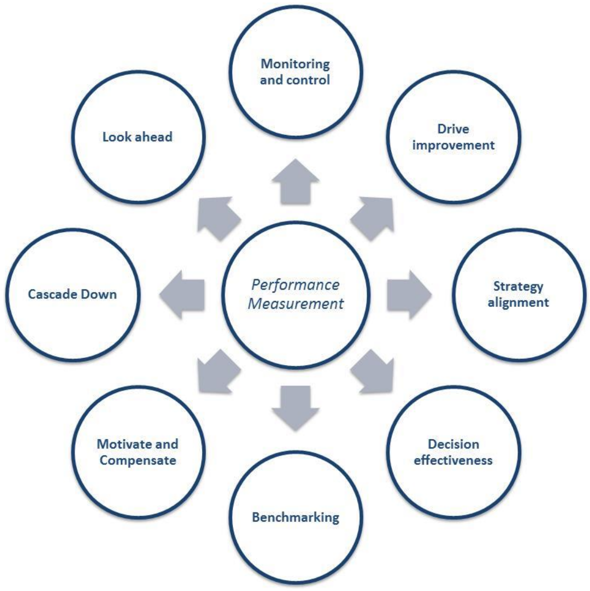

Figure 20 - Functions of Performance Measurement (Cokins, 2009)

However, more and more it has been observed that the way how performance measurement systems (PMSs) have been explored and applied within complex manufacturing systems is not suitable neither presents added-value for decision makers. In fact, if a detailed analysis is performed to current PMS implemented at not only small and medium industrial enterprises but also larger organizations, a series of bottlenecks can be found in terms of usability, adaptability and relevance, that hinder the achievement of the main objectives and purposes of a PMS. Thus, three main properties, normally despised by performance managers, can be enumerated:

- *Simplicity*: a practical measure is a simple one, with simplified data collection procedures but strongly informative.
- *Predictive ability*: the look-ahead function of a leading measure is useful to guide planning. In contrast, financial measures are lagging indicators as they purport to summarise events happened earlier in financial terms.
- *Pervasiveness*: a pervasive measure could be applied throughout the organisation in both horizontal and vertical levels. This will facilitate comparison and analysis against a highly specific single-purpose measure.

In line with this vision, and aiming to overcome these gaps of implementation, Meyer proposed that performance measures could have seven different purposes, as depicted in Figure 21. In terms of the time dimension, a measure could either look back or look forward. From the organisational perspective, a measure could be summed from the bottom to the top of the company to allow a clear visible linkage between the unit performance and the organisational performance. Likewise, it could cascade down from the centre to individual operating units. It could also be used for performance comparisons among horizontal operating units across the company to facilitate performance comparison (M. W. Meyer, 2002). Finally, from the human perspective, a measure could be used for motivational and compensation needs. In the context of manufacturing systems, all seven purposes are required from the operational and control point of view.

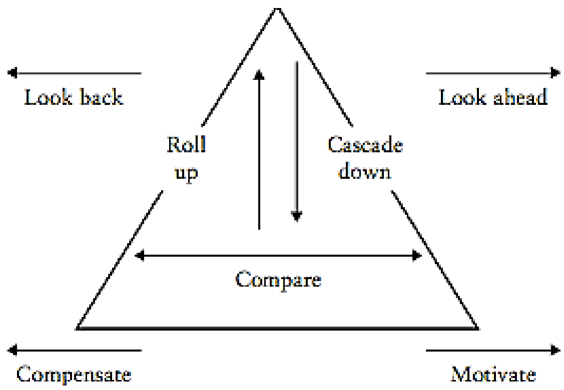

Figure 21 - The seven purposes of performance measures (M. W. Meyer, 2002)

In sum, it is possible to understand that with a successful implementation of an effective performance measurement system, it is possible to go well beyond query and reporting issues. On the other hand, the purpose of performance management is not just managing but improving performance.

2.4. Performance Measurement Systems

Several important changes that have taken place in recent years have created a favourable context for the implementation of performance measurement systems not only in large manufacturing companies but also in SMEs. For instance, the four main drivers that caught the attention from the scientific and industrial universe around the performance measurement discipline were: the evolution of the competitive environment and the propensity to grow in dimension, the evolution of the concept of quality, increased focus on continuous improvement, and significant developments in information technology. Therefore, increasing attention has been given to the study of performance measurement systems (Neely, Gregory, & Platts, 2005).

The Performance Management concept defines that in order to take the decision that will really improve the manufacturing system and support the organisation in achieving their strategic targets, it is crucial to periodically collect and assess information feedback about the real world. By using this information in a continuous way, it is possible to revise the existing understanding on the system, as well as the strategy adopted to drive the perception of the state of the system closer to reality.

Consequently, a Performance Measurement System (PMS) aims to support decision-makers by gathering, processing and analysing quantified information on performance and presenting it in a succinct format (Garengo et al., 2005; Neely et al., 2005). As depicted in Figure 22, all performance measurement systems consist of a number of individual performance measures. There are various ways in which these performance measures can be categorized, ranging from Kaplan and Norton's (1992) balanced scorecard, Bititci's Integrated Performance Measurement Systems and Lynch's Performance Pyramid Systems through to Fitzgerald et al.'s (1991) framework of results and determinants. Each of these PMS models can be categorized as vertical, balanced and horizontal (De Toni & Tonchia, 2001).

- *Vertical architectures* are defined as models that are strictly hierarchical (or strictly vertical), characterized by cost and non-cost performances on different levels of aggregation, until they ultimately become economic- financial;
- *Balanced architectures* are models where several separate perspectives (financial, internal business processes, customers, learning/growth) are considered independently;
- *Horizontal architectures* (by process) are models focused on the value chain and consider the internal relationship of customer/supplier.

However, despite the differences between PMS models, as previously described, the rationale behind a performance measurement system implementation is that performance measures need to be aligned with the strategic vision of the organization, as they define the metric used to quantify the efficiency and effectiveness of an action. On the other hand, performance measurement may be seen as the standardize process of quantification by which it is expected to stimulate actions and influence people behaviour. Indeed, as pointed out by Mintzberg (1978), it is only through consistency of action that strategies are realized. Finally, a performance measurement system should be seen as the set of metrics used to quantify, in a multi-perspective way, the performance of actions.

Based on these perspectives, it is important to highlight that when one is specifying a PMS to a certain manufacturing system, the rationale behind the methodology applied must be composed by three main stages (Figure 22) (Neely et al., 2005):

1) Analysis of the relationship between the performance measurement system and the environment within which it will operate;
2) Specification of the set of performance measures and their relationships – the performance measurement system as an entity;
3) Specification of individual performance measures.

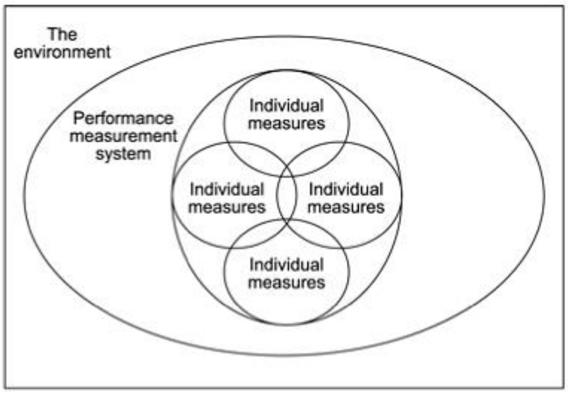

Figure 22 - A Framework for Performance Measurement System Design (Neely et al., 2005)

In order to aggregate all the information presented before and present it in a structured way, following, the main dimensions that characterize contemporary PMS models are presented (Garengo et al., 2005):

Strategy Alignment: For many years, it has been recognized that performance measurement can influence a company's behaviour and consequently affect the successful implementation of company strategy (Mintzberg, 1978). A PMS must be designed and implemented in accordance with a company's business strategy in order to link the strategy to the objectives of functions, groups of people, and individuals. An important subset of normal PMSs is the Strategic Performance Measurement Systems (SPMSs). They support the production system stakeholders through a series of distinctive features, such as: integrating long-term strategies and operational goals, providing performance measurements in the area of multiple perspectives, providing a sequence of goals/metrics/targets/action plans for each perspective and presenting explicit causal relationships between goals and performance measurements.

Strategy Development: The reciprocal relationship between PMSs and business strategy is also underlined in the literature. Although some authors stress that the design of a PMS should be based on company strategy, others explicitly state that a PMS should also support the definition, development and evolution of business strategy in order to support continuous improvement (Almeida et al., 2012; Tonchia, 2000). A PMS allows a company to gather data that quantifies the effectiveness and efficiency of its activities and helps it assess whether its strategy is appropriate and whether it has achieved the objectives of its business strategy (Neely et al., 2005). Moreover, a PMS can provide information on the effectiveness of actions before their full implementation and support changes in defined objectives (Feurer & Chaharbaghi, 1995).

Focus on Stakeholders: In the last 20 years, the attention paid to stakeholders - groups of people who can influence or who are influenced by the achievement of a company's objectives Freeman (2010) - has increased dramatically. However, the needs, wishes and levels of satisfaction of different groups of stakeholders vary, and each company has to monitor these aspects. To achieve this, in recent years some authors have adopted a stakeholder perspective in their PM systems and approaches. Indeed, currently, some of the most recent performance measurement models focus on the stakeholders' needs rather than the business strategy as the starting point in performance measurement system design, such as Integrated Performance Measurement Reference Model (Bititci, Carrie, & McDevitt, 1997) and Performance Prism (Neely, Adams, & Crowe, 2001).

Multi-Perspective Performance Measurement: The most significant criticism of the traditional PMSs is the fact that they strictly focus on financial measures. However, as already explained, balanced models (also called multidimensional or multi perspective models) should be explored in order to enhance performance measurement systems with different perspectives of analysis, aiming to manage them in a coordinated way (Chenhall & Langfield-Smith, 2007; Garengo et al., 2005; Lauras, Marques, & Gourc, 2010). Indeed, the innovations in information technology and systems have made it easier to gather and elaborate large amounts of data at a lower cost. Since the dissemination of new managerial concepts and paradigms such as JIT, TQM and others, the role of short-term financial measures within current performance measurement systems is critically impaired. Indeed, the decreased reliance on direct labour, increased capital intensity and increased contribution made by intellectual capital and other intangible resources made it invalid to rely on traditional methods of matching revenue to costs (profit analysis) as a measure of performance. Therefore, it is proposed that a selection of non-financial indicators should be employed in contemporary performance measurement systems, based on the organization's strategy, as well as including measures of manufacturing, marketing and research and also growth and development (Parmenter, 2009). For instance, companies which focus is on the improvement of product design and process flexibility should measure the total number of parts per products and the percentage of common versus unique parts, while those that focus their strategy on quality should measure scrap, rework, defect rates, customer complaints and warranty calls. Besides the information provided by these indicators at a present moment, these variables have the advantage of providing better predictors of the organisation's long-term goals rather than short-term profits and financial measures.

Indeed, it is possible to identify a series of researchers promoting the shifting of paradigm from a pure financial measurement approach to a hybrid performance assessment strategy, based on financial and non-financial metrics. Andrea Dossi and Lorenzo Patelli (2010) underline that against pure financial indicators, non-financial indicators are more forward-looking, better able to predict future performance and more adequate to measure intangible assets. Moreover, in this paper authors studied the importance of non-financial indicators in the creation of strategic alignment within international organisations. According to these authors, when performance measurement systems are empowered with non-financial indicators, these become powerful strategy tools, mainly because they contribute towards the achievement of all strategic objectives defined, through three mechanisms: (i) a better understanding of the linkages between various strategic priorities; (ii) more effective communication of the association between objectives and actions; and (iii) more efficient allocation of resources and tasks.

As previously explained, the 1980s was strongly marked for the rise in the popularity of the "quality gurus", resulting in a resurgence of interest in the measurement of operations performance, especially in terms of the three main clusters: efficiency, effectiveness and relevance. As depicted in the performance triptych (Figure 23), the effectiveness assesses whether the output of the process meets the goals for which it was created. Efficiency expresses whether the resources have been used properly to attain the results. Lastly, relevance assess if the means suit the objectives (Marques, Gourc, & Lauras, 2011). This way, it is possible to define a series of indicator types aiming to assess performance from different perspectives, aiming to achieve an optimum balance in the quality, dependability, speed, cost and flexibility dimensions. By taking a number of variables from each of the five ranges and attributing a weight to each of them it is possible to create a new global and aggregated KPI capable of evaluating the production system according to the expected behaviour, trade-offs and priorities related with the decision-maker's strategy.

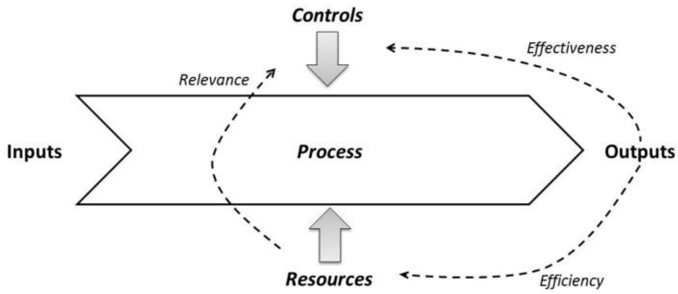

Figure 23 - Performance Triptych (Lauras et al., 2010)

Therefore, it is possible to retain three main ideas concerning the importance of a balanced performance indicators specification within a successful performance measurement system implementation. Firstly, all the perspectives enumerated before can be defragmented within different domains. For instance, the quality perspective is not simply a reference to conformance to specification, but also encompasses a variety of other dimensions, such as performance (how well the process performs its primary function), reliability (how well the process continuous to perform), technical durability (how long the product/service provided to costumers lasts before becoming technically obsolete), serviceability (how easy is the product/service to achieve costumers) and value for money.

Similarly, speed can refer to the time taken to generate quotes and deliver a product or service, the frequency with which deliveries can be made, the time to produce the product and the time to design and start producing new products (ramp-up phase). On the other hand, dependability refers to the capability to keep the schedule and contracts defined, i.e. the general ability to meet promises.

The most multidimensional of the five performance objectives is that of flexibility (De Toni & Tonchia, 2001; Neely, 2007). Within this perspective, two dimensions can be identified: range flexibility and response flexibility. While range flexibility is strictly related with the organization capability to cope with a wide range of requirements, on the other hand response flexibility is the ability to change quickly. Following, a list of variables that can affect manufacturing system's flexibility is presented:

- Material quality (ability to cope with incoming materials of varying quality);
- Output quality (ability to produce product with different levels of quality);

- New product flexibility (the ability to cope with the introduction of new products)
- Product Modification (ability to cope with modified products)
- Deliverability (the ability to cope with changed delivery schedules)
- Volume (ability to cope with changed production volumes)
- Mix (ability to cope with different production mix)
- Resource mix (ability to cope with different resource mix).

However, as previously explained, the multidimensionality issue is not the only topic to be taken into account when designing and specifying a balanced performance measurement system. In fact, it is important to have in mind that these five operations performance objectives trade off with one another, being the nature of these trade-offs time- and context-specific. For instance, high quality, defined in terms of product performance, can be delivered but potentially at a cost and so it is necessary to guarantee the trade-off between these two variables; tight delivery schedules can be met, but perhaps only by investing in additional resources. Based on this reality, operations management constantly strives to find ways of pushing back the performance frontiers of these five performance objectives by enhancing their operations capabilities so that the impact of the trade-offs can be mitigated over time.

Dynamic Adaptability: A performance measurement system should include systems for reviewing measures and objectives that make it possible both to adapt the PMS quickly to the changes in the internal and external contexts, and systematically to assess a company's strategy in order to support continuous improvement. Many scholars have studied and defined the dynamic approach (Bititci, Turner, & Begemann, 2000).

Depth and Breadth: The depth of a PMS is the level of detail to which performance measures and indicators are applied. The breadth of a PMS relates to the scope of the activities included in PMS. A broad model includes all the company's activities (managerial, operational and support) and provides a 'holistic' assessment of the company's performance. Lynch and Cross (1995) write that it is impossible to improve just one measurement of a company's performance without somehow impacting on other areas of performance, mainly due to the inter-relationships between individual measures.

Process Oriented: Performance measurement systems have been explored for a long time. Initially, the most popular measurement system was the so-called DuPont scheme, introduced in 1919 by the DuPont Company. However, during the following years the situation changed significantly. In fact, since then it has been observed a considerable evolution concerning performance management approaches, once these are becoming more process-oriented, involving not only decision makers but also processes actors (Tupa, 2010).

Due to the fact that more and more process performance management tools and methodologies are considered as being essential for enterprises continuous improvement, new approaches have been developed such as: self-assessments, quality awards, benchmarking, activity-based costing, capability maturity model, balanced scorecard and workflow-based monitoring (Kueng & Krahn, 1999; Melchert & Winter, 2004).

In general, a process oriented performance measurement system can be seen as an information system that supports organizations so that they can visualize and continuously improve processes performance, controlling its execution by comparing process models with data collected (Kueng & Krahn, 1999).

In order to achieve the main goals defined for a process-oriented performance management system, two fundamental mechanisms need to be explored:

1. *Processes performance measuring mechanism* capable of extracting performance-relevant data from operational information systems; it populates this data into a dedicated process data warehouse and provides mechanisms for flexible analysis of business processes.
2. *Engine for translating process analysis results into recommendations* for appropriate improvements in the process design. Improvements are implemented by refining the respective process models, which in turn triggers another Plan-Do-Check-Act (PDCA) cycle.

Due to the importance of this issue for current industrial companies, Gartner Group has developed a framework called Corporate Performance Management (CPM) that illustrates and materialize the concept previously presented. This framework can be described as the combination of processes, methodologies, metrics and technologies to measure, monitor and manage the performance of the business processes (Melchert & Winter, 2004). As it is possible to see in Figure 24, the process management component is one of the pillars of Gartner's framework. Aiming to continuously improve the models here designed, the corporate performance management concept explore the need to automate business processes and use real-time performance analysis, in order to support organizations performing effective process performance assessment initiatives capable of improving and innovating their overall organization’s strategy.

In order to make the procedure described before faster and in a more reliable way, techniques such as process mining[6] have been explored to automatically support weak points and bottleneck analysis, right time monitoring and dynamic organizational analysis (der Aalst & Weske, 2005; Ou-Yang & Juan, 2010).

[6] The main objective of the process mining approach is to extract the sequential relationships among the process events from the process log and thus generate the respective process model in order to find out how people work and/or procedures work (Maruster and van Beest 2009). Various mining algorithms have been developed (Ou-Yang and Juan 2010), such as: alfa miner, heuristic miner, alfa ++ miner and generic miner.

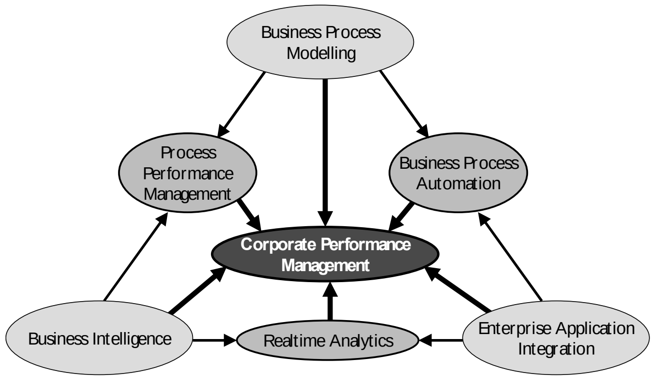

Figure 24 - Corporate Performance Management (Melchert & Winter, 2004)

Causal Relationships: Many scholars have written about the causal relationship between results and their determinants in performance measurement. Kaplan and Norton (1996) underline that identifying a causal relationship between performance indicators and objectives supports the strategy review and learning. Since performance measurement is supposed to support planning and control, a PMS should measure not only the results, but also their determinants and quantify the 'causal relationship' between results and determinants in order to help monitor past actions and the improvement process (Bititci et al., 2000; Neely et al., 2000).

Therefore, strategic objectives can be identified as well as external reasons forcing organizations to wish to excel at them. For instance, higher quality, allows the organization to deliver higher-quality products. Higher quality however also means fewer mistakes, hence less rework which is costly to the operation if it has to be performed. Speed means that organization can respond to customer requests more rapidly, but also means that the organization's capital is tied up for shorter periods of time in the form of inventories and work in progress. This analysis can be performed to all the five operations performance objectives.

Since one of the key strategic challenges for operations managers is to decide on which of the sub-dimensions of these performance objectives they wish their operation to excel and how they are going to configure the operation to do so, thus a successful performance measurement system should be capable to reflect this information in a simple and direct way. Suwignjo et al. (2000) have analysed different techniques to analyse the relationship between results and determinants, such as cognitive maps, cause and effect diagrams, tree diagrams and analytic hierarchy processes.

Clarity and Simplicity: The clarity and simplicity of a PMS are of crucial importance for its successful implementation and use (Neely et al., 2001). The literature review highlights the following components as characterizing a clear and simple PMS: clear definition and communication of the fixed objectives; careful selection of the measures to be used; clear definition of measures; clear definition of how to gather and elaborate data; use of relative instead of absolute measures; definition of how the processed information has to be presented.

As conclusion, Table 1 presents a comparison between eight PMS models, developed after the mid-1980s. For this exercise, models were compared using the dimensions discussed above (i.e. *strategy alignment, strategy development, focus on stakeholders, balance, process orientation, depth, breadth, dynamic adaptability, causal relationships, and clarity and simplicity*) and according to the three typologies defined before: vertical, balanced and horizontal.

According to these authors, a comparison of these eight models shows a clear difference between the first four generic models, i.e. those that do not consider the company's size and are prevalently vertical (Performance Measurement Matrix, Performance Pyramid System, Result and Determinants Framework, Balanced Scorecard), and the last four models, i.e. those characterized by a horizontal structure (IPMS, Performance Prism, Organizational Performance Measurement and Integrated Performance Measurement for Small firms).

In fact, most of the models analysed are characterized by strategy alignment and favour strategy improvement. However, the presence of these two characteristics decreases moving from left (generic and older models) to right (SMEs and recent models) showing a focus on stakeholders' necessity. Moreover, it is important to highlight that the use of process-oriented performance measurement is increasing, particularly in the most recent models (including the models for SMEs), reinforcing the idea stated before concerning the increasing importance of business processes as drivers to satisfy stakeholder requirements.

Table 1 - Comparison of eight PMS Models from State of the Art (adapted from (Garengo et al., 2005))

	[1]	*[2]*	*[3]*	*[4]*	*[5]*	*[6]*	*[7]*	*[8]*
Strategy Alignment	❖	❖	❖	❖				
Strategy Development		❖	❖	❖	❖	❖		
Focus on Stakeholder					❖	❖	❖	
Multi-Perspective Analysis	❖	❖	❖	❖	❖	❖	❖	❖
Dynamic Adaptability			❖		❖	❖		❖
Process Oriented					❖	❖	❖	❖
Depth	❖	❖	❖	❖	❖	❖	❖	
Breadth		❖	❖	❖	❖	❖	❖	
Causal Relationship		❖	❖	❖		❖		❖
Clarity and Simplicity	❖					❖		❖
Vertical	❖	❖	❖	❖				
Balanced	❖	❖	❖	❖	❖	❖	❖	
Horizontal					❖	❖	❖	❖

[1] Performance Measurement Matrix (Keegan, Eiler, & Jones, 1989); **[2]** Performance Pyramid System (Lynch, 1995; Lynch & Cross, 1991); **[3]** Results and Determinants Framework (Fitzgerald, 1991); **[4]** Balanced Scorecard (Kaplan & Norton, 1996); **[5]** Integrated Performance Measurement System (Bititci et al., 1997); **[6]** Performance Prism (Neely et al., 2001); **[7]** Organizational Performance Measurement (Chennell et al., 2000); **[8]** Integrated Performance Measurement for Small Firms (Laitinen, 2002).

2.5. Predictive Relevance

Historically, forecasting techniques have been of great interest to the scientific and industrial fields. From the literature, it is possible to determine three completely different performance main estimation methods: the deterministic, the heuristic and the stochastic methods (Figure 25) (Azevedo & Almeida, 2011). The deterministic methods are supported by credible sources that are aware of future values beforehand. This type of method is very interesting for quantitative planning. Furthermore, stochastic and heuristic methods are characterised as being based on past data (Seifert, 2007). Even though they are simple to apply and have low computational costs, heuristic methods require sound knowledge of the system under study and are usually associated with high levels of uncertainty. Stochastic methods, on the other hand, use mathematical methods based on regression analysis, moving averages or exponential smoothing, enabling the mathematical extrapolation of known data. If correctly applied, this type of method can generate predictions with low levels of errors, even though they require a greater effort in its implementation.

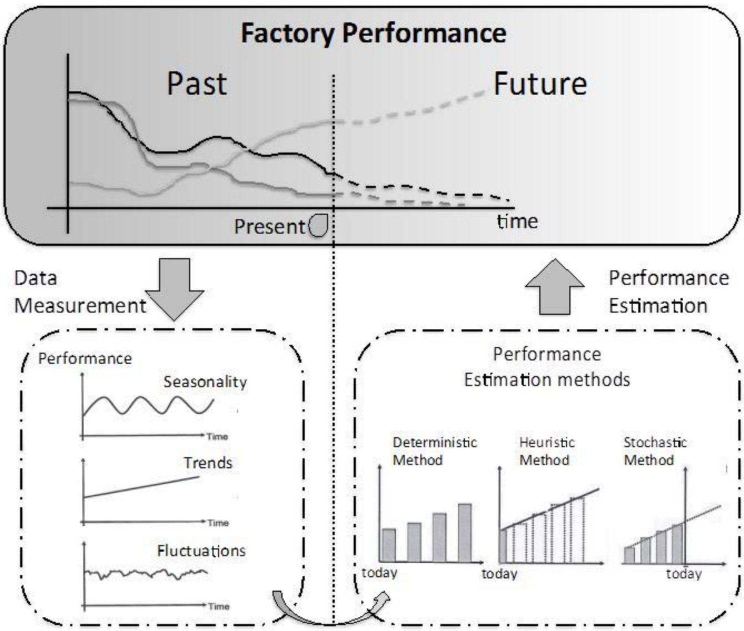

Figure 25 - Data Prediction Phases (Azevedo and Almeida 2011)

Nevertheless, when dealing with performance estimation, the simple application of the methods previously presented is not enough to produce reliable performance estimation results. Indeed, if in one hand it is critical to explore suitable methods for performance measurement, on the other hand it is essential to manage this data to better understand the manufacturing system behaviour and, consequently, estimate with high levels of confidence the future behaviour of the system in analysis.

In line with this vision, adjacent to the development of performance measurement strategies and tools, in a separate field of study, Dr Walter Shewhart developed his theory of statistical quality control, envisioning the performance behaviour prediction. Indeed, from the point of view of this quality management guru, prediction should be seen as pivotal, since it lies at the root of control definition, as following depicted:

> *…a phenomenon will be said to be in control when, through the use of past experience, we can predict, at least within limits, how the phenomenon may be expected to vary in the future. Here it is understood that the prediction within limits means that we can state, at least approximately, the probability that the observed phenomenon will fall within given limits. In all forms of prediction an element of chance enters. The specific problem which concerns us at the present moment is the formulation of a scientific basis for prediction, taking into account the element of chance, where, for the purpose of our discussion, any unknown cause of a phenomenon will be termed a chance cause.* (Shewhart, 1930).

Specifically, Shewhart developed his theory of prediction around three components of knowledge, forming the basis of Shewhart's epistemology (Figure 26): (i) evidence, (ii) prediction and the (iii) degree of belief in the prediction based on the strength of the evidence. As depicted in Figure 26, the estimation process should start with the collection of reliable data, which is presented as evidence. The evidence is then analysed and interpreted. The results of this interpretation allow a prediction to be made as to the future behaviour of the process. The degree of belief in the prediction is based on the quality of the evidence. It is important to underline that, according to Shewhart's point of view, the notion of "belief" was a result of a combination of scientific and stakeholders' intuition perspectives.

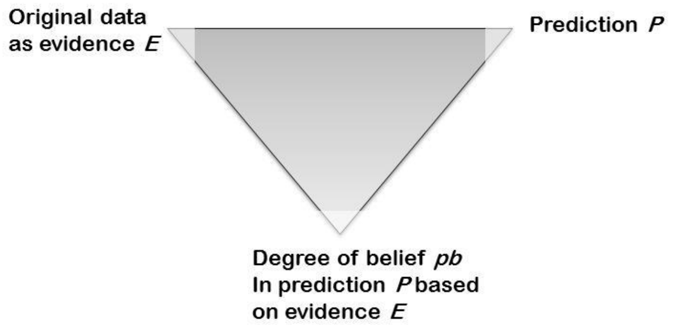

Figure 26 - Shewhart's Model for Prediction (Wilcox & Bourne, 2003)

According to Shewhart's thesis, the critical moment of the process of prediction is strictly related with the data collection stage, since it is during this stage that stakeholders will prepare the information that will be used as evidence. It is important to distinguish between data collected under controlled conditions and data that are not. If the data collection process is in statistical control, i.e the production system has achieved a suitable level of stability in which only common and known causes of variation remain, then we can make reasonably accurate predictions from this data. This then relates to the degree of belief we may have in the prediction. Conversely, if the data collection process is not in statistical control, then we cannot make accurate predictions and our degree of belief will be far less.

Not surprisingly, we find that Shewhart took the measurement process very seriously, since his theory of prediction draws on the use of the past to interpret the present in order to predict the future. Indeed, Shewhart reinforces the importance of developing a precise and accurate method of measuring the real environment, envisioning the enhancement of the predictive process. In sum, Shewhart identified that the degree of belief in the prediction is based on the quality of the evidence (real scenario analysis).

Another model presented in Figure 27 helps to explain the dynamic nature of systems thinking, and how statistical methods fit into that process. To try to explain the dynamic nature of this model Shewhart quotes C.I. Lewis with a particularly paradoxical riddle:

> *"Knowing begins and ends in experience; but it does not end in the experience in which it begins."*

This riddle encapsulates the fluid nature of systems thinking where phenomena are in a state of flux.

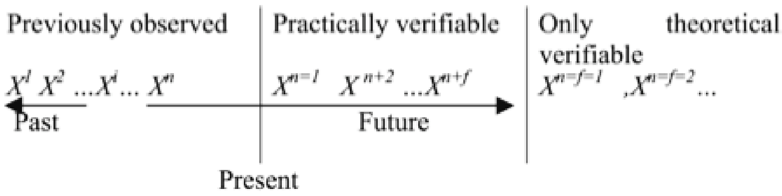

Figure 27 - Shewhart's model for linking past, present and future (Wilcox & Bourne, 2003)

An interesting method that applies the vision and concept depicted in Figure 27, and that has been widely used in industrial process management mainly due to its capability to handle a variety of process models and incorporate different types of constraints, is the Model Predictive Control (MPC) approach (Bemporad and Morari 1999; Balaji, Vasudevan et al. 2008). By definition, the designation Model Predictive Control (MPC) stems from the idea of employing an explicit model of the system to be controlled, which can be used to predict the future output behaviour taking into account the present characteristics of the system (Mayne et al., 2000).

Model Predictive Control

The Model Predictive Control (MPC) is composed by five key components (Geyer & Mastellone, 2011): **(i)** an internal prediction model of the drive system that allows the controller to predict the effect of its control actions; **(ii)** a prediction horizon, which comprises a certain number of time-steps over which the controller looks into the future; **(iii)** a cost or objective function that represents the control objectives (e.g. the minimization of the switching frequency); **(iv)** an optimization stage that minimizes the cost function and yields an optimal sequence of manipulated variables and, **(v)** the so-called receding horizon policy (Mayne, Rawlings, Rao, & Scokaert, 2000).

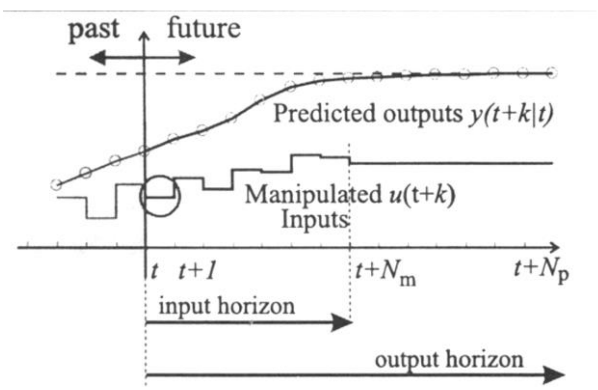

Figure 28 - Receding horizontal strategy (Bemporad and Morari 1999)

Specifically, the receding horizon policy control defines that an optimization problem should be solved at each time step, aiming to determine an action plan over a fixed time horizon. Therefore, at the following time step, this process should be repeated, solving a new optimization problem with the time horizon shifted one-step forward (Figure 28). Through feedback analysis (that is, using real-time measurements), the model can be optimized.

In 1977, Baker (1977) conducted an experimental study of the effectiveness of rolling horizon decision-making in production planning. From this study it was possible to understand that despite the fact that all production-planning problems occur in systems that operate indefinitely, there are mainly two reasons that allow implementing finite horizon models.

1. The forecasts for the remote future tend to be unreliable and are, therefore, of limited usefulness.
2. Due to practical reasons, decisions must be based on limited information about the future (Sethi & Sorger, 1991).

In order to better understand the concept around rolling horizon decision-making, it is important to underline that a forecast horizon should be a finite horizon, distant enough off so that the data beyond it have no effect on the optimal decisions in the current period. Clearly, if we can find a forecast horizon in each period on a real-time basis without any cost, then using these forecast horizons as successive rolling horizons will provide a rolling schedule that is optimal for the infinite horizon problem (Sethi & Sorger, 1991).

From the literature review, it is possible to find some interesting implementations of the MPC approach for an optimal production system planning and control. For instance, Aggelogiannaki (Aggelogiannaki, Doganis, & Sarimveis, 2008) examined the advantages of introducing an adaptive MPC in an inventory control scheme. In this research work, the goal of using a MPC controller has as main objective to keep the inventory levels as close as possible to the target values while satisfying constraints with respect to production and transportation capacities. Figure 29 shows that inventory level at time instance t is strictly related to the ordering signal, which presents an autoregressive with exogenous input model that considers customer demand as an external measured disturbance.

In other words, according to this control model, the order volume will be produced based on three main types of information:

I. *Discrepancy between inventory and target value for inventory*;
II. The *estimation of customer demand*;
III. The *model capable to emulate the normal behaviour of the manufacturing system*.

This way, it will be possible to have, at the end, the correct level of inventory, taking into account the different restrictions and constraints related with not only the market demands but also the production system.

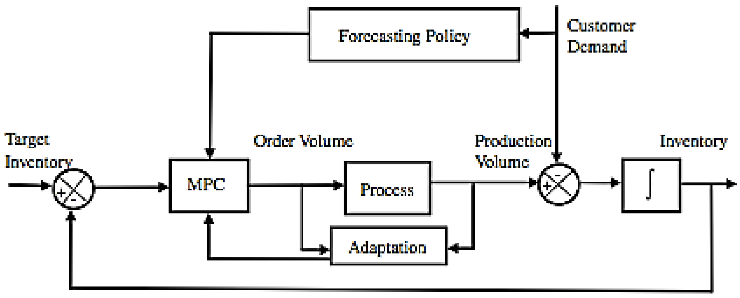

Figure 29 - Block Diagram of MPC scheme for Inventory Control (Aggelogiannaki et al., 2008)

Wenlin Wang, on the other hand, explored the MPC approach within the scope of Supply Chain Management (SCM) as a tactical decision policy, aimed to support the decision maker at achieving operational excellence (Wang, Rivera, & Kempf, 2007). Compared to traditional flow control problems, the challenges of SCM in semiconductor manufacturing result from the high stochasticity and nonlinearity in throughput times, yields and customer demands. Similarly to the application case presented before, in this specific pilot case, the MPC applied to SCM relies on *dynamical models of material flow to predict inventory changes among the various nodes of the supply chain*. Based on these SCM model predictions, current and future order quantities requested from upstream nodes can be adjusted, aiming to guarantee that inventory will reach the targets necessary to satisfy demand in a timely manner. Aiming to exemplify the normal application of a MPC approach within the SCM scope, Figure 30 shows a normal flow of information and materials within a supply chain. In this specific application case, the supply chain selected is mainly composed by three manufacturing systems, three nodes of inventory storages and one output, reflecting the market demands.

According to MPC approach, system outputs can be classified in terms of controlled variables (which must be maintained at some set-point value) and associated variables (which may not have a fixed set-point, but must reside between high and low limits). Thus, based on the problem presented in Figure 30, controlled variables consist of the three inventory levels (*I10*, *I20*, and *I30*) whose set-point targets are determined by the inventory-planning module. Associated variables include the load rates on the manufacturing nodes (*M10*, *M20*, and *M30*), which are determined on the basis of WIP.

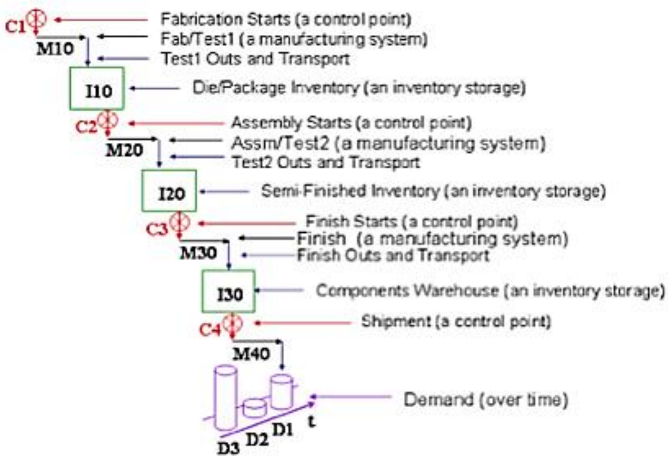

Figure 30 - Dynamic Representation of a Manufacturing Supply Chain (Wang et al., 2007)

Moreover, based on the MPC approach, input variables consist of two types: manipulated variables *u*, which can be adjusted by the controller to achieve the desired operation, and disturbance variables *d*, also referred to as exogenous inputs. Indeed, in this problem formulation, the start rates for the *Fab/Test1*, *Assembly/Test2*, and *finish* nodes (*C1*, *C2*, and *C3*) represent manipulated variables, while demand is treated as a disturbance signal. In addition, the demand signal (which dictates the shipment flow in C4) consists of two components: (1) actual demand (which is only truly known in the past) and (2) forecasted demand, which is provided to the planning function by a separate organization, such as Sales and Marketing. As noted in Figure 31, the variable demand forecast takes a critical importance on the moving horizon calculation, envisioning the anticipation of future system behaviour.

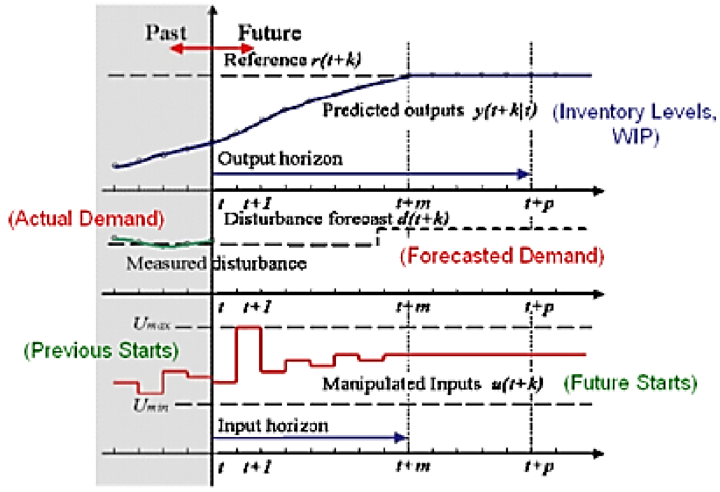

Figure 31 - Moving Horizon Representation for Supply Chain Management (Wang et al., 2007)

In order to apply the MPC approach to the problem described before, i.e. optimize the amount of inventory capable to respond to the market necessities, two main steps should be performed:

1) Prediction of future system behaviour, on the basis of current measurements and production system model; and
2) Solution of an optimization for determining future values of the manipulated variables, subject to constraints.

In MPC, predicted outputs over a horizon are computed on the basis of a system model, arising from mass conservation relationships describing the dynamics of the manufacturing, inventory, and transportation nodes. For this problem, the mass conservation relationship for die-package inventory (I_{10}) can be written as depicted in Eq.2.1.

$$I_{10}(k+1) = I_{10}(k) + Y_1 C_1(k - \theta_1) - C_2(k) \qquad \text{Eq. 2.1}$$

While for the Fab/Test node (M_{10}) an expression for the WIP can be described as presented in Eq.2.2.

$$\mathrm{WIP}_{10}(\mathrm{k}+1) = \mathrm{WIP}_{10}(\mathrm{k}) + \mathrm{C}_2(\mathrm{k}) + \mathrm{C}_1(\mathrm{k} - \theta_1). \qquad \text{Eq.2.2}$$

In the scope of this mathematical formulation, θ_1 and Y_1 represent the nominal throughput time and yield for the Fab/Test1 node, respectively, while C_1 and C_2 represent the daily (or per-shift) starts that constitute inflow and outflow streams for I_{10} and M_{10}. Similar relationships can be written for the semi-finished goods I_{20} and I_{30} inventories as well as the Assembly/Test2 M_{20} and finish M_{30} nodes. However, the main goal of the MPC decision policy is to seek a future profile for u, the manipulated variables, capable to bring the system variables to some desired conditions per the minimization of an objective function. The objective function in MPC is a multi-term expression that addresses the main tactical operational objectives in the supply network.

In sum, with this research work it was possible to demonstrate that through a proper design of a MPC controller it is possible to track targets, generated from inventory planning modules, while improving customer service levels in environments of high stochasticity and nonlinearity characteristic from manufacturing processes. A similar example of the application of a MPC approach within the SCM can be found in the research work performed by M. Braun (Braun, Rivera, Flores, Carlyle, Kempf, 2003). In short, it is possible to state that MPC provides many attractive features, such as: applicability to multi-input multi-output systems, it can handle constraints on inputs and outputs in a systematic way, it is capable of tracking pre-scheduled reference signals, and it is an easy-to-tune method (van den Boom & De Schutter, 2002).

However, normal MPC implementations rely mainly on a linear deterministic model, where simple deterministic noise-free cases are considered without any modelling errors capability. Nevertheless, ignoring the noise can lead to a bad-tracking behaviour or even to an unstable closed loop. Another issue is strictly related with errors modelling. In fact, uncertainty in the modelling or identification phase can lead to errors in the system matrices. It is clear that both modelling errors, noise and disturbances, can strongly perturb the system by introducing uncertainty in the system control. When estimation tools are applied in normal production system environments, three major factor types can affect performance behaviour (Seifert, 2007): seasonality, trends and statistical irregular fluctuations. While seasonality and trends translate the long-term behaviour of the system and can be captured mathematically, on the other hand data consisting of fluctuations critically affects the forecasting and estimation results, making them more difficult and less reliable on the short-term. Note that there are few results in the literature on noise and modelling errors in an MPC context (van den Boom & De Schutter, 2002).

Although MPC approach is being recognized as a methodology capable to support decision makers providing a close feedback analysis and robustness, mainly due to the receding horizon policy used, a fundamental question about MPC is its ability to model uncertainty and noise. In fact, when one is saying that a control system is robust, it means that stability should be maintained and that the performance specifications should be met for a specified range of model variations as well as for a class of noise signals (i.e. uncertainty range). Consequently, although the MPC approach provides an effective control schema, where feedback and feed forward loops can be merged aiming to support decision makers to be proactive, instead of taking decisions in a reactive way, the way how the production system in analysis is modelled is not as robust as expected.

In fact, there are two main characteristics that should be explored aiming to enhance the MPC concept robustness.

Firstly, it is essential to explore suitable manufacturing system modelling methodologies, capable to integrate within a mathematical formulation, not only static and dynamic constraints but also endogenous and exogenous factors in a more reliable and user-friendly way, even when managing complex manufacturing environments. Moreover, it is critical to guarantee that static variables, strictly linked with the main characteristics of the system, not only become fully aligned with the manufacturing system reality, but also can be continually updated following the normal evolution imposed by the uncertainty and shorter life cycles imposed by volatile markets.

2.6. Summary and Conclusions

It is becoming undeniable that both performance measurement and management disciplines are essential management tools that need to be effectively used envisioning industrial companies competitiveness. Nevertheless, this is not a trivial neither a static process. This means that performance measurement and management tools should be seen as evolving disciplines that, due to their multidisciplinary characteristic, must be adaptable to manufacturing systems characteristics.

However, due to the decreasing of products life cycle, imposed by the increasing of markets competition, it has been observed an increasing of manufacturing systems' variability and uncertainty. As already depicted from the literature review presented before, once complexity is directly linked with the lack of knowledge concerning the behaviour of a specific system, these are the two main variables responsible by the increasing of complexity related with the management of complex manufacturing systems. Consequently, if decision makers are capable to decrease the level of complexity of a specific manufacturing system, exploring and understanding their dynamics, then they will increase the level of effectiveness and confidence of their management processes.

In line with this vision, it becomes critical explore the research work performed until now, as well as the methodologies and tools developed, under the scope of the complexity management for manufacturing systems. If in one hand the information-theory reiterates the importance of the quality, resolution and accuracy of information to understand and decrease the levels of complexity characteristics from a specific manufacturing system, on the other hand the system dynamics approach provides a suitable modelling tool capable to represent the synergies between the different feedback loops that define each manufacturing system's behaviour.

Nevertheless, it is our strong believe that, by itself, the system dynamics approach does not presents the necessary characteristics to support contemporary decision makers, from complex manufacturing systems, to manage their systems in a proactive way. Indeed, the system dynamics approach, as developed and proposed by Jay Forrester, presents some limtations when dealing with complex manufacturing system, strongly characterized by non-linear behaviours. In fact, when the number of feedback loops increases, as well as their intricate relationships, it becomes unreasonable for a human to control or manage it in the most efficient and optimal way. Indeed, the high number of trade-offs imposed by the paradox relationship between the different strategic objectives, strongly decreases stakeholders capability to take decisions in the present based on future estimations of manufacturing system's states.

Indeed, as proposed by Dr Walter Shewhart, prediction is a key driver when it is expectable to manage a manufacturing system in an effective way. Nevertheless, as continuously stated during the literature review chapter, current industrial companies still focus their management intuitions on lagging and financial indicators that simply reflect states of the systems related with the past. Aiming to better understand the vision behind this research project, the model predictive control (MPC) approach was explored, both from the conceptual and practical points of view. Indeed, this is a methodology normally used for industrial processes control, where the knowledge concerning the system behaviour and the management objectives (optimization problem) are formalized within a mathematical model and the estimation about the system's evolution is materialized through a certain prediction horizon.

However, in addition to the gap previously described, strictly related with the lack of decision makers' capacity to foresee future system's behaviour, it is also observed that the disintegration between performance measurement and management approaches is normally critical for the effective performance assessment, especially within complex systems. A serious example of this reality based on the fact that most of the times the reason that driven the selection of a certain KPI is not reflected in its metric, giving rise to a misalignment between the performance management systems designed and the strategic objectives defined. Therefore, it is critical to overcome the static and rigid structure of these contemporary management tools, providing these tools with integrated performance measurement and management engines, perfectly aligned with the organization's strategy.

In sum, with this chapter it was explored not only the necessity to enhance the current perceptions around the performance management approach, mainly based on the shift of paradigm from a reactive to a proactive approach, but also it was identified the need to revisit and consolidate some concepts that have been supporting this area of research ever since. Indeed, based on the literature review presented before, we strongly believe that it is necessary to better understand the evolution of the performance management discipline, as well as its main pillars and foundations, in order to redesign and provide decision makers with enhanced tools, more aligned with their current needs. For instance, stakeholders' perception about manufacturing system's behaviour is not only time-dependent, but also relies on the reliability and accuracy with which it is possible to extract data from the shop floor in order to build performance information.

Therefore, only after rethinking the performance management foundations, where the way how performance should be measured takes a relevant role, it will be possible to support companies enhancing their maturity levels concerning the way how they manage their performance, i.e. evolve from a management approach strictly based on past performance measures to a proactive approach based on estimations of the manufacturing systems' states.

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Chapter Three

TOWARDS A PROACTIVE PERFORMANCE APPROACH

Presented the scope and context of investigation, during the previous chapter, it was not only identified the main areas of research but also it was explored the state of the art related with each of these disciplines. Indeed, at a first stage of this research project it was critical to clearly understand which should be the areas of research that should be integrated, as well as its main gaps and opportunities of research.

Consequently, during this chapter it will be explored how the different areas of research should be combined aimed to build a suitable vision capable to support the proactive performance management approach developed in the scope of this research project. Since this proactive performance management approach should cover the entire continuous improvement cycle, the well-known Plan-Do-Check-Act (PDCA) cycle will be used as reference to show the main enhancements that are expected to be introduced within the current state of the art on the performance management domain.

3.1. Concepts and Foundations

The roots of the Performance Management concept define that, in order to take the decision that will really improve the manufacturing system and support the organization to achieve their strategic targets, it is crucial to periodically gather information feedback about the real world. By using this new information, in a continuously way, decision makers can revise the existing understanding about the system as well as the strategy that should be taken to drive the perception of the state of the system closer to the strategic goals

As previously presented in the chapter dedicated to the state of the art, the industrial dynamics approach defines that all improvement decisions should take place in the context of feedback loops. For instance, the Plan-Do-Check-Act (PDCA) cycle, conceived by Shewhart and later developed by Deming, is a good example of that. This approach, which is considered the heart of the Total Quality Management era and the main pillar of the improvement process, stimulates the system learning through an explicit feedback process, facilitating the effective implementation of goal seeking behaviours aiming to achieve the plant's goals (remember Figure 14 and Figure 18).

By definition, the PDCA cycle is a problem solving process consisting of three sequential actions (Figure 32): (i) *decision making*, (ii) *implementation* and (iii) *evaluation*. This means that, at a first stage, decision makers should identify the system's bottlenecks and points of improvement, based on their mental models about the real system behaviour. In system dynamics, the term "mental model" includes the modellers' beliefs on the network of causes and effects that describe how a system operates, along with the boundary of the model. Indeed, it is based on this mental model about the system's behaviour that stakeholders and shareholders define their vision for the organization and consequently define the strategy, the organization and production system's structure, trade-offs as well as the decision rules.

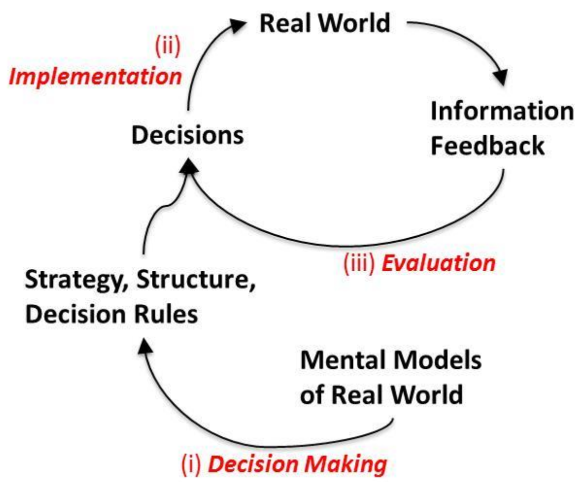

Figure 32 - Mental Model of PDCA cycle

However, this information is typically defined and managed at a strategic level of the company. Thus, the next step is mainly related with the necessity to translate this information into some rules of thumb that will prioritize and determine the decisions to be applied within the operational layer of an industrial organization. These decisions should be taken in a conscious, timely and assertive way by the different actors positioned at the different layers of the organization's hierarchical tree. That is the reason why it is so important to guarantee a high level of transparency between the strategic and operational layers.

After defining the decisions to be applied at the shop floor (*Real World*), it is essential to continuously compare the actual performance of the system (*Information Feedback*) with the expected behaviour of the system, aligned with the strategy, structure and decision rules identified by the stakeholders and shareholders of the organization. It is important to highlight that this should be seen as an iterative and evolutionary process, where not only it is expected to walk into a direction of a certain target, but also this same target can evolve in order to follow and fulfil the requirements imposed by market and manufacturing environment.

In fact, this is the normal conception concerning performance measurement and management applied not only within small and medium enterprises but also in large and world-class industrial organizations. However, more and more companies are performing in competitive markets forcing them to become more proactive than reactive. This way, a simple approach as described before is no longer suitable for this type of companies and, therefore, it is essential to have an effective approach that allows them to accelerate the learning process of their complex systems. Companies should be able to analyse their leading indicators, and to understand their meaning and the feedback loops that affect them. Only this way can decision-makers look to the future and act even before these consequences affect the systems' efficiency and effectiveness.

Nevertheless, it is observed that the performance measurement techniques used to support decision makers from complex manufacturing systems to measure and analyse their performance behaviour are still based on ad-hoc methods, since the main objective is to verify if the strategy designed has been helping companies achieving their targets following a reactive approach. As example, it is possible to highlight the supremacy of the excel tool for contemporary organizations, when calculating the performance of their manufacturing systems.

However, not only the calculation process of the performance information is a critical bottleneck for actual industrial companies. Indeed, as explored in the previous chapter strictly related with the state of the art, the capacity to handle and manage performance information should be seen as a key driver to decrease the level of complexity of a manufacturing system. Thus, we strongly believe that the decision makers capacity of increasing the knowledge and expertise about their system behaviour result, on one hand, from their mastery on the analysis and evaluation of the performance information. By knowledge and expertise about system behaviour we mean the level of control on feedback loops that compose a system as well as the trade-offs that are derived from this network of relationships.

Hence, this research work is proposing an innovative concept for the performance management discipline, through the development of a predictive and proactive approach to assess critical performance variables based on a system-thinking concept for complex manufacturing systems. Using these key-leading indicators as reference, the aim is to provide companies with a performance management framework that allows them to foresee future performance behaviours, and consequently anticipate decision-making processes, aiming at implementing corrective/improvement actions in a proactive way. Moreover, this approach should support companies so that they can establish their own ambitious and yet reachable targets. In order to better understand how this vision can be applied within a typical industrial organization, an enhanced mental model of the PDCA cycle presented before will be used as a guide to show the improvements that will be introduced with the development of the proactive performance management approach here proposed.

As depicted in Figure 33, with the development of this innovative approach, there are three main objectives to be fulfilled, aiming to improve the current vision about the performance measurement and management discipline:

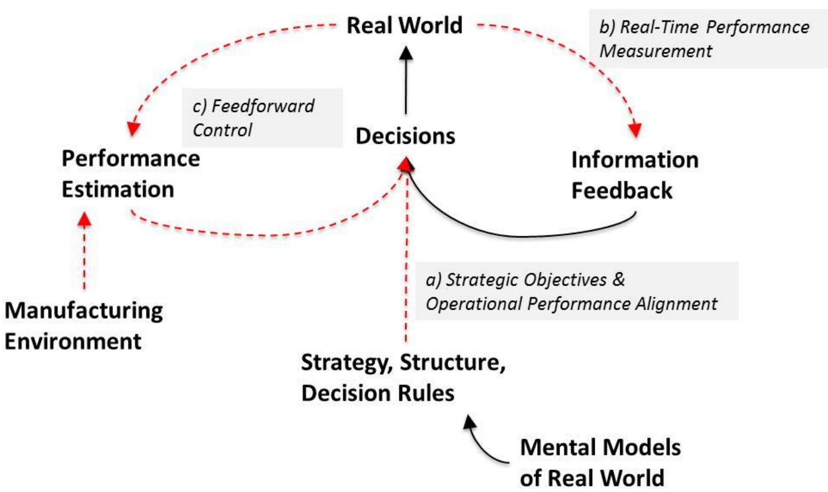

Figure 33 - Enhanced PDCA Mental Model

a) Strategic Objectives & Operational Performance Alignment

Firstly, it will be explored the necessity to streamline and make more transparent the process of information and knowledge flow between the strategic and operational layers of an industrial organization. In other words, in order to take a decision that will really enhance the system's performance, decision makers must develop their mental model about the system as closer as possible from the reality. Based on this perception about the system, decision makers will be able to identify bottlenecks, prioritize improvement actions, define targets and take decisions.

Therefore, and taking onto account that this is not the focus of this research project, it will be presented an open and scalable performance management approach capable to guarantee the alignment between managers' strategic vision and technicians' implementation, from the performance management perspective, taking into account both tactical and operational limitations of the system.

b) Real Time Performance Measurement

The second challenge is based on the necessity to develop a real time performance measurement and assessment infrastructure, capable to not only generate information concerning the system's performance in real-time but also facilitate and boost the performance assessment process. Indeed, one of the main premises of this thesis bases on the idea that in order to implement a successful proactive performance management approach within an industrial organization the first step should be to focus on the necessity to implement and maintain the ability to continuously monitor the behaviour of the production system, by analysing the performance of the core processes during its entire life-cycle (Dekkers, 2003; Dekkers & Van Luttervelt, 2006). According to Shewhart's theory, the estimation process should combine three main components: (i) evidence, (ii) prediction and the (iii) degree of belief in the prediction based on the strength of the evidence. Therefore, due to the fact that the collected data should be seen as an evidence of the system behaviour, the higher the confidence on the data collected from the shop floor, the higher reliability should be expected from the estimation process.

Thus, explored the linkage between the strategic and operational layers of an industrial organizations, following it will be analysed the requirements and steps that should be taken when designing a suitable performance management system capable to enhance the information feedback that is extracted from the real world. It is important to underline that this section will provide the main pillars and foundations for the solution development and explanation presented in the following chapter.

c) Feedforward Control

Nevertheless, in order to develop a reliable proactive performance management framework, it is expected to not only depend from the historical perspective. Therefore, an important enhancement to the current PDCA mental model, previous presented, will be performed with the introduction of a new control loop based on leading information analysis (*feedforward control approach*). Thus, as depicted in Figure 33, a performance estimation module will be included into the typical PDCA model aiming to enhance stakeholders' decisions with predictive information about the system's behaviour. In other words, based on endogenous (*Real World*) and exogenous (*manufacturing system's environment*) variables, support decision makers to foresee if the strategy defined, and respective decisions, will lead the company to achieve the strategic objectives identified.

Presented the main contributions of this innovative performance management framework, following a detailed analysis of each of the previous topics will be presented.

3.2. Strategic Objectives & Operational Performance Alignment

There is general consensus that, only linking strategic and operational performance, it is possible to improve the overall organizational performance. Despite the fact that strategy and operations are two different and sometimes not associated perspectives, when they are properly aligned, the plant is more likely to achieve specific performance goals. Both strategic and operational levels of a manufacturing organization can be defined in terms of the customer-product-process-resource (CPPR) approach (Martinez-Olvera, 2010). In the scope of this model, the strategic perspective of a manufacturing enterprise corresponds to the customer level while the operational perspective corresponds to the process level.

However, in order to approximate both perspectives, a strategic performance management life cycle should be explored, aiming to link the plant's strategy for the market and operations floor. As inspiration, a strategy management cycle depicted in Figure 34 and developed by Morita et al. (Morita, Ochiai, & Flynn, 2011) was used. This model proposes that initially, organizations must clearly define their business opportunity as well as establish their vision about the goals to be achieved. Following, the strategy should be designed, capable of supporting the organization to achieve the goals defined before. After defining the goals and the strategy, initiatives and operational processes must be designed, in order to materialize and implement the strategy defined. Finally, it is necessary to use a feedback closed-loop approach, capable to measure if the operational layer is satisfying the organizational vision. Indeed, for a performance measure to be considered as a Key Performance Indicator (KPI), it has to be linked to one or more of the organizational critical success factors, more than one balanced scorecard perspective and more than one of the organization's strategic objectives.

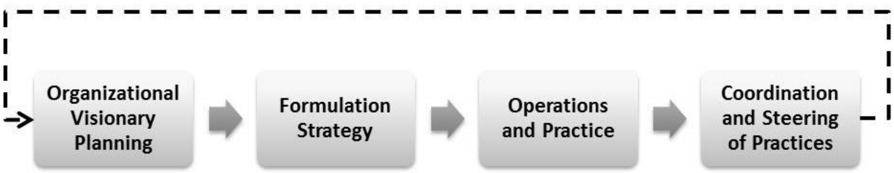

Figure 34 - Strategic Performance Management Cycle

Although, each factory is different in terms of products, processes, layout, structure, organisation model, human resources and corporate philosophy, the truth is that all of them need the ability to continuously adapt their production facilities to market necessities (Terkaj, Tolio, & Valente, 2009). Currently, one of the important paradigms explored within the industrial management scope is strictly related with idea that a factory is simply a very complex type of product (Jovane et al., 2009), called "Factory as a Product".

According to professor Westkämper, a factory should be seen as a very complex product, with its own structured and complex life cycle. This means that, similarly to the product development process, factories have to be permanently adapted for changing products, markets and technologies in order to fulfil economic, social and ecologic requirements (Constantinescu & Westkämper, 2010). However, this new kind of product itself is responsible for the manufacturing of other products with a shorter lifetime under the constraint of an ongoing operational, tactical and strategical change and the required adaption to it. This approach is referred as Unified and Sustainable Life Cycles Management and envisions an orchestration or harmonization of the specific life phases of products, production systems and corresponding design methodologies (see Figure 4 in sub-chapter Manufacturing Complexity and Modelling).

Consequently, aiming to explore this paradigm, as well as guarantee the alignment between product and factory life cycles, a functional modelling approach from product design was adapted (Almeida et al., 2012; Jufer, Politze, Bathelt, & Kunz, 2012; Politze, Bathelt, Reinhard, Jufer, & Kunz, 2010) to model the strategic goals of a factory, called Function Oriented Product Descriptions (FOPD). The FOPD constitutes an approach to combine a requirements model and a functional model. By following this approach, strategic goals may be modelled, as depicted in Figure 35.

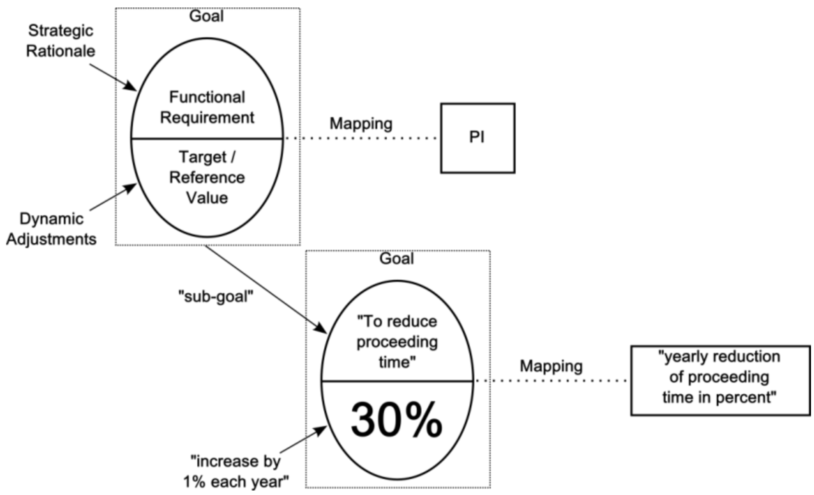

Figure 35 - Strategic Goal Modelling (Almeida, Politze at al. 2012)

In general, the modelling includes three main steps: firstly, a functional requirement has to be defined and formulated. By strictly following the rule that it has to be derived from higher goals, a specific stakeholder vision and/or the mission of the company, the rationale behind each functional requirement is captured and may be used later to justify each of the company´s goals. In a second step, one or several selected KPIs, that are seen as suitable to assess the intention that stands behind a functional requirement, are then assigned to it. Finally, a target or reference value has to be provided by the management. This value indicates the intended grade of target achievement and assures its measurability. Moreover, dynamic adjustments may be scheduled which have a direct impact on the target values and allows a dynamic adaptation of the factory goals. The FOPD approach also supports the modelling of variability information, which in turn allows defining all parts of the goal modelling with respect to specific products, areas or scenarios.

Although this seems to be a simple process, when dealing with complex manufacturing systems, achieving this level of maturity in terms of data interoperability, not always is a trivial task. Indeed, the plans defined at the strategic level not only involve the vision, the mission, the guiding principles and the goals for the business, but also define the functional requirements to be achieved, defining the specific behaviours or functions, as well as the KPIs that will evaluate these necessities.

However, in order to be effectively used, this information generated must be propagated through the tactical, technical and operational layers of an industrial organization. While the operational layer is where processes are materialized in order to convert raw material into products, on the other hand, a tactical plan is concerned with how to achieve the strategic goals. Consequently, the technical layer establishes the connection between the tactical and operational layer, in order to define the most granular and detailed production planning. Then, at the tactical layer, it is necessary to define the non-functional requirements that specify the criteria that can be used to judge the operation of a system.

I sum, as is depicted in Figure 36, the distance between the strategic and operational layer is enormous, which increases considerably the complexity of a performance management process to be aligned with the strategic goals. This way, the necessity to implement an integrated strategic performance management solution, able to cross the entire organization structure is essential in order to guarantee a rapid assessment and enhance responsiveness in low performance situations.

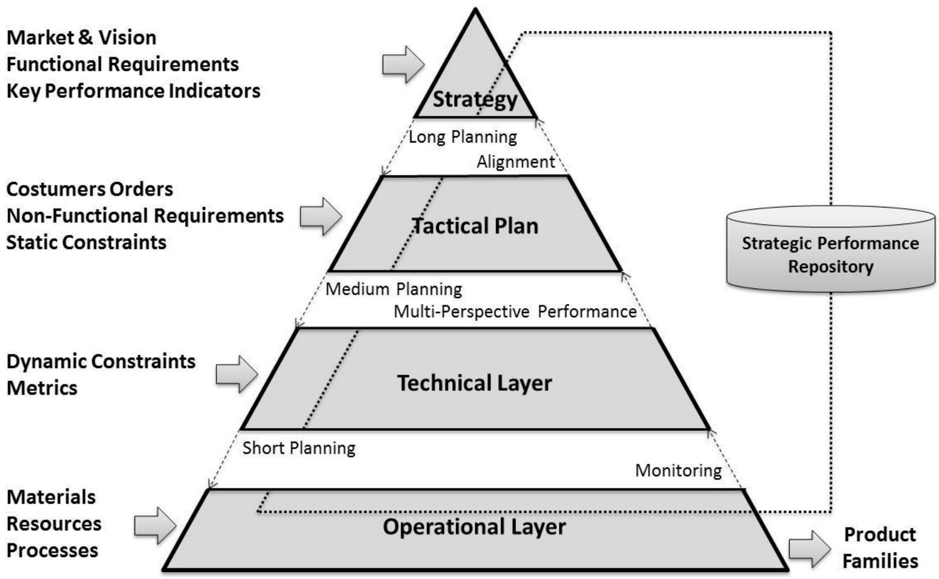

Figure 36 - Computer-Integrated Manufacturing Performance Control

From the successful implementation of this strategic performance management approach, using as driver a suitable technology capable to propagate the information generated at strategic layer of the organization until the operational level, it is not only possible to formally structure the different functional requirements from different points of view but also make this information clear and transparent for all the organizations. Specifically, guarantee alignment between the reason and motivations that lead to the creation of a specific KPI and the respective metric's calculation. In fact, this topic can lead us to the second objective of the proactive performance management framework, strictly related with the performance measurement system.

3.3. Performance Measurement

When designing a performance measurement solution there are mainly four core features that should be taken into account:

I. **Data Collection**: One of the greatest challenges in performance management is the appropriate storage and organization of an enterprise's data. To this end, performance management software incorporates support for data warehousing which key is in storing data in such a way that it can be easily accessed for the purposes of querying and analysis.

II. **Generating Information**: For data to be useful to an enterprise it is essential that tools and processes be implemented allow for its appropriate and timely analysis. Performance management software provides the means to generate reports and analysis.

III. **Key Performance Indicators**: To enable the defined understanding it is very important that an organization to define a number of key performance indicators (KPIs). Therefore, the idea of performance management software is to provide the means by which an enterprise can generate an analysis of data related to these indicators.

IV. **Response to Data Analysis**: After data gathering and organization, the primary objective of performance management software is to provide decision makers with the support systems necessary to form strategies that will drive the enterprise toward its objectives. Analysis created by performance management software creates better feedback loops. By providing timely analysis of performance information, these loops allow management to identify problems and take corrective actions before they become too large. Moreover, based on the analysis of past information the software can answer a range of "what-if" queries to aid management in creating strategy for the future.

Nevertheless, maintaining a performance measurement and management system within a complex organization can be a time consuming and expensive task. Indeed, mainly three reasons can be identified for this unexpected increasing of complexity, starting with the lack of people's commitment with the system maintenance. Surely, it has been observed that in most cases the implementation and maintenance of a performance measurement and management system fails due to human reasons. This happens because people believe that these methods will be used to punish them instead of support them improving their productivity. Due to this reason, the first step is strictly related with the necessity to break this paradigm and start using a performance measurement system as a motivational tool, where both workers and managers can identify points of improvement and, together, enhance the system performance as a whole.

The second reason for the increased complexity when implementing a performance measurement system is, due to the fact that normally key performance indicators (KPI) are defined in an unstructured way. This means that rarely stakeholders are capable to use the information intrinsic to the calculation of a specific KPI and consequently drill-down an indicator in order to find the reason that lead to the problem under analysis. It is important to clarify that, in the scope of this research study, to drill down means to move from summary information to a detailed data, more focused on an operational question than on a strategic or financial issue.

The third reason is mainly related with the fact that normally the information available on the IT systems is inappropriate and do not present a proper structuring for the metrics calculation, is difficult to access due to bureaucratic issues and can be corrupted. As consequence, it can be observed an increasing on the time required to calculate and analyse performance measurements as well as a higher probability to introduce errors during the KPIs calculation (Bititci, Mendibil, Nudurupati, Garengo, & Turner, 2006).

In sum, and as identified by several authors, traditional performance measurement and management approaches should be considered as unsuccessful, since they mainly use performance data that are extracted after a long feedback period (Figure 37), and only after this time frame T_f can the data be analysed in order to promote improvement actions for the next period (Braz et al., 2011; Lohman, Fortuin, & Wouters, 2002). In other words, problems and bottlenecks that arise at the present moment, will only be detected and explored T_f moments later. This means that, according to the current approaches, the reaction time is strongly conditioned and increased by feedback and improvement periods (Lohman et al., 2002).

Because of this reason, traditional approaches are no longer suitable. In fact, since organizations' reaction time is decreasing significantly, if stakeholders make decisions based on facts that happened on a previous T_f, they are not only losing opportunities during the time in which the problem really occurs until it is identified and solved, but they are also propagating the problem during T_f, which can definitely compromise the achievement of strategic goals because the time available to achieve the operational excellence is limited (Chen, 2008).

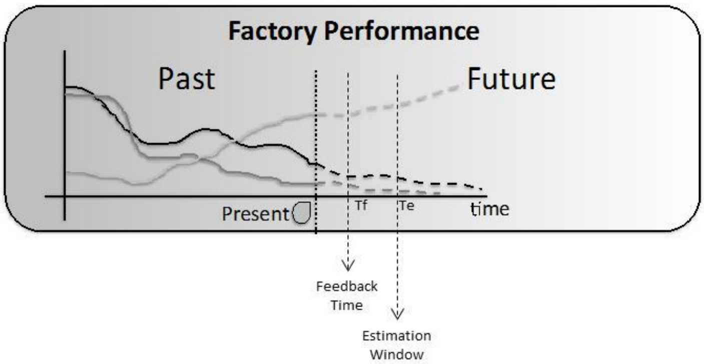

Figure 37 - Performance Management - Time Analysis

Since it is not possible to manage a system if its performance cannot be measured continuously during its entire life cycle, it is necessary to explore a flexible and agile performance measurement and management systems capable to overcome the gaps identified before (Bititci et al., 2006; Braz et al., 2011). Indeed, designing a performance measurement model involves a series of important decisions and considerations that should be taken into account since the design stage of the performance measurement system architecture. This means that issues such as the meaning of the measurement, the domain of the calculation and its multi-scale structure, the frequency of the measurement and the source of the data should be considered (Braz et al., 2011).

Based on this premise, Figure 38 presents the workflow that should be followed by a performance measurement system, in order to be achieved an automated KPIs metrics calculation process. Initially, the domain of calculation should be well defined. This means that the boundaries of the system to be managed should be carefully identified as well as the components of this system, which performance is expected to be measured and controlled, individually or not. At this stage a multi-scale structure should be used, able to represent the manufacturing system from the production network until the production locations and sites, production segments, production systems, production cells, workplaces and machines as well as processes (Figure 39) (Wiendahl & Heger, 2004).

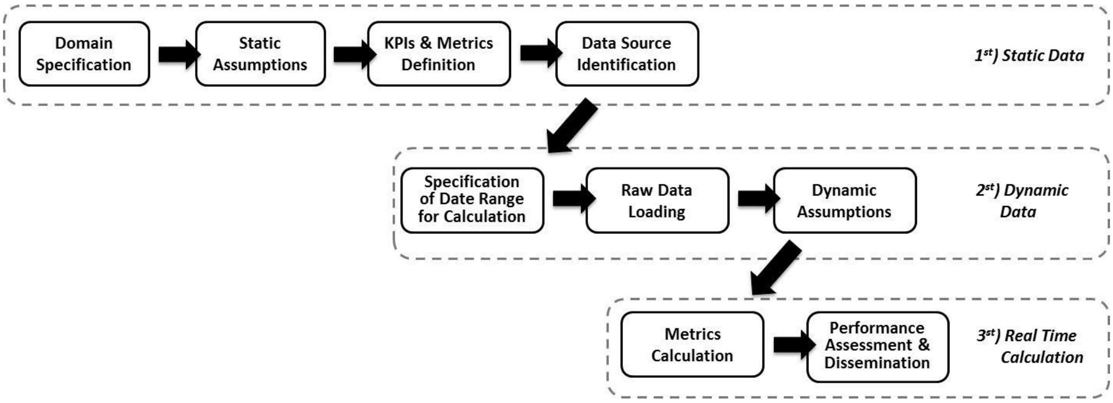

Figure 38 - Performance Measurement System Workflow

After defining the domain of calculation, following, the static assumptions characteristics from this domain should be enumerated and specified. For instance, the effective capacity can be seen as an example of a static assumption. By definition, "effective capacity" is the maximum amount of work that an organization is capable of completing in a given period due to constraints such as quality problems, delays, material handling, etc.

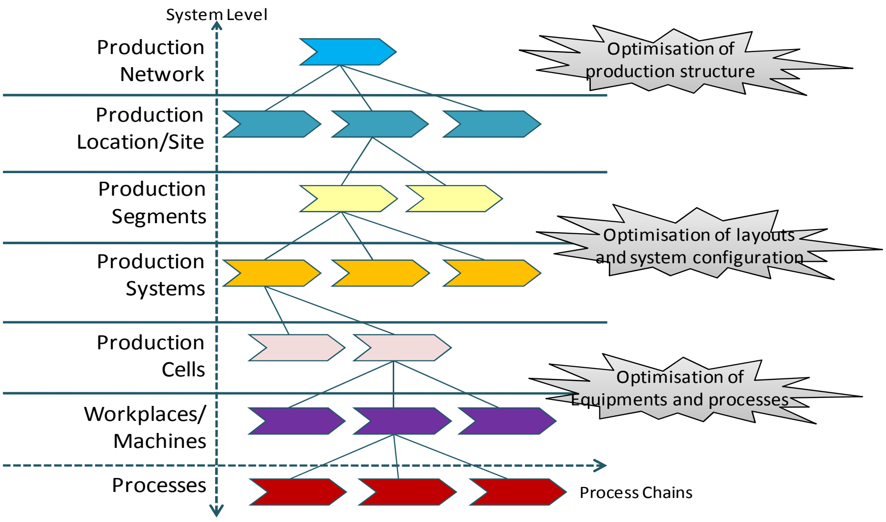

Figure 39 - Example of Multi-Scale Factory Structure

The KPIs and metrics definition is maybe one of the most critical activities developed within this proactive performance management concept. So, this process can be performed following two main perspectives: a ***process-driven*** or ***goal-driven*** perspective. Concerning the process-driven perspective, the system performance manager should start by identifying the core-processes of the system under analysis and, based on the purpose for which each process was designed, select the correct indicators that will evaluate its efficiency, effectiveness and relevance (*also known as Key Processes Indicators*). In the case that a goal-driven strategy is defined, then it is critical to start by defining the stakeholders of the system as well as their respective vision and strategic objectives. Following, the KPIs that will make it possible to evaluate if these objectives are being achieved or not should be designed (*also known as Key Result Indicators*).

Following, in order to design and formulate each KPIs' metrics, it is proposed to be followed a hierarchical approach, supporting system's performance managers to continuously mould these formulas according to the raw data available and scattered throughout the different legacy systems (i.e. data sources). In fact, this is a critical step since this is the one responsible by combining the information created at the strategic level with the raw data available at the operational level, taking into account the technical limitations available. A detailed analysis of the hierarchical metrics definition will be provided in the following chapters.

At this stage, not only all static data necessary to the KPIs calculation is available but also the mathematical formula, defining how these indicators should be calculated. However, this information is not enough since it will not make it possible to calculate, for example, each indicator per family of product. Consequently, and taken into account that almost all manufacturing systems produce more than one family of products, that can share or not resources and information, when calculating these indicators it is essential to introduce this variable within the calculation formula in order to calculate each indicator with the higher level of detail as possible. Only this way it is possible to calculate a KPI for each of the manufacturing system section/department and product life cycle.

Finally, selected the date range of calculation, as well as loaded the dynamic assumptions and raw data from respective data sources, the results of each KPIs should be compared against the target values. The result of the comparison must be carefully disseminated throughout the entire manufacturing system. At this step of the workflow, it is important to underline that both dissemination and targeting processes should be competent and efficient. For instance, when broadcasting the performance information, it is important to guarantee that an appealing interface is used in order to provide the decision maker with a clear, simple and rich visual experience. On the other hand, it is important to respect the fact that each actor involved in the manufacturing system should have access to a personal dashboard where only the KPIs that will support him improving their competences should be available. Indeed, this is an important innovation compared with the approaches normally used within current industrial organizations. Nowadays the performance information is customized according to the necessities and requirements of a limit number of actors, being after that imposed to the entire organization. However, due to the hierarchical construction of the KPIs and its metrics it becomes possible to easily mould the information available aiming to answer to necessities of all the actors involved in the production system.

Concerning the targeting process, it has been observed that even within world-class industrial organizations, both budgets and target values are defined in an ad-hoc way, strongly based on historical data. This happens mainly because stakeholders do not have the methods and tools that allow them to aggregate and formalize the knowledge available along the production system, and thus, preview future performance behaviours, taking into account endogenous and exogenous variables capable to affect the system behaviour. Moreover, from the analysis of the literature it is possible to conclude that the state of the art on performance measurement & management, even including those studies that refer to prediction or performance goals, has not addressed in detail the concept of performance planning, in order to close the entire performance measurement and management cycle.

In fact, few of these research projects include specific guidelines or steps for developing a quantitative performance planning system, based on desired improvement and forward-looking performance management. In the literature there are no suggestions to make a logical relationship between the targets of performance criteria, often developed in an arbitrary manner, and the data generated for management by prediction. Consequently, it is common to verify that during specific moments of the year, decision makers from complex manufacturing systems have to deal with critical situations where the manufacturing system's performance deviate so much from the targets defined that hinders the achievement of the annual budgets defined.

In sum, it is important to find an integrated approach that can not only reduce this reaction time, reducing the dependence on the feedback period, but also support decision makers with leading performance information capable of supporting them to envision future performance behaviours. As depicted in Figure 37, a performance prediction model, capable of estimating the system's behaviour by T_e, where the time window T_e must be higher than or equal to the feedback time $T_{f,}$, is critical. However, in order to achieve this, it is necessary to explore methods and tools that support decision makers to enhance their knowledge about the system's nature and behaviour (Braz et al., 2011). Therefore, our concept about estimation tool will be following presented.

3.4. Predictive Approach

The studies concerning performance measurement and management discipline can be categorized into three main groups: *performance measurement* (including expressions and indices definition), *performance analytics* and *performance prediction*. However, even performing a detailed and exhaustive literature review concerning performance estimation, it is possible to understand that little investigation has been successfully performed in terms of performance estimation for complex manufacturing systems. Although this is true, in the few studies that comprise this third domain of research, authors have been highlighting the importance of predict performance expressions, capable to figure the future performance of an organization, and consequently, help to make better decisions about action plans.

Indeed, in the performance management scope, the information obtained from a predictive approach can be used for three main purposes: *reachability*, *budgeting* and *targeting*. While the budgeting and targeting purposes are well known and developed within the industrial management area, on the other hand the reachability concept is a new one, mainly oriented to the necessity to assess if a manufacturing system has the right conditions to achieve the targets proposed. In the control theory, from where this concept was inspired, the reachability property of the system means an existence of a control signal, which transposes the system from the zero initial state to any designed final state (system's state target) (Hamadeh & Goncalves, 2008).

Figure 40 shows, in a simple way, the basic idea behind the reachability concept. Indeed, from t_0 until t_{final}, if the manufacturing system remains within the green triangle, point *a* and *b*, then the manufacturing system will be capable to achieve the expected target – *System's State Target*. On the other hand, if at any moment the system's state evolve to a situation located at the outer boundary of the green triangle, point *c*, then this system will not be able to achieve the target status.

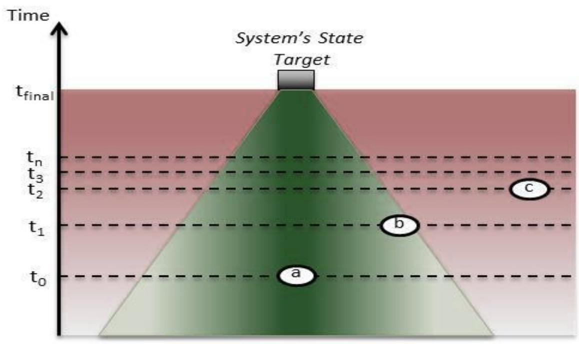

Figure 40 - Reachability Concept

Nevertheless, the methods developed until now are still very limited, presenting low levels of confidence. This implies that situations and decisions have to go wrong so that decision makers can realise what should be done in the future in order to avoid them. In other words, follow the normal path imposed by a typical learning process. However, due to the competitive environment where almost all organizations need to perform, there is no space for the selection of these inefficient strategies, strictly based on a reactive paradigm (Radnor & Barnes, 2007).

Contrarily, organizations should be capable to analyse, rethink and store data about their performance, so that decision makers become able to identify patterns of behaviour, define trends and thus anticipate problems. Moreover, since each manufacturing system is always affected by external factors, not only imposed by the market but also by the environment that surrounds the system in analysis, events such as political decisions, global economic situation, terrorism practices, climatic conditions, and others factors, can critically affect the normal system behaviour. Consequently, if it is expected to achieve reliable performance estimation then, it is necessary to take into account not only the endogenous but also the exogenous variables of a manufacturing system.

Identify and track the right drivers for the most accurate estimations should then be seen as the key driver to support decision makers estimating system's performance with the highest confidence possible. In fact, the selection of variables and business drivers with greater propensity to have a greatest impact on the strategic goals defined, as well as understand how these variables are able to hinder the system's behaviour, is of extreme importance. Consequently, it is possible to understand that more than a simple tool, this proactive performance management concept should be seen as a trigger for a shifting of mind-sets concerning manufacturing systems management.

Therefore, the idea of combining performance management with system dynamics is almost natural, since their main concepts are strictly together. For instance, while performance management intends to improve the systems performance based on feedback analysis, on the other hand the system dynamics support decision makers to understand and explore the existing feedback loops and their connections. Furthermore, if a mathematical tool is inserted within this framework, capable of correlating the different feedback loops, it is then possible to anticipate how the system will behave in the future, based on the leading factors that can be envisioned. In other words, achieve a hybrid strategy composed by both feedback and feedforward approaches.

In order to explain the importance of using a hybrid strategy, composed by both lagging and leading variables (Busi & Bititci, 2006b), the preventive maintenance indicator will be used as an example (see Figure 41). By definition, the preventive maintenance compliance is used to measure the level of accomplishment of preventive actions, taking into account what have been scheduled. In this specific case, this variable should be seen as a lagging indicator, since it represents the result of preventive actions that were performed.

However, if we evolve from an operational perspective to a planning perspective, where this same KPI can be seen as an indicator of equipment reliability, then preventive maintenance compliance should be seen as a leading indicator of the process reliability. Indeed, the higher the performance maintenance compliance, the more likely this will lead to improved equipment reliability. Similarly, improved equipment reliability will lead to reduce maintenance cost, which is a lagging indicator of the overall maintenance process. Finally, if we reduce maintenance cost then this will contribute to the increase on profitability. Figure 41 shows in a graphical way the logic and rational previously explained, following a causal loop diagram approach.

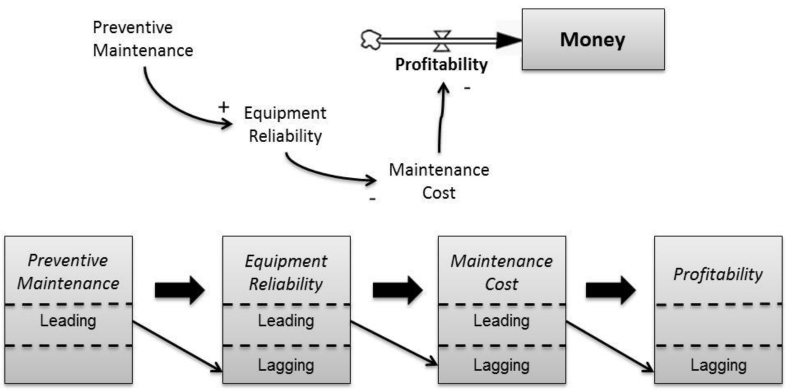

Figure 41 - Leading and Lagging Indicators Mapping

In sum, there is a need to evolve from a pure feedback control strategy to a combined approach where both feedback and feed-forward strategies should be applied, such as depicted in Figure 42. While the leading variables stimulate the estimation model with information that can be foresee for a specific time horizon, on the other hand the lagging indicators will make it possible to continuously updated this mathematical model, based on feedback information about the system behaviour.

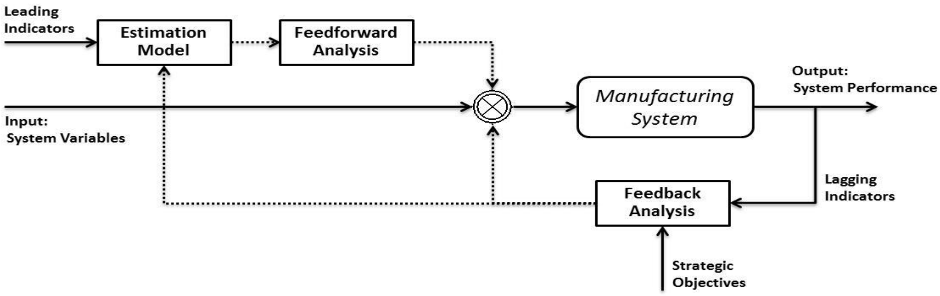

Figure 42 - Feedback Control Vs Feed-forward Control

In order to meet these challenges, this research work proposes that a framework based on the combination of the System Dynamics approach and the concept of Learning Machine should be explored. In one hand, the Performance Management Thinking methodology was developed as an extension of the Systems Dynamics approach for the process-based performance management domain. On the other, if this qualitative approach is extended by a learning machine tool, capable of correlating the different feedback loops and its measurements, then this framework should be capable of anticipating how the system will behave in the future based on the leading factors that can be envisioned.

3.5. Summary and Conclusions

During this chapter, it was introduced the main concepts and foundations behind the proactive performance management approach, developed within this research project, as well as its main components and objectives. Indeed, in order to make clearer which are the main advantages and changes of paradigm proposed by this research project, an analogy with the Plan-Do-Check-Act cycle from Shewhart and Deming was used. From this exercise it was possible to understand that not only the *decision-making* and *evaluation* stages where taken into account, but also an enhancement to the current mind-set on the PDCA cycle was introduced. This means that in addition to the feedback loop normally available, a feed-forward loop was introduced, supporting decision makers to foresee future performance behaviours, based on leading indicators measured in the present moment, and consequently take more efficient decisions.

In terms of the PDCA's decision-making stage, it was highlighted the necessity to efficiently model and propagate the organization's strategy objectives until the performance management system scope. In order to support this vision, the FOPD paradigm, from the product design area of research, was used as inspiration to drive the strategic objectives formalization in a more quantitative way, in order to be assessed and validated. Nevertheless, within complex manufacturing system this is not a simple task, mainly due to the distance between the strategic layer, where KPIs and respective metrics are defined, and the operational/technical layer where these indicators should be calculated. Therefore, it was proposed the development of a strategic performance data model capable to be a middleware between these two different universes of an industrial organization.

Following it was underlined the necessity to explore new performance measurement tools, capable to collect raw data from legacy systems, calculate indicators in a more agile manner and spread the performance information in a more efficient and transparent way for decision makers. At this stage, the necessity to explore real-time requirements was highlighted, aiming to guarantee that information concerning the manufacturing system behaviour arrives at the right person at the right moment, in order for the decisions can to be taken even before bottlenecks and low performance situations affect the overall manufacturing system performance.

Finally, a predictive performance management approach, based on feedback and feed-forward strategies was presented. As stated by Shewhart, the prediction theory should be based on the premise that estimation draws on the use of past performance information to interpret the present in order to predict the future. Thus, in the scope of this predictive performance concept, it was underlined the importance of combining lagging indicators with leading variables, aiming to increase the level of confidence concerning the performance estimation results. While lagging indicators are mainly related with historical data, on the other hand, leading variables present some previews about future behaviour of specific factors, identified as drivers of instability and uncertainty concerning the achievement of the goals identified at the strategic level.

While this chapter was mainly related with our vision for the proactive performance management concept, developed within this research project, in chapter three it will be presented the framework developed in order to materialize the concept here studied. In line with this, it will be explained how the research was conducted, as well as the restrictions and assumptions that were taken into account. Similarly to this chapter, it will also be explored some additional foundations that were used as pillars during the development of this proactive performance management framework.

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Chapter Four

FRAMEWORK PROPOSAL

Chapter three of this thesis is strictly related with the development of a performance management framework, responsible by implement and materialize the proactive management approach explored in the *previous chapter. Therefore, while on the previous section of this document it was mainly presented the functional requirements desired, aiming to improve current mind-sets concerning performance measurement and management disciplines, on the other hand, during this one it is expected to provide readers with a* strong *background about the framework developed.*

Therefore, initially, a description of the framework architecture will be presented, being explored not only the importance of each component but also the flow of information between each modules of the framework. Depicted the main architecture, following each component will be detailed analysed, mainly concerning its functional architecture or algorithm as well as the technology used to develop each of them.

4.1. Introduction

Aiming to pursuing the vision proposed for this research project, a performance management methodology, supporting decision makers to identify endogenous and exogenous variables that can hinder the achievement of their strategic objectives, should be explored. This methodology will support decisions-makers enhancing their understanding about their manufacturing systems behaviour.

Moreover, both performance measurement and estimation engines, responsible by measuring lagging indicators as well as estimate future performance behaviours, based on leading indicators, need to be fully designed and detailed. If in one hand, the performance measurement engine will guarantee the calculation of performance information with high levels or reliability and based on small number of KPIs, carrying a huge quantity of information, on the other hand the performance estimation engine will compile both qualitative and quantitative outcomes, from the performance management methodology and performance measurement engine, respectively, in order to estimate the future manufacturing systems behaviour.

While, the main objective of chapter three was to present, in a succinct way, the main concepts and objectives that driven the development of each functional component enumerated, now it is important to understand how the framework here presented was designed and developed, both from the conceptual and technical perspectives, in order to allow the (i) reliable collection/measurement of performance data, also known as *evidence* of the system behaviour; and based on this knowledge, potentiate an (ii) enhanced analysis and interpretation of the *evidence*, envisioning a more proactive decision making process.

4.2. Architecture

Based on the idea that less accurate and reliable performance information, measured from the shop floor, result on a strong restriction for the successful implementation of a proactive, or even reactive, performance measurement system, the first functional requirement identified was strictly related with the necessity to develop an expedite and reliable performance measurement system (Figure 43). If it is true that, in one hand, this functional module should be able to increase the level of accuracy and reliability of the performance information calculated, focusing at the same time on the level of granularity of each key indicator measured, on the other hand the performance measurement component should be flexible enough to gather, whenever necessary, information from multi-data sources, aiming to fuse raw data generated by different functional modules.

Nevertheless, the process related with the combination of raw data should not be performed in an ad-hoc way. This means that both the rules for raw data handling and the KPIs metrics definition should be extended from the strategic objectives defined at the management levels of an industrial organization. Since this research project is not focus on the strategy definition, the performance management framework should be scalable and holistic enough to allow 3rd party modules, strictly related with organization's strategy formalization (e.g. strategy maps, balance scorecard (BSC), and others), to feed this framework with the functional requirements defined as well as the KPIs, metrics and targets that should be assessed (see Figure 43).

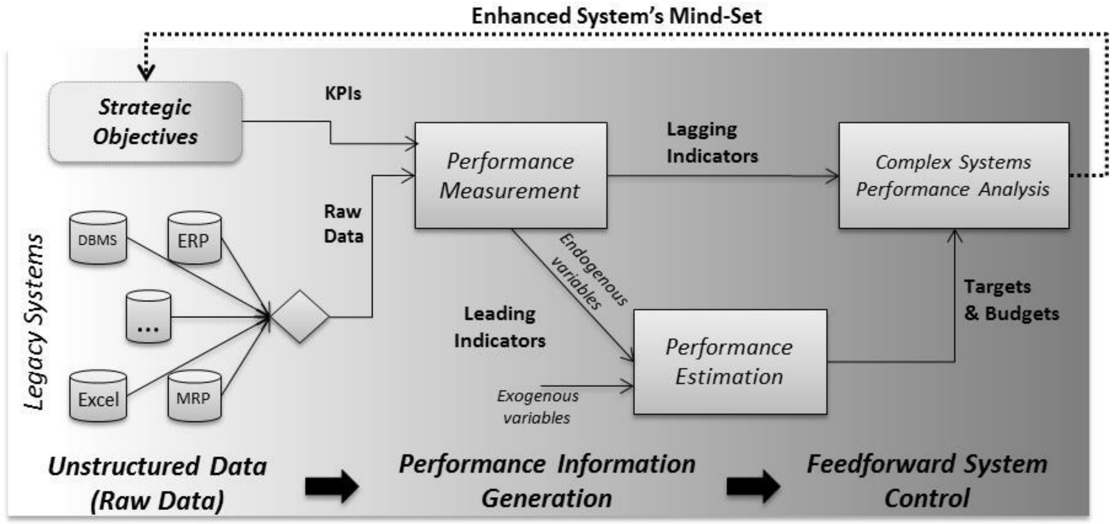

Figure 43 - Overall Framework Functional Requirements

Due to the levels of complexity characteristic from current manufacturing systems, reading and analysing the performance information is neither a straightforward nor a trivial issue, mainly due to the high number of factors that can hinder the normal behaviour of the system, as well as the trade-offs that can be observed from the synergies between these variables. Therefore, after guaranteeing that performance information is calculated with high levels of reliability, it becomes critical explore methodologies from complex systems science, capable to support decision makers to formulate their mental models about the system, validate with the different stakeholders, reuse knowledge for continuous improvement purposes and finally broadcast this conception about the system behaviour through the organization, aiming to achieve higher effectiveness and homogeneity on the decision making process.

Finally, if both stages related with performance measurement and performance information analysis are performed in a reliable way, decision makers become strongly empowered in terms of proactive control of their manufacturing systems. However, due to the high number of endogenous and exogenous factors that can affect the normal system performance, as well as due to their non-linear relationships, sometimes it becomes almost impossible to deal with this information in an ad-hoc way. Thus, an estimator engine capable to learn, correlate and manage the synergies between these different variables, and consequently, anticipate or even project future system's performance behaviours, in terms of a specific KPI, would represent a critical added-value for the effectiveness of the decision making process (see Figure 43).

Aiming to fulfil the requirements and gaps previously identified, in Figure 44 it is depicted the main architecture of the proactive performance framework developed within the scope of this research project, as well as the data flows between the different components of this framework. Indeed, one of the key drivers responsible for the flexibility requirements described before is the data model, responsible for the data interoperability not only between the different components of this framework but also with other modules, external to the proactive performance management framework, which can also be interested in absorbing the knowledge developed related with the manufacturing system performance behaviour (Chituc, Azevedo, & Toscano, 2009).

Moreover, it is important to underline that a flexible performance measurement and management system should be capable to read information not only from databases available in the manufacturing system, but also from other functional models applied by decision makers during their planning activities. For instance, if a performance management system is capable to collect the information related with a simulation performed in a specific 3D simulation tool, then it becomes possible to compare if the real system is performing as planned within the virtual world. In the same line, if a performance management system is capable to collect data concerning the layout of a plant, then this information can be used to build a more dynamic and rich domain of calculation, continuously aligned with the reality of the shop floor.

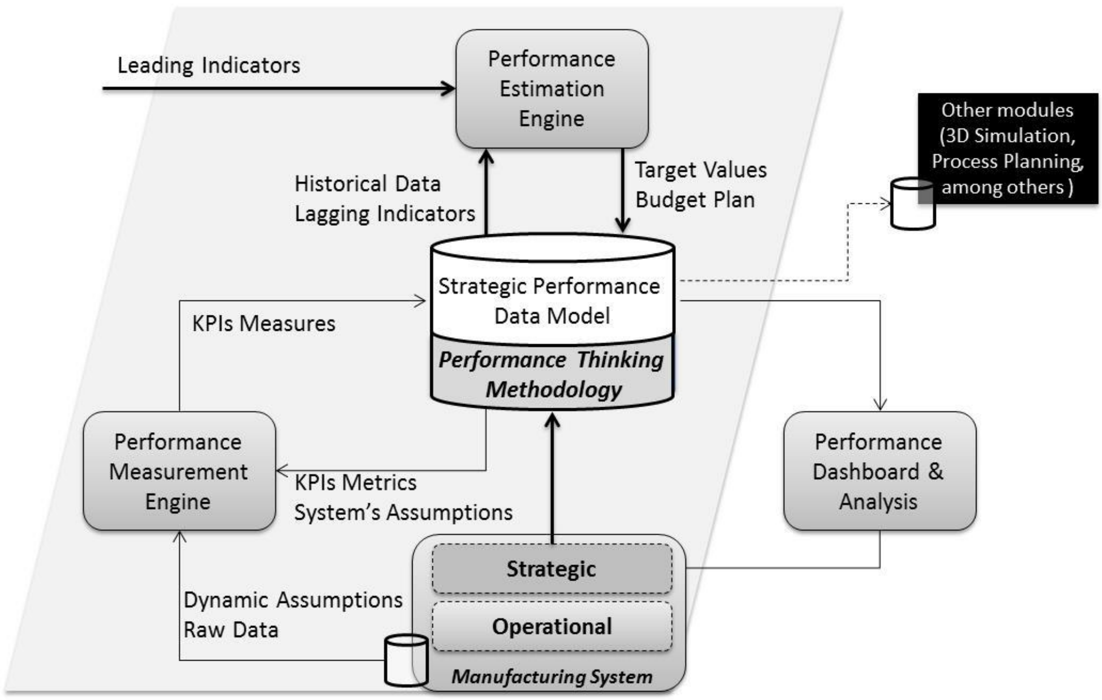

Figure 44 - Proactive Performance Management Framework

Aiming to implement this vision, as depicted in the previous figure, the strategic performance data model is the heart of this framework. This is the element responsible for defining which information should be generated as well as the relational model that rules data and knowledge management. Moreover, this data model defines how data should be stored in order to guarantee that modules, seeking for performance information and with the correct permissions, can gather or even change information (read/write).

Attached to this data model, a performance thinking methodology was developed aiming to follow decision makers to better understand the manufacturing system behaviour, by approximating as much as possible their mental model about the system to the reality.

At the basis of this methodology, an enhanced system dynamics approach, strictly oriented to processes performance management, was used. In fact, as already stated in the previous chapter, as important as the confidence and frequency that a KPI is calculated is the quality and relevance of the information selected. In other words, if the correct indicators are identified, strictly aligned with the organization strategy as well as with feedback-loops and trade-offs characteristics from the manufacturing system in analysis, then it is possible to build a more reliable and effective performance management system. Moreover, identifying the endogenous and exogenous factors capable to hinder and affect the normal system's behaviour, it is possible to increase the level of confidence regarding the performance estimation. In sum, with the implementation of a performance thinking methodology, it is expected to force decision makers to rethink their processes as well as enhance their knowledge and expertise concerning manufacturing system's performance.

The Performance Measurement Engine (PME) is a functional module developed under the umbrella of a European project called Virtual Factory Framework[7] (VFF) where the performance measurement and management issue was an essential topic, not only to support planning but also operational processes. As it is possible to see in Figure 44, the PME has mainly three dimensions that are important to be mentioned at this stage of the document. The first dimension of this performance measurement engine is mainly related with the necessity to streamline the strategic performance assessment. Thus, the PME continuously update its internal information concerning new/updated KPIs specification as well as the internal and external static variables that characterize the system in analysis. This kind of information is normally generated at the highest levels of the hierarchical structure of an industrial organization, where does not exist any kind of knowledge or even consciousness about the raw data available at the legacy systems of the organization, capable to provide with the suitable data for the KPI calculation.

Consequently, the second PME dimension is strictly related with the necessity to establish tunnels of communication, from where it will be collected, fused and filtered the correct raw data and dynamic assumptions from the shop floor. This is one of the main functionalities of the overall framework responsible for making agile and enhancing the linkage between the strategic and operational layers of an organization since it allows decision makers to easily define KPIs metrics, choose the suitable raw data available for its calculation as well as identify the databases where this information is available.

The third most important dimension of this engine is mainly related with the KPIs calculation and information broadcast. In fact, after collecting all the information related with KPIs metrics, static and dynamics assumptions, domain of calculation as well as raw data location, then it is feasible to calculate with high level of reliability each performance indicator defined at the strategic level. Finally, all the performance

[7] Virtual Factory Framework (VFF) is a collaborative research Project funded by the European Commission under the 7th Framework Programme. VFF objective was research and implement the underlying models and ideas at the foundation of a new conceptual framework designed to implement the next generation Virtual Factory, constantly synchronized with the real one.

information generated through this functional module should be stored at the strategic performance data model, aiming to make this data available to only to internal but also external modules seeking for this type of information. In the following chapters more detailed information will be provided concerning specific concepts developed for this performance measurement engine such as data fusion, high-resolution and hierarchical KPI definition.

One of the functional modules that will really take advantage from the information generated by the PME is the performance estimation engine (PEE). More and more, the estimation capabilities are seen as a critical added value for contemporary industrial organizations, since it allows them to preview a system's behaviour aiming to anticipate bottlenecks and low performance situations. Consequently, this is a mandatory module if we are planning to explore an innovative performance management approach. Regarding the proactive performance management framework here presented, the PEE is a module that collects historical data from the strategic performance data model (lagging variables) in order to build a reliable mathematical formulation of the behaviour of the system in analysis.

Similar to the performance measurement engine, also the estimation engine is deeply dependent from the performance thinking methodology. Since this is the tool developed to support decision makers to better understand industrial processes by continuously exploring the existing feedback loops, as well as the trade-offs imposed by them, then the level of confidence concerning the performance estimations will be directly dependent from the level of maturity of the organization concerning its expertise about the system's processes and the influence of the internal and external environment in its normal behaviour. This is the reason why in Figure 44 the performance estimation engine directly receives historical performance information and leading information from the performance data model and from the external environment, respectively, being the variables to be during the estimation process, imposed by the performance thinking methodology.

In conclusion, with the proactive performance management framework here explored, it is possible to go from the strategic objectives and performance management alignment, until the performance measurement calculation and estimation. According to the proactive performance management concept here developed, only combining a system thinking approach with real-time performance measurement system and a reliable but user-friendly performance estimation approach, it is possible to empower decision makers with the capability to enhance their knowledge and expertise about their manufacturing systems and thus become more proactive in terms of decision making.

This was the overview of the proactive performance management framework architecture. Following, a detailed analysis of each of the components described before will be detailed, analysed and explored. Moreover, decisions about the technologies adopted for the implementation of each element of the framework will be discussed.

4.3. Methodology for Performance Analysis

As already stated, the entire proactive performance management proposal is mainly oriented to complex manufacturing systems. This means that the focus of this research are industrial companies that present intricate manufacturing systems, where different product families are produced in parallel, competing for resources, machines and processes. Therefore, it can be observed that an enormous quantity of information, related with endogenous and exogenous factors, is continuously generated but rarely properly analysed. Thus, if this information becomes correctly and strategically studied, then it is possible to bring the stakeholder's mental model about the system's behaviour closer to the reality. As explored in the second chapter of this thesis, mainly oriented to the literature review, there is a series of tools and approaches that have been explored aimed to handle with the complexity of a manufacturing system. However, all of them agree that the quality and the way how information is used to enhance decision makers knowledge and expertise about the system in analysis should be seen as the key driver to achieve complexity dematerialization, and consequently a more proactive management strategy.

In line with this, the Performance Thinking Methodology (PTM) was developed, based on the system dynamics approach proposed by Jay Forrester at the MIT institute (Forrester, 1958; 1961; 1968; 1994; Sterman, 2000). Similarly to the system dynamic approach, the PTM aims to follow decisions makers during a series of important steps that will support them to achieve their objectives through an enhanced knowledge base concerning their core processes. Therefore, the Performance Thinking Methodology should be seen as an extension of the system dynamics approach to performance management, inspiring decision makers to think in their processes performance instead of simply using performance measures as numerical variables completely desegregated from the system's reality.

In concrete, seven main steps compose the PTM, as it is depicted in Figure 45. It is important to highlight that the implementation of this methodology should be seen as an iterative process. This means that after a first iteration, decision makers are more capable not only to enhance their expertise about the system, but also more confident to make decisions that will really improve complex manufacturing system's performance.

As initial assumption, it is taken into account that the organization under analysis follows a processes-driven strategy. This means that core and auxiliary processes should be properly defined and modelled. If this assumption is not verified, then as a prerequisite it should be performed a process modelling exercise, preferably with the support of an external company. Indeed, envisioning the successful PTM implementation, outsourcing this kind of projects is a very critical and delicate topic since manufacturing systems are composed by persons that have their own conception and mind-sets about the reality of the manufacturing systems where they are operating. This way, it is not always a simple task to develop this type of conceptual exercises without the support of an external entity capable of integrating and compiling all the perspectives available and who do not present vices, deliberated or not, neither personal agendas.

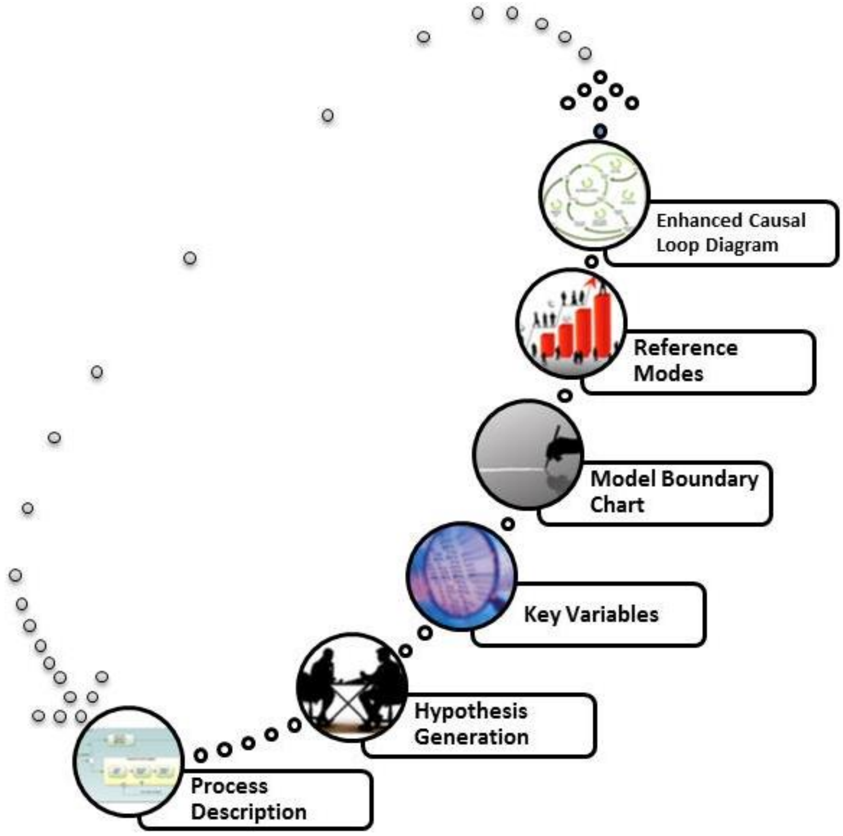

Figure 45 - Performance Thinking Methodology Road Map

A second assumption is based on the premise that the industrial organization has already defined their strategic maps and, consequently, the main objectives to be achieved in small and medium terms. This means that the implementation of the PTM should be strictly focus on a specific objective, and respective KPIs. Therefore, all the steps that compose the performance thinking methodology should always be performed envisioning the improvement of the system's performance in terms of the objectives stipulated by stakeholders as critical to be achieved.

After presenting the main vision about the performance thinking methodology, as well as the assumptions that should be verified to the successful implementation of the methodology here proposed, following a detailed analysis of each step of the PTM will be provided. It is important to underline that a practical application of this methodology will be presented in the following chapter, which is strictly related with the application cases performed in the scope of this research project.

As previously explained, at the basis of this methodology there is the necessity to clearly model and specify the core processes of the manufacturing system in analysis. Therefore, at a first stage, a detailed description of the process in analysis should be performed. Here, a BPMN approach is used in order to show the real workflow of the process, people involved and events/triggers. At this initial stage of the methodology, it is not expected to take into account the unstable behaviour of the system neither the exceptions nor non-linearity's behaviours. Contrarily, it is desired to clearly extract the normal and static characteristics of the system, following a process-based approach.

Following, after clearly understanding the core processes execution, testimonies from stakeholders involved in these processes should be collected and analysed in order to create an initial knowledge base. At this stage it is important to guarantee that the interview is mainly focused on the strategic objective, and respective KPI(s) that triggered the implementation of this methodology. Indeed, one of the main gaps in current industrial organizations is that knowledge and expertise about the system's behaviour is normally distributed through the different human resources, performing in specific areas or layers of the manufacturing system. Since this knowledge isn't normally centralized within an unique server, capable to disseminate it to all stakeholders involved in system's operations, than, at the end of the day, it is not possible to combine and cross this knowledge in order to support employees to take the most powerful decisions in short time. Envisioning the knowledge capture and enhancement, this stage of the methodology is one of the most delicate, but critical for the successful implementation of a proactive performance management approach, since it is expected to combine different points of view and mind-sets. If well performed, an important step will be taken towards the achievement of the proactive performance management vision here proposed.

However, only capturing this knowledge is not enough. Consequently, from the set of hypotheses and points of view provided by the different interviews, which should be strategically planned in order to include all the essential perspectives (e.g. product perspective, maintenance perspective, planning perspective, among others), all key variables that can affect the system and hinder the achievement of the expected objectives should be identified, enumerated, classified and described. After selecting the key variables, these should be classified as endogenous (controlled from inside the system), exogenous (affecting the system from outside of the boundary; they cannot be controlled) or excluded (if the variable is very unstable and cannot be modelled).

From this study, it is possible to execute the fourth stage of the performance thinking methodology. Indeed, this step of the methodology, called model boundary chart, is strictly related with the necessity to graphically represent the sources of the system's instability and variability, which are the main causes of the manufacturing system's complexity. Thus, the main goals of this step is to represent, in a graphical way, the overall architecture of the system and its surroundings, where the internal and external variables are represented, as well as its influence on the system behaviour. Although this stage does not have a direct impact on the outcome of the methodology implementation, its execution can have a powerful implication on the dissemination of the knowledge here generated.

Afterwards, the step called reference mode should be performed. This means that it is necessary to design and understand the behaviour of each variable, expressed and represented by its evolution curve. Thus, at this step of the methodology it is essential to guarantee that the data is properly extracted from the different databases in order to assure that the behaviour of each variable (trends, periodicity and fluctuations) will be deeply analysed for a specific time horizon. Since with this step the aim is to think in terms of graphs over time, looking for long-term dynamic behaviours, a proper selection of the time horizon will affect the overall result of the methodology implementation. This means that, if the time horizon selected to analyse the evolution of a certain variable is not well selected, then important information can be missed. For instance, if a very small time horizon is selected then it is possible that periodicity effects cannot be depicted and, consequently, analysed. On the other hand, if a time horizon too long is selected then the focus of the research may be lost, being analysed behaviours that do not reflect the current necessities or specifications of the system in analysis. Thus, for each variable it should be selected the suitable time horizon that best illustrates the normal behaviour of the factor that is expected to be analysed.

Finally, we arrive at the definition of the last step of the performance thinking methodology, strictly related with the design of an enhanced causal loop diagram (CLD). By definition, a causal diagram helps to visualise how interrelated variables affect one another (see Figure 46). When designing a CLD, variables should be related by causal links, shown by arrows. In the following example extracted from Sterman (2000), the birth rate is determined by both the population and the fractional birth rate. As it is possible to see, to each causal link it is assigned a polarity, either positive (+) or negative (-) to indicate how the dependent variable changes if the independent variable changes.

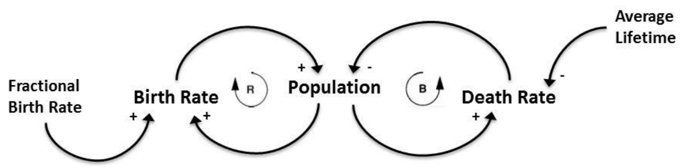

Figure 46 - Example of Causal Loop Diagram (adapted from (Sterman, 2000))

For instance, when a system is exposed to a positive link, this means that if the cause increases, then the effect will increase above what it would otherwise have been, and vice versa. On the other hand, when a system is exposed to a negative link, this means that if the cause increases, then the effect caused by this variable will decreases below what it would otherwise have been, and vice versa.

From this description, it is possible to understand that every link represented in a causal diagram must symbolize (what it is believed to be) the causal relationships between the variables, and not the correlations between them. When there is a combination of two or more causal links, strictly interrelated, then it is possible to say that we are in the presence of a feedback loop. In each CLD, it is possible to identify which are the most important feedback loops and attribute to each of them a loop identifier that shows whether the loop is a positive (reinforcing) or negative (balancing) feedback. In Figure 46 it is possible to see that there are two main feedback loops that directly affect the population variable.

Nevertheless, it is important to underline that a link polarity describes the structure of the system and not the behaviour of the variables. Indeed, an increase in a cause variable does not necessarily mean the effect will actually increase. This happens because a specific variable often has more than one input so, if it is expected to know the actual state of a variable than it is essential to analyse its memory as well as all links that converge to this specific variable. However, a standard CLD do not distinguish between stock and rate variables. In other words, in a normal CLD it is not possible to distinguish between the accumulations of resources in a system and the rate of changes that alter these stocks.

Consequently, the enhanced causal loop diagram intends to overcome this gap, since when analysing complex manufacturing systems, stocks and flows, along with feedback information, are the two central concepts of dynamic systems theory. Indeed, the stock variable is much more than a representation of physical accumulations, may in many cases be the source of disequilibrium dynamics in systems. They characterize the state of the system, imposing inertia and providing them with memory, and generate the information upon which decisions and actions are based. Moreover, stock variable also have a direct impact on time constraints. In fact, stocks are able to create delays by accumulating the difference between the inflow to a process and its outflow.

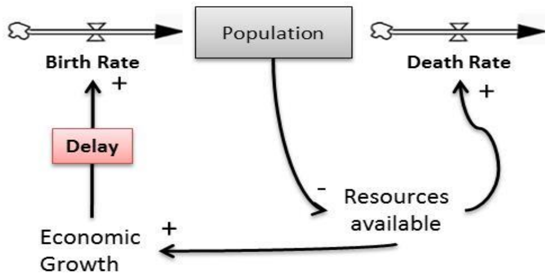

Figure 47 - Example of Enhanced Causal Loop Diagram

As it is possible to see in Figure 47, using a similar notation but enhanced by rate and stock concepts, it is possible to represent, in a clear and transparent way, more information to the reader. In fact, from a simple analysis it is possible to understand that the *population* is the stock variable (represented by a rectangle) that directly depends from both *birth* and *death* variables, which are the rate variables (represented by a valve). In addition, the *resources available* as well as *economic growth* are auxiliary variables added to the model to provide some clarity. In other words, auxiliaries can be seen as functions of stocks, constants or exogenous inputs that can be used to build feedback loops that directly affect the rate variables. Finally, clouds represent the sources and sinks for the flows. A source represents the stock from which a flow originating outside the boundary of the model arises; sinks represent the stocks into which flows leaving the model boundary drain. Sources and sinks are assumed to have infinite capacity and can never constrain the flows they support.

In sum, using the enhanced causal loop diagram it is possible to represent manufacturing systems as networks of stocks and flows, linked by information feedbacks from the stocks to the rates. Moreover, as depicted in Figure 47, it is possible to represent time constraints such as delays. This is critical information to be represented due to its impact on the dynamic hypothesis generation. Since delays give systems inertia, can create oscillations, and are often responsible for trade-offs between the short- and long-run effects of policies, it should be included a reference concerning delays within an enhanced causal loop diagram every time that this information presents a significant impact on the decisions results, due to its emphasis in relation with the time horizon selected.

Concluded the presentation of the performance thinking methodology, it is essential to evolve from a qualitative to a quantitative perspective, using the knowledge gathered and generated by this methodology to setup a performance estimation engine.

4.4. Estimation Component

4.4.1. Vision and Concepts

Previously, it was presented a methodology focused on the necessity to better understand complex manufacturing systems, through the rethinking of industrial organization's processes as well as design of enhanced causal loop diagrams, aiming to represent the relationships between stocks and rate variables based on complex feedback loops. Although this information is important to support decision makers to bring their mental models about the system closer to the reality, it becomes critical the development of a mathematical solution capable to use this knowledge to project future system's behaviours. This way, it is proposed the development of a so-called grey-box model in order to not only make agile the performance estimation process but also increase its reliability. From a practical point of view, the grey-box modelling is a very convenient way to model nonlinear processes, since, part the system behaviour can be derived from the existing knowledge, converted into a mathematical model, while the nonlinear characteristics of the process can be captured by an iterative learning algorithm.

Similarly to a model predictive control (MPC) approach (Aggelogiannaki et al., 2008; Braun et al., 2003), previously explored in the sub-chapter Predictive Relevance, through the definition of a mathematical model capable to emulate the system behaviour, it becomes possible to estimate how the system will perform in the future based on the preview of the leading factors for a specific time horizon. In other words, taking as reference the enhanced causal loop diagram, developed to describe and relate the different feedback loops existing within a complex manufacturing system, the main challenge should be to design this model, using as reference the historical data to isolate and classify the synergies between feedback loops.

However, as previously underlined, contemporary industrial organizations are dynamic systems, with considerable changes at a high frequency. Consequently, a mathematical equation capable to aggregate all the endogenous and exogenous variables identified as capable to hinder the normal behaviour of the system is not enough. Indeed, it should be explored a tool capable to continuously synchronize the mathematical model according to the system evolution.

Therefore, a hybrid-learning algorithm called Performance Estimation Engine (PEE) is proposed as complement of the performance thinking methodology. This algorithm is proposed as a learning machine for discrete time stochastic systems, whose evolution can be influenced by some control input, composed by both Neural Network (NN) and Kalman Filter concepts (Haykin, 2004; Linsker, 2008). Thus, a predictive performance management framework arises from the combination of the performance thinking methodology with this performance estimation engine.

Aiming to successfully answer to the requirements previously imposed, the PEE tool uses the Neural Networks (NN) concept to model and extract information from the historical performance data, according to the identified variables that can hinder the performance of the system according to a specific KPI perspective. Following this approach, it is possible to achieve accurate values since this estimator tool is capable of learning the system's behaviour and, using the generalisation capability, retrieves the expected results imposed by the environment. A detailed analysis about this important characteristic from NN will be provided next. Moreover, the NNs are nonlinear, which is a crucial advantage due to the fact that in the real world almost all systems present nonlinear characteristics.

Nevertheless, noises related with modelling and measurement processes, which critically affect the reliability of an estimation algorithm, are common to find mainly in complex manufacturing systems. Moreover, even small changes in a manufacturing system can affect the predefined mind-set about the system's behaviour and, consequently, the estimation result. Thus, in order to reduce the impacts caused by these dynamics issues, the Kalman Filter is applied to improve the accuracy of the estimation values by filtering these types of noises (Haykin, 2004). This stochastic controller is known for being capable of supporting estimations of the instantaneous "state" of a linear dynamic system for past, present and future states, even when the accuracy of the system modelling is not known or disturbed by white noise.

In sum, the PEE should be seen as a component that operates in a virtual environment, parallel with the system to be emulated (Figure 48). In order to be extracted the most accurate estimation results, three main moments can be identified: (i) initial model specification, (ii) system's performance estimation and the (iii) continuous model optimization.

At a first stage, the estimation engine should be trained, based on past performance data related with the endogenous and exogenous variables identified during the enhanced causal loop design. At the end of this stage, the function $G(w_i, x_i)$ characteristic from a neural network is already expectable to represent a reliable curve of behaviour of the system in analysis. Following, specified the predictive model through the definition of the correct weights of the neural network w_i, this is willing to receive the leading measurements x_i that positively or negatively influence the system. With this information, the PEE should be capable of deploying the estimation model in order to provide accurate performance estimations for the KPI chosen, over time.

Nevertheless, the estimations generated for these indicators should also be monitored and assessed, aiming to continuously optimize the estimation model. Thus, the third moment is strictly related with the necessity to continually optimize the estimation model in order to decrease as much as possible the errors caused by gaps in measurement and modelling processes. Therefore, as it is possible to see in Figure 48, through the comparison of the real performance of the system with the estimated, it is possible to calculate the error of estimation for a specific moment in time.

If a Kalman filter is allowed to continuously observe the evolution of this error, then this tool becomes capable to adjust the internal variables of the estimation model w_{i+1}, aiming to optimize its outcome. This way, two main objectives can be fulfilled. At a first stage, decrease as much as possible the estimation errors caused by process modelling or sensing errors and, on the other hand, decrease estimation errors origin from the continuous evolution of complex manufacturing systems. Since this is an iterative process, in the following performance estimation stage, it is expectable that the new estimation model is closer to the reality and consequently capable to provide better estimation results (Bolland & Connor, 1997).

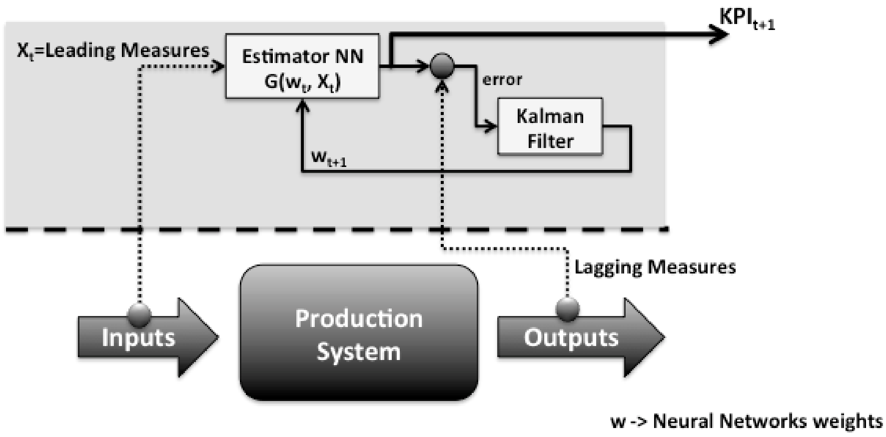

Figure 48 - Performance Estimation Engine Concept

Most research on Machine Learning has dealt with methods that employ a single learning strategy (*monostrategy methods*). However, aiming to develop systems capable of being applied to a wider range of problems, algorithms that integrate multiple inference types and learning mechanism should be explored (*multistrategy approach*). Therefore, following it will be presented some information about learning machines and estimation error observer's concepts due to its preponderance on the building of the performance estimation engine here proposed. Concerning the learning machines issue, a strong relevance will be provided to neural networks while, on the other hand, in terms of the estimation error observer concept, the focus will be the Kalman Filters. Moreover, the global architecture of the estimation engine will be presented and discussed.

4.4.1.1. Learning Machine

Over the past decades, the field of Artificial Intelligence (AI) has been explored toward computerising human reasoning capabilities, in order to handle with specific problems identified within the manufacturing scope, such as scheduling, part routing and order processing. Three specific methods for perception and cognitive processes modelling have been explored:

- **Expert knowledge**: representing information utilised by recognised experts;
- **Heuristic knowledge**: representing information that has been proven to work well in prior circumstances. This usually takes the form of correlational links between system conditions and actions to be taken to achieve a specific objective;
- **Derived knowledge**: representing correlational information about conditions and actions that is inferred from a set of data pertinent to the system at hand.

An important trend within the derived knowledge representation domain is the machine learning. Machine learning essentially seeks to acquire knowledge from available data and facts and use it to create new theories about the domain in question, in an entirely automated manner, reusing this acquired knowledge in future decision-making situations. A specific approach of machine learning involves the definition of an algorithm that mimics the processing characteristics of the nervous system, called artificial neural networks (NNs). Investigations have been confirmed that adaptive NN technique is a viable solution in a wide range of disciplines, such as economy, robotics and engineering systems, pattern recognition, medicine, among other areas, due to its wide number of applications: hierarchical control and systems monitoring with real-time operation, uncertainty handling, sensor integration, learning features, and others (Monostori, 2003).

Indeed, NN presents a high level of application within a wide range of subjects. However, within the scope of this thesis we will explore in which way NN can provide an important contribution for complex systems modelling, envisioning its performance estimation. By definition, a Neural Networks is a non-linear tool with data-driven self-adaptive capability, which makes it possible to approximate any continuous function to any desired accuracy. However, its powerful learning capability is not the only feature that makes NN a suitable technology for estimation exercises. In addition, due to the generalization capability, NN are capable to continuously adapt to different conditions, respond to new situations and fits tolerance to structural and parametric changes, rejecting input noise. Finally, since the learning algorithm is performed at an offline mode, then the NN technology presents a faster processing capacity, allowing to obtain performance estimation very quickly. In conclusion, the NN tool allows the non-linear modelling, without *a priori* knowledge of the relationship between input and output variables (Zhang & Eddy Patuwo, 1998), what represents an important added-value for the performance estimation engine.

Neural networks, whose concept is inspired in the biological nervous system, can be defined as a composition of simple elements called nodes, which are the artificial equivalents of biological neurons. On the other hand, synapses, which represent the biological neurons behaviour, within the NN scope are modelled by a variable also known as weight W_{ji}. In each node, every input stimuli X_j is multiplied and added to the other weighted inputs before they are sent to the node activation σ. Afterwards, the activation is compared with a threshold. If the activation exceeds the threshold Θ value, the unit produces a high-value output. Otherwise, the output is zero. In summary, the output value of each neuron Yi depends on the potential of the neuron, the threshold (or bias) and the activation function σ. Below, Figure 49 prototypical example of the behaviour of neurons/nodes is presented.

The term "network" refers to any system of artificial neurons that may range from a single node to a large collection of nodes, in which each one is connected to every other node in the net. A neural network should be composed of at least by: one *input* layer, one *hidden* layer and one *output* layer. However, depending on the level of complexity of the system in analysis, the number of hidden layers of the network can increase in order to enhance the polynomial function generated by this mathematical tool. As in nature, the network function is determined largely by the connection function between elements.

As it is possible to see in the fFigure 50, a circle represents each node, being the weights implicit to all connections. Nodes are distributed in a layered structure where signals flow from an input to an output, going through a series of hidden layers. Among the various NNs architectures available, the radial basis function network (RBFN) is the most currently used and which present better results regarding the forecasting tasks.

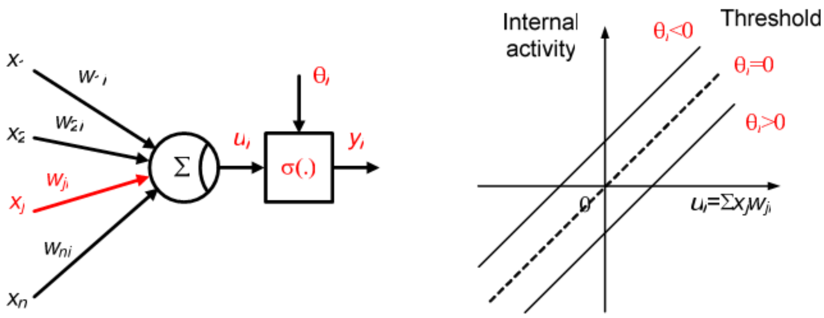

Figure 49 - Basic Diagram of an Artificial Neuron and its Internal Activity

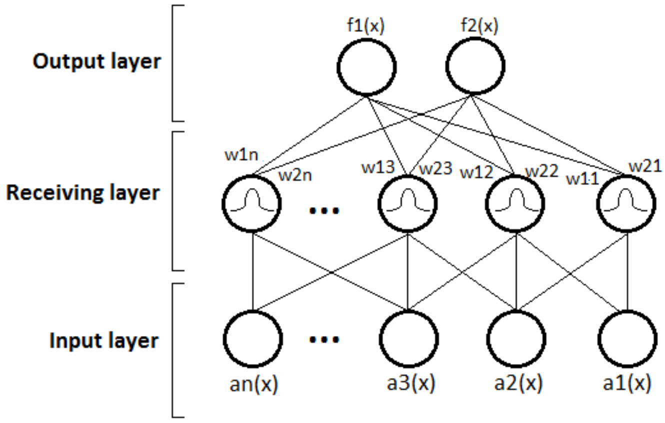

Figure 50 - Simple Example of a Neural Network (RBFN)

Commonly, neural networks are trained in order to assure that a particular set of inputs leads to a specific target output, thus emulating the real system behaviour. This way, a training algorithm capable of capturing the system behaviour should be explored. Usually, neural network training is an iterative method based on the comparison of the network's output with the real value, measured from the real system, until the network output matches the target. The most used training algorithm is the backpropagation (BP). This is a batch training that propagates the error observed at the output of the network, through the different layers, until its input layer, in order to correctly update the weights of each neuron, and thus approximate the curve of behaviour to reality, maintaining the generalisation capability. This generalisation feature represents the neural network's aptitude to infer information, even when the set of input values is entirely new. This means that, if well specified, a neural network is capable to emulate the outcome of the system even if the set of leading variables does not match with the training set. This happens because a neural network does not memorize the relations between inputs and outputs of a system. In opposition, a NN mould the suitable mathematical curve that best fit the system behaviour.

Therefore, when training a Neural Network, generalization is an important feature to maintain in order to avoid over fitting. This can occur when the error on the training set is forced to a very small value. If this happens, the network will perform very well for that particular training set, because it has memorized the training examples, but it should not be expectable that this network should be capable to adapt to new situations.

In order to decrease the possibility to build a neural network with a reduced generalization capability, there are several methods that can be applied aiming to enhance the generalization capability of a specific Neural Network, without sacrificing its accuracy. The first method, and maybe the most recommended one, is specifying a network that is just large enough to provide an adequate fit. With increasing hidden neuron number, NN mapping accuracy increases given the training events. By varying the number of hidden neurons, the validation subset allows one to control the accuracy level with respect to the noise level. Not only will it improve generalization but also it will speed up training stage.

The second method is known as *Regularization* and it is strictly related with a modification of the performance function. Normally, the performance function used is the mean sum of squares of the network errors (MSE). Another method is known as *Early Stopping*. This method uses a validation process to stop training if the network begins to over fit the data. In other words, passing a validation set to the training function, at a certain point in training, will evaluate how the network is responding for other inputs. If the error of the validation set begins to rise, which is a signal that indicates over fitting, then the training stage must stop.

Despite all the advantages and satisfactory characteristics of NNs, building a neural network forecaster is not a trivial or a consensual task. In fact, one critical decision is to determine the appropriate architecture, or in other words, the number of layers, the number of nodes in each layer and the number of arcs that interconnect with nodes. Moreover, it is important to study and select some aspects such as the activation functions of hidden and output layers, the training algorithm, normalization methods, training and test sets and also the performance measures.

In sum, the neural network approach belongs to the learning machine concept, with which complex system behaviours can be easily emulated without any extensive quantitative knowledge of the system. However, within world-class industry scope, manufacturing systems should be seen as living entities that continuously change their behaviour in order to meet market requirements. This way, the simple application of a neural network approach, in which the learning algorithm is normally based on past measurements of the real world, may prove to be unreliable since it is not capable of envisioning the evolution of manufacturing systems. Hence, in order to predict behavioural changes, this predictive framework proposes the implementation of an estimation error observer, such as the predictive Kalman algorithm and its nonlinear extensions, in parallel with the Neural Network tool, as following explained.

4.4.1.2. Estimation Error Observer

In classical linear estimation and control theory, a system is described by a state vector x_t, whose value at each discrete time t follows the dynamic rule depicted in equations 4.1 and 4.2 (Haykin, 2004).

$$x_{t+1} = Fx_t + Bu_t + m_t \qquad \text{Eq. 4.1}$$

$$y_t = Hx_t + n_t \qquad \text{Eq. 4.2}$$

where, m_t and n_t represent the plant and measurement noise, respectively, while the optional vector u_t is an external driving term and/or a computed control term.

The Kalman Filter, developed by Rudolf Emil Kalman in 1930, is a tool used to optimize the estimation of state models. This filter is known for being capable of supporting estimations for past, present and future states, even when the system modelling accuracy is not known. In a higher mathematical layer of abstraction, the aim of an optimal filter (or, respectively, one-step-ahead predictor) is to compute a posterior state estimate $\hat{x}_t$ (or respectively, a prior state estimate $\hat{x}_{t+1}$) that minimises the generalised mean-square estimation error.

In the scope of his research, Kalman showed that under a variety of conditions the optimal estimation solution for both filter and predictor could be achieved following the equation depicted next,

$$\hat{x}_{t+1} = \hat{x}_t^- + k_t e_t \qquad \text{Eq. 4.3}$$

where k_t represents the Kalman gain, $\hat{x}_t^-$ represents the estimation provided by the linear model, and e_t represents the error between the estimated and the measured values. The Kalman gain is learned iteratively, starting with an arbitrary matrix and converging to its real value, as each new measurement is obtained.

The Kalman Filter uses a model of the estimation problem that distinguishes between *phenomena* (what one is able to observe), *noumena* (what is really going on), and the state of knowledge about the *noumena* that can be deduced from the phenomena. That state of knowledge is represented by a probabilistic distribution. Moreover, because it uses a finite representation of the estimation problem, by a finite number of variables, it can be defined as ideally suited for the implementation in digital computers. Also, the Kalman Filter does not require that the deterministic dynamics or the random processes have stationary properties and, at the same time, it is also compatible with the state-space formulation of optimal controllers for dynamic systems, providing useful properties of estimation and control. Aiming to achieve optimal estimation results both process and measurement noises must have a Gaussian.

Consider a linear, discrete-time dynamical system described by the block diagram shown in Figure 51. The concept of state is fundamental to this description. The state vector or simply state, denoted by x_k, is defined as the minimal set of data that is sufficient to uniquely describe the unforced dynamical behaviour of the system; the subscript k denotes discrete time. In other words, the state is the least amount of data on the past behaviour of the system that is needed to predict its future behaviour.

Typically, the state x_k is unknown. To estimate it, we use a set of observed data, denoted by the vector y_k.

In mathematical terms, the block diagram of Figure 51 embodies the following pair of equations:

1. *Process Equation*

$$\boldsymbol{x_{k+1}} = \boldsymbol{F_{k+1,k}x_k} + \boldsymbol{w_k} \qquad \textbf{Eq.4.4}$$

where $F_{k+1,k}$ is the transition matrix taking the state x_k from time k to time k+1. The process noise w_k is assumed to be additive, white, and Gaussian, with zero mean and with covariance matrix defined by

$$E[w_n \quad w_n^T] = \begin{cases} Q_k & for\ n = k \\ 0 & for\ n \neq k \end{cases} \qquad \text{Eq.4.5}$$

where the superscript T denotes matrix transposition. The dimension of the state space is denoted by M.

2. *Measurement Equation*

$$\boldsymbol{y_k} = \boldsymbol{H_k x_k} + \boldsymbol{v_k} \qquad \textbf{Eq.4.6}$$

where y_k is the observable at time k and H_k is the measurement matrix. The measurement noise v_k is assumed to be additive, white, and Gaussian, with zero mean and with covariance matrix defined by

$$E[v_n \quad v_n^T] = \begin{cases} R_k & for\ n = k \\ 0 & for\ n \neq k \end{cases} \qquad \text{Eq.4.7}$$

Moreover, the measurement noise v_k is uncorrelated with the process noise w_k. N denotes the dimension of the measurement space.

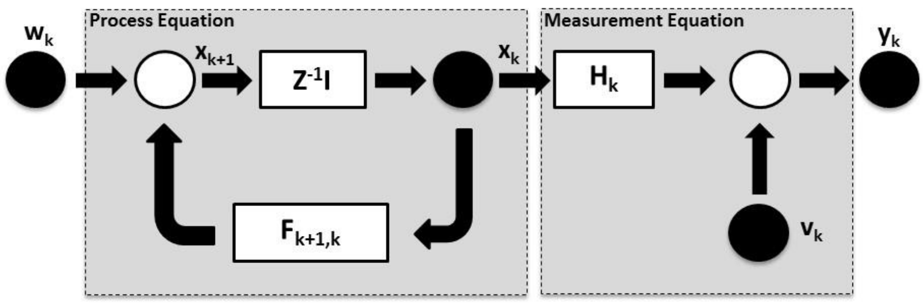

Figure 51 - Signal Flow Graph Representation of a linear discrete-time dynamical system (adapted from (Haykin, 2004))

From the analysis of the previous equations (Eq.4.6 and Eq.4.7), it is possible to understand that the Kalman filtering problem, namely, the problem of jointly solving the process and measurement equations for the unknown state in an optimum manner is strictly related with the use of the entire observed data, consisting of the vectors $y_1; y_2 \dots y_k$, to find for each $k \geq 1$ the minimum mean-square error estimate of the state x_i. It is important to underline that the problem is called filtering if $i = k$, prediction if $i > k$, and smoothing if $1 \leq i < k$.

After understanding the vision behind the Kalman Filter concept, it is now important derive its mathematical formula. Suppose that a measurement on a linear dynamical system, described by equations 4.4 and 4.6, has been made at time k. The requirement is to use the information contained in the new measurement y_k to update the estimate of the unknown state x_k.

Let $\hat{x}_k^-$ denote a priori estimate of the state, which is already available at time k. With a linear estimator as the objective, we may express the a posteriori estimate $\hat{x}_k$ as a linear combination of the a priori estimate and the new measurement, as shown by

$$\hat{x}_k = G_k^{(1)} \hat{x}_k^- + G_k y_k \qquad \text{Eq.4.8}$$

where the multiplying matrix factors $G_k^{(1)}$ and G_k are to be determined. Nevertheless, to find these two matrices, there are some basic concepts from optimum estimation that are important to be explored, such as *conditional mean estimator* and *principle of orthogonality*.

Supposing it is provided the observable $y_k = x_k + v_k$, where x_k is an unknown signal and v_k is an additive noise component. Let $\hat{x}_k$ denote the a posteriori estimate of the signal x_k, given the observations $y_1; y_2 \dots y_k$. In general, the estimate $\hat{x}_k$ is different from the unknown signal x_k. To derive this estimate in an optimum manner, we need a cost (loss) function for incorrect estimates. The cost function should satisfy two requirements:

- The cost function is nonnegative;
- The cost function is a non-decreasing function of the estimation error $\tilde{x}_k$ defined by $\tilde{x}_k = x_k - \hat{x}_k$.

These two requirements are satisfied by the mean-square error defined by $J_k = E[(x_k - \hat{x}_k)^2] = E[\tilde{x}_k{}^2]$, where E is the expectation operator. The dependence of the cost function J_k on time k emphasizes the nonstationary nature of the recursive estimation process. To derive an optimal value for the estimate $\hat{x}_k$, we may invoke the two theorems previously identified and taken from the stochastic process theory:

Theorem 1

Conditional mean estimator: *If the stochastic processes $\{x_k\}$ and $\{y_k\}$ are jointly Gaussian, then the optimum estimate $\hat{x}_k$ that minimizes the mean-square error J_k is the conditional mean estimator:*

$$\hat{x}_k = E[\hat{x}_k | y_1; y_2 \dots y_k] \qquad \text{Eq.4.9}$$

Theorem 2

Principle of Orthogonality: *Let the stochastic processes $\{x_k\}$ and $\{y_k\}$ be of zero means; that is,*

$$E[x_k] = E[y_k] = 0 \text{ for all k.} \qquad \text{Eq.4.10}$$

Then:

I. the stochastic process$\{x_k\}$ and $\{y_k\}$ are jointly Gaussian; or
II. if the optimal estimate $\hat{x}_k$ is restricted to be a linear function of the observables and the cost function is the mean-square error,
III. then the optimum estimate $\hat{x}_k$, given the observables $y_1; y_2 \dots y_k$, is the orthogonal projection of x_k on the space spanned by these observables.

With these two theorems at hand, the derivation of the Kalman filter follows. The state-error vector is defined by $\tilde{x}_k = x_k - \hat{x}_k$(Eq.4.11). Applying the principle of orthogonality to the situation at hand, we may thus write

$$E[\tilde{x}_k y_i^T] = 0 \text{ for i=1,2,...,k-1} \quad \text{Eq.4.12}$$

Using equations 4.6, 4.8, 4.11 and 4.12

$$E\left[\left(x_k - G_k^{(1)}\hat{x}_k^- - G_k H_k x_k - G_k v_k\right)y_i^T\right] = 0 \text{ for i=1,2,...,k-1} \quad \text{Eq.4.13}$$

Since the process noise w_k and measurement noise v_k are uncorrelated, it follows that $\mathrm{E}\left[\mathrm{v_k y_i^T}\right] = 0$. Using this relation and rearranging terms, we may rewrite the previously equation as $\mathrm{E}\left[\left(\mathrm{I} - \mathrm{G_k H_k} - \mathrm{G_k^{(1)}}\right)\mathrm{x_k y_i^T} + \mathrm{G_k^{(1)}}(\mathrm{x_k} - \hat{\mathrm{x}}_\mathrm{k}^-)\mathrm{y_i^T}\right] = 0$ (Eq.4.14), where I is the identity matrix. From the principle of orthogonality $E\left[(\mathrm{x_k} - \hat{\mathrm{x}}_\mathrm{k}^-)\mathrm{y_i^T}\right] = 0$.

Accordingly, equation 4.14 simplifies to

$$\left(\mathrm{I} - \mathrm{G_k H_k} - \mathrm{G_k^{(1)}}\right)E\left[\mathrm{x_k y_i^T}\right] = 0 \text{ for i=1,2,...,k-1} \quad \text{E.q.4.15}$$

For arbitrary values of the state $\mathrm{x_k}$ and observable $\mathrm{y_i}$, Eq. (4.15) can only be satisfied if the scaling factors $\mathrm{G_k^{(1)}}$ and $\mathrm{G_k}$ are related as $I - \mathrm{G_k H_k} - \mathrm{G_k^{(1)}} = 0$, or equivalently $\mathrm{G_k^{(1)}} = I - \mathrm{G_k H_k}$.

Substituting equation 4.15 on equation 4.8 it is possible to express a posteriori estimate of the state at time k as

$$\hat{x}_k = \hat{x}_k^- + G_k(y_k - \mathrm{H_k}\hat{x}_k^-) \quad \text{Eq.4.16}$$

in which, the matrix G_k is called the Kalman gain. Equation 4.17 is the desired formula for computing the Kalman gain G_k, which is defined in terms of the a priori covariance matrix P_k^- and the covariance matrix $R_k = E\left[v_k v_k^T\right]$ of measurement error v_k.

$$G_k = P_k^- H_k^T [H_k P_k^- H_k^T + R_k]^{-1} \quad \text{Eq.4.17}$$

In Table 2 it is possible to find a summary of the Kalman Filter algorithm.

Table 2 - Summary of Kalman Filter Algorithm (adapted from (Haykin, 2004))

State-space model

$$x_{k+1} = F_{k+1,k}x_k + w_k$$

$$y_k = H_k x_k + v_k$$

Where $\boldsymbol{w_k}$ and $\boldsymbol{v_k}$ are independent, zero-mean, Gaussian noise processes of covariance matrices $\boldsymbol{Q_k}$ and $\boldsymbol{R_k}$, respectively.

Initialization: For k=0, set

$$\hat{x}_0 = E[x_0]$$

$$P_0 = E[(x_0 - E[x_0])(x_0 - E[x_0])^T]$$

Computation: For k=1,2,..., compute:

State estimate propagation	$\hat{x}_k^- = F_{k,k-1}\hat{x}_{k-1}^-$
Error covariance propagation	$P_k^- = F_{k,k-1}P_{k-1}F_{k,k-1}^T + Q_{k-1}$
Kalman estimate matrix	$G_k = P_k^- H_k^T [H_k P_k^- H_k^T + R_k]^{-1}$
State estimate update	$\hat{x}_k = \hat{x}_k^- + G_k(y_k - H_k\hat{x}_k^-)$
Error covariance update	$P_k = (I - G_k H_k)P_k^-$

The basic Kalman filter is a linear, discrete-time, finite-dimensional system, which is endowed with a recursive structure that makes a digital computer well suited for its implementation. However, if the system presents a non-linear behaviour, an extension of the Kalman filter should be explored throughout a linearization procedure. The resulting filter is referred to as Extended Kalman Filter (EKF). The basic idea of the EKF is to linearize the state-space model at each time instant around the most recent state estimated.

To set the stage for a development of the extended Kalman filter, consider a nonlinear dynamical system described by the state-space model (Bavdekar, Deshpande, & Patwardhan, 2011; Haykin, 2004)

$$x_{k+1} = f(k, x_k) + w_k \qquad \text{Eq.4.18}$$

$$y_k = h(k, x_k) + v_k \qquad \text{Eq.4.19}$$

where, as before, w_k and v_k are independent zero-mean white Gaussian noise processes with covariance matrices $\mathrm{R_k}$ and $\mathrm{Q_k}$, respectively. Here, however, the functional $f(k, x_k)$ denotes a nonlinear transition matrix function that is possibly time-variant. Likewise, the functional $h(k, x_k)$ denotes a nonlinear measurement matrix that may be time-variant, too.

The basic idea of the extended Kalman filter is to linearize the state-space model of equations 4.18 and 4.19 at each time instant around the most recent state estimate, which is taken to be either $\hat{x}_k$ or $\hat{x}_k^-$, depending on which particular functional is being considered. Once a linear model is obtained, the standard Kalman filter equations are applied. More explicitly, the approximation proceeds in two stages.

Stage 1:

$$F_{k+1,k} = \left.\frac{\partial f(k,x)}{\partial x}\right|_{x=\hat{x}_k} \qquad \text{Eq. 4.20}$$

$$H_k = \left.\frac{\partial h(k,x_k)}{\partial x}\right|_{x=\hat{x}_k^-} \qquad \text{Eq. 4.21}$$

That is, the ijth entry of $F_{k+1,k}$ is equal to the partial derivative of the ith component of $F(k, x_k)$ with respect to the jth component of x. Likewise, the ijth entry of H_k is equal to the partial derivative of the ith component $\mathrm{H}(k, x)$ with respect to the jth component of x. In the former case, the derivatives are evaluated at $\hat{x}_k$, while in the latter case the derivatives are evaluated at $\hat{x}_k^-$. The entries of the matrices $F_{k+1,k}$ and H_k are all known (i.e., computable), by having $\hat{x}_k$ and $\hat{x}_k^-$ available at time k.

Stage 2:

Once the matrices $\mathrm{F}_{k+1,k}$ and $\mathrm{H}_{k+1,k}$ are evaluated, they are then employed in a first-order Taylor approximation of the nonlinear functions $\mathrm{F}(x, \hat{x}_k)$ and $\mathrm{H}(x, \hat{x}_k^-)$ around $\hat{x}_k$ and $\hat{x}_k^-$, respectively. Specifically, $\mathrm{F}(k, x_k)$ and $\mathrm{H}(k, x_k)$ are approximated as follows:

$$F(k, x_k) \approx F(x, \hat{x}_k) + F_{k+1,k}(x, \hat{x}_k) \qquad \text{Eq. 4.22}$$

$$H(k, x_k) \approx H(x, \hat{x}_k^-) + H_{k+1,k}(x, \hat{x}_k^-) \qquad \text{Eq. 4.23}$$

With the above approximate expressions at hand, we may now proceed to approximate the nonlinear state equations (4.18) and (4.19) as shown, respectively,

$$x_{k+1} \approx F_{k+1,k}x_k + w_k + d_k \qquad \text{Eq. 4.24}$$

$$\bar{y}_k \approx H_k x_k + v_k \qquad \text{Eq. 4.25}$$

where we have introduced two new quantities:

$$\bar{y}_k = y_k - \{h(x, \hat{x}_k^-) - H_k\hat{x}_k^-\} \qquad \text{Eq. 4.26}$$

$$d_k = f(x, \hat{x}_k) - F_{k+1,k}\hat{x}_k \qquad \text{Eq. 4.27}$$

The entries in the term $\bar{y}_k$ are all known at time k, and, therefore, $\bar{y}_k$ can be regarded as an observation vector at time n. Likewise, the entries in the term d_k are all known at time k.

Following, Table 3 shows, in summary, the complete algorithm of the Extended Kalman Filter.

Table 3 - Summary of Extended Kalman Filter (adapted from (Haykin, 2004))

State-space model

$$x_{k+1} = f(k, x_k) + w_k$$
$$y_k = h(k, x_k) + v_k$$

Where $\boldsymbol{w_k}$ and $\boldsymbol{v_k}$are independent, zero-mean, Gaussian noise processes of covariance matrices $\boldsymbol{Q_k}$ and $\boldsymbol{R_k}$, respectively.

Definitions

$$F_{k+1,k} = \frac{\partial f(k,x)}{\partial x}|_{x=x_k}$$
$$H_k = \frac{\partial h(k,x)}{\partial x}|_{x=x_k^-}$$

Initialization: For k=0, set

$$\hat{x}_0 = E[x_0]$$
$$P_0 = E[(x_0 - E[x_0])(x_0 - E[x_0])^T]$$

Computation: For k=1,2,…, compute:

State estimate propagation	$\hat{x}_k^- = f(k, \hat{x}_{k-1})$
Error covariance propagation	$P_k^- = F_{k,k-1} P_{k-1} F_{k,k-1}^T + Q_{k-1}$
Kalman estimate matrix	$G_k = P_k^- H_k^T [H_k P_k^- H_k^T + R_k]^{-1}$
State estimate update	$\hat{x}_k = \hat{x}_k^- + G_k y_k - h(k, \hat{x}_k^-)$
Error covariance update	$P_k = (I - G_k H_k) P_k^-$

Due to its foundations, the EKF presents characteristics that allow it to be used as the basis of a second-order neural network training method. Therefore, it is a practical and effective alternative to the batch-oriented approach described before. The essence of the recursive EKF procedure is that, during training, in addition to evolving the weights of a network architecture in a sequential (as opposed to batch) fashion, an approximate error covariance matrix that encodes second-order information on the training problem is also maintained and evolved.

The Kalman Filter is certainly one of the major discoveries in the history of statistical estimation theory because it has made it possible to achieve results that, without this tool, would be very complicated to reach. For instance, in order to control a complex and dynamic system, it is crucial to observe and follow what the system is doing. However, it is not always possible or desirable to measure all the variables that it is necessary to control. So, in order to overcome this problem, the Kalman filter may, from indirect measurements, perform as a means to infer the missing information. Similarly, the Kalman filter is usually used to predict the likely future courses of dynamic systems that are not likely to be controlled, such as the prices of traded commodities, stock market values, and other factors that are strongly influenced by stochastic factors.

In sum, this research work proposes that the Kalman Filter should be used as an estimator error observer that estimates and compensates possible errors introduced by modelling inaccuracies verified at the neural networks and, consequently, improves the final results. Following, it will be introduced the overall architecture of the performance estimation engine where the relationship between Neural Networks and Kalman Filters will be explored.

4.4.2. Estimation Component Architecture

As previously explained, during this section it will be explored the main architecture and logic behind the predictive performance estimation engine developed in the scope of this research work. The Performance Estimation Engine (PEE), which is a mathematical tool composed of Neural Network (NN) and Kalman Filter approaches, was developed to enhance the performance management discipline, envisioning its proactivity. From the combination of the NN and Kalman Filter approaches, it is possible to model a complex system, in a simple and intuitive manner for the final user and to guarantee that this model is capable of following the natural evolution of the manufacturing system. Figure 2 shows the architecture of the performance estimation engine.

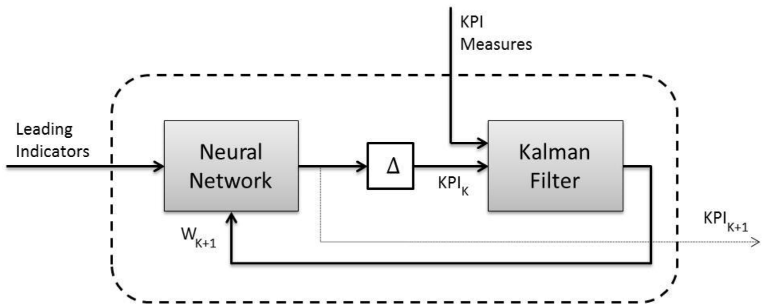

Figure 52 - Performance Estimation Engine Architecture

As previously demonstrated, a neural network critically depends on the set of weights (w_k) that emulates the system behaviour curve. Nevertheless, if a batch-training algorithm is used, then it is not feasible to assure that this network is capable of adjusting itself or even following the continuous evolution of the system, maintaining or even increasing the estimation reliability of future KPI values (KPI_{k+1}). Therefore, a combination of a batch and incremental training algorithms is proposed, composed of both backpropagation and Kalman approaches. While the first one will provide a first approximation of the weights of the network, the Kalman filter is responsible for continuously estimating the correct weights of each node of the network, comparing the real KPI measurements with the estimations provided by the NN. Next, a detailed description is provided.

Initially, the network goes through a learning process where a backpropagation algorithm is used to adjust the weight of each neuron in order to guarantee that the behaviour curve, represented by this graph, generates a good approximation of the real output for each set of inputs. Since the main objective of this step is to capture the behaviour shown by the manufacturing systems in the past, at the end of this stage the network should be capable of estimating the future performance of the system (Eq.

4.29) with some measurement error (e_k). For instance, one of the reasons why the set of weights defined by the training algorithm is not as reliable as expected, directly affecting the process error (r_k), is due to the fact that during the learning stage it was not possible to gather a complete and rich training data set. Therefore, the estimation results depend mainly from a weak generalisation capability of the network, which should be enhanced in future iterations.

$$w_{k+1} = w_k + r_k \qquad \text{Eq. 4.28}$$

$$KPI_k = NN(x_k, w_k) + e_k \qquad \text{Eq. 4.29}$$

Hence, at this stage it was not yet possible to achieve the expected level of reliability and the algorithm is still not capable of dynamically following the evolution of the manufacturing system. Thus, aiming to decrease the variable error (e_k) as much as possible and to guarantee that the estimation model is capable of continuously reducing the error index, even over time, the following step is coupling the Kalman filter at the output of the network. With this add-on, the algorithm is capable of continuously monitoring the error e_k and adjusting the weights of each neuron. This way, it is possible to achieve a dynamic learning machine that is continuously changing its parameters in order to approximate the estimation model to reality.

The Kalman filter used in this algorithm is the Unscented Kalman Filter (UKF). This special variant of the Kalman concept is very similar to the EKF explored before, presenting some details that make it more efficient. Since the EKF algorithm only provides an approximation to the optimal nonlinear estimation, the Unscented Kalman Filter (UKF) can be seen as an important alternative to increase the estimation reliability in more complex systems analysis (Kandepu, Foss, & Imsland, 2008; Terejanu, 2011; Van der Merwe, 2004). Indeed, the basic difference between the EKF and the UKF is the way in which Gaussian random variables (GRV) are propagated through dynamic systems. In the EKF, the state distribution is approximated by a GRV, which is then propagated analytically through the first-order linearization of the nonlinear system. This can introduce large errors in the true posterior mean and covariance of the transformed GRV, which may lead to suboptimal performance and sometimes divergence in the filter. On the other hand, the UKF addresses this problem by using a deterministic sampling approach. The state distribution is again approximated by a GRV, but is now represented using a minimal set of carefully chosen sample points (called sigma points). These sample points completely capture the true mean and covariance of the GRV, and, when propagated through the true nonlinear system, they capture the posterior mean and covariance accurately to second order (Taylor series expansion) for any nonlinearity (see Figure 53).

The UKF is a straightforward extension of the unscented transformation (UT). This is a method for calculating the statistics of a random variable that undergoes a nonlinear transformation. Consider propagating a variable w with dimension L using a nonlinear function, $KPI = NN(w, f_{leading})$. In this specific case, the function NN is related with the structure of the neural network specified to emulate the system under analysis. Thus, as previously explained one of the key inputs of this function is the variable w that is strictly connected to the set of weights of the neural network that better models the system behaviour.

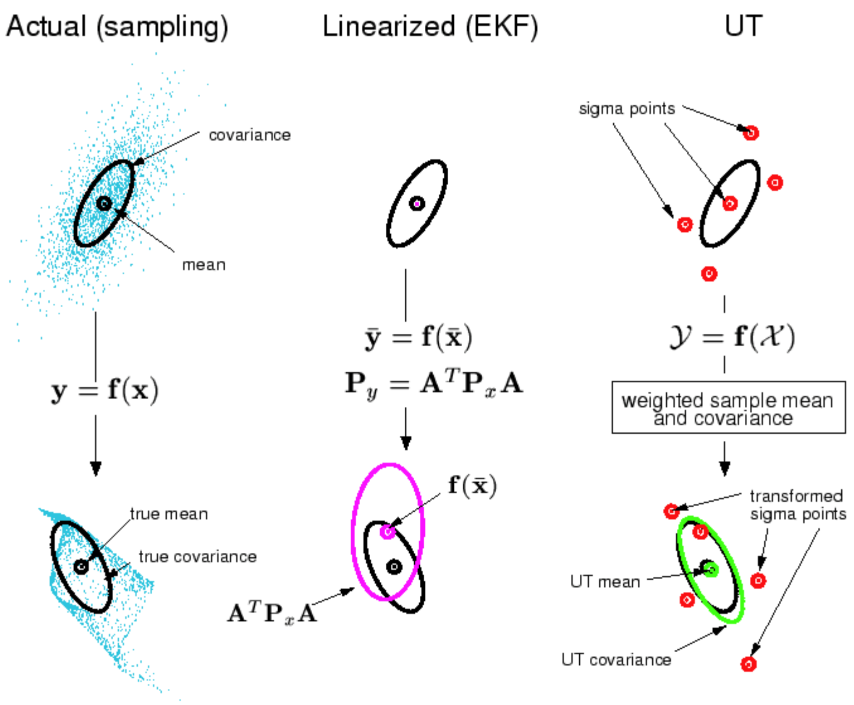

Figure 53 - Example of the UT for mean and covariance propagation. a) actual, b) first-order linearization (EKF), c) UT

Now, assuming that w has mean $\overline{w}$ and covariance P_w, in order to calculate the statistics of KPI, it is possible to form a matrix χ of 2L + 1 sigma vectors χ_i according to the following equation (Eq. 4.30):

$$\chi_{k-1} = [\overline{w}, \overline{w} + \left(\sqrt{(L+\lambda)P_x}\right)_i, \overline{w} - \left(\sqrt{(L+\lambda)P_x}\right)_{i-L}] \quad \text{Eq. 4.30}$$

where $\lambda = \alpha^2(L+k) - L$ is a scaling parameter, the constant α determines the spread of the sigma points around $\overline{w}$, and the constant k is a secondary scaling parameter, which is used to incorporate prior knowledge on the distribution of w. The mean of these sigma points is calculated using a weighted sample (W_i) of the posterior sigma points (Eq. 4.31),

$$\hat{w}_k^- \approx \sum_{i=0}^{2L} W_i^{(m)} \chi_{k-1} \quad \text{Eq. 4.31}$$

$$P_w \approx \sum_{i=0}^{2L} W_i^{(c)} (\chi_{i,k-1} - \hat{w}_k^-)(\chi_{i,k-1} - \hat{w}_k^-)^T \quad \text{Eq. 4.32}$$

Finally, the weights set of the network should be updated as presented in equation 4.33,

$$\hat{w}_k = \hat{w}_k^- + \mathcal{K}_k\left(kpi_k - \widehat{KPI}_k^-\right) \quad \text{Eq. 4.33}$$

$$KPI_{k+1} = NN(\hat{w}_k, f_{leading}) \quad \text{Eq. 4.34}$$

where $\mathcal{K}_k$ is the Kalman gain, kpi_k is the measured KPI value and $\widehat{KPI}_k^-$ represents the estimated KPI in the previous time slot. The estimated KPI value for the following time period is calculated by a nonlinear function defined by the estimated weights for each neuron of the graph and the expected leading factors (Eq. 4.34).

Presented the overall architecture of the performance estimation engine, as well as its linkage with the performance thinking methodology, is thus explored the predictive component of this framework. However, as previously explained, in order to achieve a reliable proactive performance management approach, this is not enough. Thus, following it will be presented the data model that will support both performance estimation and performance measurement engines.

4.5. Data Model

One of the challenges of this research is mainly related with the necessity to bridge the gap between the strategic and operational layers of an organization. In fact, the need to maintain a manufacturing system as efficient and effective as possible, in order to be achieved the company's strategic goals, makes it critical to explore methods and tools capable to harmonize the knowledge and more specifically the performance information generated at each layer of an organization. Only this way it is possible to guarantee that the KPIs defined by managers at the strategic level will be well calculated by the technicians at the operational layer.

Aiming to solve this interoperability issue, a performance data model was designed with the main objective of establishing a data model capable to act as a broker capable to connect different functional modules, belonging to different layers of an organization. Therefore, in order to implement this data model, it was investigated the importance and suitability of the Semantics approach, in comparison with the well-known XML Schema language (XSD), for the interoperability between two different universes of people, using different tools and presenting different perspectives and mind-sets related to the same manufacturing system.

It is a fact that, for a long time, the eXtensible Markup Language (XML) was seeing as the de facto standard method for information exchange. Therefore, based on this premise, at an initial stage, the author started with a conceived mind-set that a rich and useful reference data model could be defined as a set of XSD files, defining the structure of the XML files that would be stored and managed by a server capable to manage them. This solution could offer relevant advantages in terms of:

- Syntactic validation of the XML files according to the defined XSD files.
- Rich expressiveness since several default data types can be further extended and complex constraints and properties can be modelled.
- Possibility to integrate several XSD files within a single project.

However, since the first stages of the project it was also possible to understand that the XSD technology, alone, would present a reduced capability to manage and represent knowledge, having been identified a series of limitations:

- No explicit characterization of data with their relations on a semantic level.
- Intra–document references are supported but inter–document references (cross-references) are poorly modelled, thus endangering referential consistency.

- Distributed data can be hardly managed.
- The integration of different knowledge domains can be cumbersome.

Thus, the presented considerations led to evaluate and finally adopt the Semantic Web technologies (W3C, W3C Semantic Web Activity) which offer key advantages:

- Represent a formal semantics.
- Efficiently model and manage distributed data.
- Facilitate the interoperability of different applications.
- Process data outside the particular environment in which it was created
- Exploit generic tools that can infer from and reason about an ontology, thus providing a generic support that is not customized on the specific domain.

Although the semantic concept is normally linked to the Semantic Web, the truth is that Semantic technologies cannot be only valuable in open environments, such as the Web, but also in closed systems such as industrial environments. Indeed, Semantics provides a meaning to entities, using words or concepts, so that people or machines that speak different languages and belong to different universes can understand what these entities represent. Moreover, with the support of semantic technologies, it is possible to describe the logical nature and context of the information being exchanged, providing means to relate various information concepts in an easier and reusable way (Janev & Vraneš, 2011).

In line with this, semantic interoperability aims not only at assuring that the meaning of the information exchanged is interpreted correctly by the different actors, but also guaranteeing a greater transparency and dynamism within processes which strictly dependent on the interaction between the different stakeholders. An important element of the semantic concept, responsible for achieving this goal, is ontology. Ontology is a formal and explicit specification of a shared conceptualisation, where the relevant concepts and characteristics are identified and modelled. Moreover, the types of concepts used and their constraints should be explicitly defined as part of ontology (Chituc & Azevedo, 2008).

Ontologies are very popular mainly because of what they promise: a shared and common understanding of a certain domain that can be communicated across people and computers. In order to deploy ontologies in the respective environment, two languages have been presented by the W3C (Breslin, O'Sullivan, Passant, & Vasiliu, 2010) as standard proposals: the Resource Description Framework Schema (RDFS) and the Web Ontology Language (OWL).

Resource Description Framework Schema (RDFS): this approach is normally used to express metadata about resources. Each resource is identified using a URIs (Uniform Resource Identifier). These identifiers provide unique and non-ambiguous identification at Web-scale, enabling interoperability between various applications.

Web Ontology Language (OWL): the OWL language appeared as a new solution to overcome some of the limitations of the RDFS. With this approach, ontology developers can use OWL to define more precise axioms within their ontologies, such as: transitivity, symmetry or cardinality constraints. In addition, ontologies also act as a support for reasoning systems, either to derive new facts or to check the consistency of the model.

After the metadata are specified using one of the languages described above (RDF(s) or OWL), this information can be published and accessed via Web whenever necessary. For that, query languages are required to make full use of that information. The SPARQL (Protocol And RDF Query Language) aims to meet this goal and provides both a query language and a protocol for accessing RDF data (Sbodio, Martin, & Moulin, 2010). In simple terms, the SPARQL can be seen as the SQL of the Semantic approach, offering a powerful means to query RDF triples and graphs.

However, gathering, building and searching knowledge is still a challenge although there are a series of tools for RDF data (such as editors, browsers, stores or RDF triple-stores). Tools for vocabulary/ontologies are also available (such as tools to check consistency and maintenance). However, since such approaches are still at an early deployment stage, important gaps for industry can be identified, such as unfriendly of user interfaces. In this scope, an important framework is the Protégé, composed of a knowledge base methodology and an open source ontology editor. Protégé presents a graphical editor that simplifies the modelling effort and makes it possible to validate the consistency of the ontology designed, through the activation of its reasoners. With this approach, it is possible to formally model knowledge in specific Protégé ontology, which can afterwards be exported as RDFS or OWL files.

Indeed, this was the framework selected to design and validate the strategic and performance data models. These important components for the data exchange within the framework was developed within a European project, which focused on the need to streamline the introduction of new products within the production system, decreasing the ramp-up, increasing the production system's capability and efficiency, through the development of a reference data model, called Virtual Factory Data Model (VFDM), capable to agile the data flow between different and independent functional modules used during an entire factory life-cycle.

Given the wide range and heterogeneity of the knowledge domains that need to be covered by the VFDM, aiming to follow the entire factory life cycle, it was necessary to integrate various knowledge domains (Colledani, Terkaj, & Tolio, 2009; Colledani, Terkaj, Tolio, & Tomasella, 2008; Valente, Carpanzano, Nassehi, Newman, 2010). Therefore, the VFDM was decomposed into a series of macro areas, creating a hierarchical structure of ontologies capable to dematerialize the problem and reduce its complexity, keeping a holistic approach. Consequently, the following topics were considered as critical to be addressed by this virtual factory data model (VFDM):

- **Factory**, describing the factory during its lifecycle.
- **Building**, modelling the data related to the physical structure of the factory (e.g. walls, columns, floor, power supply lines, etc.).
- **Product**, modelling the data related to the product, i.e. the production goal of the factory.

- **Resource**, modelling the data related to the resources that are used by a system with the final goal of transforming the product (or a work in progress). These resources can be human operators, machines, conveyors, AGV, etc.
- **Process**, modelling the data regarding the processes that are adopted by the system to directly (e.g. manufacturing system, assembly system) or indirectly (e.g. logistic processes, maintenance processes) transform a product.
- **System**, modelling the data of a transformation system (e.g. manufacturing system, assembly systems) that affects a product by means of physical resources and/or human resources within a process.
- **Strategy**, modelling the data related to the company strategy and the market (e.g. orders, etc.). It aims at capturing the goals that are envisioned by the factory management. In addition, the mapping to KPIs and information regarding the target objectives need to be modelled.
- **Performance Management**, modelling the data related to the behaviour of the factory (and its components) in terms of actual performance (KPI values related to factory planning activities or factory operation, etc.).

As final result, the VFDM is available as a network of ontologies (Annex A), implemented as OWL files, where each ontology can relate its data with attributes available on other ontologies of the network. This way, the VFDM defines only the so-called Metadata (i.e. the classes, properties and restrictions), whereas the actual instances (i.e. the individuals) are stored in a data repository.

However, not all ontologies of the VFDM have been developed from scratch. Therefore, in order to assure reliability and confidence on the data model developed, it was taken into account different technical standards available in the state-of-the-art of different domains. For instance, it was taken into consideration the Industry Foundation Classes[8] (IFC), STEP-NC[9], and ISA-95[10]. In sum, Table 14 in Annex A enumerates the ontologies developed for each VFDM area, as well as the referenced technical standards that were taken into account, when applicable.

8 The Industry Foundation Classes (IFC), maintained by *buildingSMART* International, is an open vendor-independent neutral file format that captures both geometry and properties of 'intelligent' building objects, and their relationships, within building information models. This facilitates the coordination of information across incompatible applications, which is a prerequisite for improving building workflows using building information modelling (BIM) methods.

9 The STEP-NC standard is the result of a ten year international effort to replace the ISO 6983 standard with a modern associative language that connects the CAD design data used to determine the machining requirements for an operation with the CAM process data that solves those requirements. The integrated simulation and verification enabled by STEP-NC promises to guarantee that every part will be made correctly and that production will stop whenever cuts are about to be made that do not meets design requirements.

10 ISA-95, from the International Society of Automation, is the international standard for the integration of enterprise and control systems. ISA-95 consists of models and terminology. These can be used to determine which information, has to be exchanged between systems for sales, finance and logistics and systems for production, maintenance and quality.

Nevertheless, in the scope of this research work, the emphasis was on both the strategic and performance management areas of the VFDM. As previously mentioned, the enhanced strategic performance management concept critically depends from the capacity to make maximum use of the information extracted from the performance measurement system, normally performing at the operational layer, at the strategic level of an organization. While at the strategic layer people define what to measure and the targets to be achieved, on the operational side people are focused on defining the metrics, taking into account the data sources where the suitable information for a reliable KPI calculation is, as well as the methods that should be used to extract the most meaningful information from the huge amount of data available.

Therefore, when designing the performance data model, the main objective was to define in one hand the boundaries between the performance and strategy areas of research, and on the other hand, understand which should be the points of contact between them, envisioning to bridge the gap between the strategic and operational layers of an industrial organization. In line with this, the strategy area of the VFDM was developed aiming at modelling the data related to the company strategy, envisioning the alignment between the manufacturing system performance and the market needs. In other words, with this ontology it is expected that the goals envisioned by the stakeholders of the system can be formalised; the KPIs can be mapped with the requirements defined for the manufacturing system and; the information related to the target objectives can be modelled (Dekkers, 2003).

On the other hand, the Performance Management area of the VFDM aims at modelling the data related to the behaviour of the production system, assessing its performance against the expected target values. Therefore, the linkage point between the strategy and performance management areas should be at a KPI definition. This means that, when defining a set of KPIs/PIs, which are seen as suitable to assess the intention that stands behind a functional requirement, we are crossing the frontier between the strategic and operational domains. That is the reason why a KPI should not be seen as a simple variable represented by a measure, but, on the other hand, should be seen as an entity carrying a huge quantity of information. For instance, when defining a KPI, it must be specified if the indicator under analysis is being used to evaluate a planning or operational process, or even in which terms this indicator will evaluate a specific object of the manufacturing system: Cost, Quality, Time, Flexibility or Reliability. Moreover, to a specific KPI, it should be attributed a metric, that will make it possible to calculate and attribute a measure to this variable, as well as a target value.

Based on this paradigm, a holistic and generalized data model was developed using the semantic concept as pillar. In Annex B it is depicted the Ontograf[11] of the strategic and performance management ontologies, as well as a short description of this integrated data model.

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[11] The ontograf is a technology developed by the Protégé consortium that gives support to interactively explore and navigate throughout the relationships of a specific OWL ontology.

4.6. Measurement Component

4.6.1. Vision and Concepts

By definition, a suitable performance measurement and management (PMM) system aims to support decision makers by gathering, processing and analysing quantified information on performance and presenting it in a succinct format (Gimbert, Bisbe, Mendoza, 2010). When designing a PMM for complex manufacturing systems, there are issues that need to be taken into consideration as this involves gathering multi-disciplinary themes.

For instance, it is expectable to find a number of difficulties related to data collection from multi data sources (Jain, Triantis, Liu, 2011). Consequently, during this stage, it is important to solve the conflicts that can occur between different performance measurement sources, guaranteeing an appropriate balance between internal and external measures, as well as cataloguing and providing meaning to the data for further use. However, as it is possible to see in Figure 54, issues related with data handling are just the bottom of the pyramid of requirements for a suitable SPMS implementation within complex manufacturing environments. In line with this, since this type of systems presents dynamical behaviours, it is necessary to guarantee the flexible link between tactical manufacturing planning and the different strategy perspectives, which should be formalized by KPI's metrics and respective measurements.

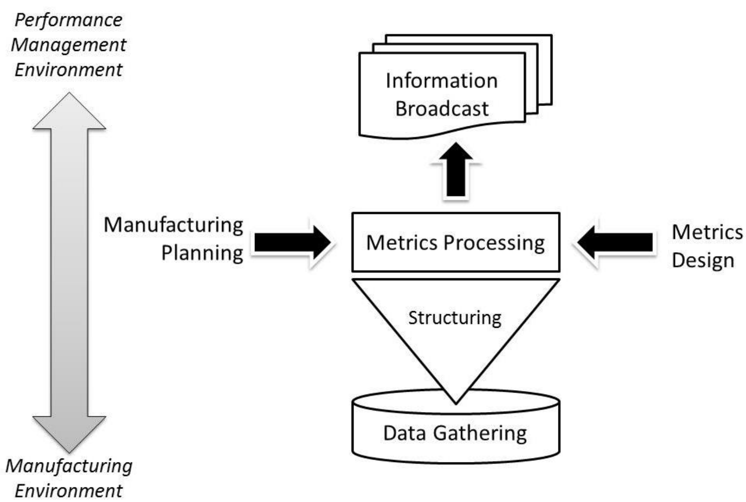


Figure 54 - Requirements Pyramid for Complex Manufacturing Systems

Therefore, the Performance Measurement Engine (PME) was designed and developed aiming to overcome and simplify all the small details that characterises a dedicated performance measurement solution. Indeed, the main objective was create a software solution easy to install, setup and maintain but, capable to provide powerful information to stakeholders, shareholders and decision makers. Thus, the biggest contribution of this research work based on the set of concepts, and respective technological implementations, developed to streamline and boost the performance measurement and management strategy to be implemented in a specific organization. In order to show the main differences between the PME and the solutions currently available into the market, the core features enumerated before for performance management software's will be used as plumb line.

Data Collection: Within complex manufacturing systems, it can be a challenge when the technology infrastructure makes it difficult to obtain or extract the right information to calculate the suitable KPIs in a reliable way. Therefore, the PME was developed with the aim of supporting users, during the process of data gathering from the different data sources available in the factory facility. With this in mind, the gathering of data for the calculations was defined in a way that it is possible to combine data from multiple sources, and establish relations between them, so that, more relevant information can be extracted. With this possibility, the manufacturing system manager can have more meaningful information without having the hard work of dealing with the data, everything is made through the PME and it is only necessary to define rules and relations using a simple graphical user interface.

Key Performance Indicators: it is critical that an organization defines a number of Key Performance Indicators (KPIs) capable of measuring its core processes or activities. However, in order to better interpret this important information, sometimes it is necessary to go deeper and study the reason for bad performance behaviours. In line with this, the PME follows an innovative and distinctive approach that defines a KPI according to a hierarchical tree, which enables companies to perform a series of performance management actions and retrieve more information capable to support decision makers.

Moreover, the PME allows production system managers to adapt the performance measurement system to complex manufacturing environments. In order to simplify the KPIs definition, the PME solution allows the manufacturing system manager to build and store the different KPIs using Drag & Drop functionality. However, it is also possible to define new KPIs to be calculated using other functional modules. To do that, the PME solution has a synchronizing functionality that reads formulas stored by other modules in specific data repositories and then presents it to the user so that he can define the data sources for the new KPI. Therefore it is possible to integrate information generated by different functional modules aiming to bridge the gap between the strategic, tactical and operational layers of a manufacturing company.

Generating Information: According to the KPI's metric definition, the PME solution supports decision makers to visualize and analyse the current status of a specific KPI, in an interactive way. Using a hierarchical KPI metric definition, where a KPI can be seen as a combination of different indicators, decision makers cannot only assess the KPI value but also all the variables used for its calculation, due to the continuous capability of the measurement engine to power different charts and tables with real performance values. This information can be used not only to better understand the system behaviour, but also to detect bottlenecks.

However, the hierarchical KPI metric definition is not the only concept developed to enhance the quality of performance information generated. If it is true that start analysing a KPI as a function and not as a variable allows decision makers to have a wider view of the system, it is also true that there should be, at the same time, a greater concern in providing more detailed information about the performance of a complex manufacturing system.

This perception about current necessities of stakeholders of large and complex manufacturing systems led us to another concept called High-Resolution (HR). The HR concept defines that, similarly to the image resolution concept, in the scope of this research, high resolution means the ability to increase the level of detail of a manufacturing system's performance picture. The idea is to present a solution capable of providing performance measurements with high levels of granularity, which can be adjusted for the different stakeholders belonging to different hierarchical layers of the organisation. In the application case chapter it will be presented an example of both hierarchical KPI metric definition and High-Resolution concepts and its advantage for industrial companies.

Response to Data Analysis: Following a defined schedule, the PME solution is able to generate performance reports that can be broadcast through the factory using email services features. The Key Performance Indicators values can be easily consulted, inside and outside the factory, through a web-based application. Permissions were also implemented. Depending on the user logged in, different actions can be performed. Thus, some users might have all the permissions to create and calculate KPIs, while others can only see the calculation results.

Since the PME allows the user to analyse the KPI in a more detailed way, with this performance management system becomes possible to anticipate and prevent low performance behaviours. Indeed, according the PME approach, the different components of the KPI calculation can be used as leading factors. Therefore, with the PME solution, it becomes very simple and quick to perform "what-if" scenarios activities, understand the reason of low performance rates as well as supporting the prediction of future performances according to leading factors.

4.6.2. Measurement Component Architecture

The Performance Measurement Engine (PME) was developed in order to materialise the concept explored by the performance data model as well as provide the right answers to the requirements mentioned before for SPMS. Next, the main layers that compose the PME are presented, from the data extraction and data models to the KPI calculation and performance management functions.

In order to perform the functionalities already described, the PME solution was designed according to a layered architecture approach. This kind of approach was selected as it makes it possible to share the concerns on the application into stacked groups and, therefore, there is a higher level of flexibility to capture and handle data from different sources and afterwards to calculate the right metrics in order to evaluate the performance of the current strategy. The main components, and respective benefits, of this layered architectural are:

PME WebService

The WebServices connector is at the foundation of the PME structure. This module is responsible for managing all the communications with the semantic repository. Therefore, when it is necessary to read or write any kind of data from the repository, this module selects the suitable SPARQL query template, completes with the missing data and invokes it, using the Suds gateway. The Suds web services client is a lightweight soap-based client for Python that is available to the public. Further details about this PME's layer will be provided in the following section of the chapter.

Raw Data Fusion & Extract Transform Language Layer (ETL)

For a reliable dynamic KPI calculation it is necessary to gather three kinds of performance data: real-time shop floor data, production system constraints data, and finally strategic data. In line with this, the Raw Data Fusion module is responsible for identifying the data source, selecting the data fields desired, applying filters capable of increasing the performance calculation reliability and expressing the correlation between data available from different sources.

According to Hall and Llinas (1997), Data Fusion is "A process dealing with the association, correlation and combination of data and information from single and multiple sources to achieve refined position and identity estimates, and complete and timely assessments of situations and threats, and their significance". In other words, fusion means the integration of information from multiple sources to produce specific and comprehensive unified data about an entity. It can be seen as a group of techniques that combine data from multiple sensors (performance databases) and related information from associated databases, so as to achieve improved accuracies and more specific inferences that those achieved with a single sensor. Automated data fusion processes are generally employed to support human decision-making by refining and reducing the quantity of information that system operators need to examine to achieve timely, robust, and relevant assessments and projections of the situation.

Thus, aiming to generate as much information as possible with the raw data available, an Extract-Transform-Load (ETL) technology was adopted. By definition, an ETL tool aims to extract data from heterogeneous sources, transforms and cleanses this data, and finally loads it into a data warehouse. In fact, when developing this kind of technology, it is important to take into account that within complex manufacturing systems, raw data can come from different data sources (Oracle, MySQL, among other), files (csv, excel files, among others) as well as platforms (email, phone-call, databases). Moreover, the source of this raw data can also be dynamic. This means that quickly the source or format of information can change. Therefore, it is critical to continuously guarantee data consistency, by continuously refreshing the mapping between data and its source. In addition, within complex manufacturing systems, raw data rarely is available in the suitable mode. Therefore, different filtering and transform algorithms should be applied in order to shape and aggregate the raw data available into a usable format. Based on these requirements, the ETL concept shows itself as a powerful tool to be applied as a pillar to a successful and added value performance measurement system implementation (Behrend & Jörg, 2010).

As a demonstrative example, in figure 54 it is depicted a simple application of the ETL technology. For this example it was used the IBM InfoSphere DataStage ETL tool and the source relations have been adopted from the TPC-W benchmark from where it was extracted data on customers, addresses, and states (Behrend & Jörg, 2010). The TPC Benchmark is a transactional web benchmark where the workload is performed in a controlled Internet commerce environment that simulates the activities of a business oriented transactional web server.

As it is possible to see in figure 54, the address data is joined with the state data along a foreign-key relationship using a so-called lookup operation (which actually corresponds to a hash join). Another join is performed for connecting address and customer information. Two standard data cleansing operations are employed to standardize the formatting of customer telephone numbers and to parse address data.

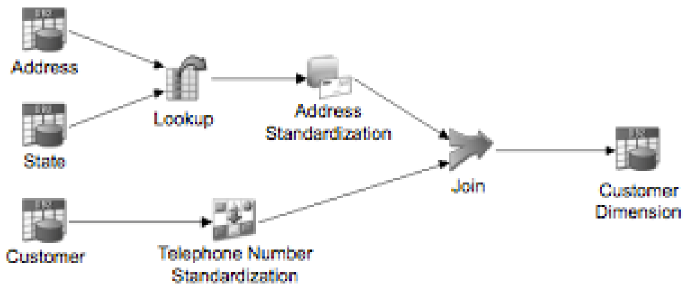


Figure 55 - Sample ETL Job (Behrend & Jörg, 2010)

A common language, such as SQL for relational database systems, does not exist in the ETL world yet. Instead, commercial ETL tools usually provide proprietary scripting languages or graphical user interfaces for defining ETL jobs. In the following equation, a relational algebra expressions is used to describe ETL data transformations. It is considered a generalized projection operator – denoted by the capitalized letter Π – that additionally implements cleansing operations. Thus, the above ETL job can be represented by the following algebra expression:

$$D \rightarrow \Pi_{addr}(A \bowtie S) \bowtie \Pi_{Tel}(C) \qquad \text{Eq.4.35}$$

where A, S, and C denote the source relations address, state, and customer, respectively, and D the derived customer dimension. An ordinary join symbol is used for representing various join variants typically used in ETL jobs such as hash or merge joins in our example. Most common and relevant ETL operations can be represented this way according to the overview provided by the Transaction Processing Performance Council.

Actually, due to its importance for industrial organizations, but not only for them, ETL processing has received considerable attention in the data integration community and numerous commercial ETL tools are currently available. For instance, the ETL tool explored during the development of the performance measurement engine was the CloverETL. This is a Java based data integration framework that can be used to transform, map or manipulate data in various formats. This is an open source solution that can be used in a standalone mode or embedded as a library.

Production System Emulator

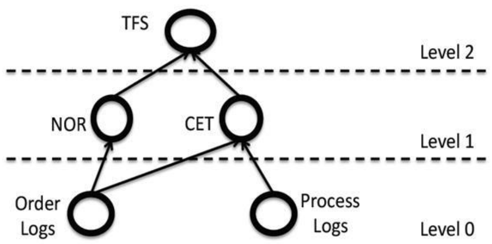
After the performance data required to calculate the KPI metric are defined and archived, it is necessary to extract the variables (assumptions/constraints, as well as production system outputs and resources) from the production system. These variables must be taken into account during the calculation process of the indicators since they can influence the detail and reliability of the measurements. In line with this, the production system emulator has the responsibility of characterising each manufacturing agent (collaborative network partner, departments or production sections), organising for each of them the static variables, the main strategic objectives, mapping them with the different manufacturing objects (machines, human resources or products) and respective KPI instances. In sum, this module aims at approximating as much as possible, the KPI calculation to the real behaviour of the production system.

KPI Manager

This module intends to manage generic KPIs. In other words, this module is responsible for creating the KPI hierarchical structure and connecting each entity of this structure to the respective Raw Data.

Aiming to guarantee that operational, tactical and strategic information could be fused within a single but rich aggregated performance indicator, aiming to relate different perspectives, a hierarchical KPI definition was explored. Three levels of indicators have been defined for the performance indicator structure: Raw Data, Performance Indicators (KPI0) and Key Performance Indicators (KPI1+).

The Raw Data level gathers the information available on the production system, providing meaning to the measurements obtained from the different sensors available. Therefore, the measurements available in external sources, such as, xls, xlm, csv documents and database tables can be located and modelled to be reused every time this kind of information is required in order to calculate indicators affected by them. Examples of these kinds of data are the data source locations of the following information: order logs and process event logs.



$$TFS = \frac{\Sigma\, CET(h)}{EWT\ (h/day) * NOR}$$

Figure 56 - Aggregated KPI Structure and Metrics

The Performance Indicator level can be seen as a combination of Raw Data to build linear and simple indicators. In fact, added value information is not expected from these metrics but they do represent critical data that allow key performance indicators to be calculated and analysed swiftly. Examples of this kind of indicators are: elapsed time for the completion of each order type (CET), the number of orders received (NOR), the working duration of each activity in the process (TPA) and the percentage of an order type (POT).

In order to obtain significant and meaningful indicators capable of retrieving a clear and reliable picture of the system's behaviour, it is important to define Key Performance Indicators (KPI). These indicators can be seen as a combination of performance indicators, from different perspectives, and manufacturing system assumptions. Indeed, the manufacturing system assumptions are another important variable used by KPIs that should represent the limitations and characteristics of the system. An example of this kind of indicator is the average number of days necessary to complete the shipment process, per activity and order type (TFS). For the dispatch of the order, the order date is tracked against the shipping date (CET) and the number of days necessary is calculated, taking into account the fact that the company's back office works eight hours a day (EWT), which is an assumption.

However, when dealing with KPIs, it is important to integrate in the calculation not only Raw Data but also other indicators. This fact makes this management process more complex, but, on the other hand, it provides interesting add-value to the production system managers as it simplifies performance assessment.

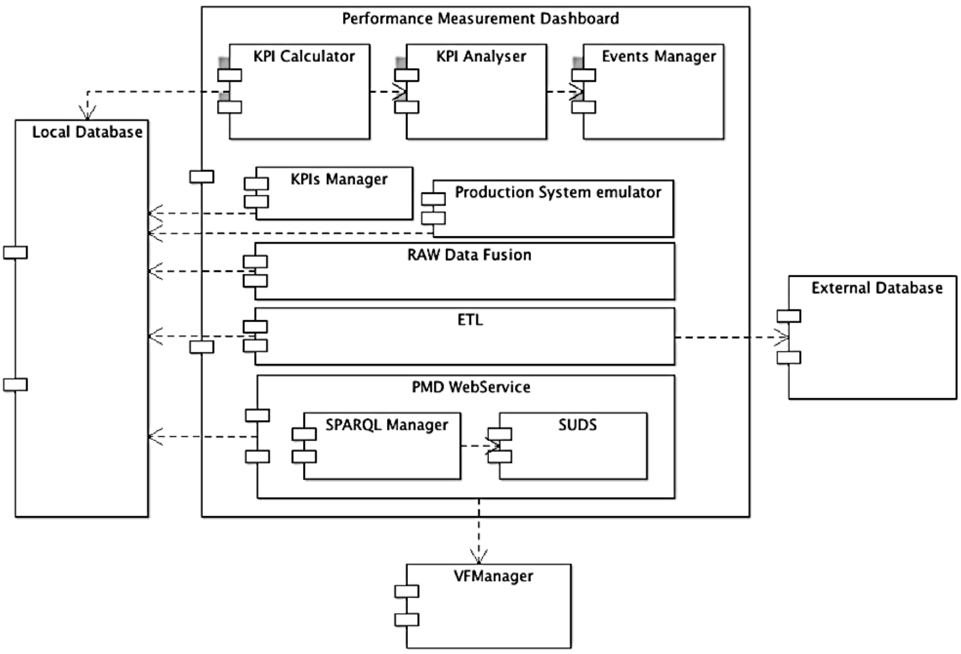


Figure 57 - Performance Measurement Engine Architecture

KPI Calculator

This module is responsible for compiling all the data retrieved from the KPI Manager, Production System Emulator and Raw Data Fusion components, and for calculating the indicators according to the manufacturing system manager specifications.

KPI Analyser and Event Manager

Finally, after the strategic, tactical and operational data are identified, the PME calculates the indicators when necessary (user orders or event triggers), confirms whether the object analysed performs as desired by the different stakeholders, and sends reports (alarms) with charts and possible reasons for low performance rates using KPI Tree analyses.

4.6.3. Implementation

The performance measurement engine was completely developed under the umbrella of this research project. Consequently, due to the time constraints and resources available, it was critical to use a methodology and a programming language capable to boost the development and programming phases. Therefore, the programming language selected to develop the prototype of the PME solution was the Python language. Indeed, this is a very attractive technology for rapid application development since this is a high-level programming language that presents powerful and optimized built in data structures combined with dynamic typing and dynamic binding approaches. Dynamic binding is the property of object-oriented programming languages where the code executed to perform a given operation is determined at run time from the class of the operand(s) (the receiver of the message). In sum, it can be considered that python is a language with a hybrid behaviour, aiming to optimize the overall program execution, presenting initially a compilation[12] phase to bytecode, which is interpreted[13] during runtime.

For instance, a Python programmer wastes no time declaring the types of arguments or variables, and Python's powerful polymorphic list and dictionary types, for which rich syntactic support is built straight into the language, find a use in almost every Python program. In practice, Python programs are typically three to five times shorter than equivalent Java programs and five to ten times shorter than a program developed in C++ language.

Despite the interesting advantages, characteristic of this technology, the Python language, such as any dynamical typed language, presents a lower performance in contrast with other static typed languages. Because of the run-time typing, Python's run time must work harder than Java's. For example, when evaluating the expression **a+b**, it must first inspect the objects **a** and **b** to find out their type, which is unknown until the bytecode interpretation moment. It then invokes the appropriate addition operation, which may be an overloaded user-defined method. Java, on the other hand, can perform an efficient integer or floating point addition, but requires variable declarations for a and b, and does not allow overloading of the + operator for instances of user-defined classes. However, in the scope of the PME, this disadvantage is not critical, since this solution will not be used for control purposes, where this problem could be seen as a preponderant factor to reject this solution.

In sum, due to the Python specifications previously described, there is a series of features and characteristics such as simplicity, portability, interactivity as well as the set of 'batteries included' libraries available and the meta-programming strategy that supported the selection of Python as the programming language.

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[12] Compiled: a high level language whose code is first converted to machine code by a compiler (a programming which converts the high-level language to machine code) and then executed by an executor (another program for running the code)

[13] Interpreted: A high level language run and executed by an interpreter (a program which converts the high-level language to machine code and then executing) on the go. In sum, it processes the program a little at a time.

As explained before, one of the most delicate and time consuming stage of the PME development was strictly related with the connection of the performance measurement engine with the data repository, aiming to guarantee the synchronization of the local database with the semantic repository. By definition, a semantic repository is an engine similar to a database management systems (DBMS) that permits the storage, querying and handling of structured data. In addition, a semantic repository uses ontologies as semantic schemata to automatically reason about the queried data.

As previously stated, the data model responsible for this data repository, was developed within the scope of the Virtual Factory Framework (VFF) European project. Since this project was developed aiming to deal with data interoperability during all the stages of a factory life cycle, then it is not complicated to understand that the quantity and types of data that needed to be taken into account would be enormous. Consequently, it was important to select one of the most advanced knowledge management system that could make it possible not only to store and manage huge quantities of data but also enhance the types of queries that could be performed to the data repository, aiming to enrich and increase the accuracy of the knowledge extracted from these repositories.

However, these kinds of repositories are still in the early stages of their development, being the solutions available very closed, complex and not so transparent for integration since there is little quantity of documentation available. For instance, one of the most advanced semantic repositories, and used in the scope of the VFF project to guarantee data interoperability, is the Sesame platform. This is a framework for storing and querying RDF data that includes different storage backends (memory, file, database), query languages, inferences, and client-server protocols. Sesame has two main communication interfaces: the Sail API and the Repository API.

- **Storage And Inference Layer (Sail) API** is a low level system API for RDF stores and inferences. Its purpose is to abstract from the storage details, allowing various types of storage and inference to be used.
- **Repository API** is a higher level API and is meant to be the main API that people can program against. It offers various methods for uploading data files, querying, and extracting as well as manipulating data.

Due to the continuous necessity to communicate with the semantic data repository, through the Sesame's repository API, the PME development was totally benefited by the rich set of standard libraries available for the Python language. Therefore, during the PME implementation process, the *Suds client module* was identified as a useful package to develop the connector responsible for guaranteeing the connection between the PME module and the data repository, called Virtual Factory Manager (VFManager). The *Suds web services* client is a lightweight soap-based client for Python, publically available. The goal of Suds is to present a similar Remote Procedure Call (RPC) interface into soap-based web services. This means that with this library, users do not need to be concerned with the complexities of the WSDL and referenced schemas. With this client module, it becomes very easy to establish a communication tunnel with the VF Manager server and access to the functions exposed by this repository. On the other hand, the answers retrieved by the VF Manager arrive at the PME in a string format that only need to be parsed using the python language capabilities.

Due to this technological solution, it was possible to develop all the PME functionalities independently from data interoperability constraints, being the communication between the performance measurement engine and the Sesame's IEP Web service transparent both for PME programmer. Thus, when necessary, the PME is capable to execute SPARQL queries/updates, which are embedded directly in the core routines of the engine, to extract/modify data from ontology files. Therefore, driven by events, the PME is allowed to connect with the VF Manager, not only to extract the necessary data from the repository, but also to share the performance values with other modules, using SPARQL queries/updates in a transparent way for the final user.

In terms of data exchange strategy, every time that the PME needs to retrieve information from the VFManager, then a heuristic approach is used. This means that, the performance measurement system here presented does not have any specific knowledge about the individuals to read/write from/to the model. In contrast, the PME keeps a list of templates of SPARQL queries and updates that allowing it to read and write the required individuals from/to the repository when user event happens. Thus, the PME module is limited to the individuals of those ontology classes that support him to calculate and broadcast performance indicators.

For instance, an important interaction between the PME and VFManager is when the software synchronizes its KPIs library with the repository in the VFManager. In fact, when this happens, PME uses SPARQL queries in order to retrieve the list of all the KPIs available in the VF Manager, as well as its specifications. If the KPIs retrieved already exist in the PME local database, the software will not present it to the user, since these KPIs are already defined. However, if the KPIs are not recognized by the PME, then the software will ask the user to specify these KPIs and respective raw data sources.

Following, it is presented a flow chart where a routine is implemented to extract the target values for a certain KPI, for a specific time window, as well as auxiliary routine to gather common KPI attributes. As depicted in Figure 58, the performance measurement engine makes no assumptions about individuals presented in the data repository. In fact, every time data is needed from the VFManager, the PME uses the classes' definition to restrict and correctly retrieve individuals to be used. On the code shown below, it is depicted how the queries are built, thus, materializing the flow chart from Figure 58.

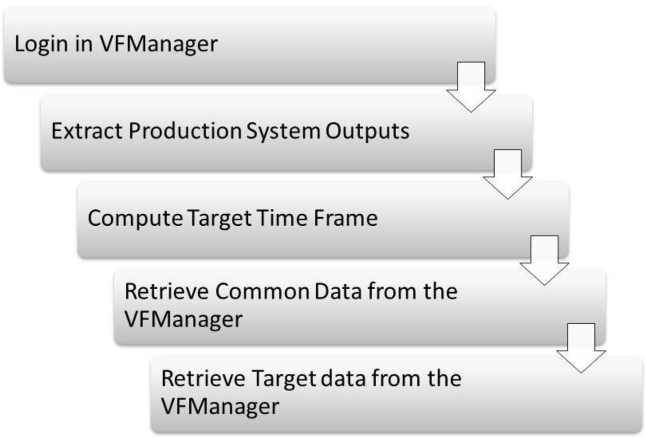

Figure 58 - Target Query Flow Chart

Envisioning the good performance management, the PME needs to retrieve from the VFManager the target values for a specific KPI defined in a scope of a certain Domain and for a specific production system output (product family). Therefore, the PME has already some information to refine the search in the VFManager such as: KPI name, classification and strategic level; the objects whose performance is evaluated using this KPI and the time window for the required target. Thus, initially, the PME needs to identify which individuals in the VFManager are related with the information already known by this performance measurement engine, in order to proceed with the target values extraction. In Annex C it is presented the SPARQLs necessary to extract each of the individuals related with the information enumerated before.

4.7. Summary and Conclusions

The fourth chapter of this document is responsible by presenting, the main components of the proactive performance management framework. Therefore, at a first stage, were identified the main requirements defined for this research project, as well as the architecture of the framework developed to fulfil the necessities previously identified. In order to simplify this process, two schemes representing in a graphical way both functional requirements and the framework overview, were presented and detailed.

The main premise of this research project based on the idea that if both activities of performance measurement and performance information analysis are performed in a reliable and mature way, decision makers become strongly empowered in terms of proactive control of their manufacturing systems. However, due to the high number of endogenous and exogenous factors that can affect the normal system performance, as well as due to their non-linear relationships, sometimes it becomes almost impossible to deal with this information in an ad-hoc way.

Therefore, based on the necessity to support decision makers to better understand manufacturing systems and, consequently, estimate with higher reliability their future performance behaviour, both methodology for performance analysis and the performance estimation engine were explored. In the case of the performance thinking methodology, each step was detailed analysed and contextualized. On the other hand, concerning the performance estimation engine, not only an overview of the algorithm was presented, but also a more detailed analysis of each of the components selected to be included into this algorithm, more specifically the neural network approach and the Kalman filter, was performed. Due to the necessity to guarantee performance data interoperability and standardization, in this same chapter it was also explored the performance data model and the performance measurement engine developed. While the first one is mainly responsible for the performance data management and broadcast, on the other hand the performance measurement engine makes it possible to calculate indicators in an automated and formal way.

In sum, it was demonstrated that the research work done under the umbrella of this doctoral program focus on the necessity to explore both a qualitative and quantitative approaches capable to not only model the synergies existing within a specific complex manufacturing system, but also, based on this knowledge, design a mathematical model capable to relate the different feedback loops of the system and, based on leading indicators, estimate future performance behaviours. Nevertheless, as stated by Shewhart on his predictive theory, the reliability on the estimation of the future performance of a manufacturing system is strictly dependent from the confidence on the historical data of the system performance as well as on the accuracy with this data is collected and stored. Therefore, in order to become the predictive performance management framework more robust, an innovative and flexible performance measurement engine was included.

In the following chapter, three different application cases will be presented, with the main objective of demonstrating the real purpose of each module of the framework, as well as prove their validity and consistency.

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Chapter Five

APPLICATION CASES

During the previous chapters, an innovative predictive performance management approach has been explored *where both qualitative and quantitative methods are combined in order to support decision makers thinking about their manufacturing systems synergies and, from this knowledge, foresee future performance behaviours.*

Aspiring to support companies rethinking the way that performance measurement and management disciples are used within their management processes, three main advantages were identified for companies who decide to implement this framework: intuitive KPIs metrics specification for a proper KPI calculation, agile root causes analysis for decision making purposes as well as reliable performance estimation for a more proactive performance management and also for budgeting and/or targeting issues. In order to evaluate and exemplify the implementation of the proactive performance management framework, envisioning the achievement of the advantages enumerated before, this chapter presents three pilot cases, strictly related with real industrial scenarios.

5.1. Validation Approach

Aiming to validate the proactive performance management framework here explored, both in terms of reliability and real impact for current manufacturing organizations, three validation scenarios were designed with the main purpose of demonstrating how an organization should be able to implement and maintain, with low efforts, a performance measurement and management system capable to use the performance information generated in a proactive way.

The first pilot case here presented illustrates one of the first attempts, performed within the scope of this research work, to demonstrate how a machine-learning tool could be capable to estimate with high reliability the future performance behaviour of a complex manufacturing system. Thus, aiming to achieve this purpose, a Brazilian supply chain called G3 was used. Here, it was expected to analyse, understand and model the synergies between the different elements of this supply chain in order to estimate this network's efficiency in terms of order delivery fulfilment, i.e. number of nonconformities and probability of delay on orders delivery, and consequently costumers' satisfaction.

The second pilot case was designed in partnership with Volkswagen Autoeuropa's department of industrial and lean management. The main goal of this pilot case was to demonstrate how a real time performance measurement tool, based on an innovative KPIs metrics design, could be capable to not only decrease the effort required to maintain an enterprise performance measurement solution, but also find the causes of a low performance behaviour in a more agile and proactive way, and thus empower decision makers to make the right decisions at the right moment. In specific, this application case was conducted in the scope of a European project called Virtual Factory Framework (VFF), where the author had an important role on the definition of the foundations and pillars of the performance measurement and management dimensions for this European project.

Finally, the third pilot case was performed at paint and body departments from the Volkswagen Autoeuropa plant, aiming to test and validate the entire proactive performance management framework within a real industrial environment. The main objective defined for this scenario implementation was to prove that it is possible to estimate performance behaviours of complex manufacturing systems, when these are performing under statistical control. Thus, in this specific use case, it was estimated the manufacturing system's behaviour in terms of sustainability issues, envisioning budgeting and operational planning purposes. Consequently, it was proposed the estimation of energy consumption with levels of reliability not achievable with the current methods used in the industry. In order to setup this pilot case, two organizational areas were selected, the paint line and the body shop. Despite the fact that both operational areas are located physically within the Volkswagen Autoeuropa plant, the truth is that each of these scenarios presented different requirements and challenges, since the topology and strategy used in each of them are completely different. This way, it was possible to apply the proposed framework in different environments with specific characteristics and levels of complexity.

5.2. Food Supply Chain Effectiveness

5.2.1. Problem Definition and Foci of Study

The first pilot case developed within this research project was performed at a food supply chain called G3, belonging to the Mabel Group[14] and performing mainly within the Brazilian market. This is a collaborative network (CN) consisting of three companies: Cepalgo Films, Cepalgo Conversion and GSA. While Cepalgo Films is mainly responsible by producing the polypropylene and polyethylene films, the Cepalgo Conversion use this output to create the packages that will contain the food (cookies, biscuits and other food products) produced at GSA plant.

Within the G3 network, each partner has a distinct role, since each of them has a specific product answering to specific requirements of the supply chain. However, despite the fact that each company has a strategy and policies oriented to the Mabel Group, it is also true that each one has defined its own market segment, maintaining the collaborative network as a priority. The intention is to supply this network, offering low prices and better delivery times, while exploring the Brazilian and global markets where coextruded films are required. In line with this, with the participation in this collaborative network, each partner is strongly advised to continuously refine their processes and products, in order to remain as a key partner, but also to develop new products aiming to answer to new customers requirements.

Therefore, the key strategy is the improvement of the overall network performance, envisioning the enhancement of each partner competitiveness and knowledge, seeking to face the emerging business challenges imposed by the external markets. In line with this, the G3 network decided to integrate the individual performance measurement systems, concerning specifics KPIs, in order to support the inter-organizational processes alignment and consequently evaluate the strategy defined in a proactive way.

G3 Network Strategy and Topology

The G3 network topology is based on a dynamic partnership, without a dominant participant. This kind of network topology, classified as a linear bus, is normally applied at process-oriented manufacturing industries. The challenge is how to improve the manufacturing and logistics performances, aiming at provide customers with high quality products and without delays.

Within G3 network, all nodes are connected throughout a common transmission infrastructure that has exactly two endpoints. Disregarding propagation delays, all data and materials transmitted to or from a certain node are performed along this transmission infrastructure, as depicted in Figure 59. While products flow from suppliers to costumers, the information flow concerning market needs follows on an opposite direction. External synergies will not be considered for this pilot case. This means that the indirect involvement of external stakeholders,

[14] The Mabel Group, responsible for the coordination of this network, is one of the key players in Latin America, producing cookies and other similar food products. They cover more than a hundred products that are produced by five industrial units, supplying the Brazilian market and more than 35 countries.

such as common suppliers or services, is not considered in this scenario. The operations among participants are restricted to product orders and transportation.

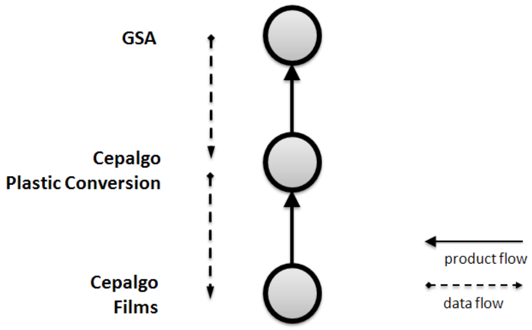


Figure 59 - G3 Network Topology

The G3 supply-chain strategy follows a well-known customer-supplier relationship. Initially, Cepalgo Films receives an order from Cepalgo Conversion. After that, the first one sends the goods to the second factory. This process is managed through a feedback loop, which will allow Cepalgo Films to improve its performance in order to meet Cepalgo Conversion needs and requirements. This process is repeated between the Cepalgo Conversion and GSA factories. As it is possible to understand, GSA becomes very dependent on the two suppliers of the G3 chain. So, it becomes crucial to establish a framework that will allow GSA to prevent and compensate possible nonconformities and delays that can occur along the supply-chain network.

In order to support CN controller taking decisions in a proactive way, concerning orders handling, a pilot case scenario was designed to show the role of the performance estimation engine in such kind of problems. The main goal of this pilot case scenario was not only to provide the CN controller with insights about future performance behaviours of each network partners, but also understand its impact on the global network performance, and thus, avoid the uncertainty and variability caused at the endpoint of the network.

Therefore, the main perspectives proposed to be evaluated with this pilot case were the number of nonconformities and the number of order delivered with delay. Two key performance indicators were defined, and the respective meaning and metrics fully specified:

- **DDT** representing the percentage of orders delivered with delay and;
- **NON** representing the percentage of orders delivered with nonconformities.

The KPI DDT refers to the amount of orders delivered, in certain periods of time, with delay. Since the G3 network follows a customer-supplier relationship, each partner can be a customer and a supplier at the same time. Therefore, the proactive management of the KPI DDT can critically contribute to decrease the delay's downstream propagation through the collaborative network, since decision makers become capable to foresee and anticipate delays and then implement corrective actions even before it affects the final client. Following this perspective, the DDT should be seen as a leading indicator, capable to improve the agility of the network and to enable each participant in the chain to reduce the delivery time so that it becomes possible to meet the due date stipulated with the final client.

Nonconformity (NC) is a term arising from the ISO quality standards (ISO, 2008) that means refusal or failure to conform to accepted standards, conventions, rules, or laws. Nevertheless, the delivering of products and services with a higher degree of quality is an imperious challenge in order to reach competitiveness. In this context, with the timely identification of non-conformities, it becomes possible to improve products and processes design, as well as training people and establish appropriate policies to manage the quality and productivity of internal and inter-organizational processes.

In line with this, the KPI NON was created as an indicator responsible for representing the percent of orders with product nonconformities. Due to the usage of this KPI in parallel with the predictive performance management framework, it is not only possible to calculate the number of orders that presented nonconformities, in certain periods of time, but also explore the factors responsible for affecting this indicator. By correlating this knowledge with the data retrieved from past measures, it is then possible to estimate, for a specific situation, the number of nonconformities expected in future periods. It is also important to underline that, the correlation between KPIs DDT and NON should also be taken in account. In fact, if a bad budgeting concerning nonconformities is performed, than the possibility to affect delays on orders deliver increases.

5.2.2. Implementation

Envisioning the achievement of the objectives proposed before, the G3 supply chain was modelled following the strategy depicted in Figure 60. As it is possible to understand, a multi-core strategy was used to emulate each partner's behaviour. This strategy was followed since each element of the network presents a specific characteristic and curve of behaviour. Therefore it would be almost impossible to design a single engine capable to model the performance of the three companies and generalize the global network performance. This way, it was defined that each core of the performance estimation engine (PEE) should emulate the curve of behaviour of each partner of the network, in terms of the KPIs defined. Through the exchange of information between the different cores of the estimation engine, it would be possible to emulate the global network behaviour.

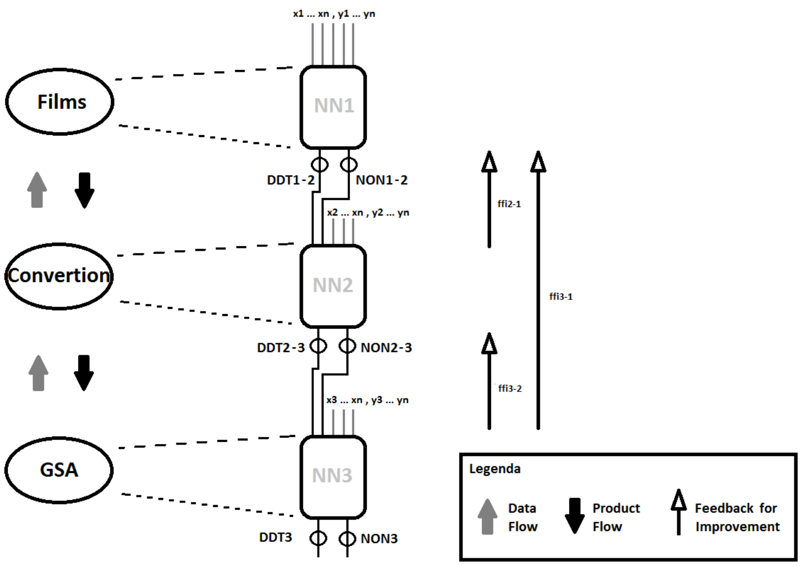


Figure 60 - G3 Network Modelling

Initially, the endogenous and exogenous factors that affect the normal behaviour of each of the elements in the network, concerning the KPIs selected for this pilot case, were identified and classified. This important task was performed in strict connection with the G3 network controller since this is the stakeholder responsible for managing the relationship between the partner of this supply chain, and thus, holds the knowledge concerning the network behaviour. Following, Table 4 and Table 5 present the leading indicators selected as disturbance factors for each of the KPIs selected, i.e. NON and DDT respectively.

Table 4 - Disturbance Factors for NON

Endogenous	Exogenous	Excluded
Personal Skills	Absenteeism	
Equipment Reliability	Raw Material Quality Reliability	
Storage Handling Reliability	Environmental Factors	

Table 5 - Disturbance Factors for DDT

Endogenous	Exogenous	Excluded
Preventive Maintenance	Supply Reliability	
Overbooking	Transportation Reliability	
Production Performance		

Following, the causal diagrams representing the feedback loops that directly or indirectly affect the normal behaviour of the indicators DDT and NON were designed. Figure 61 and Figure 62, now presented, show the most important feedback loops affecting each of the KPIs. While the indicator DDT is strictly related with the delivery time, the indicator NON is strongly linked with the rate of nonconformities generated.

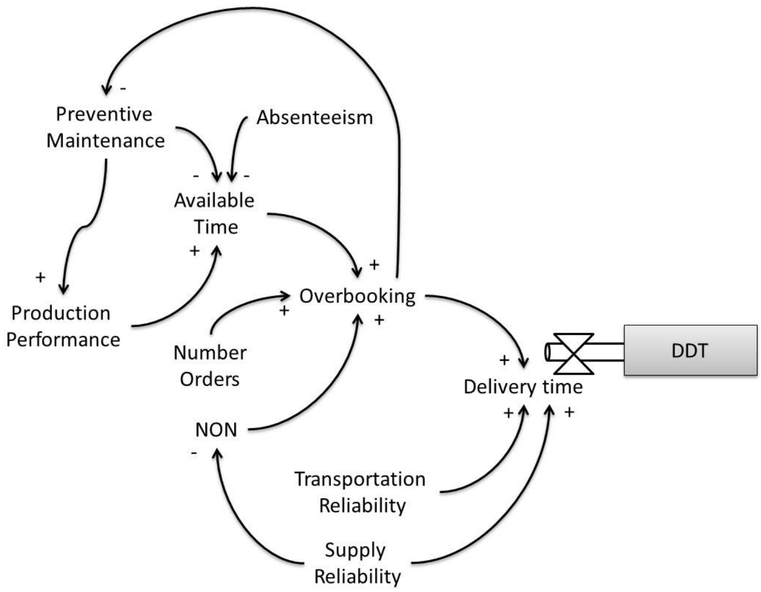


Figure 61 - Causal Loop Diagram for DDT

The leading indicators that increase the delivery time of a specific order are the transportation reliability, strictly related with logistics issues, suppliers' reliability and overbooking. While the suppliers' reliability integrates the information concerning nonconformities and delays imposed by the previous elements of the network, the overbooking represents if a certain partner´s production is above its capacity. Due to the nature of the companies participating in this network, this factor is strongly related with the number of orders received in a specific time horizon and the available time to produce.

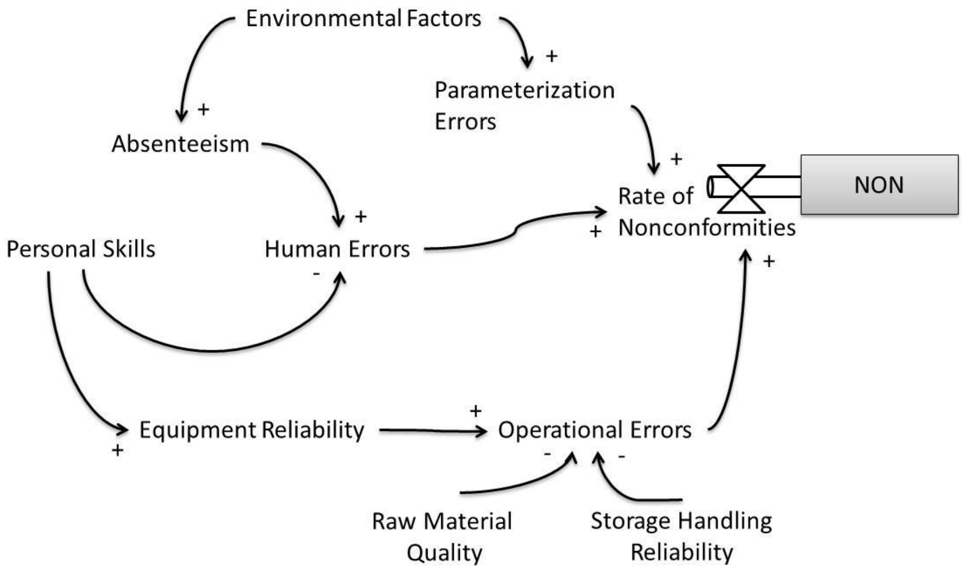


Figure 62 - Causal Loop Diagram for NON

On the other hand, it is possible to identify three main feedback loops capable to increase the number of nonconformities generated. The first one is related with the impacts of environmental factors on the parameterization of industrial processes. The second one is mainly related with the human errors affecting the overall partner performance due to lack of employees' experience and expertise. The third feedback loop is related with the operational errors caused by equipment, raw material and storage and handling reliability.

Performed the qualitative perspective of the predictive performance management framework, where the exogenous and endogenous factors were identified and the causal diagrams that represent the synergies between the leading factors responsible by the disturbance of indicators NON and DDT were designed, following, the estimation tool should be parameterized based on the knowledge generated.

Aiming to model the multi-core estimation engine responsible for emulating the global behaviour of the network, initially, each core (Core 1, Core 2 and Core 3) should be trained in order to learn the curve of behaviour of each elements of the network, and thus become capable of emulating the different factories of the supply-chain (Figure 60). To do that, while the two KPIs defined (DDT and NON) were used as the output of each core, the series of factors identified as responsible for influencing/disturbing the chosen KPIs (such as personal skills, absenteeism, supplier reliability, and others) were used as inputs. After compiling the historic measures related with this metadata, the data should be provided to the learning algorithm, responsible for training and modelling each core to the respective factory dynamics.

At this stage, each core should be capable of receiving the different leading factors and project into the future, which should be the factory reaction and the respective KPIs. However, it is important to understand that a supply-chain like this presents a "snowball" behaviour. In fact, all the nonconformities and delays verified at upstream of the network will have a crucial impact at the bottom of the supply-chain. This is the reason why there is not only a constant feedback between the different factories (ffi2-1, ffi3-1, ffi3-2), but also the output of the previous factories (DDT1-2, NON1-2; DDT2-3, NON2-3) should be used as input (factors) of the ensuing factory (Core 2 and Core 3 respectively) on the estimation process (Figure 60). So, it becomes possible to easily compile all the information at the supply-chain and to support decision-makers to offer better services to the final costumer.

5.2.3. Analysis of Results

After the estimation engine tool parameterization, this was deployed within the pilot case designed in order to be possible to extract conclusions about the framework accuracy, reliability and flexibility. In line with this, in collaboration with the G3 controller, a specific scenario was created for each relationship between companies, aiming to simulate the scope and environment where each partner would have to perform. In the following table (Table 6), the leading factors and respective data used to simulate the behaviour of company FILMS is presented.

Aiming to validate the proposed predictive approach, the expert and GSA planner raised two research topics:

1) The G3 planner showed interest in estimating the KPIs values for the next six months in order to support KPI targeting for a medium- and long-terms. The intention was to support the commitment of the production team in order to manage the factors that negatively affect KPIs behaviour, and thus manage the network performance. Figure 63 shows the results to this question
2) The planner also intended to estimate KPI values for the following month, aiming to continuously tuning the estimation of the leading factors. For instance, specific improvement actions can occur, being capable of enhancing production performance or the supply reliability.

In order to clarify the information presented in Figure 63, the blue line represents the real KPIs measures while the green line represents the output of the neural network and the red line represents the output of the Kalman filter. As it is possible to observe, after eighteen months of training, the performance estimation engine (PEE) was launched to forecast the following six months. Especially in the chart where the KPI NON is depicted, there is a smooth offset error derived from a modelling error caused by the neural network (difference between green and blue lines). However, the Kalman Filter fulfils its function, nullifying this constant error as proposed for the PEE tool.

Also, it shows that the tool does not just follow the past trend, but takes a proactive behaviour taking the factors that influence each month into consideration. Thus, one can say that this is a consistent tool because the admissible error is low and the degree of confidence is high, approximately 97%.

Table 6 - Scenario for Films Simulation

Factory	Factors	Months											
		January	February	March	April	May	June	July	August	September	October	November	December
Films	Nº Orders	15	20	25	31	19	21	22	32	36	40	25	18
	Preventive Maintenance	1	0	0	0	1	0	1	0	0	0	0	1
	Production Performance	0.2	0.2	0.2	0.2	0.15	0.15	0.15	0.15	0.1	0.1	0.1	0.1
	Supplier Reliability	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	Transportation Reliability	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.15	0.15	0.15	0.15
	Overbooking	0	0	0	1	0	0	0	1	1	1	0	0
	Personnel Skills	0.35	0.35	0.35	0.35	0.32	0.32	0.3	0.3	0.3	0.28	0.28	0.28
	Abseenteism	0.015	0.012	0.008	0.005	0.009	0.007	0.014	0.009	0.005	0.005	0.007	0.01
	Equipment Reliability	0.2	0.2	0.2	0.19	0.2	0.2	0.2	0.2	0.2	0.19	0.19	0.2
	Storage Handling Reliability	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
	Environmental Factors	0.9	0.8	0.6	0.3	0.2	0	0	0	0.1	0.2	0.5	0.7
	Raw Material Quality	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

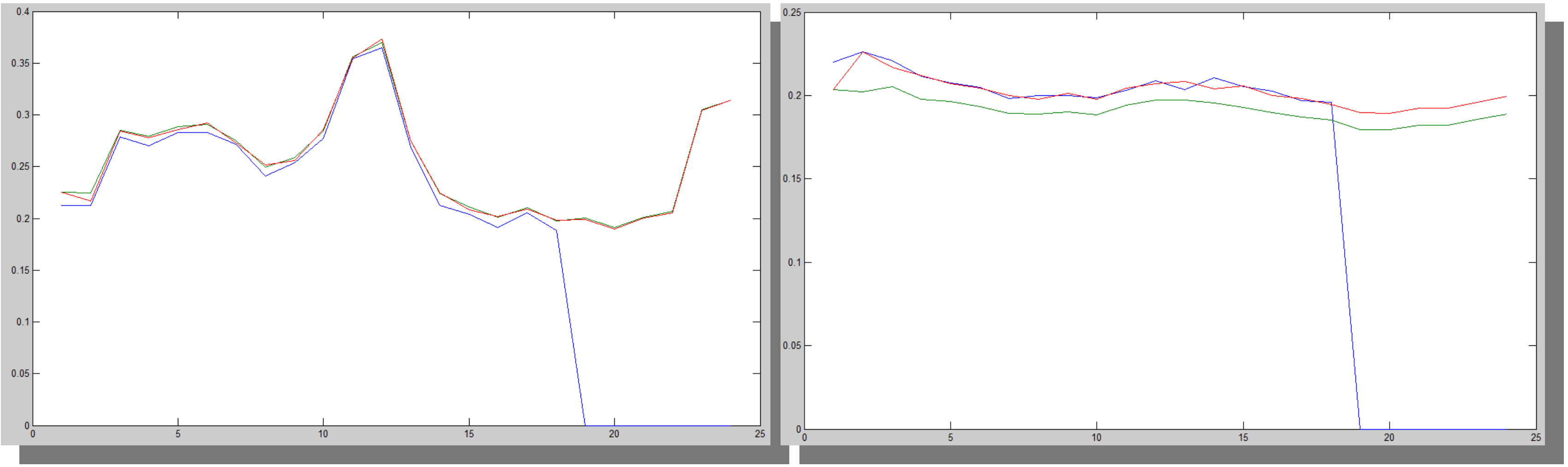


Figure 63 – G3 behaviour simulation for six months (left Chart related with KPI DDT and Right chart related with KPI NON)

Table 7 - Performance Estimation Algorithms Comparison

	Analysis of Estimation Algorithm per KPI					
	Films		*Conversion*		*GSA*	
	Delay	**NC**	**Delay**	**NC**	**Delay**	**NC**
Moving Average	0.1386	0.1351	0.2924	0.1790	0.3190	0.1512
Exponential Smoothing	0.1063	0.0197	0.1273	0.0266	0.1147	0.0145
PEE	0.0055	0.0035	0.0135	0.0073	0.022	0.0090

In order to validate the proposed estimation framework, a comparison with other methods currently used to estimate performance values can be seen in Table 7. In this demonstration case, the PEE tool achieved a very low error percentage of 2,2% for DDT, and 0,9% for NON, which is less than what was registered using other methods such as the Moving Average and Exponential Smoothing.

In order to answer to the second issue raised by the G3 controller, a similar exercise to the one described before was performed. However, in this stage, the confidence about the leading factors used is much higher, since the time horizon is small and thus it was easier to the G3 expert to estimate the environment where the simulation would be performed. Moreover, this short-term strategy can guarantee that more updated values regarding the leading factors changes are obtained. In line with this, the graphics of the three relationships are presented in Figure 64, Figure 65 and Figure 66.

As it is possible to see, a mismatch can be observed between the three sets of figures. This happens mainly because it was defined that the effects that occurred at a certain node of the network would only affect the subsequent node in the following month. This is a typical behaviour in a costumer-supplier relationship, which was successfully understood by the multi-core performance estimation engine (PEE).

Because of this effect, if it is necessary to estimate the performance of the global network on following month, then it is possible to use the real measures of the first and second elements of the network, concerning previous and actual months respectively. In this specific case, despite the fact that the real measures were available, it was decided to also estimate the behaviour of the previous months, aiming to present the reliability and confidence level of this framework, and consequently use this information to estimate both KPIs DDT and NON at the endpoint of the network.

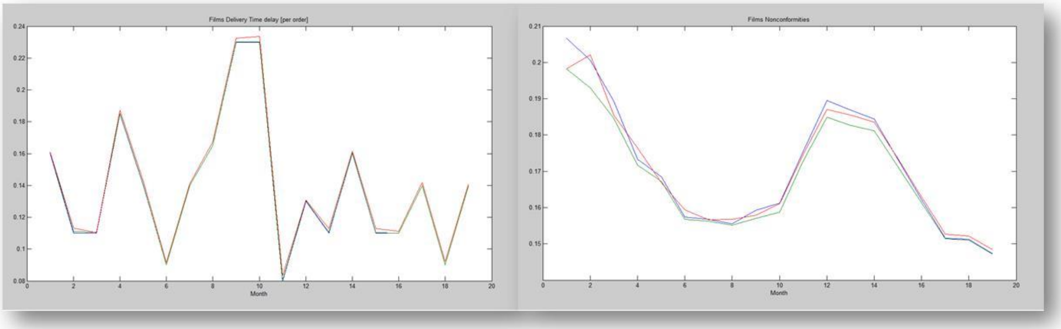


Figure 64 - Films Performance Estimation (left Chart related with KPI DDT and Right chart related with KPI NON)

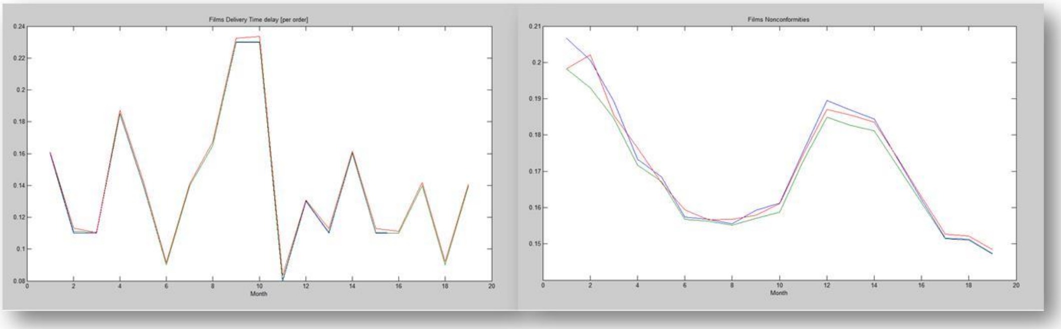


Figure 65 - Conversion Performance Estimation (left Chart related with KPI DDT and Right chart related with KPI NON)

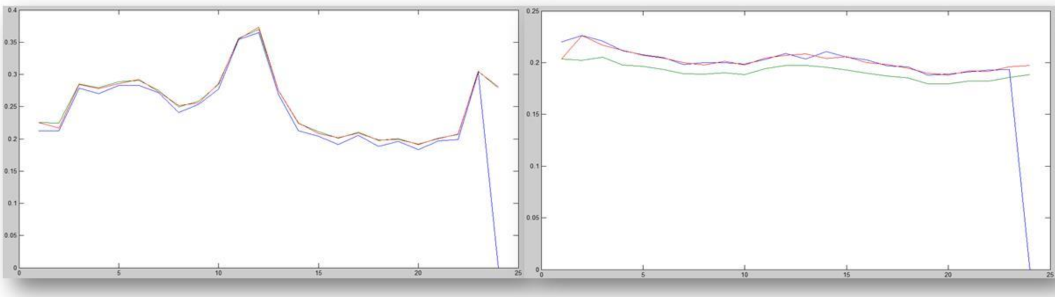


Figure 66 - GSA Performance Estimation (left Chart related with KPI DDT and Right chart related with KPI NON)

5.2.4. Case Validity

As previously explained, the pilot case presented during this chapter was mainly designed in order to be used as a demonstration case. In other words, this scenario was used as prove of concept. Despite the fact that the scenario here described is strictly related with a real collaborative network performing in the Brazilian market, the data used was totally simulated based on the experience of the network controller that actively participated in this test case.

Taking into consideration the purpose of this pilot case, it is possible to state that the objectives defined were completely achieved, since the predictive performance framework was capable to not only understand the normal behaviour of each element of the network, concerning order delays and nonconformities, but also estimate with high levels of reliability the future KPIs measures for the entire supply chain. It is also true that the results obtained were also achieved due to the innovative multi-core performance engine architecture designed.

From the deployment of this pilot case, two important goals were achieved. Firstly, with the successful demonstration of the predictive performance management concept and fundamentals, explored in detail during chapter two, it was possible to convince the stakeholders of one of the most important Brazilian group performing in the food industry, that performance measures could be used for a proactive management approach instead of simply using these values to evaluate past behaviours or compare factories performances based on a benchmarking approach. The other main achievement of this pilot case, and maybe the most important, was that with this proof of concept as a demonstrator, it was possible to persuade managers from Volkswagen Autoeuropa, the largest Portuguese exporter, to rethink the way they calculate and use performance measures within their management processes.

5.3. Automotive Plant Productivity Measurement

5.3.1. Problem Definition and Foci of Study

In order to fully test and validate the framework developed and presented in this thesis, the Autoeuropa plant, from the Volkswagen group, was selected as scenario of this application case implementation. Indeed, the VW Autoeuropa not only is the larger Portuguese exporter but also presents one of the more complex layout and structure of the entire Volkswagen group. This happens because within the same plant are produced three distinct cars, sharing processes and resources, that belong to two different family types of vehicles: sportive (*EOS* and *Scirocco* cars) and MPV – Multi-Purpose Vehicle (*Sharan* and *Alhambra* cars). Moreover, this production line is divided into five main organizational units, presenting their own characteristics and requirements: *Stamping*, *Painting*, *Body*, *Assembly* and *Quality*. Therefore, it is also necessary to calculate each indicator, not only for each product but also according to the structural division of the production system. While some resources are shared between all of the cars, others are shared by a subgroup of families of cars and others are specific to each product.

In order to remain competitive and survive, the same production line should be flexible enough to produce these different families of vehicles, but at the same time present high levels of productivity. Nevertheless, this level of complexity is not restricted to the operational level, spreading to the strategic layer of the company, and more specifically to the performance management domain.

Nevertheless, the Volkswagen Autoeuropa, as almost all world class companies in the world, support their procedures for performance measurement and management on a distributed architecture, where different databases, several excel worksheets and a series of charts compiling the most important information from a stakeholder point of view are used. Due to this traditional architecture, two important disadvantages can be identified:

1. Firstly, although KPIs metrics are by definition simple mathematical formulas, due to the distributed architecture described, the process related with KPI calculation not only become complex, requiring a huge effort to be accomplished, but also is strongly receptive to human errors.
2. Secondly, due to the static and rigid characteristic of this solution, the linkage between the strategic and operational layers is strongly compromised. This means that strategic changes requiring a performance measurement and management system update needs a long training and transition period, which can strongly affect the success of a new strategy implementation.

In sum, due to the structural architecture of the VW Autoeuropa plant, responsible by increasing the level of complexity of this manufacturing system, as well as acknowledged the strategic bottlenecks existing within the Volkswagen Autoeuropa management processes, this automotive factory was identified as a key partner where it could be possible to test and validate the proactive performance management solution, developed within this PhD research.

As previously stated within the framework proposal chapter, for a performance measure to be considered as a Key Performance Indicator (KPI), it has to be linked to one or more of the organizational critical success factors, more than one balanced scorecard perspective and more than one of the organization's strategic objectives. However, due to the physical dimension and intricate relationship between the different departments of a large and complex manufacturing system, guarantee the integration of the strategic and operational performance layers is not a trivial matter, neither represents the only requirements necessary aiming to achieve the maturity in performance production system control.

In fact, in addition to the requirement raised before, it is necessary to develop flexible Strategic Performance Management Systems (SPMSs) suitable for organizations that perform in complex and dynamic environments. These systems should allow the organization simultaneously to achieve *high empowerment* (necessary to adapt to rapidly changing environments) and *high alignment* (assure that different parts of a complex system work effectively together). In sum, systems that combine alignment and empowerment, and make appropriate use of performance targets and indicators over time, could prove an effective means of implementing changes in strategy and promoting intended behaviours.

Hence, this chapter has as main objective to show how the performance measurement engine (PME) can be seen as the key to support companies achieving high levels of empowerment and alignment. Therefore, a pilot case was designed, in collaboration with the ETH Zurich[15] and Volkswagen Autoeuropa, covering both strategic and operational layers of an organization. As it is possible to see in Figure 67, the Performance Measurement Engine is located between the strategic and operational levels, aiming to compile raw data according to the KPIs specifications as well as planning constraints and assumptions retrieved from the tactical and strategic level.

In this pilot case, ETH Zurich was mainly responsible for developing a tool where strategic maps modelling the organization's policies and visions could be designed. On the other hand, Volkswagen Autoeuropa was mainly responsible for defining the scope and restrictions of this pilot case. In line with this, the Harbour Report[16] was selected as the conceptual pillar supporting the validation of this strategic performance management system. In the scope of the Harbour Report, one of the main perspectives evaluated is the productivity related with the vehicles assembly, where each company and respective plants are detailed analysed. Here, the Key Performance Indicator used is the Hours per Vehicles, also known as HPV measure. This is a KPI oriented to the productivity perspective, whose metric mainly combines information related with the manpower, directly linked with the production line, and the number of vehicles produced by these resources (more detail about the Harbour Report in Annex D).

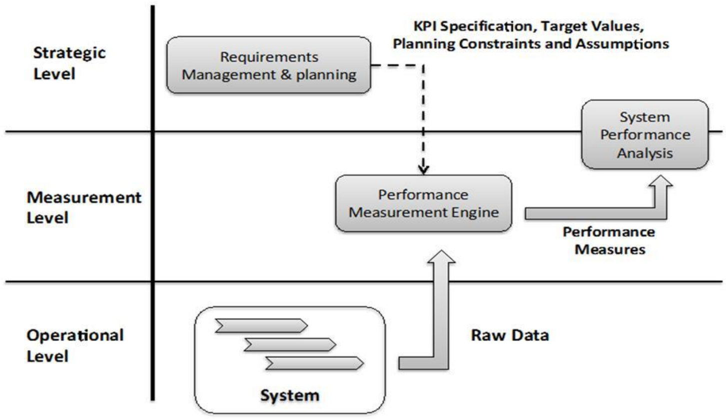


Figure 67 - Integrated Strategic Performance Management

[15] ETH Zurich is one of the leading international universities for technology and the natural science. It is well known for its excellent education, ground breaking fundamental research and for putting its new findings directly into practice. Nowadays, ETH Zurich has some 18000 students from over 100 different countries, 3800 of whom are doctoral students. 21 Nobel Laureates have studied, taught or conducted research at ETH Zurich, underlining the excellent reputation of the institute.

[16] Harbour Report is one of the most important benchmarking reports in the automotive industry, aimed not only to ranking the efficient automotive plants but also support organizations involved within this comparison exercise enhancing their manufacturing systems and the entire supply chain. Two leading companies on consultancy joined forces aiming to be a reference on the automotive industry, they are the Oliver Wyman and Harbour Consulting. These companies are providing services covering the entire supply chain of some of the most powerful automotive groups, such as BMW, Mercedes-Benz, PSA Peugeot Citroen, GM Group, Ford, FIAT, Toyota and also Volkswagen Group.

5.3.2. Implementation

Following the paradigm that a factory is simply a very complex type of product, the ETH Zurich used as inspiration a functional modelling approach from product design to model the strategic goals of a factory called Function Oriented Product Description (FOPD). The FOPD constitutes an approach to combine a requirements model and a functional model. This model can be refined stepwise and may be seen as a detailed specification of the desired functions and the goals of a factory.

As shown in Figure 68, the resulting specification may then be used as an input for further design activities and to assure properties throughout the whole design process. In addition to that, it also enables an assessment of the final factory design and thus to monitor the current performance of the factory. In other words, an adequate performance measurement system may be obtained from the information that is contained in a FOPD model. This way, the definition and modelling of the factory or company goals become an ex-ante activity that is totally aligned with the specification and consequently with the rationale design of a factory.

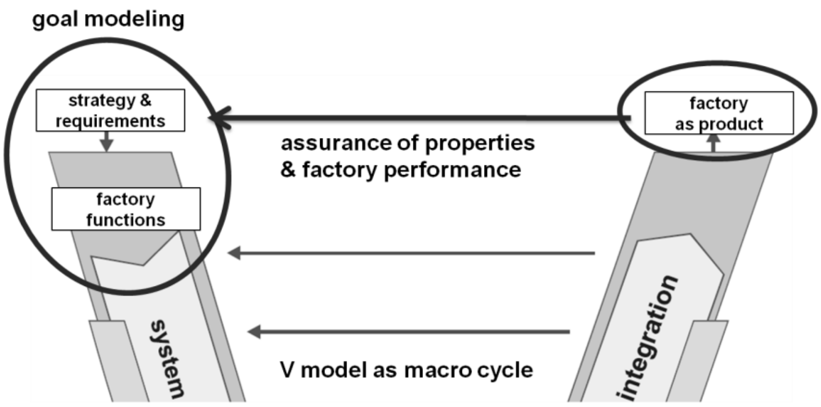


Figure 68 - Unified modelling of strategy, requirements and functions ((Almeida et al., 2012))

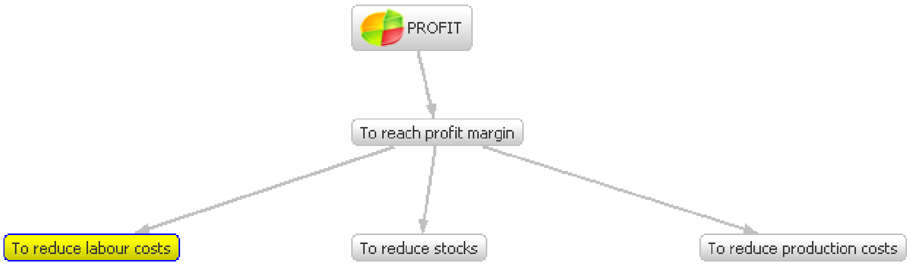
In Figure 69, it is presented how the FOPD approach described before was materialized within a software solution called Requirement Management Planning (RMP) by the ETH Zurich team. As it is depicted, through the RMP solution it is possible to define a hierarchy of functional requirements and for each the respective KPIs and corresponding target values are mapped.

The table in the bottom part of this figure lists all the assigned goals (each consisting of a KPI, the type of optimization and a target value) of the highlighted functional requirement. In this example, different targets have been defined for different types of products. Moreover the RMP offers the possibility to input and manage global assumptions and/or constraints (e.g. the number of working hours per day – effective time) and also to assign responsible persons for the fulfilment of each functional requirement. All the collected data is intended to serve as an input for the measurement level, which aims to guarantee a continuous monitoring of the factory or system on the operational level.

As depicted in equation 5.1, the HPV's formula takes into account all of the hours worked by the direct plant personnel divided by the number of units produced, with the expected levels of quality, in the time interval defined.

$$HPV_{Plant} = \frac{Manpower\ (persons) * EffectiveTime(time/person)}{Volume\ (unit)} \qquad \text{Eq. 5.1}$$

$$Attending = Payroll - Absenteeism - Training - TransfersIn + TransferOut - Sickness \qquad \text{Eq. 5.2}$$



KPI Name	Type	Formula	Unit	Op	Target Value	Product/Output	Current value
manpower	Cost	payroll-absenteeism	person	<=	1000	EOS	315.7998
manpower	Cost	payroll-absenteeism	person	<=	1200	Sharan_NF	1377.3651
manpower	Cost	payroll-absenteeism	person	<=	800	Scirocco	602.8552
HPU	Cost	(manpower*effectivetime)/volume	h	<=	25	EOS	29.172
HPU	Cost	(manpower*effectivetime)/volume	h	<=	22	Sharan_NF	29.172
HPU	Cost	(manpower*effectivetime)/volume	h	<=	23	Scirocco	24.9843

Figure 69 - Functional Requirements hierarchical Tree

However, the calculation of the variable Attending is not a straightforward calculation. Thus, in order to calculate this performance indicator it is necessary to know the list of people that directly interact with the production line, the list of people in absenteeism or in training and the list of people that moved from an organizational area to another.

Since Volkswagen Autoeuropa plant produces more than one type of vehicle and the line has five distinctive areas (stamping, body, paint, trim & assembly and quality), the calculation must be performed per car, taking into account the entire line, but also splitting up the production line stages, as depicted in Figure 70. In other words, the domain/universe of calculation is the production line, divided by the five areas and its output, represented by the volume of cars per type.

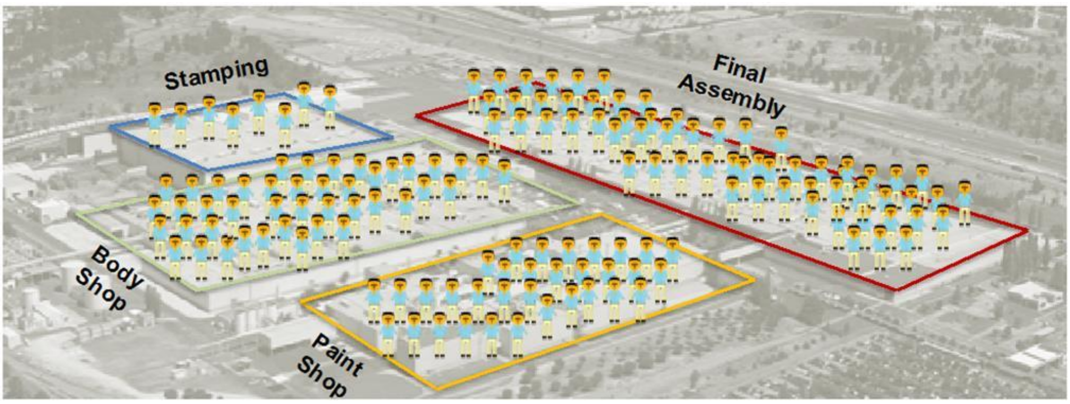


Figure 70 - Volkswagen Autoeuropa plant from HPV perspective

Based on the high-resolution approach, explored during chapter three, the more detailed the calculation of a certain KPI is, the, more information is possible to extract in terms of management issues. Therefore, aiming to automate and increase the level of information extracted from the HPV measure, the PME was used as the engine of calculation of the KPI HPV. Therefore, the following stage of the pilot case was divided into two main steps: *KPIs metrics parameterization* and *KPIs calculation*.

While the first stage is mainly responsible for the definition and specification of a certain KPI as an object, during the KPI calculation the main objective is to instantiate the object created in order to answer to the requirements imposed by performance management strategy, such as domain/universe of calculation, static and dynamic assumptions as well as percent of resources allocation per product type.

KPIs metrics parameterization

As previously described, at a first stage, the KPI HPV was specified using the data fusion and metrics formalization capabilities of the performance measurement engine (PME). Thus, the first task performed within the pilot case here presented was identifying the raw data sources (databases or flat files) available and, create the tunnels for data communication. In line with this, Figure 71 shows the PME identifying the database where the table Absenteeism was available, download the respective metadata for the selection of fields and finally define the loading rules for filtering purposes. In sum, at a first stage, all tables containing information about the necessary raw data for the HPV calculation were identified, such as: list of all Cost Centers, the payroll table, list of absenteeism, list of people in training and list of people transferred temporarily from one organizational area to another,

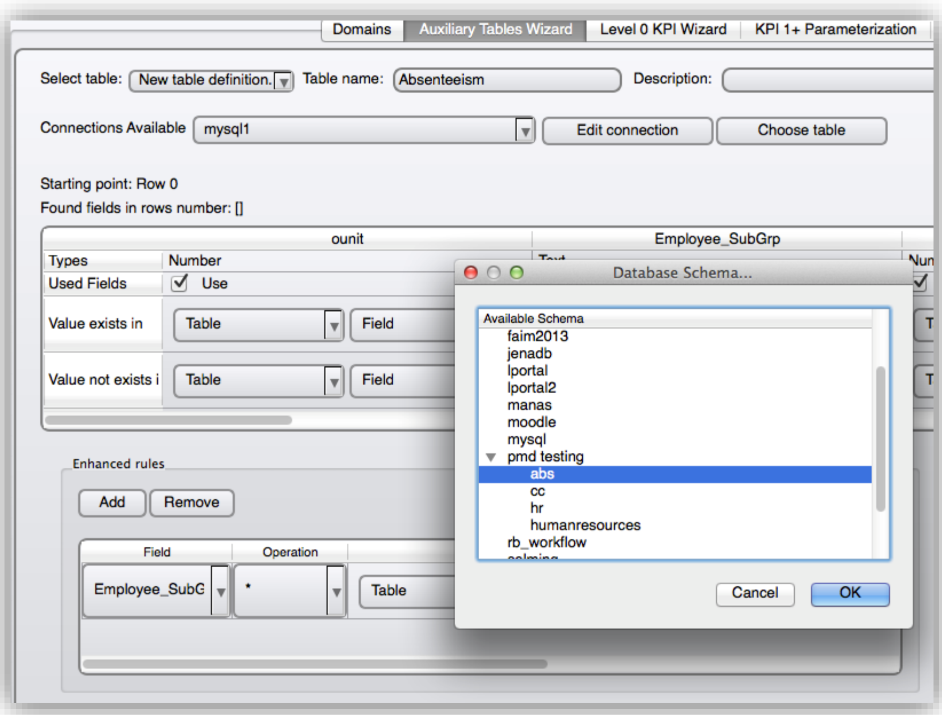
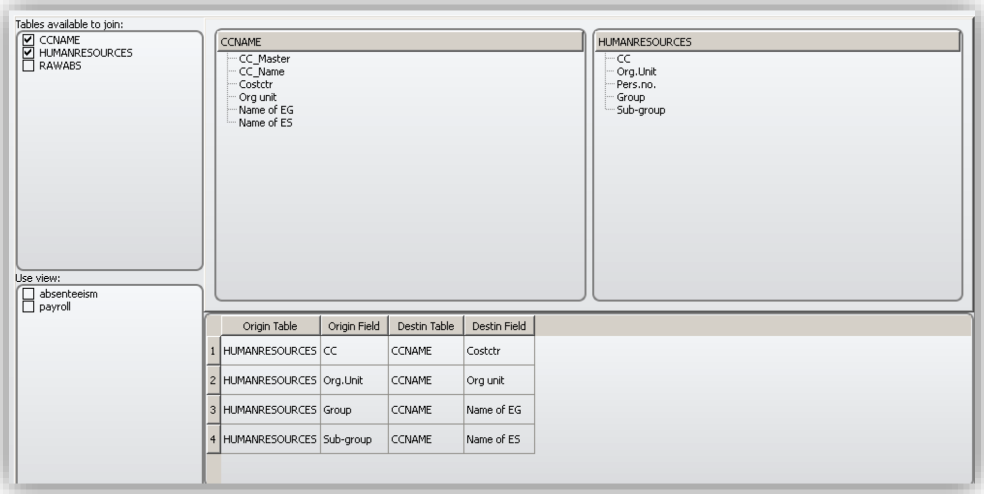


Figure 71 - Raw Data Sources Identification and Routing

After identifying the data sources where the raw data will be available, the following step was strictly related to the Performance Indicators of level 0 (KPI_0) specification. As previously explained, this type of indicators is mainly responsible by the structuring of raw data through a data fusion approach. As an example, Figure 72 shows how it is possible to join two distinctive datasets, due to the data fusion approach developed for the PME, in order to create a new variable where data is structured and ready to be used as a mathematical variable, at a vector format. For instance, in this figure it is depicted how it is possible to merge the list of cost centers ("*CCNAME*") with the payroll list ("*HUMANRESOURCES*") in order to obtain the number of persons working in each cost center. This step is critical, since it is expected to calculate the KPI HPV per organizational areas, which are composed by cost centers.

Due to the drag and drop functionality, the user is not required to have any knowledge of SQL language, being only necessary to link the similar attributes from the selected tables. At the table located at the bottom of the figure, it is depicted a series of attributes already connected. For example, the attribute called "*CC*" from table "*HUMANRESOURCES*" has a correlation with the attribute *"Costctr"* from table *"CCNAME".*



	Origin Table	Origin Field	Destin Table	Destin Field
1	HUMANRESOURCES	CC	CCNAME	Costctr
2	HUMANRESOURCES	Org.Unit	CCNAME	Org unit
3	HUMANRESOURCES	Group	CCNAME	Name of EG
4	HUMANRESOURCES	Sub-group	CCNAME	Name of ES

Figure 72 - PI Human Resources Specification

After identifying the data sources as well as specified the KPI_0 it is now possible to specify the mathematical formulas for each of the key performance indicators (KPI_{1+}) identified before: *Attending* and *HPV* (see equation 5.1 and 5.2). In this specific pilot case, the PME was capable to download from a knowledge-based served, where the strategic and performance measurement and management ontology was deployed, the information created by the RMP software concerning KPIs formulas and respective target values. However, if the PME was being used as a standalone solution, then, similarly to the previous step, the formula could be constructed using the drag and drop functionalities of the PME tool, as depicted in Figure 73.

Here, the formula designed at the bottom of this picture was built based on the KPI_0 and KPI_{1+} available, as well as the mathematical functions developed for this pilot case and the static and dynamic assumption characteristic from the domain in analysis.

It is important to underline that, due to the innovative hierarchical approach explored within this performance measurement engine, it is possible to define KPIs that are composed not only by KPI_0 and assumptions but also by others KPI_{1+}. For instance, the KPI HPV is composed by one KPI_{1+} from level two (*Attending*) and three KPI_{1+} from level one (*absenteeism*, *train* and *sickness*), which, consequently are composed by a set of KPI of level zero (*payroll*, *different types of absenteeism*, *training* and *transfers*). This hierarchical structure, built according to each KPI metric, can be seen in Figure 74.

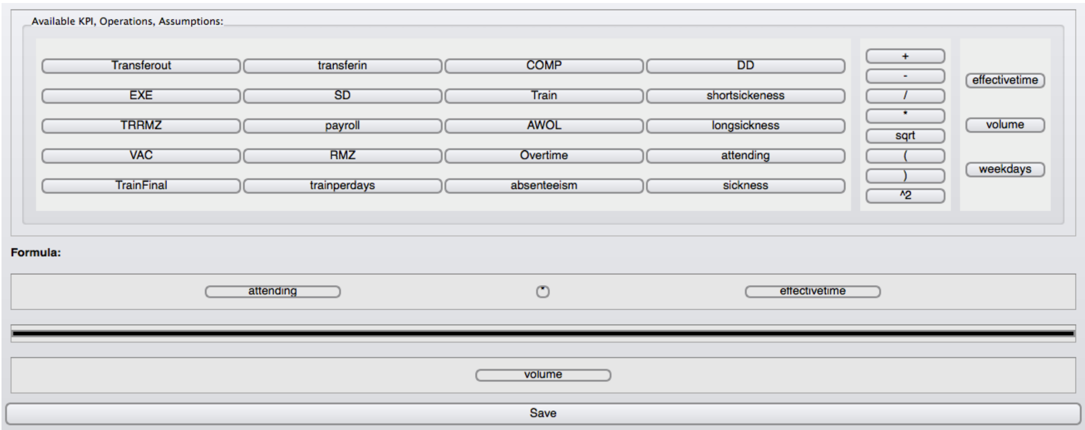


Figure 73 - KPI HPV Metrics Specification

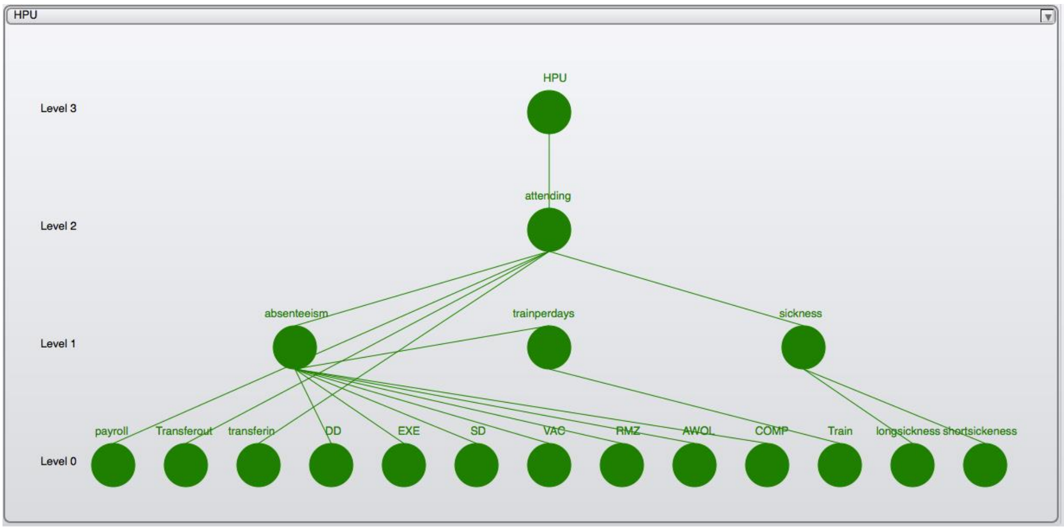


Figure 74 - HPV Hierarchical Tree

HPV Metric Calculation

After specifying the metrics of the desired KPIs, the following step of the pilot case is strictly related with the metric calculation. In fact, this is a second process that allows approximating as much as possible the KPI calculation from the real characteristics of the complex manufacturing system.

Therefore, aiming to calculate the HPV for the Volkswagen Autoeuropa, initially the static and dynamic assumptions were defined. Since the moment that this pilot case was performed, it was not possible to establish a direct connection with the data sources where it would be possible to extract the real volume of cars produced, then this information was manually introduced into the system using the window presented in Figure 75. Here it was also possible to update the value of the static assumption "EffectiveTime" and compare the real production with the planned one (tables *Real Dynamic Assumptions* and *Planning Dynamic assumptions* respectively).

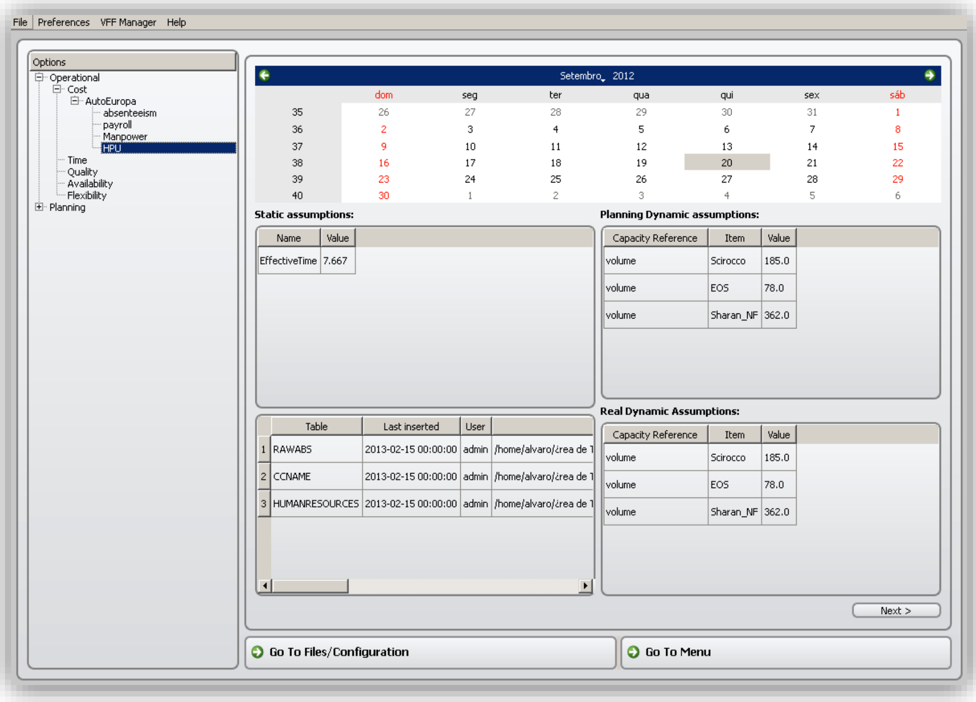


Figure 75 - KPI HPV calculation according to Domain static specifications and dynamic requirements

In fact, one of the main advantages of this approach is the capability to calculate a certain KPI with a higher level of detail but with lower effort. Therefore, during the description of the pilot case it was stated that it would be important to calculate the KPI HPV not only per product but also per organizational area. Therefore, the following steps are related with the specification of the performance measurement domain and the percentage of effort allocated for each car family. In line with this, Figure 76 and Figure 77 show how it is possible to specify both information, using the functionalities developed for the performance measurement engine.

Figure 76 is mainly divided into two areas: Volkswagen Autoeuropa cost centers and Volkswagen Autoeuropa Organizational Units. While the first group of information is automatically downloaded from a specific database where the updated list of the cost centres that compose the entire production line is maintained, on the second one it is defined the main clusters of the Volkswagen Autoeuropa performance management strategy, representing how the cost centres available are expected to be grouped. In fact, if it is true that it is expected to achieve highly detailed performance measures, it is also true that a calculation with an excessive detail is not appropriated. Therefore, through the windows presented in Figure 76 it is possible to achieve a trade-off between the existing information concerning cost centers and the desired structure for the performance management strategy.

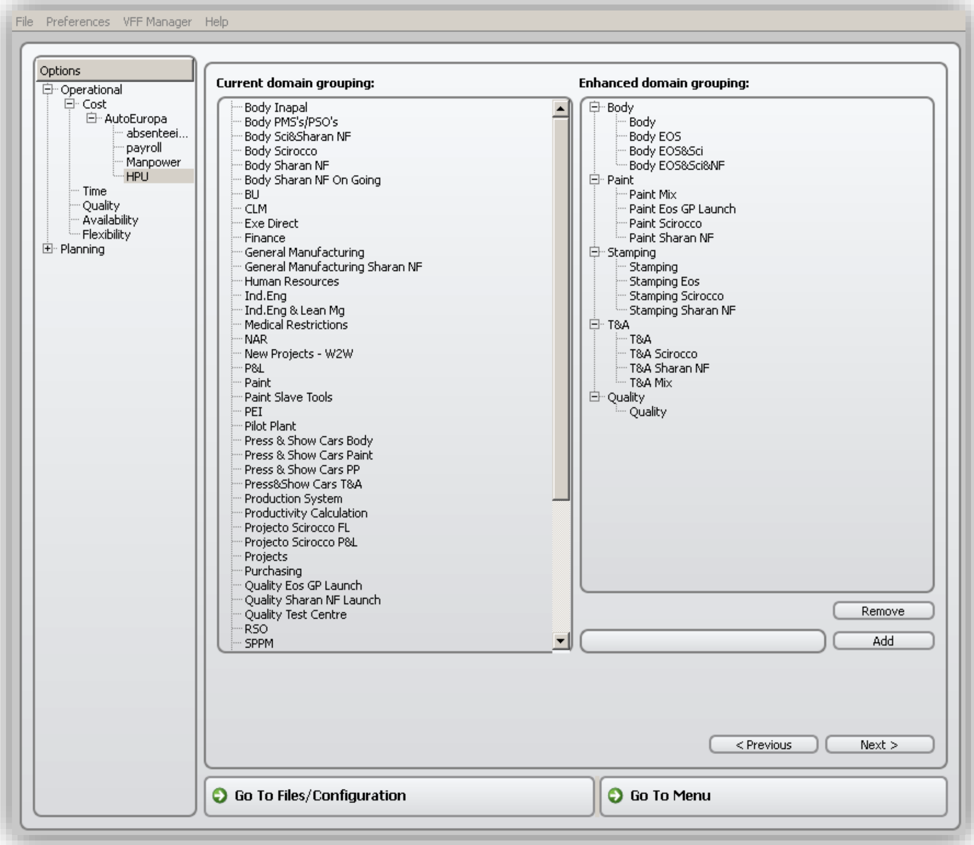


Figure 76 - Volkswagen Domain Specification

On the other hand, Figure 77 shows how it is possible to specify, for each cost center selected to be part of the performance management strategy clusters, the effort allocated for each car family. In line with this, for each cost center it is possible to indicate which car family used the resources available and the percent of usage (in this case human resources). The calculation of this percentage can be done automatically by the PME, through the planned volume of production, or introduced manually by the system's performance manager.

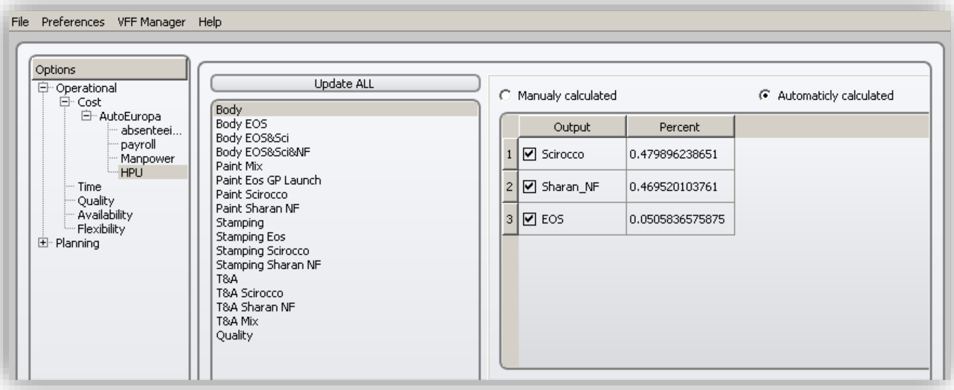


Figure 77 - Production Line effort allocation per Family of Vehicles

Finally, reports can have different formats: KPI hierarchical trees (Figure 78), charts, tables (Figure 79) or pre-defined emails. For instance, the KPI trees represent an innovative approach for analysing and assessing a performance indicator measurement. With this approach, it is not only possible to visualise the entire structure of a KPI (raw data and performance indicators used) but also detect the reasons for low performance rates. Therefore, it is feasible to detect watermelon situations and anticipate possible production system malfunctions. This means that, by using different colour tones from light green/red to dark green/red, managers can instantly understand if KPIs are far (darker) from or close (lighter) to the target. Besides these colour tones, there are also white coloured circles that identify which are the KPIs that currently do not have a defined target, and therefore could not be provided with a more meaningful colour that would make it possible to identify the KPI status. To provide more detailed information on status to managers, the possibility of clicking on each of the KPIs was implemented so that they could see the real values compared to targets, by domain, thus providing an even more detailed view of KPI status and its calculated values.

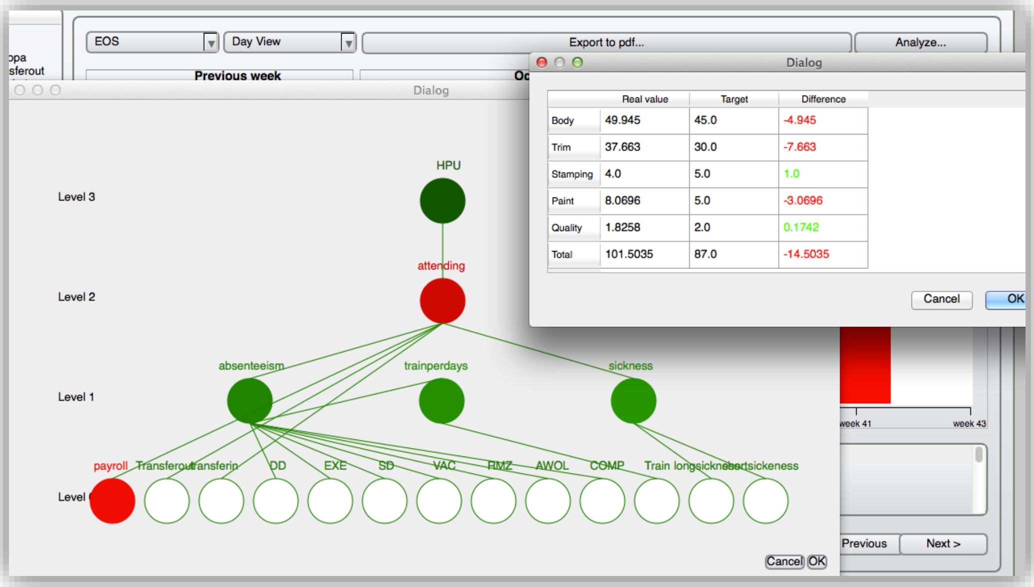


Figure 78 - Root causes analysis through innovative PME drill-down approach

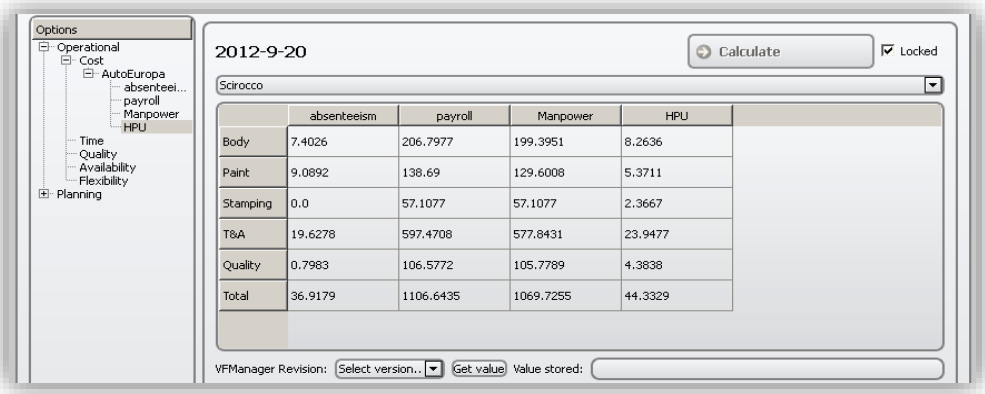


Figure 79 - Hierarchical KPI HPV calculation per car family and organizational areas

5.3.3. Analysis of Results

This research project was developed on the premise that aiming to support decision makers to become more proactive, in terms of performance management strategies, it is necessary to enhance the way how organizations execute their performance measurement activities, as well as improve the reliability, confidence and granularity on their KPIs metrics and measures.

Therefore, within this application case, it was explored the importance of approximate as much as possible the strategic and operational layers, in terms of performance information exchange, since, only this way, it is possible to assure that the functional requirements that motivated the building of a set of KPIs will be clearly assessed at the operational layer. However, within complex manufacturing systems, such as the one where this application case was performed, the strategic and operational layers are two different universes that have different actors, with different mind-sets, speaking different languages, pursuing different objectives and using different tools.

This way, the main achievement verified with the implementation of this application case was that, due to the development of an automated, user-friendly and intuitive functional module, strictly focus on the necessity to measure and manage performance, stakeholders become empowered to define their own KPIs, using if necessary external tools to the framework here developed, as well as deploy its calculation. Indeed, the different tests performed in the scope of this application case showed us that the KPIs defined by the VW AE stakeholders obtained exactly the same results, as the ones defined and calculated by the technicians at the operational layer, using the traditional approach, but requiring less effort and time.

This reality give us the confidence that, in the future, stakeholders can focus their attention on the improvement of their KPIs metrics, in order to approximate as much as possible their mind-set about the system behaviour to the reality. Moreover, due to the simplicity and effectiveness of the technology developed, it was possible to break with the stigma linked to the performance management discipline, where the effort required to obtain interesting performance information neither complies with the added-values obtained nor reinforce the organizational core business processes.

Nevertheless, in addition to the reliability and quality of the data calculated, it was demonstrated that based on this approach it is possible to extract more powerful information, envisioning knowledge creation. In other words, providing decision makers with the capability to build multi-perspective and aggregated KPIs, it is possible to decrease, significantly, the number of KPIs necessary to make decisions but keeping, at the same time, a multi-perspective vision of the manufacturing system.

Thus, with the implementation of this application case, it was demonstrated that it is possible to innovate and enhance the way how decision makers interpret this important information, drilling down a problem and study the reason behind a poor performance, in a high resolution way. In this specific case, it was proved that with low effort, it was possible to calculate the KPI HPV for each cost center, clustered in well-defined organizational units, as well as assess the strategy deployed, and materialized by the manufacturing system performance, per product family. Moreover, by following an innovative approach that structures KPIs in a hierarchical tree, combining multi-perspectives indicators, the PME allowed not only decision makers to analyse the impact of a specific indicator within the KPI structure but also integrate both tactical and operational information, and thus achieving a powerful "what-if" analysis.

In sum, by implementing the proposed integrated strategic performance management approach within a real case, it was possible to validate this concept within three perspectives:

- ***Time constraints***: the time required to calculate each indicator and to broadcast a performance report by the different stakeholders (time constraints) was measured using both the PME method and a traditional method.
- ***Effort***: the number of resources required in both processes was also measured (required effort) taking into account the performance assessment and bottlenecks identification error obtained.
- ***Learning curve***: the time required to train a new performance measurement technician (learning curve). In addition, the time necessary to introduce a new goal and respective KPI(s) was also assessed.

From the application case implementation, the industrial partner verified that the proposed framework was capable of:

i. Reducing the time taken to calculate the KPI by 85% (*Time constrains*);
ii. Reducing the training time by 75% for a new performance measurement technician (*Learning curve*) and;
iii. Reducing operational costs by 70%.

5.3.4. Case Validity

Although the strategic performance management approach here presented was designed and developed within a European research project scope, real company needs were also taken into account. In line with this, this proposal was tested and validated in company belonging to the automotive industry, which presents the characteristics normally observed in a complex manufacturing system (see chapter 2.1 Manufacturing Complexity and Modelling from State of the Art).

In sum, the Performance Measurement Engine (PME) proved to be flexible enough to understand the manufacturing system environment, compile and calculate the resources available on the shop floor and then distribute these resources for the different products, taking into account the different sections of the production line. We strongly believe that, following a straightforward static approach, it was not possible to adapt the performance management system to this level of complexity, and guarantee that it could be easily updated by non-experts when the manufacturing system changes.

5.4. Energy Consumption Indicators Estimation

5.4.1. Problem Definition and Foci of Study

The last pilot case conducted in the scope of this research project is strictly related with the implementation of a predictive performance framework, aiming to manage in a proactive way KPIs related with the sustainability development of an automotive plant. In simple terms, a sustainable development is the realistically attainable growth that a manufacturing system should keep in order to maintain the risk in a controllable range, without achieving a no-return point. Therefore, one of the main challenges becomes finding the optimum Sustainable Rate, which represents the maximum growth rate that a company can sustain without having to increase financial leverage or without affecting the environmental and social dimensions.

Indeed, the sustainable thinking is a management topic that is gathering high relevance within industrial organizations. Companies are realizing the importance of improving environmental and social performances in order to save money, enhance products quality, improve the company's image, as well as stimulate optimized operational performances, in order to build a competitive advantage. In line with this new paradigm, the Volkswagen Group defined, as one of the main pillars of its strategic vision the recognition of the importance of the environment within all aspects of its activity - "Think Blue"[17] program.

Indeed, in the scope of this campaign a series of actions, extended to all premises of Volkswagen group, have been deployed aiming at ensuring a continuous improvement of environmental performance of their premises taking into account their external surroundings. More specifically, the VW group defined as key object the decreasing of the environmental impact of Volkswagen plants of approximately 25%, until 2018. This means producing wealth, consuming less natural resources and energy, as well as producing less waste and emissions.

Consequently, an important pilot case was designed aiming to test and validate the predictive performance management framework developed, within a real industrial environment, taking as inspiration issues related with the sustainable development of a manufacturing system. After a series of meetings with some of Volkswagen Autoeuropa stakeholders, it was decided that it would be interesting, not only for scientific purposes but also for this automotive manufacture, to explore KPIs that could be strictly related with sustainability issues, more concretely with the energy consumption.

In fact, for Volkswagen Autoeuropa, the capability to estimate with high levels of reliability a series of KPIs presents very important advantages, mainly for targeting and

[17] The Volkswagen's "Think Blue." campaign addresses the question as to how to reconcile individual mobility and sustainable actions. The initiative not only concerns the development of eco-friendly products but also technologies and resources for efficient production processes.

budgeting purposes. Every year, when planning the annual production, this Portuguese plant is required to inform Volkswagen headquarters, which is the expected consumption value of energy for the entire plant, using KPIs as reference. This is a critical moment for Volkswagen Autoeuropa since these values will not only position this plant on the benchmarking ranking, created and maintained by the group, but also restrict the current and following year of production. This happens mainly because this productivity ranking, for which KPIs related with energy consumption are critical, gives an idea of which is the cost of production per vehicle. The shorter this value is, for a specific plant, higher are the possibilities to attract the confidence of the group and thus guarantee bestseller cars. In fact, in such a competitive world, where plants from all around the world struggle for survival, this is a critical issue for decision makers.

Consequently, two important organisational units were selected: the body area and the painting line. If it is true that these two areas are the ones responsible for the highest energy consumption, of both gas and electrical energy, it is also true that these organisational units have the most complex manufacturing behaviour in the entire plant. For instance, while the painting shop is defined by a single production line where multifamily products, with different and specific characteristics, share complex industrial processes and resources, the body area presents a job shop layout where the knotty flow of information, materials and products, substantially increases the level of complexity of this organisational area.

For each of these organizational areas, two important KPIs for budgeting purposes were defined as object of analysis: *Gas per Vehicle* (GPV) and *Electrical Energy per Vehicle* (EPV). Following, a detailed analysis of the Predictive Performance Framework implementation within Paint and Body areas are presented, aiming at estimate both KPIs for budgeting purposes.

5.4.2. Implementation at Paint Shop

Vehicle painting is positioned in the middle of the production process between Body Framing & Final Assembly and is subject to a number of trade-offs involving batch sizes, line optimisation and body availability. Externally, the boundary of this manufacturing system comprise the output of the body shop and the input of the trim area, as well as the external suppliers that provide the materials, being owners and responsible for some internal industrial processes of this area. Internally, this organisational area is divided into four main operational sections: Sealer, Primer, Enamel and Final Line. Figure 80 presents the paint shop layout considered in this application case. However, this is the normal layout that can be found at almost all automotive plants.

Despite the fact that, due to its layout, the paint shop seems to be a straightforward area, it has been proved that this is one of the critical bottlenecks within a normal automotive industry. Surveys have been showing that out of Body, Paint and Assembly around 50% of managers generally consider the Paint shop to be the most disruptive. In fact, it is true that a significant increase in vehicle complexity occurs when a body colour is introduced, decreasing the possibility to enhance production line flexibility, since the introducing of batch sizes of one as standard become almost impossible due to the following reasons: loss of efficiency; waste of solvent & dumping of paint through excess emptying & flushing of the lines; cost up, quality down.

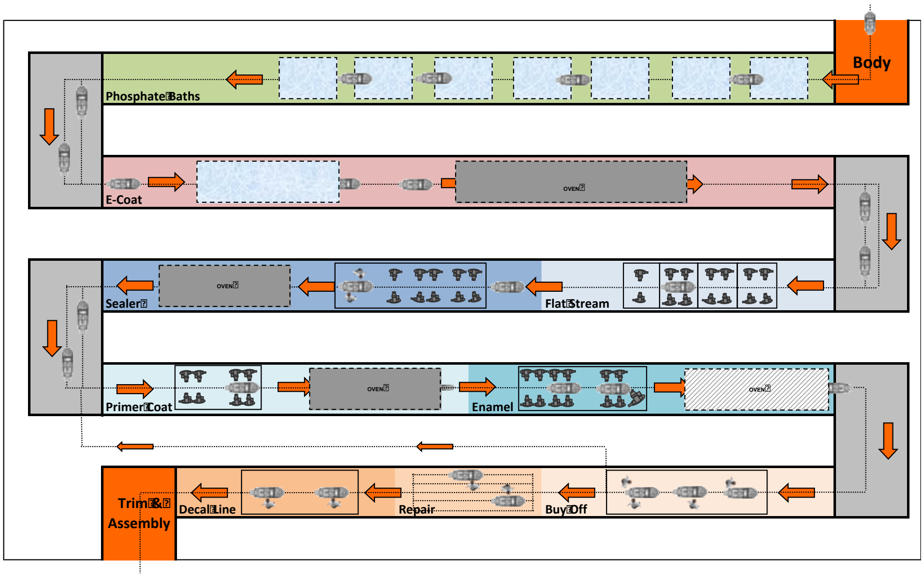


Figure 80 - Paint Shop Layout

Moreover, in automotive production, paint is the area of greatest concern to environmentalists, not only because of paint waste and solvent emissions but also because here it is consumed approximately 60% of the entire energy required by the VW Autoeuropa Plant. Thus, it is the focus of this research work to implement the predictive performance framework to, at a first stage, evaluate and model the factors that can strictly influence the energy consumption in this organizational unit, aiming to estimate with high levels of reliability which should be the daily energy consumption.

As previously explained, the KPIs selected were the gas per vehicle (GPV) and electricity per vehicle EPV, whose equation can be following depicted (Eq. 5.3 and Eq.5.4).

$$GPV = \frac{Total\ Gas\ Consumption}{Volume\ of\ Vehicles} \qquad \text{Eq. 5.3}$$

$$EPV = \frac{Total\ Electricity\ Consumption}{Volume\ of\ Vehicles} \qquad \text{Eq. 5.4}$$

As it is possible to understand, these are very straightforward indicators, which depend mainly from the total of gas and electricity consumption as well as the volume of vehicles produced. If it is true that, for an automotive industry the volume of vehicles per car family is linear and, because of that, easy to foresee, the same is not true both for gas and electricity consumption, which present high levels of non-linearity's. In line with this, the modelling efforts were strictly oriented for the estimation of total gas and electricity consumption, since after that, the calculation of estimated GPV and EPV would be direct and trivial.

Following, the different steps token within this pilot case in order to create a mathematical model capable to estimate with high levels of reliability both KPIs GPV and EPV, will be presented and described.

1) *Painting Process Description*

Firstly, a detailed analysis of the painting process was performed. In order to do that a Business Process Modelling Notation (BPMN) was used to graphically represent its workflow. The reader can find more information concerning the painting process in Annex E.

However, it is important to highlight that, due to the fact that this first perspective of the process is rigid and static, is not expectable to represent, at this stage, the dynamic behaviours of the system. Thus, the main purpose of this section was to build an overview of the painting process and provide the infrastructures capable of supporting the identification of the activities that request a deeper investigation in terms of energy consumption.

In order to accomplish this initial step of the methodology, not only was followed a research strategy based on the reading and analysis of organizational documentation (i.e. annual reports, access to historical data and other internal documentation), but also several guided tours to the panting line were performed different, in order to gather the most reliable mind-set about the system's workflow and behaviour.

Designed and validated the painting process BPMN, the author was empowered to schedule and conduct the following stage of the performance thinking methodology strictly related with the hypothesis generation throughout unstructured interviews.

2) *Hypothesis Generation*

This section, hypothesis generation, has as main purpose to collect and structure the different testimonials gathered from the different stakeholders of this process. Thus, during the fieldwork, three persons were interviewed with different responsibilities and perspectives of the painting process. The first one (#1), more related with the maintenance management, the second one (#2), more linked with the operational perspective of the maintenance and finally, stakeholder #3, with a closer perspective of the 3rd shift. In fact, this last one presents a special interest due to the variability/uncertainty of this shift.

Hypothesis 1:

According to stakeholder #1, the main factors responsible for the energy consumption are ovens (consuming gas) and air handling units also known as ARP (consuming both gas and electricity). Moreover, according to this interview it was possible to understand that these two resources responsible for the energy consumption are strongly subject to the influence of the external environment conditions, such as temperature, precipitation and humidity.

Another factor that can influence energy consumption lies in the effects of quality issues that can happen at the Buy Off section. In fact, with the increasing of the number of cars that are produced with major non-conformities, which forces the car to return to the sub-activity Enamel, not only increases the rework, but also increases the extension of the 3rd shift that, because of its high variability, presents lower level of efficiency and consequently will increase the consumption of energy. However, it was agreed that at this stage of the research, this factor should be taken as unpredictable and should be seen as noise. Nevertheless, this could be seen as an interesting theme of research for future projects.

From the standpoint of this stakeholder, the mix of production imposed by the previous organizational unit (Body) present little or no influence in the energy consumption. On the other hand, the number of cars produced can be seen as an important factor to be taken into account since this variable can or cannot affect the extension of the 3rd shift.

Finally, were discussed the effects of preventive maintenance and cleaning actions (during periods of shutdown and weekends) as factors of energy consumption, even when the output of this process is null. In fact, this is a trade-off question. On one hand, the energy consumption increases with the number/extension of the preventive maintenance. On the other hand, with the increase of this type of actions, the occurrence of quality issues decreases as well as the energy consumption.

Hypothesis 2:

According to Stakeholder #2, the mix of production and its production volume can be seen as a factor of oscillation of the energy consumption. For example, a product family such as the SHARAN, having a greater mass and contact area tends to cool more phosphate solution, which consequently must be heated in order to reach the desired temperature set point.

However, according to his knowledge and experience, the two main factors are both the external temperature and humidity. For instance, If the temperature is below 23°C then it is necessary to heat the kiln, consuming gas. On the other hand, If the external temperature is above 25°C, it is necessary to spend electric energy to cool the air! Similarly, if the humidity is very high, it will be necessary to cool the air to condense and afterwards reheat the air. In this particular case, the primer and enamel kilns are heavily dependent on external environmental conditions.

Finally, it was analysed the impact of downdays and shutdown periods in the daily energy consumption, since these two factors can have critical impact on the energy consumption. While it is true that in downdays and shutdown periods the energy consumption is almost zero, on the other hand it is also true that the restart from shutdowns or downdays will also increase the peak of energy consumption.

Hypothesis 3:

The final stakeholder interviewed #3 was, during last year, responsible for the 3rd shift. Thus, it was essential to gather his experience and knowledge related with the energy consumption in this period of work.

The 3rd shift, has as main purpose to accomplish the daily production volume estimated for a certain day, as well as preparing the production for the following day. In fact, this period of work is subject to a high variability mainly due to two main reasons: uncertainty on the production volume and reduced manpower compared to the 1st and 2nd shifts. Therefore, the strategy of production can change everyday which can negatively influence the efficiency of this shift and consequently its analysis and modelling.

3) Key Variables

The third step performed was mainly oriented to enumerate and describe the key variables and concepts that should be considered in order to start defining the mental model of the energy consumption behaviour at the painting line. In other words, the list of variables described in this section is a sum-up and a synthesis of the hypothesis transcribed in the previous section.

Table 8 - Key Variables

Variable	*Description*	*Unit*	*Type*	*Lower Value*	*Upper Value*
External Temperature	Value of the Temperature registered outside by the AE meteorological station (lower and upper values per day)	ºC	double	0	40
External Humidity	Value of the Humidity registered outside by the AE meteorological station (lower and upper values per day)	%	double	0	100
Production Volume/ Mix of Production	Volume of production by section and product family per week	cars	vector	0	650
DownDays	Number of scheduled days per week without production.	-	int	-	-
Shutdowns/ restart from Shutdowns	This variable indicates if during a certain week the factory is in shutdown or restarting from a period of shutdown	-	binary	-	-
Preventive Maintenance	This variable indicates the number of scheduled maintenance per week.	-	int	-	-
3rd Shift	Extension and intensity of the 3rd shift. In fact, since this shift works as a buffer capable of avoiding the uncertainties imposed by the daily shift, the energy consumption during this period is very dependent of the malfunctions verified in the previous shifts.	shifts	int	0	3

4) Model Boundary Chart

A model boundary chart summarizes the scope of the model by listing which key variables are included endogenously, which are exogenous, and which should be excluded from the model. In fact, model boundary diagrams are surprisingly useful but shockingly rare. By explicitly listing the concepts that were not chosen to be included, at least for the moment, the modeller provides a visible reminder of the caveats to the results and limitations of the model.

Table 9 - Model Boundary Chart

Endogenous	***Exogenous***	***Excluded***
Downdays	Ext. Temperature	3rd Shifts
Mix of Production	Ext. Humidity	
Maintenance	Shutdowns	

Endogenous: Since the endogenous perspective aims to gather the variables that belong to the inbound of the system, and because of that can be controlled by its stakeholders, the number of *downdays* and *maintenance* actions are suitable factors for this perspective.

Despite the fact that the number of *downdays* per month is defined at an administrative layer, the organizational unit is responsible to use these days if necessary (e.g. for maintenance issues). On the other hand, the map of *preventive maintenance actions* is well established since the beginning of the year. However, this calendar is not static and can be subject to changes during the year, based on the unexpected breakdowns. Finally, although the *mix of production* is strictly dependent from the input flux of vehicles imposed by the previous area, the body area, internally, stakeholders are capable to change the mix of vehicles to paint in order to optimize the paint line. Although this variable was considered as endogenous variable, we strongly believe that this factor will have a very small impact on the overall gas and electricity consumption.

Exogenous: On the other hand, the exogenous perspective aims to gather the variables that belong to the outbound of the system, and because of that cannot be controlled by its stakeholders. Therefore, the *external temperature and humidity* as well as the existence and longevity of the *shutdown periods* are suitable variables for this perspective. In fact, the external temperature and humidity as well as shutdown periods are essential variables that cannot be controlled at all but critically influence the consumption of gas and electricity.

Excluded: Finally, the excluded perspective intends to gather the variables that, because of its uncertainty and consequent difficulty of analysis, are left aside of the modelling exercise. Thus, as explained at the hypothesis generation section, since the 3rd shift variable presents high levels of variability, it was decided to discard this factor at this stage of the research work.

5) Reference Modes

System dynamics modellers seek to characterize the problem dynamically, that is, as a pattern of behaviour, unfolding over time, showing how a certain problem arose and how it might evolve in the future.

Therefore, this section intends to explore a reference mode, which is a set of graphs and other descriptive data that shows the evolution of the problem over time. Thus, with the set of graphs here presented, it is possible to analyse the evolution of the gas and electricity consumption from 2008 to 2011, taking as reference the factors that can affect its consumption.

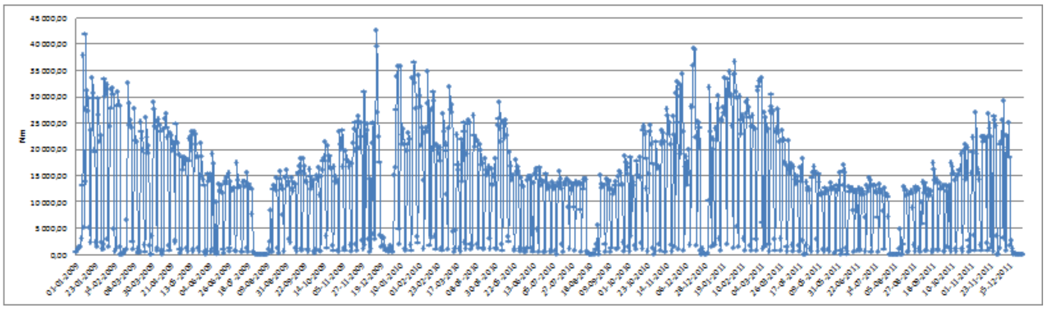


Figure 81 - Gas consumption since 2009 until 2011

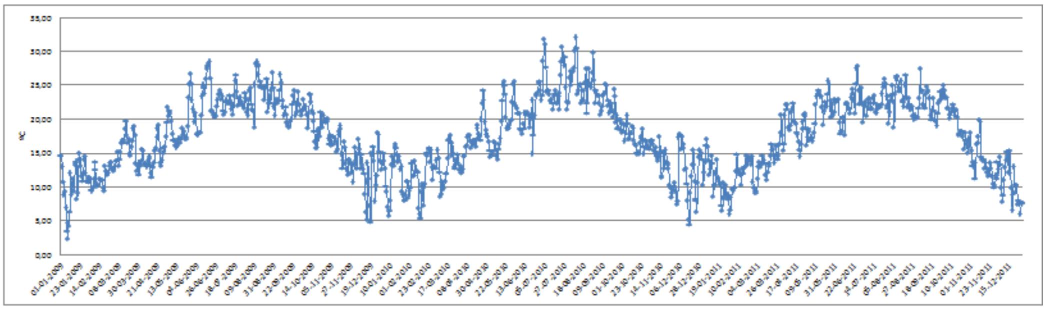


Figure 82 - External Temperature measured since 2009 until 2011

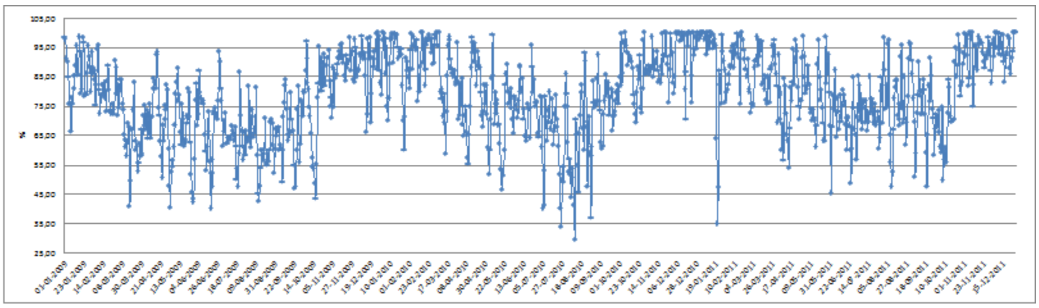


Figure 83 - External Humidity measured since 2009 until 2011

From the graphical analysis (Figure 81), it is easily depicted that the gas consumption presents a seasonal characteristic. In fact, as it is possible to see, there is a higher consumption of gas during the winter and a lower consumption during the summer time. One of the reasons for this seasonality is strictly related with the external temperature, as proposed at the hypothesis generation section. This fact can be easily observed from the comparison of gas consumption with external temperature charts (Figure 81 and Figure 82, respectively).

Concerning the electrical energy consumption, it is possible to visualize that since 2008 until 2011 it is being observed a significant decrease of the energy consumption at the painting area. Moreover, it is important to underline the increasing of homogeneity during this period of time. This fact shows that important internal projects has been deployed aimed at enhancing the environmental issues and consequently guarantee the sustainable growth of the Autoeuropa plant, on the environmental perspective.

However, in addition to the external temperature, with a detailed analysis of the graphs related with the electricity consumption (Figure 85), it is possible to understand that also the variable humidity presents a critical impact on the electricity consumption. As it is possible to see in Figure 84, more concretely for day 25-05-2010, with the substantial increasing of the humidity, the electrical energy also increases. It is important to underline that day 24 is Monday, and thus it was expected to have an extra consumption due to the necessity to achieve some temperature and humidity set points at the beginning of the week. However, although it was observed that during days 24, 25 and 26 the average temperature per day was almost the same, i.e. 18ºC, the truth is that in Tuesday the electrical consumption also increased, strongly affected by the increasing of the humidity rate.

This happens due to the fact that when the humidity value is superior to an offset value and the external temperature is high, then it is necessary to use more electricity to cool the air and thereby condense the existing relative humidity, aiming to establish the internal painting line environment. Indeed, this situation is more likely to happen during the summer and spring months.

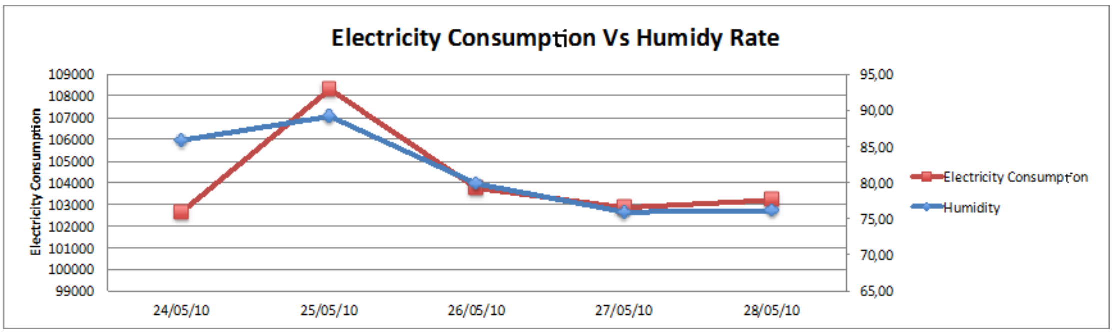


Figure 84 - Analysis of impact between Humidity and Electricity Consumption

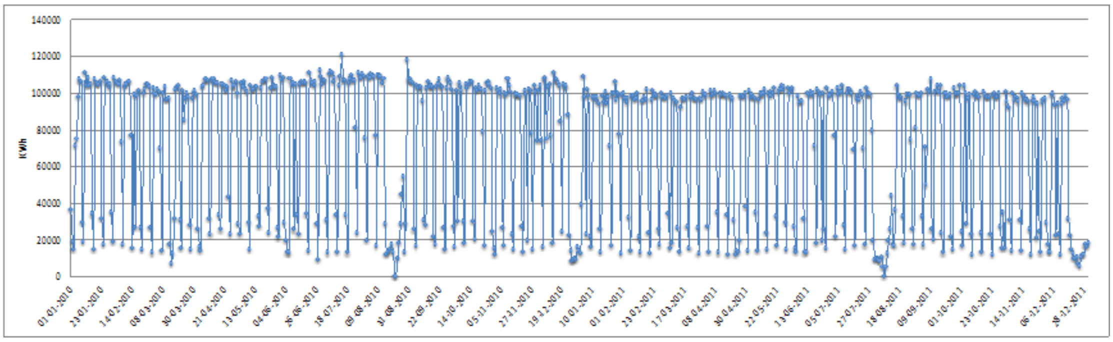


Figure 85 – Electric Energy Consumption since 2010 until 2011

From this analysis, it is possible to understand that the energy consumption at the painting area presents a smooth changing of behaviour along the years, becoming more and more immune to the endogenous factors. Indeed, it is possible to visualize the importance of the implementation and maintenance of best practices, focused on the improvement of the sustainable issues.

Therefore, due to the fact that more and more the endogenous factors have been controlled through the implementation of rigid and well implemented rules / best practices, the impact of the exogenous factors is more evident than before. Thus, the modelling research should be more focused on this perspective in order to increase the overall reliability of the model. Due to the homogeneity and statistical control of this industrial process, it is possible to anticipate that the estimation engine designed to model the energy consumption behaviour will have all the conditions to have a curve of behaviour very similar to the reality.

6) Causal Loop Diagram

The causal loop diagram represents an extension to the process modelling performed at the first step of this methodology, where a BPMN approach was used. In fact, with the process modelling performed before, using the BPM notation as driver, the main idea was to design the normal flow of activities that should be performed during the painting of a single car. However, at this step of the methodology, it is expected to explore the causal relationship between the variables identified at the hypothesis generation stage, and enumerated at the model boundary definition, and the different activities of the painting process.

With the main purpose of representing the different feedback loops that affect the gas consumption in the painting unit, in terms of flow and stocks of materials, resources and information, the following causal diagram was designed (Figure 86). Moreover, at this stage, a parallelism will be established with the BPM charts, aiming to locate in the process execution where each feedback loop affects the gas consumption.

In order to simplify the causal loop diagram analysis, next a clear description of each causal loop is presented as well as its relationship with the painting process.

Balancing Loop 1 (B1): it was already shown that the external temperature is a critical variable that affects the gas consumption at the paint shop. In fact, since ARPs use external air to feed the different painting areas (mainly Primer and Enamel stations), guaranteeing that these units of production are at a specific temperature (temperature set-point of 23ºC), the lower the external temperature, the bigger should be the burners' gas consumption capable of maintaining the internal temperature at the set-point.

This balancing loop is strictly connected with the following activities: *Sealer coat*, *Primer coat* and *Enamel*.

Balancing Loop 2 (B2): However, the external temperature not only affects the gas consumption due to the ARPs, but also due to the different ovens present on the painting line. In fact, the lower the external temperature is, the bigger is the difference between the ovens temperature and the external temperature. As consequence, at each night, downday or shutdown period, the rate of ovens cooling increase, forcing that in the following period of production activity, the consumption of gas is bigger, until the ovens temperature set-point is reached.

The Volume is another factor that can decrease the temperature of each oven. In fact, every time that a new car enters an oven, an exchange of energy happens until the car body is at the ovens' temperature. Thus, the more cars are introduced in the ovens, the bigger should be the exchange of energy and the bigger should be the gas consumption to overcome this fact.

This balancing loop is strictly connected with the following activities: *E-coat*, *Sealer Line*, *Primer coat* and *Enamel*.

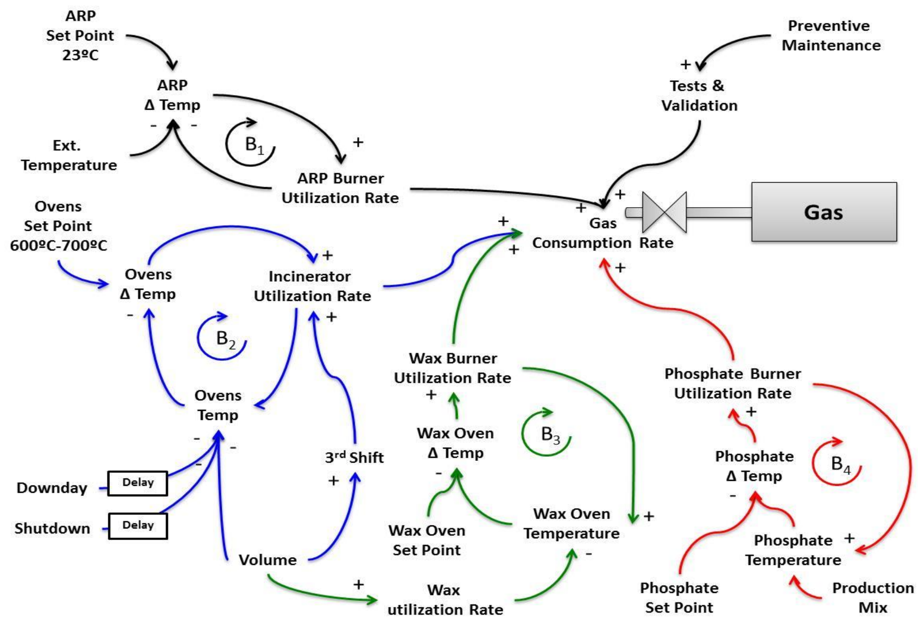


Figure 86 - Gas Consumption Causal Loop Diagram

Balancing Loop 3 (B3): the wax application is another important topic that should be taken into account. In fact, in order to apply the wax in a proper way, two different scenarios should be verified: the wax should be at a certain temperature, in order to be at a liquid state, and the oven where this activity is performed should be also at a specific temperature.

The volume of cars produced can critically affect these two scenarios. Similarly to the previous balancing loop, every time that a new car enters the wax oven, an exchange of energy happens until the body is at the ovens' temperature. Thus, the more cars are introduced in this specific oven, the bigger should be the exchange of energy and, consequently, the gas consumption to overcome this fact. On the other hand, the more cars enter in the wax oven, the bigger is the quantity of wax that is required. Consequently, a bigger rate of wax will enter in the repository which will force the respective burner to consume more gas in order to keep this sealant at the expected temperature.

This balancing loop is strictly connected with the following activity: *Wax cavity coat*.

Balancing Loop 4 (B4): similarly to the wax application activity, the phosphate bath can also affect the gas consumption due to the volume of cars produced. In fact, during this cleaning activity, there are different stages with different requirements and specifications. One of them is the temperature that the phosphate solution should be at each bath. Thus, the volume of cars produced at this stage of the process can also affect this scenario.

Similarly to the previous balancing loop, the more cars are subject to these baths, the bigger should be the exchange of energy between the phosphate solution and the cars´ body, which consequently will increase the gas consumption of the respective burner, responsible for keeping the phosphate solution at the right temperature.

Moreover, the mix of production is also an important factor in this balancing loop. In fact, a car model like a SHARAN has a bigger mass and contact zone with the phosphate solution then a sports car like a SCIROCCO.

This balancing loop is strictly connected with the following activity: *Phosphate bath*.

Balancing Loop 5 (B5): it was already shown that the external humidity is an important variable that affects the gas consumption at the paint shop. In fact, since ARPs uses external air to feed the different painting areas (mainly Primer and Enamel stations), guaranteeing that these units of production are at a specific humidity, the lower the external humidity value, the bigger should be the burners' gas consumption capable of maintaining the internal humidity at the correct set-point.

This balancing loop is strictly connected with the following activities: *Sealer coat*, *Primer coat* and *Enamel*.

To sum up, the painting process model is now presented with the critical activities subject to the balancing loops described before. As it is possible to see, almost all the activities, except the Buy Off, Repair and Decal Line are critical points of gas consumption inserting uncertainty on the gas consumption. In other words, if none of these variables exist, the consumption of gas would be constant during the entire year.

Following, the BPMN of the painting process will be presented with the critical activities subject to the balancing loops described before. In line with this, in this graphical representation, each activity will be coloured with the same colours of the balancing loops that affect its performance.

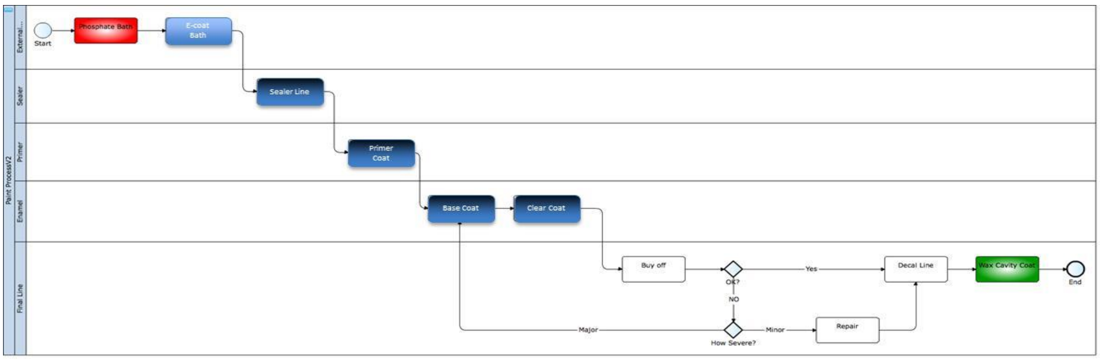


Figure 87 - Parallelism between Painting Causal Loop Diagram and BPMN

Similarly to the case described before, the following causal diagram was designed aiming to represent, in a graphical way, how and why each key variable affects the electricity consumption in the paint shop. Moreover, at this stage, a parallelism will be established with the BPM charts, aiming to locate, in the process execution, where each feedback loop affects the electricity consumption.

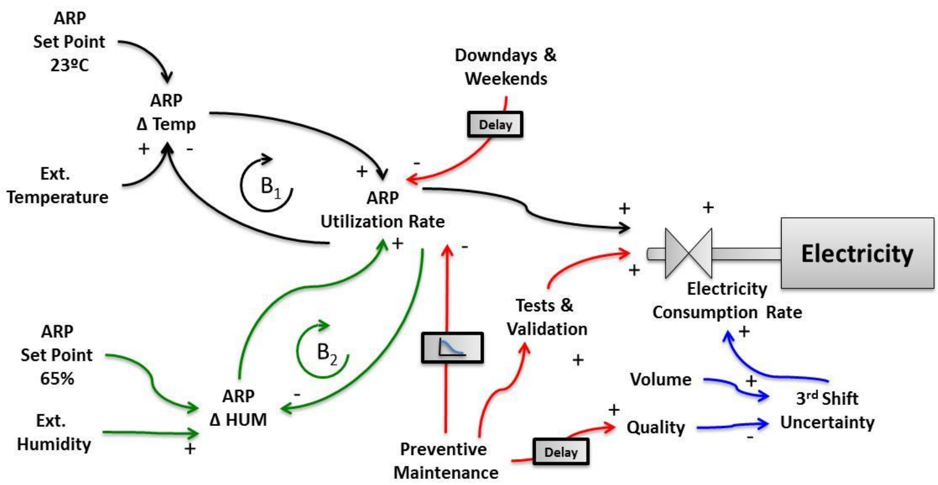


Figure 88 - Electric Consumption Causal Loop Diagram

In order to simplify the graph analysis, following it is presented a clear description of each causal loop as well as its relationship with the painting process.

Balancing Loop 1 (B1): it was already shown that the external temperature is a critical variable that affects the electric energy consumption at the paint shop. In fact, since ARPs uses external air to feed the different painting areas (mainly Primer and Enamel stations), guaranteeing that these units of production are at a specific temperature (temperature set-point of 23ºC), the higher the external temperature, the bigger should be the electric energy consumption to maintain the internal temperature at the set-point.

This balancing loop is strictly connected with the following activities: *Sealer coat*, *Primer coat* and *Enamel*.

Balancing Loop 2 (B2): however, the external temperature is not the only factor that influences the electric energy consumption. Thus, humidity should be another factor to be taken into account. In fact, the higher the external humidity is, the bigger should be the ARP utilization rate to keep the internal humidity at the desired level. As a consequence, when the external humidity and temperature are higher than desired, the system should decrease the air temperature, in order to condense this humidity, and then increase the air temperature in order to guarantee the temperature and humidity set point. In case the temperature is low, this process can be avoided since the simple fact of air heating is capable of decreasing the relative humidity.

This balancing loop is strictly connected with the following activities: *Sealer Line*, *Primer coat* and *Enamel*.

The *Mix of Production* and *Volume* is another factor that can affect the electric energy consumption. In fact, it's known that mainly during the E-coat bath activity that the size and structure of the automotive body have a significant impact on the overall electrical resistance of the system, and thus the amount of current that must be delivered. On the other hand, the more are the cars expected to be painted, the bigger should be the impact of the 3rd shift regarding the electric consumption, due to its variability and low efficiency. In line with this, the quality factor is another issue to be taken into account. In fact, in addition to the volume, if we decrease the *Quality* of production, then the variable re-work will increase, reinforcing the preponderance of the 3rd shift.

Finally, the *preventive maintenance* is another important factor to be taken into account. In fact, the existence of preventive maintenance actions will impose energy consumption, even in *weekends*, *holidays* and *downdays* when the production is null.

Next, the BPMN of the painting process will be presented with the critical activities subject to the balancing loops described before. In line with this, in this graphical representation each activity will be coloured with the same colours of the balancing loops that affect its performance.

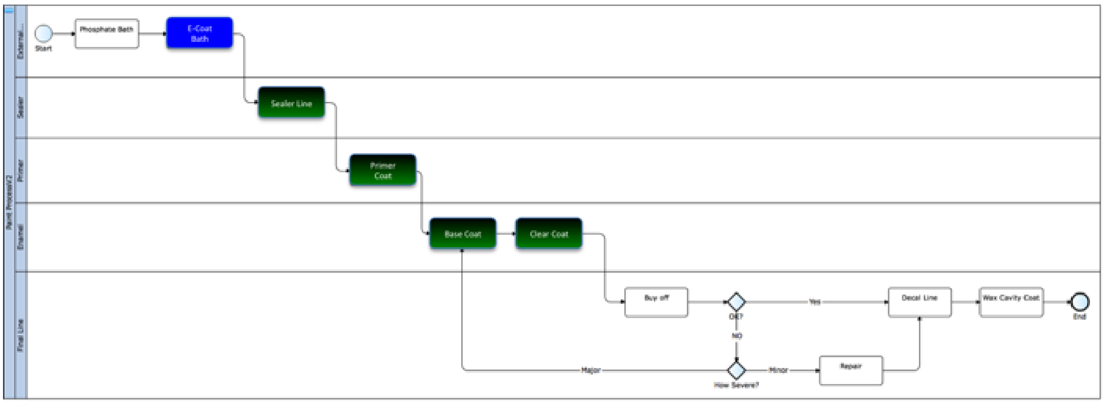


Figure 89 – Parallelism between the Painting Causal Loop Diagram in terms of Electric Consumption and BPMN

7) Predictive Model Setup

In this section, a detailed analysis of the gas consumption predictive model setup will be explored. Since it is very similar to the electric consumption predictive model setup, only the mathematical model setup related with gas consumption will be presented as example.

In order to setup the mathematical model that will allow the manager of the process to estimate his KPI, the user only needs to perform three main steps: Network Specification, Network Training and Model Running.

The first step of the mathematical model setup is the Network Specification. At this stage the user should already have a good knowledge of the system that will be analysed. In other words, all the stages previously described should be well performed, in order to have, at this stage, the list of endogenous and exogenous factors.

Thus, a network should be specified with the correct number of inputs (the same number of endogenous and exogenous factors) and one output that represent the KPI under analysis. On the other hand, the number of hidden neurons (name given to each element of the network) is variable and depends on the complexity of the system to be analysed. Consequently, the more complex the system is, the bigger the number of neurons. However, this is not a linear issue and because of that an iterative approach should be adopted in order to assure that the suitable number of hidden neurons is used. Figure 90 shows an example of the network designed for the gas consumption at the painting line.

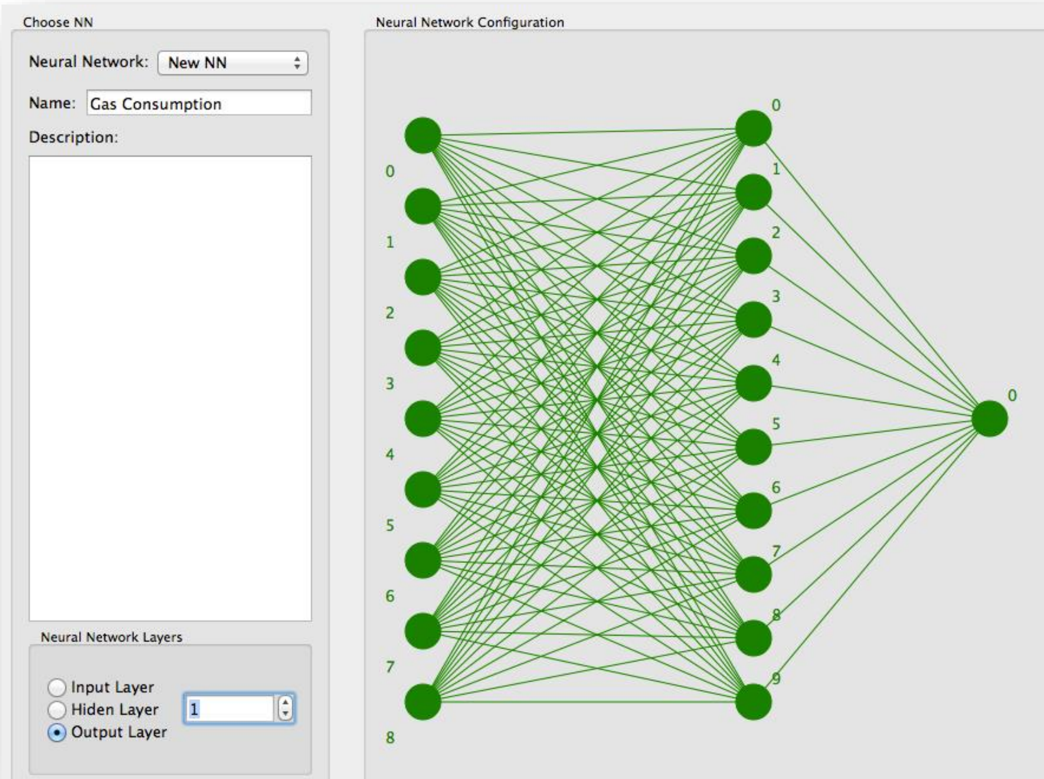


Figure 90 - Mathematical Model Setup for Gas Consumption at Painting Line

The second step is the Network Training. This stage will be responsible for explaining to the estimation engine how its behaviour should be in a different range of situations. It is important to highlight that, the richer and complex the sample of information provided to the software is, the more reliable and flexible the predictive model will be.

In order to execute this step, using the form depicted at Figure 91, the user must select the network in the 1st combo box and upload the excel file with the structured data concerning past behaviours. Following, once the first network weights specification is done based on a backpropagation algorithm, it is important to specify which should be the Momentum and Learning rate, as well as the searching and learning epochs. This variables are pre-defined, however, if the final user has the sensibility to optimize these variables, he is allowed to change them aiming to enhance the modelling effort.

Finally, the learning process can start, being only necessary to press the start button. This process can take 5 to 10 minutes depending on the computer where this software is running and on the quantity of data used.

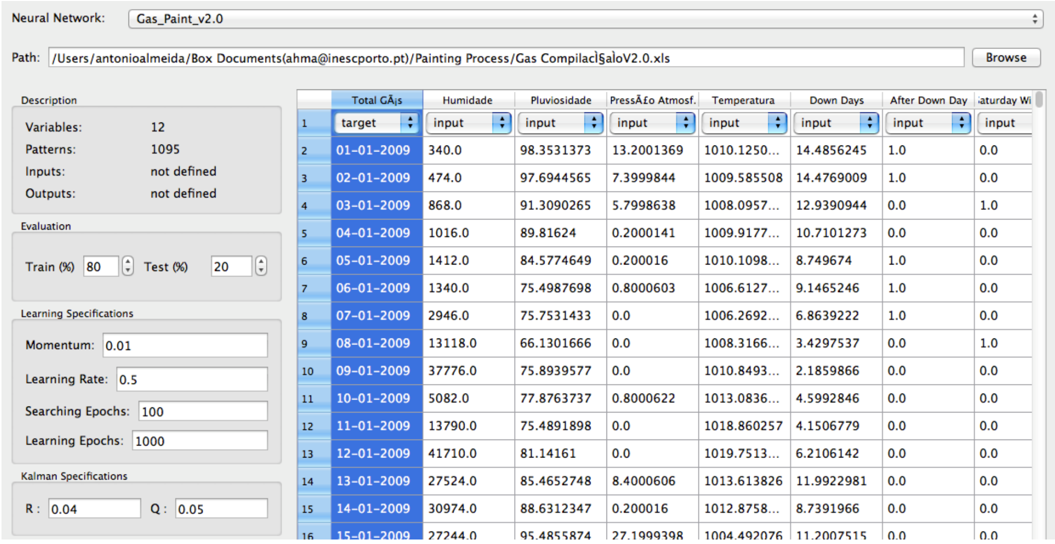


Figure 91 - Network Training Process

Finally, in order to get the estimation for the next periods of time, the user must perform the 3rd stage that is the Model Running. This step is the one where the user should select the respective network and provide the leading factors, following a similar approach as described before. As depicted in Figure 92, in order to estimate the gas consumption at the painting line, it was selected the network Gas_Paint_v2.0 as well as the excel file where the estimation concerning the leading factors were enumerated. After identifying the network and the leading factors that will characterize the environment where the manufacturing system will behave, it is only necessary to deploy the estimation algorithm. This step should take only a few seconds to provide a graphical representation of the evolution of the KPI during the period of time requested.

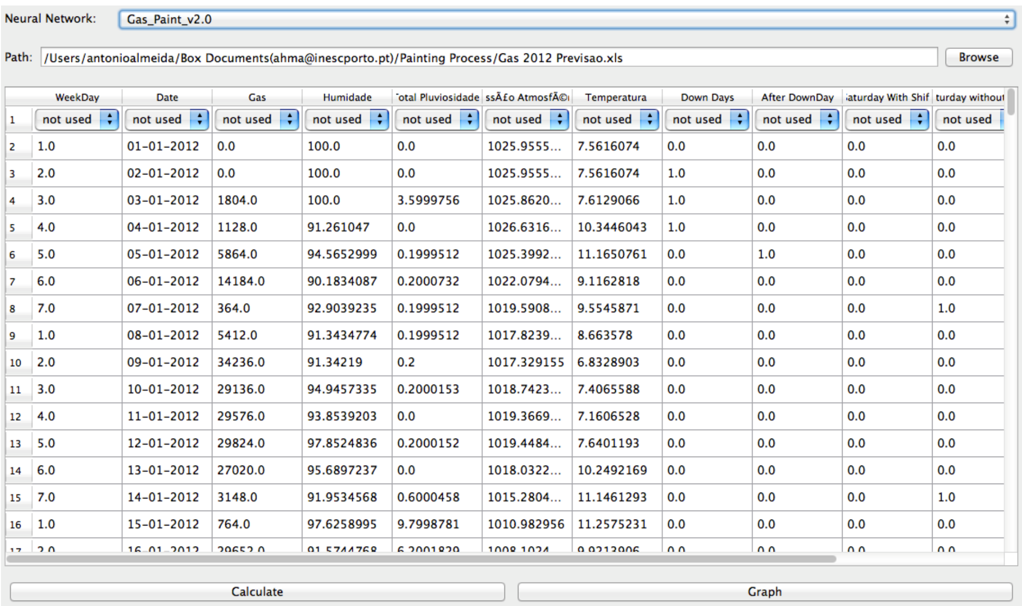


Figure 92 - 2012 Gas Consumption Estimation Process

5.4.2.1. Analysis of Results

In this section, the results obtained from the proactive performance management framework implementation within the painting line, and more specifically the activity described in step 7 of the methodology titled Predictive Model Setup, will be presented and analysed.

Gas Consumption per Vehicle (GPV)

As previously explained, the KPI gas per vehicle (GPV) was selected to test and validate the estimation framework here proposed. Since this is a very straightforward indicator mainly composed by two variables (i.e. gas consumption and volume of production), the objective was to estimate the KPI GPV by understanding and foresee the behaviour of variable gas consumption. Note that variable volume production in an automotive industry is a predictable variable and well established for the entire year of production.

In line with this, a qualitative analysis was performed aiming at understanding the normal behaviour of the gas consumption at the painting line. From this analysis, it was not only possible to enumerate which variables are responsible for imposing variability in the gas consumption, but also design the causal loops diagram where internal and external synergies can be depicted.

After finishing the qualitative analysis, it was possible to transpose the knowledge generated into a mathematical model, envisioning the manufacturing system behaviour modelling. In order to achieve this, a network constituted by one input, one hidden and one output layers was designed. During this design stage, a training algorithm was performed aiming to calculate the correct weights capable to enhance the manufacturing system modelling and, consequently, improve the estimation reliability.

The idea was to capture the normal behaviour of the production system, in this case the painting line, concerning the KPI GPV. Aiming to accomplish this objective, during the training process a dataset containing information of the painting line behaviour from 2008 to 2011 was used.

After capturing the system's behaviour, the next step was to prepare an excel file with the expected leading factors from the 1st of January of 2012 to 17th of September of 2012, in order to deploy the estimation model and thus estimate the gas consumption during this time interval. In Figure 93, it is depicted the real gas consumption (in blue colour) and the estimated gas consumption (in red colour). From the analysis of the results obtained, it is possible to enumerate the following achievements:

- The Root-Mean-Square (RMS) error was approximately of 3083.64 Nm^3.
- The normalized root-mean-square deviation (NRMSD) is approximately 7,5%, whose value is significantly lower than the maximum error expected (approximately 15%);
- The gas consumption estimation was performed at a daily perspective (more vulnerable to the daily oscillation),
- Predictive model capable of following, without delays, the impacts imposed by nonlinearities such as: shutdowns, weekends and downdays periods.

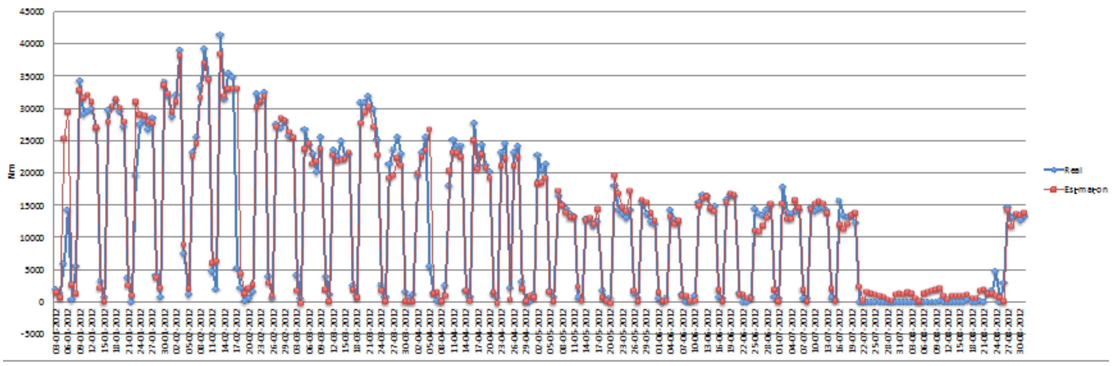


Figure 93 - Comparison between Real and Estimated Gas Consumption

From the analysis of the results presented, it is possible to understand that this framework provides important advantages, in comparison with the current methods used, concerning the estimation of gas consumption at the painting process.

Firstly, the estimation engine was capable of understanding that during the *weekends*, *holidays* and *downdays*, the gas consumption is inferior (almost, but not zero) in comparison with normal production days. Moreover, the predictive model understood that with the increase of the external temperature, the gas consumption is inferior, following the base of knowledge built at previous steps of the framework.

This way, it is proved that a proactive approach was achieved where estimation of performance is done based on insights about the future and not only on past behaviours. As depicted in Figure 94, where gas consumption is estimated on a monthly bases, not only the estimation presents a very small error but also is completely crumbled from the gas consumption from 2011 due to the leading factors influence. As an example, Figure 95 shows the differences of temperature behaviours between years of 2011 and 2012. More specifically, the month April shows that in 2011 there was a significant decreasing of gas consumption, relative to 2012, since the average temperature during this month was superior to the one verified in 2012.

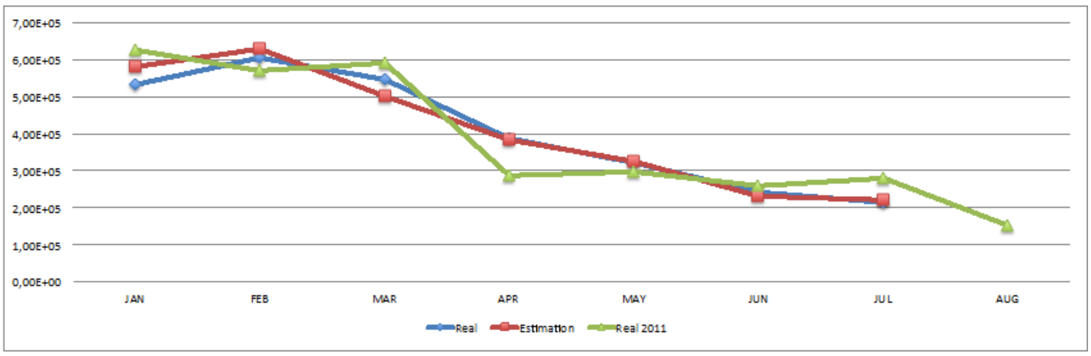


Figure 94 - Gas Consumption Real Vs Estimation

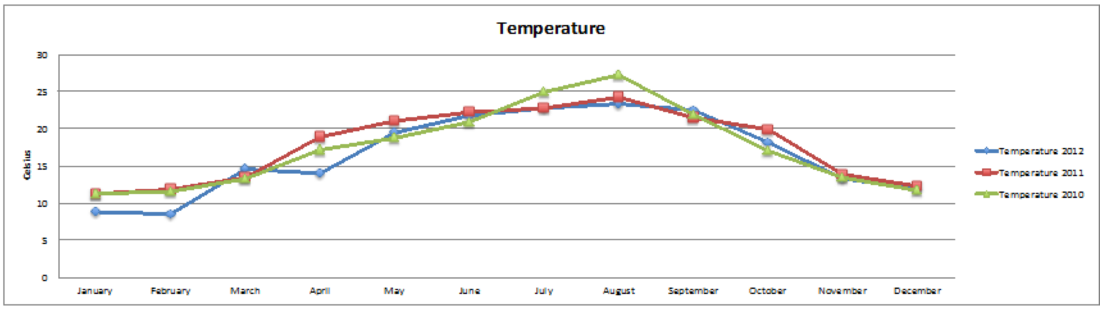


Figure 95 - Temperature Evolution

In fact, it is possible to state that the estimation of gas consumption for the interval of time between January 2012 and September 2012 was successfully performed. However, the main goal was the estimation of the KPI GPV. In order to validate the predictive model designed, for this KPI it will be compared the real and estimated GPV values. The first one was calculated using the real gas consumption and production values, while the estimated GPV was calculated using the estimated gas consumption and planned production values. Figure 96 shows the comparison between these two variables.

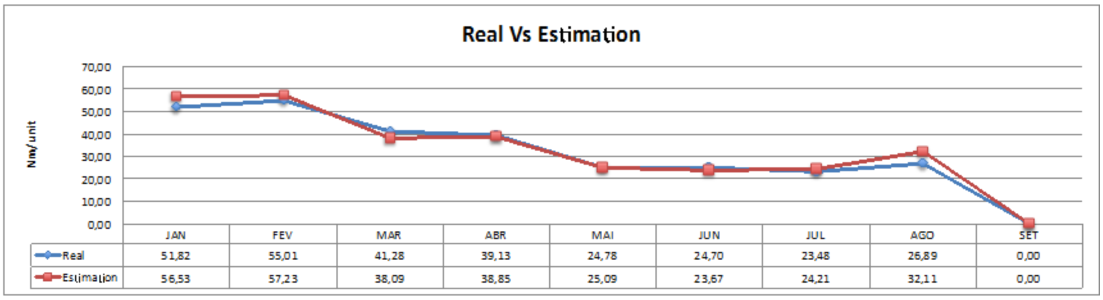


Figure 96 - Gas per Unit Real Vs Estimation

Indeed, from the analysis of this result, we can state that the output of the framework is promising, presenting a high level of reliability. For the delta time defined, the medium error of estimation is 1,62 Nm^3 per vehicle and the maximum error of 5,22Nm^3 (August). It is important to highlight the fact that, the estimation was done based on the leading factors extracted from the fieldwork done, and not based on a simple regression analysis. However, concerning the estimation model, there are still some improvement actions to be performed, since this should be seen as an iterative approach. An example of that is the gas consumption during the shutdown periods and weekends. It is expected that, with the inclusion of the variable "scheduled preventive maintenance" it would be possible to increase the reliability of the mathematical model, significantly decreasing the error.

In conclusion, using this estimation model, stakeholders responsible for the painting process became capable to define annually the expected budget necessary for the gas consumption per vehicle. Moreover, in cases that the difference between the real and estimated GPV measures are higher than expected (more than 10%), there are only two possibilities: the system changed, requiring a new learning process, or there is some kind of malfunction that is affecting the performance of the system. Thus, this approach also supports decision makers to increase their capability to detect system's breakdowns, normally invisible to the current quality programs.

Electricity Consumption per Vehicle

After presenting the outcomes from the predictive performance framework oriented to the KPI GPV, the results obtained from the application of the mathematical model designed to emulate the electricity consumption at the paint shop will be presented and analysed. Similar to the gas consumption estimation, during the training process of the mathematical model for electricity consumption, the information used was the one presented in the Reference Mode section. However, due to the lack of information regarding the production volume, the training process was designed in order to capture the behaviour of the system from 2010 to 2011.

Having captured the system's behaviour, it was prepared an excel file with the expected leading factors from the 1st of January of 2012 to 20th of July of 2012. The output can be seen in the following figure.

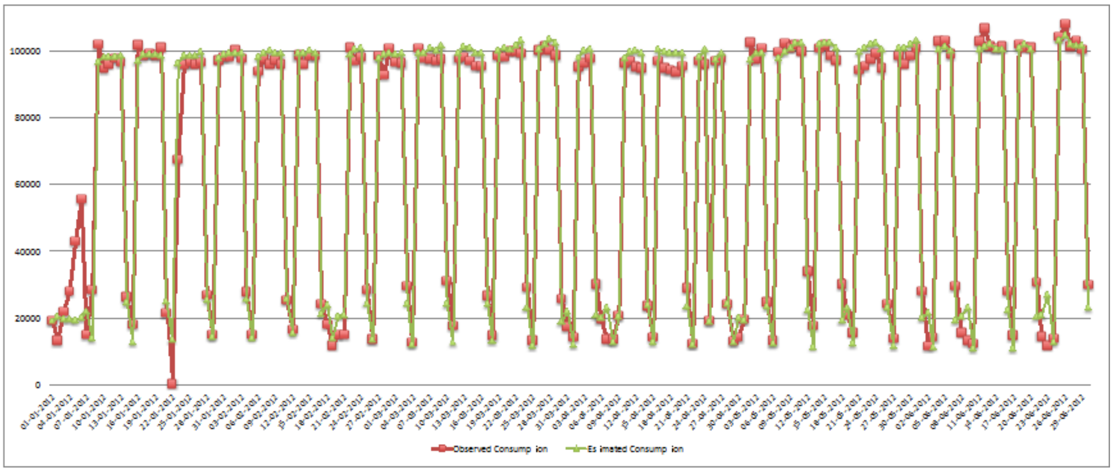


Figure 97 - Electricity Consumption Estimation

In the previous figure it is depicted the real electric consumption (in red colour) and the estimated electric consumption (in green colour). From the analysis of the results obtained, it was possible to enumerate the following achievements:

- The Root-Mean-Square (RMS) error was approximately of 5757.60 KWh.
- The normalized root-mean-square deviation (NRMSD) was approximately 5,33%, whose value is significantly lower than the maximum error expected (approximately 15%);
- Electricity consumption estimation performed at a daily frequency (more vulnerable to the daily oscillation),
- Predictive model capable of following, without delays, the impacts imposed by the nonlinearities such as: shutdowns, weekends and downdays periods.

Similarly to the test case presented before, during the training session, only the "allegedly known" variables were used. However, in this case, due to the lack of information, it was only possible to use data from 2010 to 2011. Thus, despite the fact that the results achieved are quantitatively better, the model did not presented a robust behaviour, as desired. Two reasons can be contributing for this situation: the lower quantity of data used during the learning stage and the different policies that have been implemented in the shop floor, and are affecting positively the behaviour of the production system regarding the electricity consumption.

In order to investigate the reliability and importance of the output of this model, the KPI Electricity per Vehicle (EPV) will be analysed. The EPV has the following mathematical formula:

$$EPV = \frac{TotalElectricityConsumption}{VolumeProduction}$$

Similar to the KPI GPV, this new KPI is also composed by two variables: Electricity Consumption and Volume of Production. While the variable volume of production is strictly related with the planned production defined at the beginning of the year, the variable electricity consumption presents a nonlinear behaviour, being the main variable responsible by variability in the EPV estimation. In line with this, the estimate EPV was calculated as the division between the estimated electricity consumption, presented before, and the planned production volume. Figure 98 shows the EPV value per month, since January until June of 2012.

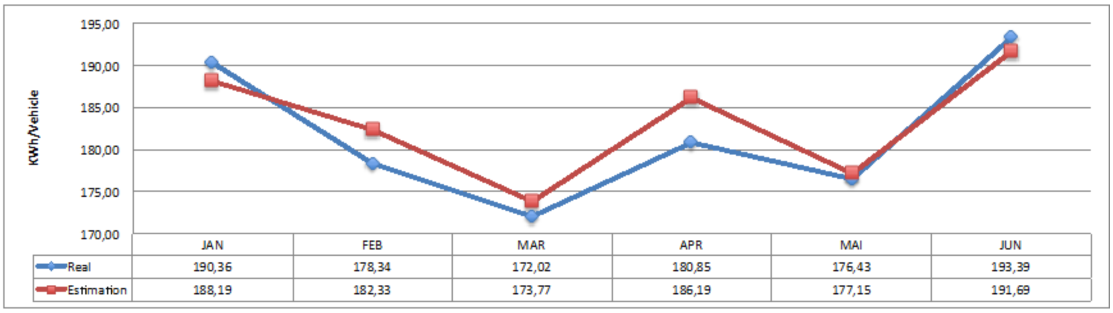


Figure 98 - Observed Vs Estimated EPV

From the analysis of the previous chart, it is visible that the estimated EPV is very similar to the observed one. In fact, from the analysis of the results achieved, the maximum error of estimation was approximately 6Kwh per vehicle, which shows that the mathematical model presents a realistic view of the painting area, regarding the electricity consumption.

However, the difference between the estimated and real KPI values shouldn't be simply analysed as error. In fact, another perspective of analysis is that, the paint shop is a dynamic system, which is in a continuous evolution mode. In line with this, it is possible to visualize that the policies and best practices that had been implemented as improvement actions from the beginning of the year, within this organizational area, affected positively the KPI EPV, representing an optimization of electricity consumption. Nevertheless, throughout error analysis, the estimation engine was capable to understand this evolution and compensate this deviation.

Nevertheless, this second example reiterates the fact that this predictive performance management approach should be seen as an iterative process. In fact, there are still some improvement actions that should be performed in order to increase the strength of this mathematical model. Example of that is the influence of the Quality issues and the extension of the 3rd shift for the overall energy consumption. It is strongly expected that, with the development of a parallel research capable of better understanding the quality issues and its behaviour, not only in the paint shop but along the entire production line, and using this information within this model, it would be possible to increase the reliability of the mathematical model, decreasing even more the estimation error. In fact, peaks of electricity consumption, as the ones depicted in Figure 97, could be better understood not only from the qualitative perspective, but also from the analytical perspective of the framework here presented.

In conclusion, with this application case it was proved that using the methodology and mathematical estimation model, stakeholders responsible for the painting process became capable of defining, annually, the expected budget necessary for the electrical consumption per vehicle.

5.4.2.2. Estimation Performance Analysis

After presenting the results obtained from the predictive performance framework implementation within the Volkswagen Autoeuropa painting line, it is now important to explore the level of accuracy of the solution here presented comparing its performance with some of the most used methods of estimation, both in industry and academia.

Therefore, at a first stage, a fundamental question is how two estimation methods should be compared? Supposing that we have a time series Y_i to be estimated and there are two methods with estimations $\hat{Y}_{i,1}$ and $\hat{Y}_{i,2}$ of Y_i performed at time $i - 1$ based on the series itself up to Y_{i-1} and/or possibly with leading variables. The forecast errors are $e_{i,1} = \hat{Y}_{i,1} - Y_i$ and $e_{i,2} = \hat{Y}_{i,2} - Y_i$ for the two estimation methods, respectively. This means that, under a simplifying assumption on the estimation errors, normally two estimation methods can be ordered consistently in terms of prediction risk under any reasonable loss function.

Estimation accuracy measures can be divided into two main types. The first category is based on stand-alone measures, which was previously performed based on the premise that an evaluation process focused on a specific estimation method can determine estimation accuracy. The second type is the relative measures, where a benchmarking of available estimation methods can be performed. The main idea of a relative measures technique is to rank a series of estimation methods based on a performance evaluation of an estimation method relative to that of benchmark estimation.

In line with this, the Geometrical Mean of Relative Absolute Errors (GMRAE) was selected as the loss function for the estimation methods comparison. This relative-error metrics was recommended in studies by Armstrong and Collopy (1992) as well as by Fildes (1992) for assessing estimation accuracy across multiple series, due to the fact that GMRAE is not scale dependent.

$$RAE_t = \frac{\left|\frac{y_t - \hat{y}_t}{y_t}\right|}{\left|\frac{y_t - \hat{y}_N}{y_t}\right|}$$

$$GMRAE = (\prod_t RAE_t)^{1/m}$$

where:

y_t= observed value at time period t;

$\hat{y}_t$= value obtained from the estimation method in analysis at time period t;

$\hat{y}_N$= benchmark estimation (Naive method);

m= number of observations to calculate GMRAE.

The range of the loss function presented before varies from 0 to ∞. A value of 1 means that the accuracy of the method being used is the same as that of the benchmark method. A value smaller than 1 means that the method is better than the benchmark while a value greater than one means the opposite. As a benchmark method, the Naïve approach was used. This is a very straightforward method where for any period t it is simple projected the previous period's actual value.

For instance, the Naïve method can be applied to a data set that exhibits seasonality or a trend. Thus, if the seasonal demand for a certain product in October were 100 units, then the Naïve estimation for next October would equal the actual demand for October of this year. Despite its simplicity, the accuracy of a Naïve forecast can be used as a standard against which to judge the cost and accuracy of other techniques; being the stakeholders and decision makers´ responsibility to decide whether or not the increase in accuracy of another method is worth its additional cost.

Aiming to better understand the levels of accuracy and reliability of the performance estimation engine, the estimation values obtained from the framework implementation within the painting line were compared with the estimation values obtained from the utilization of well-known forecasting methods such as the Exponential Smoothing method, the Linear Regression method and the Holtwinters approach.

While exponential smoothing is the simplest estimation form, normally used for data without any systematic trend or seasonal components, on the other hand, the Holt's method introduces an extra variable to take into account the possibility of a series exhibiting some form of trend, whether constant or non-constant. In other words, while in single exponential smoothing, the estimation function is simply based on the latest estimate of the level, in the Holtwinters method with the addition of a slope component, which itself is updated by exponential smoothing, both trend and seasonality characteristics can be taken into account.

Since the main objective of this estimation exercise was to provide Volkswagen decision makers with reliable estimation values for targeting and budgeting purposes, it was decided that for this evaluation scenario it would be expected to estimate both gas and electricity consumption for the entire year of 2012, in a monthly perspective. While Table 10 presents an analytical comparison of the different estimation methods used, Figure 99 and Figure 100 present a graphical perspective of this evaluation exercise.

As it is easily depicted from the tables' analysis, while Holtwinters and the PEE tool presents a much better performance, in comparison with the benchmark method (Naïve method), the Exponential Smoothing and the Linear Regression presented, almost in all cases, a worse performance.

Nevertheless, it is important to underline that the estimation engine purposed in this research work not only was the one that presented the best and most reliable performance in the two estimation exercises, but also presents a robust behaviour. This happens mainly because, unlike the other methods, the PEE tool is capable to not only analyse the trend and seasonality variables but also correlate different leading factors in order to estimate future performance behaviours. Therefore, from this test case, it was possible to demonstrate that this is a tool capable to support decision-making concerning budgeting and targeting issues in a proactive way, where the normal behaviour of the system is not the only element of decision.

Table 10 – Gas and Electricity consumption estimation accuracy comparison

Geometrical Mean of Relative Absolute Errors (GMRAE)	*Exponential Smoothing (ES)*	*Linear regression (LR)*	*Holtwinters (HW)*	*PPE*
Gas Consumption	1,32	0,58	0,53	0,17
Electricity Consumption	2,26	2,66	0,75	0,26

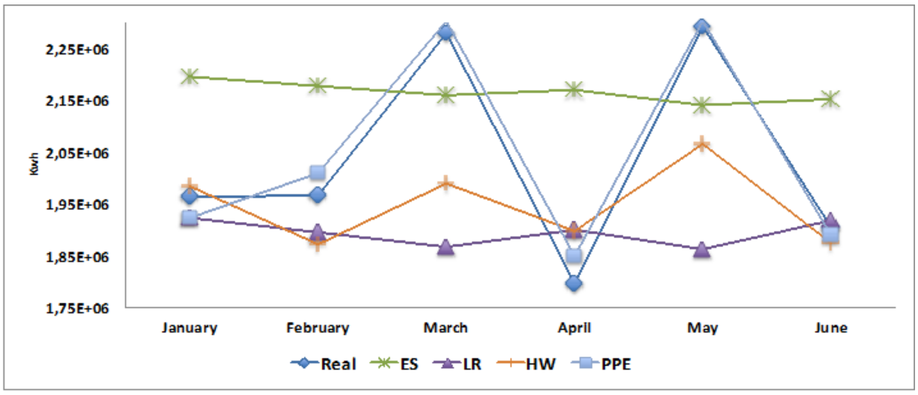


Figure 99 - Monthly Gas Consumption Estimation Accuracy Analysis

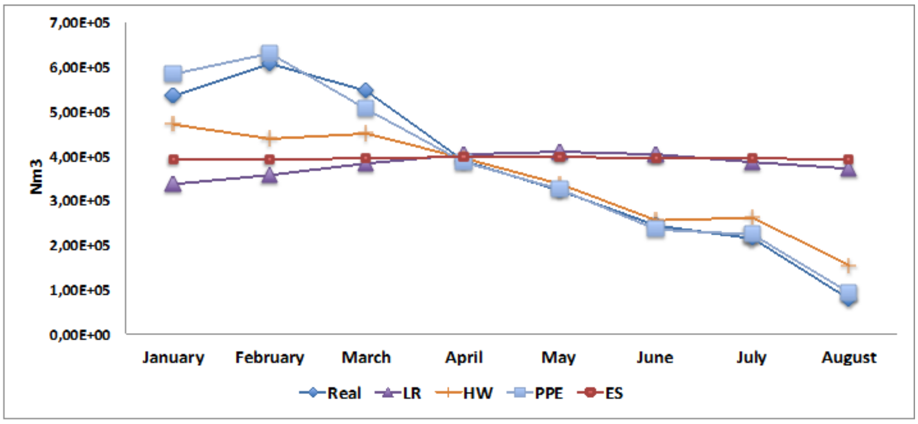


Figure 100 - Monthly Electricity Consumption Estimation Accuracy Analysis

5.4.3. Implementation at Body Shop

Contrarily to the paint shop, the body area is responsible for most of the electricity consumed by the entire plant. Externally, the boundary of this area is the output of the press area and the input of the paint line. Internally, this organisational area is divided into six main operational areas, scattered along the facility: Underbody Subparts, Clinching, Body-sites, Underbody, Framing, Doors to Body (DTB), and Metal Finish. Despite the complexity already imposed by the operational structure of this area, each section can be also divided by family or groups of product families.

As it is possible to see in Figure 101, within the body shop there are distinct areas responsible for the production of specific parts of a car body. For instance, while *Sharan* and *Scirocco* underbody parts and body-sides parts are produced within the same cell, on the other hand, *EOS's* underbody parts and body-side parts are produced on the opposite side of the body facilities, in separated cells. However, the doors to body process is performed at the middle of the body facility where all the parts converge in order to be assembly. In this case, *EOS* and *Scirocco* are handled in the same line while the *Sharan* is managed separately.

Due to this intricate structure, the body parts and products flow increases exponentially the level of complexity of this manufacturing system, which consequently affects the modelling efforts necessary to approximate the structured knowledge about the system's synergies as much as possible to reality. Figure 102 shows, in a brief way, the level of complexity linked with this manufacturing system.

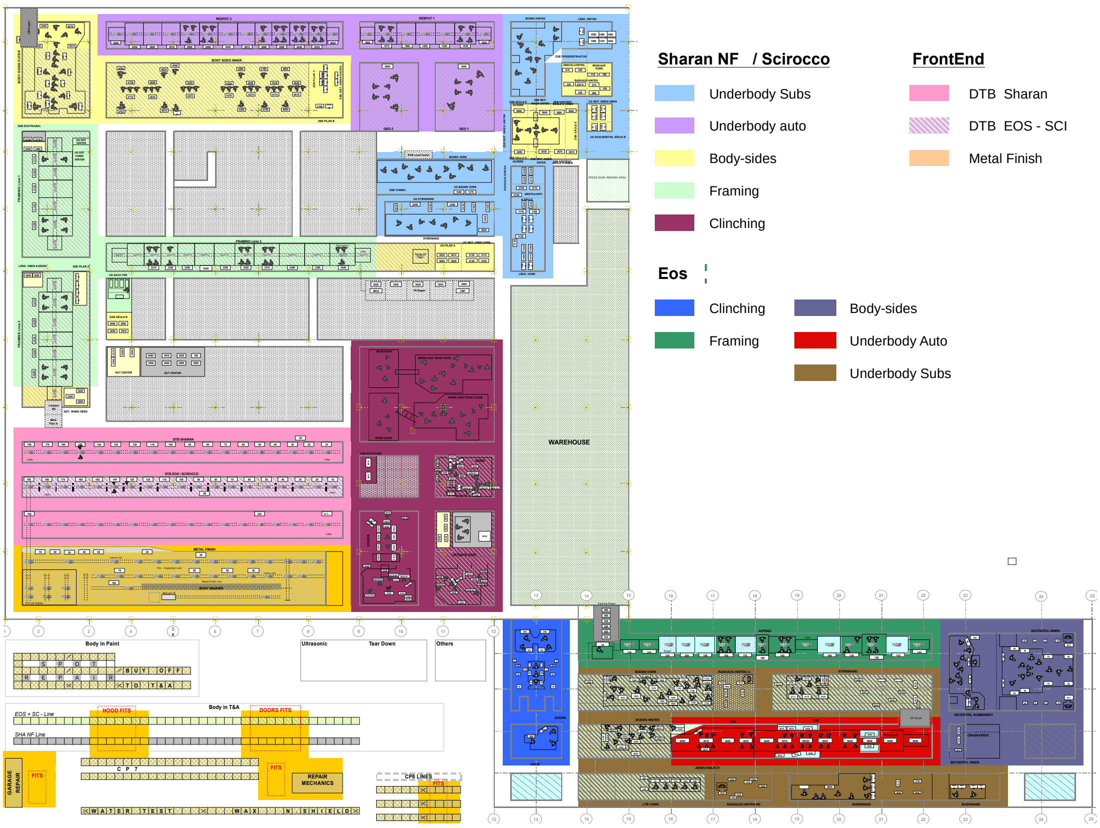


Figure 101 - Body Shop Layout

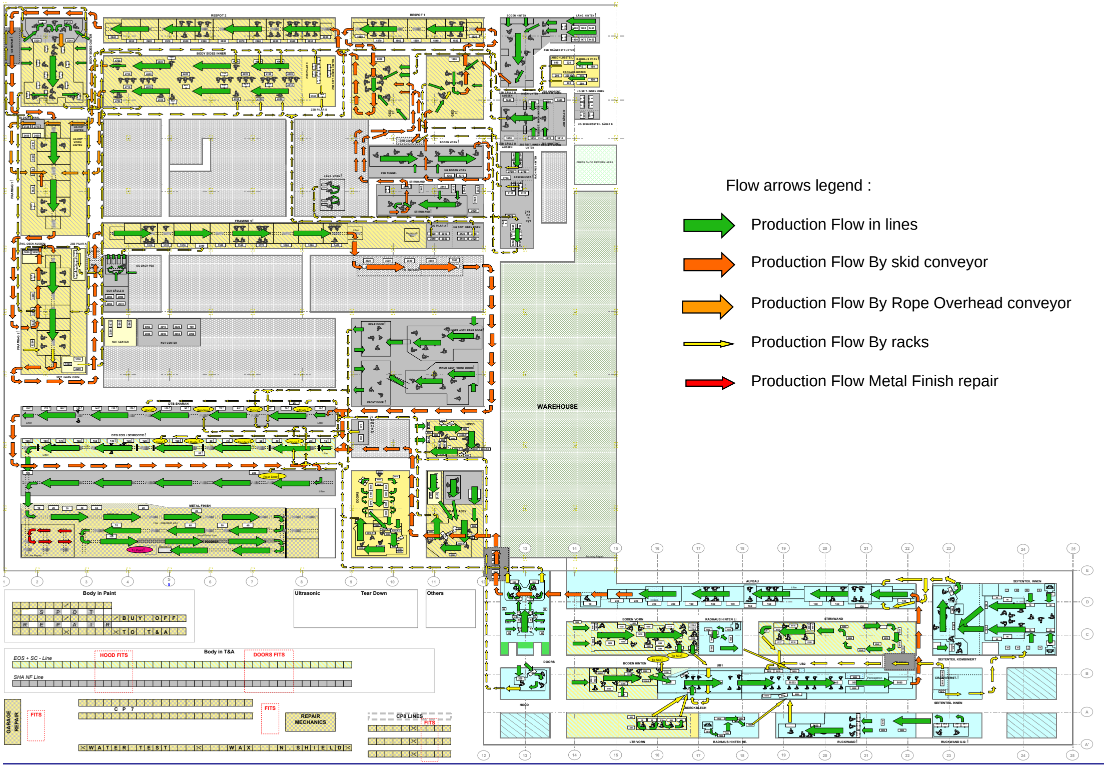


Figure 102 - Body Shop Complexity

In order to assess the sustainable production index at this complex production area, the indicator selected was the electricity consumption. A plant with a daily output of 1,000 vehicles can easily use several hundred thousand megawatt-hours (MWh) of electricity per year, as much as a medium-sized town, being one of the main reasons linked with the robots responsible for assembling vehicle bodies with thousands of welding spots and glue dots.

Similarly to the research work performed within the paint shop, it is the focus of this research work to implement the predictive performance framework to, at a first stage evaluate and model the factors that can strictly influence the energy consumption in the body area, aiming to estimate with high levels of reliability which should be the daily energy consumption. Due to the small impact of the gas consumption within the overall energy consumption, in this specific case it was only selected the KPI electricity per vehicle (EPV) to be explored. Following a detailed analysis of the predictive performance framework implementation will be presented.

1) Body Process Description

As already explained, the first stage of the predictive performance methodology based on the design of the main industrial processes deployed at the body shop, using the BPM notation as modelling tool. As depicted in Annex F, each car family has a specific industrial process flow, despite the fact that same activities are shared between them. For instance, when a EOS's process is deployed, after receiving the necessary components from the stamping area, a series of activities are launched aiming to produce the necessary parts of the EOS body: Underbody front and back, cockpit, stringers, back support and wheel arches.

After producing the different components enumerated before, these underbody parts should be fused in order to build the body structure. This task should be performed under the auto *underbody* activity. Following, the body-on-frame task should be performed under the *framing* activity. This is an automobile construction method aiming at mounting a separate body to a rigid frame that supports the drivetrain. Finally, doors should be applied to the body (*DTB* activity) before this goes to the *Metal Finish* activity, where the body should be prepared according the painting requirements.

Despite the fact that this is the main flow, characteristic from all car families produced within this organizational area, in a detailed view, the EOS and Sharan models are produced in distinct areas with distinct activities, while Scirocco share some of the activities performed for the EOS and Sharan Models.

2) Hypothesis Generation

In this section, hypothesis generation has as main purpose to collect and structure the different testimonials gathered from the different stakeholders of this process. Thus, during the fieldwork, one stakeholder with a wide view of the body area was interviewed. This important element for the body structure is the person responsible for the maintenance management, where all issues related with energy consumption are fully controlled and managed. Due to restriction of time, it was not possible to interview a different stakeholder from the body area. However, due to the position and expertise of the individual interviewed, it is strongly recognized that the main issues responsible by energy consumption were explored.

According to the stakeholder interviewed, the main factors responsible for the energy consumption are the volume of production and the mix of production. This happens because for each body that is produced, there is a constant quantity of energy that is consumed related with parts transportation, robots operation and welding dots. However, this constant value depends on the type of car that is produced. For instance, a vehicle like Sharan required for much more welding spots compared with the other two car models. It is also important to underline that, depending on the mix of production that should be supplied to the painting area in order to fulfil market requirements, the setup efforts and consequently the energy necessary to change tools increases.

Moreover, the volume of cars that should be produced per family car also affects the percentage of time that each cell should be "activated". In line with this, the stakeholder interviewed revealed that, at the moment that this research work was performed, due to the low volume of cars produced of EOS type, the cells linked to this family of cars were only performing during a time period corresponding to one shift.

Another factor identified by this stakeholder, was the energy consumed by the air handling units also known as ARP responsible for keeping the internal temperatures below the maximum value of 18ºC. Therefore, according to this interview, it was possible to understand that these resources, responsible for the energy consumption, are strongly subject to the influence of the external environment conditions, such as temperature. Thus, during the summer periods, when the external temperatures are higher than the target value, it is expected a higher consumption of electricity.

Finally, were discussed the impacts of preventive maintenance on the energy consumption rate, even when the output of this process is null. In fact, this is a trade-off question. On one hand, the energy consumption increases with the number/extension of the preventive maintenance. On the other hand, with the increase of this type of actions, the occurrence of nonconformities decreases as well as the energy consumption.

3) Key Variable

The third step of this pilot case was mainly oriented to identify and enumerate the key variables and concepts that should be considered in order to start defining the mental model of the energy consumption behaviour at the body shop. In other words, the list of variables described in this section is a sum-up and a synthesis of the hypothesis transcribed in the previous section.

Table 11 - Key Variables

Variable	*Description*	*Unit*	*Type*	*Lower Value*	*Upper Value*
External Temperature	Value of the Temperature registered outside by the AE meteorological station	ºC	Double	0	40
Production Volume/ Mix of Production	Volume of production by section and product family per week	Cars	Vector	0	650
DownDays	Number of scheduled Down Days per week	-	Binary	-	-
Shutdowns/ restart from Shutdowns	This variable indicates if, during a certain week, the factory is in shutdown or restarting from a period of shutdown	-	Binary	-	-
Preventive Maintenance	The number of scheduled maintenance per week (per types of maintenance from the energy consumption point of view.).	-	Integer	-	-

4) Model Boundary Chart

A model boundary chart summarizes the scope of the model by listing which key variables are included endogenously, which are exogenous, and which should be excluded from the model.

Table 12 - Model Boundary Chart

Endogenous	Exogenous	Excluded
Downdays	Ext. Temperature	
Maintenance	Shutdowns	
	Mix of Production	

Following, a brief description of the variables allocation by the different perspectives will be presented. This step will be important to understand which variables can be managed by the stakeholders involved within this pilot case, which are the external variables that affect the system and even which should be excluded.

Endogenous: Since the endogenous perspective aims to gather the variables that belong to the inbound of the system, and because of that can be controlled by its stakeholders, the number of **downdays** and the **preventive maintenance** were the variables identified for this perspective capable to influence the electricity consumption. Despite the fact that the number of downdays per month is defined at an administrative layer, the organizational unit is responsible to use these days if necessary (e.g. for maintenance issues).

Exogenous: On the other hand, the exogenous perspective aims to gather the variables that belong to the outbound of the system, and because of that, cannot be controlled by its stakeholders. Therefore, the **external temperature**, the existence and longevity of the **shutdown periods** and the **mix of production** were the identified variables for this perspective.

In fact, despite the fact that the external temperature variable critically influences the consumption of electricity, this variable cannot be controlled or managed aiming to optimize the electrical energy consumption. Similarly, the shutdown periods and the mix of production are two variables that are imposed by the administrative layer and the entire production line, respectively, being also important factors for the quantity of energy consumed.

5) Reference Modes

Similarly to the research exercise performed for the paint line, one important step performed was the analysis of the pattern of behaviour, concerning the electricity consumption at the body shop, aiming at understanding how this variable has been evolving throughout the years and how it might progress in the future.

Therefore, this section intends to explore a reference mode, which is a set of graphs and other descriptive data that shows the development of the problem over time. Thus, with the set of graphs here presented, it is possible to analyse the evolution of the electricity consumption from 2010 to 2011, taking as reference the factors that can affect its consumption.

From the graphical analysis (Figure 103), it is easily depicted that contrary to the reference mode designed for the painting line concerning the electrical energy consumption, in this specific case it is not possible to say that there is a clear seasonal characteristic. Despite the fact that, there is a higher consumption of electricity during the summer months and a lower consumption during the wintertime, this is not the main challenge for this pilot case. Indeed, as anticipated by the maintenance manager from the body area, another important cause of nonlinearity is the mix of production.

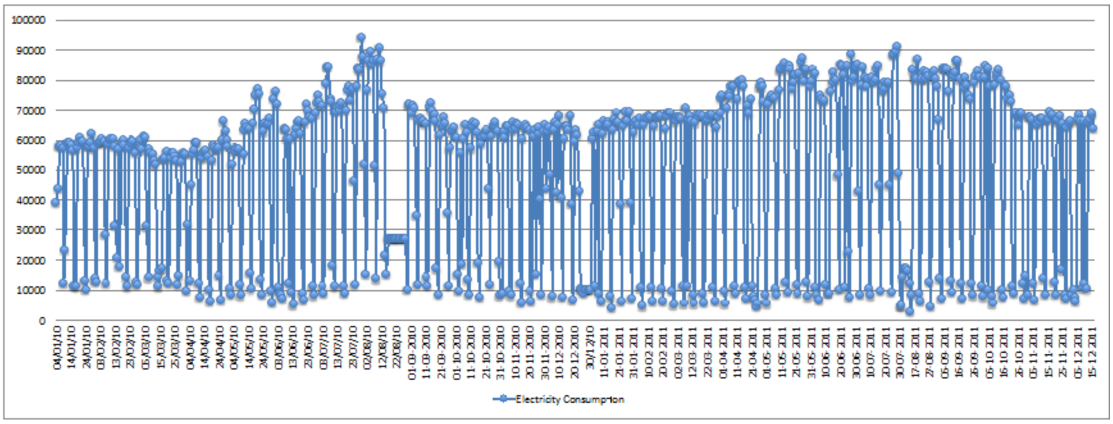


Figure 103 - Gas consumption since 2010 until 2011

As it is possible to depict from Figure 103, there is a lower consumption of electrical energy during 2010, compared with 2011. On the other hand, during 2010 there is a higher volume of production, mainly focused on the production of EOS and Scirocco cars, while in 2011 there is a lower production volume but much focused on the production of the Sharan model (see Figure 104 and Figure 105). Therefore, with a detailed analysis of the graphs presented next, it is possible to depict that, aligned with the vision of the interviewed stakeholder, with the increasing of the number of Sharan produced, also the quantity of energy consumption increases. Please note that the end of 2010 and the beginning of 2011 was a launch period, where a new and innovative model of the Sharan family was introduced for production.

In sum, it is possible to understand that for the reliable EPV estimation, it is critical to successfully achieve the correlation between three important variables: *external temperature*, *mix of production* and *volume of production*. Nevertheless, similarly to the painting line, it is important to have into account the nonlinearities imposed by the *weekends*, *downdays* and *shutdown* periods, where, despite the fact there is no production, there is always electrical energy consumption due to corrective and preventive maintenance activities.

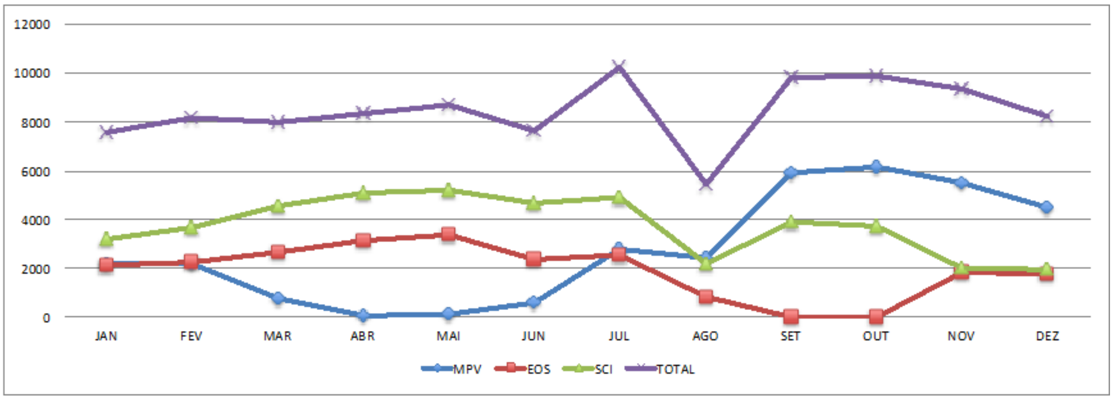


Figure 104 - Volume Production 2010

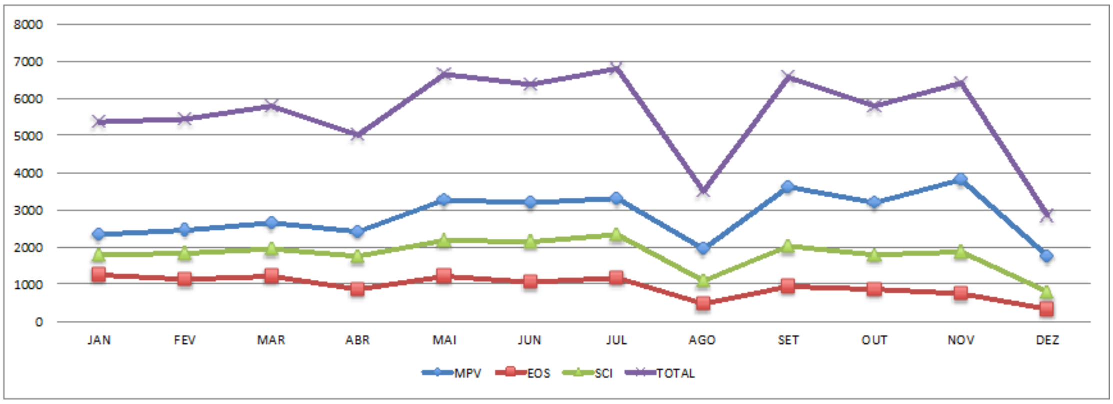


Figure 105 - Volume Production 2011

6) *Causal Loop Diagram*

This step of the methodology is expected to explore the causal relationship between the variables enumerated at the model boundary definition and the different activities of the body process, and thus, explore its feedback loops in terms of flow and stocks of materials, resources and information.

With this main purpose in mind, it was designed the following causal diagram, where it is synthesized, in a graphical way, how and why each key variable should affect the electrical energy consumption in the body area (Figure 106). Moreover, at this stage, a parallelism will be established with the BPM charts, aiming to locate, in the process execution, where each feedback loop affects the gas consumption. Moreover, in order to simplify the graph analysis, following it is presented a clear description of each causal loop as well as its relationship with the painting process.

Balancing Loop 1 (B1): preventive maintenance and all activities performed aiming at assuring machinery availability and consequent high levels quality is a trade-off situation. Indeed, if it is true that with the implementation of a rich preventive maintenance scheduling it is possible to enhance the quality of production and, consequently, decrease the number of nonconformities as well as delays on the production scheduling, on the other hand it is expected to increase the electricity consumption rate.

Balancing Loop 2 (B2): it was already shown that the external temperature is a critical variable that affects the electrical consumption at the paint shop. In fact, since ARPs use external air to refresh body facilities, guaranteeing this way the good conditions of work for the employees, the higher the external temperature, the bigger should be the electricity consumption necessary to maintain the internal temperature at the expected set-point (approximately 18ºC).

Balancing Loop 3: another important variable which should be taken into account in terms of electricity consumption is the mix of production and the volume of production for each product families. In fact, if it is true that with the increasing of the number of bodies produced it is expected to be achieved a higher electrical energy consumption, it is also true that this is not a linear issue. Indeed, if more bodies are produced for the Sharan model and less for the Scirocco than usual, then it is expectable to increase the consumption of electricity, since this model required for a higher effort in terms of parts transportation and welding spots. It is also important to underline that this fact is not only linked with the size and volume of a car model, although these are important characteristics that affect the energy consumption per model. Therefore, the number of parts that compose the structure of the car as well as the way how the body should be assembled, critically specify the electrical consumption per model. This is a clear example where the product design stage has a direct impact on the production efficiency.

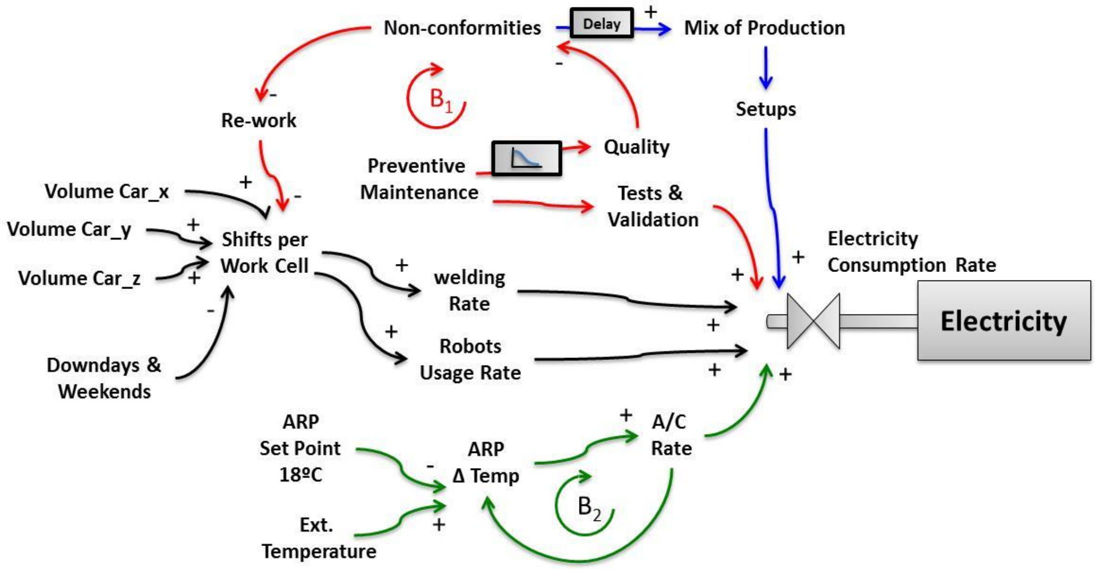


Figure 106 - Electricity Consumption Causal Loop Diagram at Body Shop

7) Predictive Model Setup

In order to setup the mathematical model that will support body area stakeholders to estimate with high levels of reliability the KPI EPV, three more steps should be performed: Network Specification, Network Training and Model Running. Since the activities performed within this final stage of the framework are very similar to the ones performed and explored in detail in the previous pilot case, performed within the scope of the paint shop, the description of this stage of the framework will be skipped.

5.4.3.1. Analysis of Results

In this section, the results obtained from the series of steps described before will be presented and analysed. As previously explained, initially the KPI electricity per vehicle (EPV) was explored aiming to test and validate the predictive framework within a complex environment such as the body area. Since this is a very straightforward indicator mainly composed by two variables (i.e. electricity consumption and volume of production), the objective was estimating the variable electricity consumption aiming to calculate the estimated EPV.

In line with this, a qualitative analysis was performed aiming at understand the normal behaviour of the electricity consumption at the body area. From this analysis, it was not only possible to enumerate which variables were responsible for imposing variability in the gas consumption, but also design the causal loops diagram where internal and external synergies can be depicted (Figure 106).

After finishing the qualitative analysis, it was possible to transpose the knowledge generated into a mathematical model, envisioning the manufacturing system behaviour modelling. The idea was to capture the normal behaviour of the production system, in this case the body area, concerning the KPI EPV. In other words, transpose the qualitative analysis done at the Reference Mode section to an analytic perspective, where a mathematical formula that fits the prediction system behaviour is designed. Aiming to accomplish this objective, during the training process, a dataset containing information of the body area behaviour from 2010 to 2011 was used together with the backpropagation algorithm at a first stage and the UKF algorithm at a continuous mode.

Once captured the system's behaviour, the next step was to prepare an excel file with the expected leading factors from the 1st of January of 2012 to the 31st of December of 2012, in order to estimate the electrical energy consumption during this time interval. In Figure 107, it is depicted the observed electrical consumption (in blue colour) and the estimated consumption (in red colour). From the analysis of the results obtained, it is possible to enumerate the following achievements:

- The Root-Mean-Square (RMS) error was approximately of 3915,25 Kwh.
- The normalized root-mean-square deviation (NRMSD) is approximately 4,07%, whose value is significantly lower than the maximum error expected (approximately 15%);
- The gas consumption estimation was performed at a daily perspective (more vulnerable to the daily oscillation),
- Predictive model capable of following, without delays, the impacts imposed by nonlinearities such as: shutdowns, weekends and downdays periods.

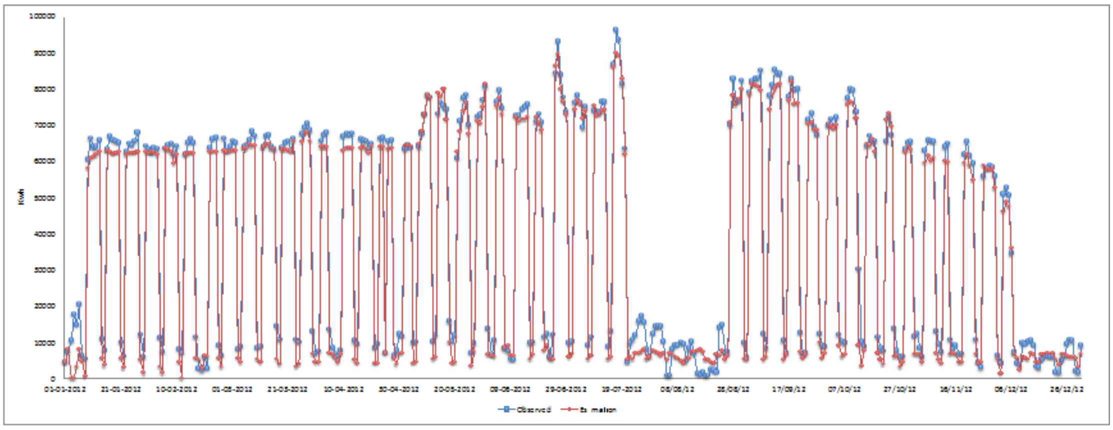
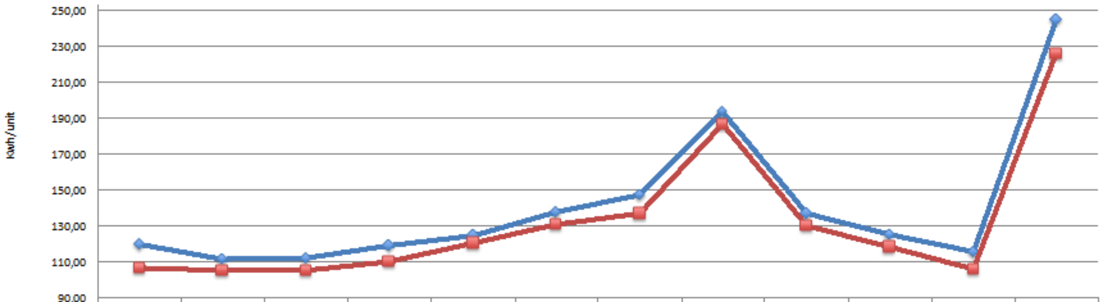


Figure 107 - Comparison between Observed and Estimated Electrical Energy Consumption

From the analysis of the results presented, it is possible to visualize that, despite the structural complexity identified and described during the qualitative perspective of the framework, it was possible to overcome this challenge focusing on the correlation of endogenous and exogenous factors capable of disturbing the electricity consumption at the body shop. Following this approach, it was possible to not only model the normal behaviour of this organizational area in terms of electricity consumption but also estimate these indicators, in a long-term, with high levels of reliability. In fact, it is possible to state that the estimation of electricity consumption for the interval of time between January 2012 and December 2012 was successfully performed.

However, the main goal was the estimation of the KPI EPV. In order to validate the predictive model designed for this KPI, it will be compared the real and estimated EPV values. The first one was calculated using the real electricity consumption and production values, while the estimated EPV was calculated using the estimated electricity consumption and planned production values. Figure 108 shows the comparison between these two variables.



	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Real	119,92	111,36	111,93	118,84	124,52	137,50	147,05	193,45	136,79	125,54	115,47	244,32
Estimation	107,00	105,66	105,33	109,93	120,33	131,21	136,75	186,76	129,95	118,62	106,17	225,82

Figure 108 - Gas per Unit Real Vs Estimation

Indeed, from the analysis of this result, we can state that the output of the framework is promising, presenting a high level of reliability. For the delta time defined, the medium error of the monthly estimation is approximately 6,87 Kwh per vehicle.

However, the difference between the estimated and real KPI values shouldn't be simply analysed as error. In fact, another perspective of analysis is that, the body shop is still capable of increasing its performance and decreasing the electricity consumed per unit. Therefore, from another data analysis it is possible to say that there is a margin of improvement to be overcome, being the saving of 7 Kwh per car an ambitious but achievable challenge.

5.4.3.2. Estimation Performance Analysis

Similarly to the estimation method comparison exercise performed within the pilot case developed in the scope of Volkswagen Autoeuropa paint shop, it is now important to evaluate the reliability and accuracy of the performance estimation engine (PEE) designed for the body area. Therefore, similarly to the previous case, the Geometrical Mean of Relative Absolute Errors (GMRAE) technique was used as the algorithm to rank the different estimation methods using the Naïve approach as benchmark.

From the analysis of the results obtained (Figure 109 and Table 13), it is possible to understand that again, the performance estimation engine is the one that presents a better performance, both in terms of reliability and accuracy. While Table 13 shows that PEE tool is the method with minor absolute error, in Figure 109 it is depicted that with the estimation method proposed for this research work, it is possible to anticipate the manufacturing system performance oscillations. This happens because, contrary to the Holt's methods, which critically depend on the trends and seasonality's characteristics from the system in analysis, the performance estimation engine (PEE) also uses the values of the leading factors identified during the qualitative perspective of the framework to project the system's behaviour into the future. Since the body area presents a job shop feature, and because of that an intricate and complex behaviour, the advantage described before gains a greater importance. In fact, if in the previous pilot case the Holtwinters method was the second one with better performance, in this specific case, the same method was the one with the worst performance.

In sum, it is possible to state that despite the characteristics and levels of complexity of the manufacturing system under analysis, through the predictive performance framework, it is possible to design a mathematical model shaped to its features. Based on this mathematical model and from the correlation of past, present and future information it becomes possible to decision makers estimate, with high levels of accuracy and reliability, the performance behaviour of their manufacturing systems.

Table 13 – Electricity Consumption Estimation Accuracy Comparison

Estimation Methods	*Exponential Smoothing (ES)*	*Linear regression (LR)*	*Holtwinters (HW)*	*PEE*
Geometrical Mean of Relative Absolute Errors (GMRAE)	1,03	0,84	1,30	0,29

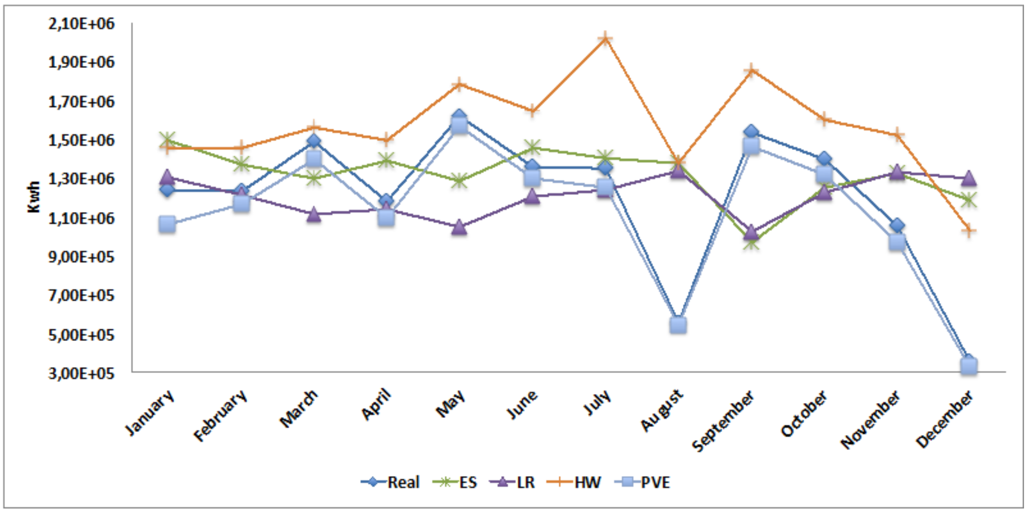


Figure 109 - Monthly Electricity Estimation Accuracy Analysis

5.4.4. Cases Validity

Concerning the validity of the application cases previously presented, it is important to highlight that they were completely performed within the Volkswagen Autoeuropa facilities. This means that, not only the data used were real, extracted from the distributed legacy systems, but also the descriptions and analysis performed to the manufacturing system are strictly related with the Volkswagen Autoeuropa reality. Moreover, it is important to underline that the stakeholders of this important Portuguese car manufacturer validated both inputs and outputs of the predictive performance framework. Unfortunately, due to the complexity of the overall framework implementation, it was not possible to design and implement a broader scenario capable of integrating both measurement and estimation engines. However, due to the results obtained from the three scenarios enumerated before, INESC TEC and Volkswagen Autoeuropa decided to initiate a new and dedicated project, completely independent from external factors and obligations, and totally focused on the necessity to shift from a reactive to a proactive performance management approach.

This project was divided into two main streams. The first one is strictly related with the implementation of the performance measurement engine as well as its integration within the managerial processes. On the other hand, the second stream of this project will be responsible for the setup and implementation of a performance estimation engine for each of the KPIs that are used for benchmarking purposes and, because of that, support the Portuguese plant not only to survive within the Volkswagen universe but also to capture the car models that present a higher demand and a higher return of investment (ROI). As a result, it is expected to obtain a performance management system capable to follow the entire PDCA cycle, enhanced by the predictive management paradigm proposed by this research thesis. Moreover, with the development of a second R&D project it will be interesting to demonstrate how a complex and more aggregated KPI can be fragmented, in order to generate a series of simple indicators that can be easily estimated, as demonstrated by this thesis.

In conclusion, it is possible to state that the main challenges proposed for this fieldwork were successfully achieved. In fact, after the framework developed, it was possible to gather, structure and enhance the knowledge around the issues of gas and electricity consumption both at the painting and body assembly areas. Moreover, it was possible to validate the estimation engine capable of designing the curve of behaviour for each of the production system and thus, estimating with high level of confidence the future manufacturing systems' performance behaviour.

5.5. Summary and Conclusions

Aligned with the vision for a proactive performance management approach, described at chapter three and four, this chapter had, as main goal, not only to exemplify how the predictive performance framework can be applied within a complex manufacturing system, but also show the levels of accuracy and reliability that can be achieved with the performance measurement and estimation engines. Therefore, three application cases were fully explored. While the first one is mainly a proof of concept where synergies and behaviours were completely simulated, although it is related with a real Brazilian supply chain reality, the other two application cases were performed in strict partnership with a Portuguese car manufacturer.

As already explained, the *first application case* had as main objective to demonstrate how the predictive performance estimation engine could be used within a supply chain to estimate future performance behaviours. In this specific case, two important KPIs for the supply chain controller, concerning non-conformities and orders delays, were used as object of analysis. For each of these KPIs, were identified the endogenous and exogenous factors (driven factors) that could positively or negatively affect the manufacturing system behaviour concerning the identified indicators. Following, the estimation engine (PEE) was deployed aiming at learning the level and extension of correlations between the different driven factors, in the scope of each KPIs identified.

At the end of this pilot case it was successfully demonstrated that, following the Performance Thinking Methodology (PTM), developed within this research project, it is possible to not only enhance, rethink and formalize the existing knowledge concerning the manufacturing system behaviour, in terms of a certain strategic objective, but also, based on the knowledge created, estimate with high levels of accuracy the future behaviour of a system, and thus, provide decision makers with reliable and powerful information capable to sustain their strategic choices.

The *second application case* explored during this section of the document is mainly related with the implementation of a performance measurement engine capable to not only provide performance measurements in real time, but also analyse a KPI measure using a drill-down approach based on a hierarchical KPI metric definition. With this application case it was possible to demonstrate that, the implementation of a suitable performance measurement engine should be seen as the first landmark to be achieved aimed at supporting a proactive performance management approach implementation, taking into account the strategic, tactical and operational dimensions.

Indeed, from the economical perspective it can be observed a critical added value. Since the PME allows an organization to formalize and calculate their KPIs in a simple and automated way, with the implementation of the Performance Measurement Engine (PME) it is not only possible to enhance the decision making process but also reduce the human resources effort necessary to the KPIs metrics calculation, reallocating this effort to other tasks more related with the core business of the organization. On the other hand, from the tactical perspective, it was demonstrated that through the implementation of a dedicated performance measurement tool, such as the Performance Measurement Engine (PME), it is not only possible to detect if the system is performing as desired, but also, due to the drill-down capabilities of this performance measurement engine, identify the internal or external factors that are affecting the system's performance, as well as the watermelon situations[18] even before it prevents the achievement of the strategic objectives.

Finally, and equally important, from the strategic perspective it was demonstrated that the PME provided an important contribute aiming to be crossed the gap between the strategic and operational layers of an organization. In fact, companies performing in volatile markets are forced to continuously redefine their strategic objectives as well as enhance their tactical operations, aiming to remain competitive. Consequently, a performance management system should be seen as a dynamic system, capable to be adjusted to this evolution, both at strategic and tactical levels. In line with this, the capability to define KPIs on the fly as well as shape the domain of calculation to the reality as necessary is a critical advantage envisioning the delivering of the right information to the correct person in order to be taken the suitable decisions.

The third application case should be seen as an extension of the first pilot case, however, at this stage the predictive performance framework was applied within a real industrial case, completely connected with the reality. In this application case, two organizational areas were used as scenario for the implementation of the predictive performance framework, the paint and body areas. In these specific cases, two important KPIs for the automotive industry, concerning gas and electrical energy consumption per vehicle produced, were used as object of analysis. Since each of these organizational areas presents a specific set of characteristics and requirements, the framework was implemented during two distinct time periods.

The paint shop is mainly composed by a production line, where a mix of cars flows within this organizational unit in order to be painted. From the performance thinking methodology implementation, it was observed that from the energetic point of view, this manufacturing system is very stable and performing under statistical control. Indeed, the main exogenous factors that can affect the paint shop energy consumption (i.e. both gas and electrical energy) are strictly related with the weather and other environmental conditions. Due to this reality, and based on Shewhart vision, it was expected that the predictive framework was capable to foresee both gas and electrical consumption per vehicle produced with high level of reliability, as it turned out.

Nevertheless, in the body shop the scenario is completely different. In this case, we deal with an application case completely different from the paint line. Here the organizational unit is constituted by a job shop layout where, contrary to the paint shop, not only exists a mix of products but also a large movement of body components along the entire unit. Although this higher complexity imposed by logistic issues, it was surprisingly interesting to understand that the predictive performance framework was capable to project the future system behaviour from the energy consumption perspective with success. To prove that, in both scenarios the results obtained were

18 Watermelon phenomenon occurs when something is green on the outside, but bright red on the inside. Effectively, this has more impact when measures show that everything is fantastic, but customers or employees are reporting that low performance situations.

compared with algorithms currently applied within industrial organizations to foresee future system's behaviours.

Despite the good estimation results obtained, it is important to underline that one of the main advantages of this framework was the time and effort necessaries to develop the qualitative research, responsible for obtaining and organizing the knowledge about the manufacturing system under analysis, as well as the setup of the mathematical engine capable of estimating the future performance behaviours. For instance, in order to implement the framework within the painting line, in order to cover two KPIs strictly related with gas and electricity consumption, it was required four full days of work at the automotive plant, while for the body implementation it was necessary three full days. It is important to mention that, at the beginning of each intervention, there was not any previous knowledge about the organizational area in analysis. Therefore, a great deal of time spent within this car manufacturer was used in order to create the mental model about this manufacturing system in terms of energy consumption. Consequently, it would be expectable that an expert on each of these systems would be capable to achieve the same results in a shorter amount of time, since during the time spent within this company it was simply followed the methodology and deployed the estimation engine in a "mechanized" way.

In sum, during this chapter different scenarios were explored aiming at demonstrating how a predictive performance management approach can be deployed within a real and complex manufacturing system. Nevertheless, as further research work it will be interesting to explore the combination of both measurement and estimation engine, within the same scenario, in order to be obtained a fully automated self-supervisory mathematical model.

Chapter Six

CONCLUSIONS AND FUTURE RESEARCH WORK

Presented the proactive performance management framework idealized for this research project, as well as described the different applications cases designed and used as proof-of-concept, chapter six is strictly related with the generalization stage of the project. Therefore, during this chapter it will not only be presented some considerations related with the current status of the performance measurement and management disciplines, but also it will be summarized the work done to answer each of the research questions presented in chapter one. Moreover it will be described the main outcomes of this research project, both from scientific and industrial perspectives, as well as the directions to be followed in future research.

6.1. Overall Conclusions

Due to the mass customization requirements imposed by the volatile market demands, it has been observed a problematic increasing of products variety and complexity as well as decreasing of products life cycles. This scenario has been directly affecting the manufacturing systems management, due to the increase of both static and dynamic complexities.

While the static complexity is directly linked with the system's structure and configuration, the number and the variety of the products, the system's variety of components (e.g. labours, machines, buffers, transportation mechanisms), as well as their interconnections and interdependencies; on the other hand the dynamic complexity is related to the uncertainty of the system's behaviour for a specific time period, dealing with the probability of the system to be in control.

When exploring a manufacturing system's dynamic complexity, it is important to understand that this dimension of analysis is time-dependent, being strictly related to system's real-time operation, material flow patterns, modules reliability and failures. Thus, the drivers responsible for leading to unpredictable behaviours or even causing deviations from the norm/steady-state, may be internal to the system (e.g., machines reliability, breakdown and maintenance and scheduling policies) or external (e.g., suppliers reliability causing variation in the quantity and timing of materials and tools).

This reality has been reinforcing decision makers necessities to not only extract performance data capable to assess the static complexity in a timely and reliable way (Cavalluzo & Ittner, 2004; Dossi & Patelli, 2010), but also build a robust mind-set about the system's dynamic complexity, in order to improve the way in which decision-makers use and manage the information generated along the manufacturing system, or even externally.

Our research demonstrated that both information and complexity are two concepts that are in close association. For instance, the information theory, which is a branch of applied mathematics and computer science for information quantification, has as main goal quantify the information necessary to model and represent the system behaviour. Obviously, higher the complexity of a specific manufacturing system, higher is the quantity of variables that need to be taken into account envisioning its control. Based on this concept, the information-theory discipline has the entropy variable as the key measure of uncertainty for complex manufacturing processes (Abad and Jin, 2011).

Thus, the performance management discipline arises as a key driver to generate information related with the manufacturing system behaviour. From its roots, the performance management discipline has been stipulating that in order to take the decisions that will really improve the manufacturing system behaviour and support the organisation in achieving their strategic objectives, it is crucial to periodically collect and assess information feedback about the real world. Indeed, this is the main concept and purpose that support the performance management approach, Nevertheless, only shifting from a reactive to a more proactive performance management approach it is possible to aim for decreasing manufacturing systems uncertainty, and thus enhance the decision making effectiveness. Thus, we believe that the purpose for which companies implement performance management systems must evolve and mature, not being so much dependent from the feedback time characteristic from this area of research. In other words, decision makers must use this information not only to take decision but mainly to continuously revise their understanding on the system, and thus drive their perception of the state of the system closer to the reality.

However, take this step ahead in the context of complex manufacturing system is not a trivial issue, mainly due to the methods and mind sets currently used. When designing and developing a suitable performance management approach, two main perspectives are normally stressed: *information process management* and *operations research* domains. While the information process management concept stresses the information link between the operational and control levels, in order to guarantee information availability, on the other hand, operations research focuses on the decision process itself.

By doing so, operations research creates a mental model about the system in analysis based on a set of system states, determined by the available information and, based on this knowledge arrives at a specific but isolated decision. As it is possible to understand from the previous analysis, a gap strictly related with which information should be available to enhance a decision making process, can be identified. Indeed, neither the information management nor the operations research focus on the necessity to explore and understand the system's behaviour as a whole, aiming to extract the suitable variables that support decision makers to bring their mental model of the system closer to reality.

Aiming to overcome this gap, these approaches should not be treated independently or without any component enhancing its linkage. In line with this vision, systems dynamics approach has been emerging, as a fundamental tool to support the stakeholders of complex manufacturing systems on understanding which information should be available at a decision point, as well as the consequences that arise from defects and gaps in the information used to take a decision. Only this way can organisations provide decision-makers with the right information that will allow them to fulfil all the strategic objectives or optimize the final solution in case that trade-offs arise from paradox objectives (Smith et al., 2010).

Envisioning a more proactive management approach, also mean shifting the way how decision makers see and use their performance indicators. Based on this vision, Kaplan and Norton created a distinction between variables that simply reflect behaviours that occurred in the past and the ones which information provides decision makers insights about what can happen in the future. To these variables Kaplan and Norton called them lagging and leading indicators.

Combining a robust and competent performance measurement system with an enhanced methodology for complex manufacturing systems design, it is possible to not only identify which variables are able to hinder the system's stability but also analyse and understand its natural evolution along the time. Obviously, if to this logic we add the leading indicators concept, than we have the rational that will lead us to estimate future manufacturing systems behaviours with a high level of confidence.

Thus, the main outcome of this research work pursued is a performance management framework supporting seamless interoperability, which helps to systematically and comprehensively estimate performance in complex manufacturing systems, envisioning a more proactive approach. It comprises four elements: *performance-thinking methodology*; *strategic performance management data model*; *performance measurement engine;* and *performance estimation engine.*

The research pursued gave the possibility to answer the main research questions, which have guided this research work.

RQ1. *How can we use raw data to generate performance information?*

One of the main premises when developing a suitable performance measurement system for complex manufacturing environments is directly linked with the availability and accessibility of the raw data. The first barrier to the creation of meaningful and powerful performance information is strictly related with the type and quality of the raw data available on the different legacy systems of an organization. However, this raw data, if available, is normally not easy to be accessed, neither is available in the suitable format. Thus, before being used for KPIs calculation, there should be a data treatment stage where the raw data should be extracted from the respective data sources and shaped in order to respond to the performance calculation requirements. Nowadays, this type of activities deeply depends on the IT support services, since these are the ones that have the access and knowledge to perform this type of activities. Nevertheless, due to its practical limitations and bureaucratic constraints, this reality can represent critical bottlenecks when decision makers need to update, setup or validate KPIs metrics.

Therefore, the main contributions of this research question is strictly related with the necessity to explore an innovative performance measurement system, focused on the capability to extract in real-time, and in an user-friendly way, the most important and reliable performance information from an enormous raw data set.

Aiming to achieve this goal, during this research project it was proposed the implementation of a *Data Fusion* approach based on a *JDL model*, from the conceptual point of view, and based on an *Extract Transform and Load* (ETL) approach, from the technological perspective. From the materialization of this vision, it was possible to define a workflow that supports decision makers to not only identify which raw data is available in the different legacy systems, but also, fuse this data in order to build more aggregated and meaningful information, capable to be easily used during the KPIs metrics definition. Due to this achievement, a *critical step was taken aiming to cross the gap between the strategic and operational layers of an industrial organization*.

Nevertheless, within the performance management scope not only the accuracy and reliability of the calculation process is important. Another dimension to take into account, is strictly related with the quality and objectivity of the KPIs metric design process (Cohen & Roussel, 2005). Indeed, if stakeholders are not capable to clearly transpose the organizations strategy to a set of KPIs and respective metrics, then the performance management solution will only be used for show, not presenting practical advantages.

Moreover, aspiring to manage the different trade-offs and paradox strategies imposed by current market demands, decision makers have been forced to take decision based on numerous indicators. Nevertheless, in case that a long list of indicators is used, then decision makers capability to understand trade-offs and make the correct decisions will decrease. Therefore, an important work of systematization and objectivity was performed, aimed to not only eliminate all the indicators that do not present an added value for the strategy implementation, but also aggregate indicators in order to build powerful and meaningful KPIs[19].

Aiming to solve these problems, two main concepts were explored: (i) a *hierarchical KPI metric definition* and (ii) the *high-resolution approach for KPIs metrics calculation*. It is well known that any manufacturing system is a multi-layer structure, whereas the lower layers present low levels of information but high requirements in terms of times constraints, while the higher level layers, on the other hand, present huge quantities of information and lower requirements in terms of time constraints.

Following this paradigm, the hierarchical KPI metric definition allows stakeholders to build aggregated KPIs based on indicators that are propagated from the lowest layers of the organization up to the one where the stakeholder is managing the manufacturing system's behaviour. This approach not only support decision makers to systematize the KPIs metrics definition, combined with the raw data gathering process, but also make it possible to graphically visualize the status of a specific KPI. In other words, since each KPI is composed by a series of other performance indicators, thus when analysing the behaviour of a certain KPI it is possible to understand which perspective (PI) is hindering the achievement of the strategic objective. This graphical representation can be used not only to detect bottlenecks but also to foresee low performance behaviours, since each PI that composes the KPI in analysis should be seen as leading factors that support decision makers to project future scenarios.

Nevertheless, due to the static complexity previously identified and characterized, current manufacturing systems are, by definition, composed by different units, which are managed by different stakeholders and produce different families of products, imposing a multi-dimensional problem when calculating and managing their performance. Thus, aiming to overcome this problem, the high-resolution approach raised as PME's functionality that support decision makers to increases the level of detail when calculating any KPI, so at any moment decision makers can obtain a micro or macro perspective of the manufacturing system's performance. In other words, guarantee that not only it is possible to see the performance of the manufacturing system as a whole, but also analyse the performance of a department in terms of production of a specific product family. In sum, only through the combination of these two approaches, it is possible to identify whether the system is performing at non expectable state, and then, drill-down the problem until find the reason that caused the unusual performance behaviour.

Another challenge arises from the fact that in order to build a suitable performance management approach, different actors with different backgrounds and expertise need to

[19] Kaplan and Norton recommended no more than 20 KPIs should be used, while Hope and Fraser suggest fewer than 10 KPIs must be defined and Parmenter (2009) advise to follow the 10/80/10 rule. The rule 10/80/10 shows that decision makers must define no more than 10 Key Result Indicators; up to 80 Performance Indicators and 10 Key Performance Indicators

share knowledge and information. This scenario requires for the development of methods and tools capable to harmonize the knowledge and more specifically the performance information generated at each layer of an organization. Only this way it is possible to guarantee that the KPIs defined by managers at the strategic level will be well calculated by the technicians at the operational layer.

Aiming to solve this interoperability issue, the semantic approach was used as platform for the design and development of a data model capable to act as a broker capable to connect different functional modules, belonging to different layers of an organization. Thus, it was investigated and validated the importance and suitability of the Semantics approach, in comparison with the well-known XML Schema language (XSD), for the interoperability between two different universes of people, using different tools and presenting different perspectives and mind-sets related to the same manufacturing system.

Although the semantic concept is normally linked to the Semantic Web, it was demonstrated that semantic technologies could be considered for closed systems such as industrial environments. Indeed, with the support of semantic technologies, it is not only possible to describe the logical nature and context of the information being exchanged, but also guarantee that people or machines that speak different languages and belong to different universes can understand what these entities represent, since semantics provides a meaning to entities, using words or concepts

RQ2. *How should the performance information and the system's knowledge be used to project future performance behaviours?*

As depicted from the topics previously enumerated, research question one is mainly related with the necessity to enhance decision-makers capability to visualize and understand current or past performance behaviours, envisioning the enhancing of decision makers mind-set about the system's behaviour. Thus, based on this knowledge, research question two has as main objective develop a framework that demonstrates that it is possible to foresee how a manufacturing system will behave in the future, based on an enhanced knowledge about the system's dynamics and an effective analysis of lagging and leading indicators.

It was proposed that by using methodologies and algorithms, normally assigned to mature areas of research such as Systems Dynamics approach, from complex system theory, as well as learning machines and state error observers algorithms, from robotics and automation disciplines, it is possible to capture the normal behaviour of a specific complex manufacturing system, in terms of a specific KPI.

While the Systems Dynamics approach is mainly responsible by formally compile and represent the manufacturing system's feedback loops and respective variables, on the other hand the enhanced learning machine, composed by Neural Networks and Unscented Kalman Filter algorithms, guarantees the definition of a fully automated self-supervisory mathematical model of the system's behaviour. As an important result of this research project, it was validated and assessed the main advantages of using an enhanced Kalman Filter approach based on the unscented transformation (UT), which is a method for calculating the statistics of a random variable that undergoes a nonlinear transformation.

Indeed, with this enhancement, it was possible to reach a most stable and reliable error observer that not only presents a non-linear behaviour but also decreases significantly the error that arises from the linearization process.

Finally, it was demonstrated that stimulating the mathematical model obtained from the framework implementation, with a set of leading indicators for a specific estimation time horizon, then it should be expectable to project with high levels of accuracy the future behaviour of a system.

As an important conclusion, it was reinforced and validated Shewhart thesis that even under strong static and dynamic complexities, it is possible to estimate future performance behaviour since the manufacturing system in analysis is performing under statistical control. This means that, if a process has already achieved a suitable level of stability then it can also be considered predictable, independently of its complex structure. In other words, once the natural variation of the process has been determined, as well as the variable that affects its normal behaviour, it is possible to predict its future performance.

6.2. Research Contributions

During the previous section, some of the main conclusions about the current state of the performance measurement and management disciplines were explored. In line with this, it was identified a series of gaps that characterize this area of study, in terms of current industrial company's needs, as well as the trends and innovative solutions that were developed aimed to overcome these bottlenecks. Following, will be described in summarized way the main outcomes of this research project, envisioning the enhancement of performance measurement and management disciplines.

I. **Performance Measurement Engine**

The Performance Measurement Engine (PME), which is a flexible IT Solution that can be easily integrated within the Production System Environment, was developed with the main purpose of streamlining and expediting the assessment of manufacturing systems performance. With this solution it is possible to gather and combine, in a transparent and automatic way, the necessary information from different sources, in a user-friendly approach. The idea is to present a solution capable of calculating performance measurements with high levels of granularity, which can be adjusted according to the performance management requirements, defined by the different stakeholders. Moreover, the PME allows decision makers to customize the way how stakeholders want to analyse their manufacturing system's performance, in order to keep the performance management solution aligned with the organization's strategy and vision. Among the most important benefits, it is possible to underline the fact that decision makers become capable of specifying and calculating KPIs on the fly, enhancing their what-if analysis capabilities.

From this study resulted a functional module, currently installed in VW Autoeuropa plant and strictly integrated within their business processes and four research papers submitted to international conferences and international journals:

- António Almeida, Américo Azevedo, Álvaro Caldas (2013) "A Multi-Perspective Performance Management Approach for Complex Manufacturing Environments" *submitted to Robotics and Computer-Integrated Manufacturing*;
- António Almeida, João Bastos, Roberto Piedade Francisco, Américo Azevedo, Paulo Ávila (2013) "Sustainability Assessment Framework for Proactive Supply Chain Management" *submitted to International Journal of Industrial and Systems Engineering*
- António Almeida, Américo Azevedo, Filipe Ferreira, Álvaro Caldas(2013) "Process Performance Assessment in Collaborative Manufacturing Environments: A Role Oriented Approach", *accepted to be published in Advances in Sustainable and Competitive Manufacturing Systems Lectures Notes in Mechanical Engineering*;
- António Almeida, Daniel Politze, Américo Azevedo, Álvaro Caldas (2012) "Linking Strategic Goals with Operational Performance: An Integrated Approach", *accepted to be published in proceedings from the IEEE International Conference on Industrial Engineering and Engineering Management*.

II. Framework for Performance Estimation

Within the scope of this performance estimation framework, a performance thinking methodology (PTM) and a performance estimation engine (PEE) were successfully developed. The performance thinking methodology, which has its roots on the system dynamics approach, has as main objective to guide decision makers to formally design the feedback loops and respective variables that shape the more immediate threats to stability, enhancing the propensities for instability.

Nevertheless, due to the number and nature of variables that can affect the manufacturing system behaviour, and consequently stakeholders' decisions, the performance estimation engine materialize the necessity to develop a mathematical model capable of emulate the normal behaviour of the system and, based on empirical data and observable cases, project future performance behaviours. Exploring knowledge and algorithms from automation and control areas of research it was possible to develop an innovative and user-friendly estimation engine that easily compiles the information generated at the performance thinking methodology and then, based on leading indicators, estimates with high levels of confidence the future behaviour of a system.

Based on this framework, stakeholders become not only capable to define consistent and solid KPI's targets but foresee if the strategic objectives defined will be achieved within the expected time period.

The results of the aforementioned contributions are *five research papers* submitted to international conferences and international journals and *one prototype*:

- António Almeida, Américo Azevedo, Álvaro Caldas (2013) "Prediction of Energy Consumption Indices in the Automotive Industry", *accepted to be published in proceedings from the IEEE International Conference on Industrial Engineering and Engineering Management*.

- António Almeida, Américo Azevedo (2013) "Performance Framework Geared by a Proactive Approach", *accepted to be published in Advances in Sustainable and Competitive Manufacturing Systems Lectures Notes in Mechanical Engineering*.
- Roberto da Piedade Francisco, Américo Azevedo, António Almeida, (2012) "Alignment prediction in collaborative networks", *accepted to be published in Journal of Manufacturing Technology Management*.
- António Almeida, Américo Azevedo, Roberto Da Piedade Francisco, João Bastos (2011) "Using key alignment indicators for evaluating performance in collaborative networks", *accepted to be published in Adaptation and Value Creating Collaborative Networks*
- Américo Azevedo, António Almeida (2011) "Factory Templates for Digital Factories Framework", *accepted to be published in Robotics and Computer-Integrated Manufacturing*.

6.3. Future Research Directions

As road map for future research initiatives, a series of investigation directions have already been defined in order to enhance the research work here presented. The first main trend of investigation will be oriented to the necessity of exploring and combining other performance estimation models, based on data mining algorithms. Indeed, the Business Intelligence is today a critical and popular area of investigation when dealing with big data. Therefore, we strongly believe that the adoption of methods and tools already explored within the BI discipline to estimate the future performance behaviour of complex manufacturing systems would be a critical step ahead for the performance management discipline. In special, it will be explored the process mining as an innovative and agile tool to model real processes from data logs.

The second trend of investigation will explore a more conceptual work aiming to develop a methodology that will support decision makes to identify the suitable KPIs, and respective metrics, that will assess if the stakeholders' strategic vision is being achieved or not. For this line of investigation, the performance thinking methodology developed and presented in this document, will be used as a starting point.

Nevertheless, these are not the only objectives for the period after the finishing of this doctoral program. In line with this, a more robust research will be performed aiming to explore the implementation of a proactive performance management approach within supply chains and, more concretely, in the retail industry. Indeed, one of the most interesting challenges for the future is the management of multi supplier/partner relationships, within supply chain networks. However, this topic raises a series of challenges since different organizations, or even different departments within the same organization, can have different methods for measuring and communicating performance expectations and results. Therefore, aiming to better understand current performance and opportunities for improvement as well as enhance trustability between entities of a network, managers must avoid internal biases and align their vision with the entire strategy for the network.

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Annex A.

VFF Virtual Factory Data Model

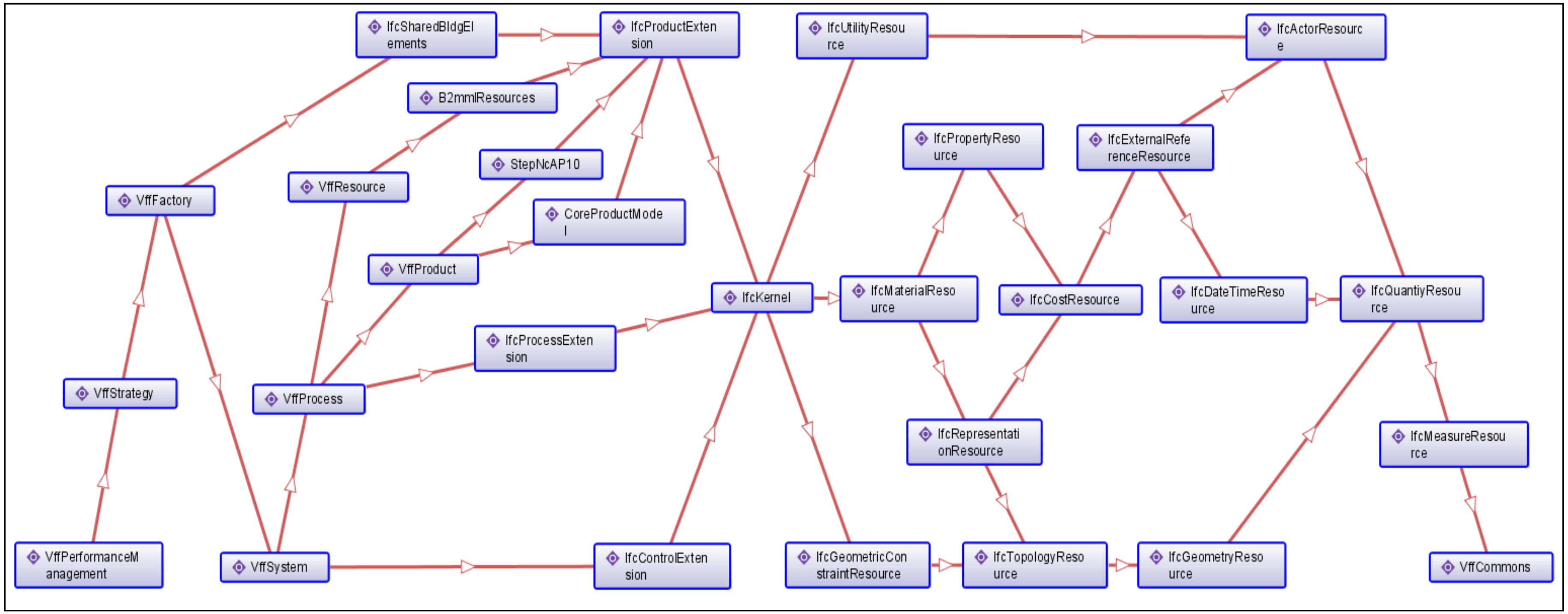

Figure 110 - VFDM Ontograf

Table 14 - VFDM Areas and Ontologies

VFDM area	Description	Ontologies	Technical Standard
Commons	Definition of common classes and properties that are imported by the ontologies belonging to the other VFDM areas.	VffCommons	N/A
IFC Resource	Definition of IFC supporting data structures.	IfcActorResource, IfcCostResource, IfcDateTimeResource, IfcExternalReferenceResource, IfcGeometricConstraintResource, IfcGeometryResource, IfcMaterialResource, IfcMeasureResource, IfcPropertyResource, IfcQuantiyResource, IfcRepresentationResource, IfcTopologyResource, IfcUtilityResource	IFC 2x4 RC2
IFC Core	Definition of the basic structure, fundamental relationships and common concepts of IFC.	IfcKernel, IfcProductExtension, IfcProcessExtension, IfcControlExtension	IFC 2x4 RC2
Building	Description of the data related to the physical structure of the factory (e.g. walls, columns, floor, power supply lines, etc.).	IfcSharedBldgElements	IFC 2x4 RC2
Product	Description of the data related to the product, i.e. the production goal of the factory.	CoreProductModel, StepNcAP10, VffProduct	CPM, STEP-NC
Resource	Description of the data related to the production resources that are used by a system with the final goal of transforming the product (or a work in progress)	VffResource, B2mmlResources	ISA-95
Process	Description of the data related to the processes that are adopted by a system to directly (e.g. manufacturing system, assembly system) or indirectly (e.g. logistic	VffProcess	(IFC 2x4 RC2), (STEP-NC)

VFDM area	Description	Ontologies	Technical Standard
	processes, maintenance processes) transform a product.		
System	Description of the data of a transformation system (e.g. manufacturing system, assembly systems) that affects a product by means of physical resources and/or human resources within a process.	VffSystem	(IFC 2x4 RC2)
Factory	Description of the factory project during its whole lifecycle.	VffFactory	(IFC 2x4 RC2)
Strategy	Description of the data related to the company strategy and the market (e.g. demand forecasts, received orders, etc.) where the factory owner is playing.	VffStrategy	DIN 4991
Performance Management	Description of the data related to the behaviour of the factory (and its components) in terms of both planned and actual performance.	VffPerformanceManagement	N/A

- The ontologies containing only novel definitions of classes and properties have a name starting with "Vff" (e.g. *VffComons*), whereas the ontologies that are created by importing/transforming third party ontologies or technical standards have a name starting with the acronym of the source (e.g. IfcKernel), according the following description: Vff (Virtual Factory Framework); Ifc (Industry Foundation Classes standard); *StepNc* (STEP-NC standard); Cpm (Core Product Model); B2mml (Business To Manufacturing Markup Language from ISA-95 standard).

Annex B.

Strategic Performance Data Model

The Strategic Performance Management ontology here presented results from the merger between the *VffStrategy* and *VffPerformanceManagement* ontologies. Thus, after clearly defining the boundaries between these two universes, three concepts gain a higher dimension when dealing with strategic performance assessment, they are: *measurements*, *metrics* and *performance indicators*. Despite the similarity between these three concepts, it is important to clarify the main differences between them. A measurement is a number that is quantified at a certain point in time. However, in the performance measurement sphere, this value only represents an add-value if it contains a certain meaning associated, which makes it a metric. On the other hand, in the performance management scope, a metric only becomes useful if it has a target associated which makes it possible to evaluate these variables. In sum, while a key performance indicator is responsible for representing a certain non-functional requirement, by a measurable concept capable to evaluate quantitatively a certain object in a specific scope, a metric is a characteristic of a KPI responsible for formulating it into a mathematical way, with a well-defined objective function.

In line with this, the strategy part of the SPM ontology was developed aiming at modelling the data related to the company strategy, envisioning the alignment between the manufacturing system performance and the market needs. In other words, with this ontology it is expected that the goals envisioned by the stakeholders of the system can be formalised; the KPIs can be mapped with the requirements defined for the manufacturing system and; the information related to the target objectives can be modelled (Dekkers, 2003).

But, how it is possible to map this vision using the semantics and ontologies as pillars? The main premise of the strategy ontology is based on the idea that a manufacturing system (since a supply chain until a micro-factory) is a very complex product, composed by a series of entities (from industrial partners to factory departments, respectively). Each of these entities has a specific reality that can be modelled with *VffScenarioDetail* class (Figure 111). Moreover, each of these entities should have a strategy well defined. Therefore, each manufacturing entity should define its own strategy map, aligned with the entire vision of the manufacturing system.

Consequently, each strategic map is composed by a series of functional requirements. By strictly following the rules that each functional requirement has to be derived from specific stakeholder's goals, which, consequently, should be aligned with the organization vision, the rationale behind each functional requirement should be captured in order to justify and compose each of the company's goals. Therefore, each of the functional requirements, which should be modelled by the *FunctionalRequirement* class, may be linked with a criteria (*Non-FunctionalRequirement* class) and a certain solution (*SolutionProperty* class)(see Figure 111).

In a second layer of the ontology, strictly focus on the performance management issue, one or several selected KPI/PI, which are seen as suitable to assess the intention that stands behind a functional requirement, should be mapped. The KPI class focuses on storing the main characteristics and specifications of an indicator in order to provide meaning to the measurements obtained. For instance, each KPI must be catalogued according to its classification and strategic level. By strategic level, it means that the controller must specify if the KPI/PI under analysis is used to evaluate a planning or operational process. On the other hand, in the classification level, it is specified in which terms a KPI/PI evaluates a specific object in the production system: Cost, Quality, Time, Flexibility or Reliability.

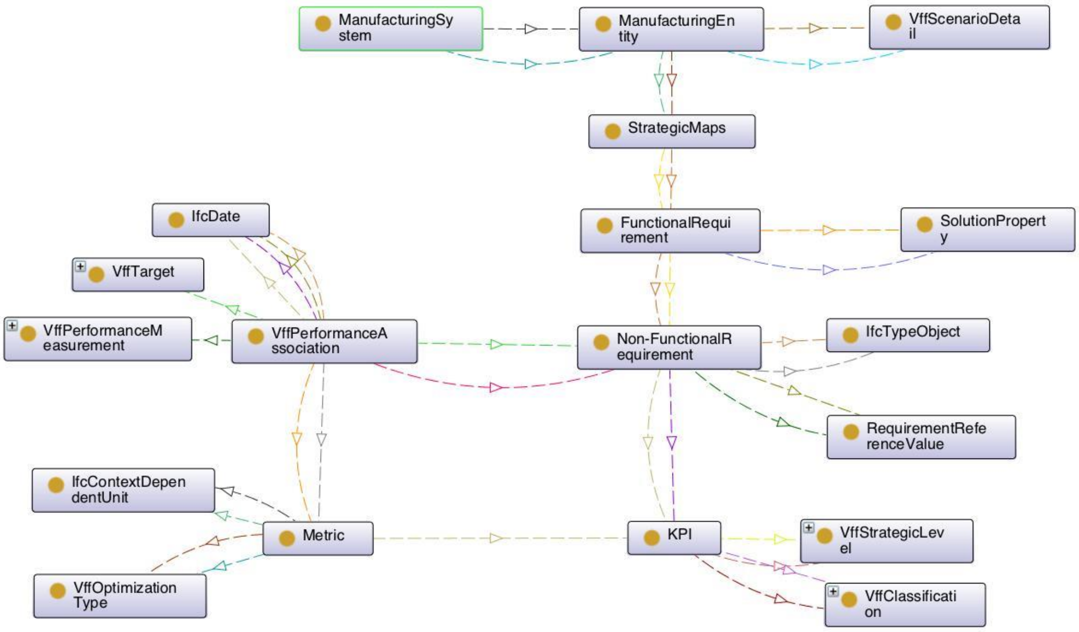

Figure 111 - Strategic Performance Management Ontograf

On the other hand, the Performance Management part of the SPM ontology aims at modelling the data related to the behaviour of the production system, assessing its performance against the expected target values. However, the performance measurement should be explored as a dynamic process that alters according to the specific environment that characterises the manufacturing system under analysis. In line with this, the *VffPerformanceAssocation* class was designed to link a performance target with the performance measurement, calculated with a specific metric, designed to mathematically formulate a certain KPI, for a certain time window (see Figure 111).

In sum, it is important to explore the gold rectangle defined by the four main concepts of this ontology: *VffNon-FunctionalRequirements*; *VffKPI*; *VffMetrics* and *VffPerformanceAssociation*. Indeed, the *VffNon-FunctionalRequirements* defines which should be the concrete objectives to be achieved by the manufacturing system, similarly to what was already explained when the FOPD concept was presented. However, in order to measure if this goals are being achieved or not, a KPI should be defined (*VffKPI class*). Indeed, a KPI is not more than an indicator strictly related with a certain goal. Moreover, it should be attributed a metric to this KPI that will bring this theoretical concept closer to the operational layers and thus make it possible to attribute a measure to this variable (VffMetrics class).

However, this information is not enough to clearly assess if a certain non-functional requirement is being achieved or not. Indeed, in order to assess something it is always necessary to have a reference that make it possible to beacon our mind-set about the performance of a manufacturing system. In line with this, the *VffPerformanceAssociation* intends to aggregate the information concerning the non-functional requirement in analysis, the actual value of the KPI assigned to this non-functional requirements (*VffPerformanceMeasurement*) and the target value defined by the system's stakeholders (*VffTarget*), for a certain time interval. Indeed, as much as we approximate the vertex of the rectangle, the richer and proactive is the strategic performance management system.

Annex C.

Semantic Data Gathering

Following are presented the SPARQL necessary to extract each of the individuals related with the following information: KPI: HPU; classification level: 'Cost'; strategic level: 'operational'; time window that comprise the date for which the target value is required and the specified KPI's frequency.

- extract the individual that represents the classification type 'Cost'

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX VffPerformanceManagement: <http://www.vff-project.eu/VffPerformanceManagement.owl#>
PREFIX fn: <http://www.w3.org/2005/xpath-functions#>
PREFIX VffCommons: <http://www.vff-project.eu/VffCommons.owl#>;
PREFIX VffAutoEuropaUseCase: <http://www.vff-project.eu/VffAutoEuropaUseCase.owl#>
PREFIX IfcKernel: <http://www.vff-project.eu/IfcKernel.owl#>
PREFIX B2mmlResources: <http://www.vff-project.eu/B2mmlResources.owl#>
SELECT ?ft
WHERE {?ft rdf:type VffPerformanceManagement:VffClassification.
?ft VffPerformanceManagement:hasClassification ?class.
FILTER (regex(fn:lower-case(str(?class)),fn:lower-case(\"http://www.vff-project.eu/VffPerformanceManagement.owl#Cost")))}
```

Figure 112 - SPARQL Query to Extract Individual from VffClassification

- extract the individual that represents the strategic level 'Operational'

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX VffPerformanceManagement: <http://www.vff-project.eu/VffPerformanceManagement.owl#>
PREFIX VffStrategy: <http://www.vff-project.eu/VffStrategy.owl#>
PREFIX fn: <http://www.w3.org/2005/xpath-functions#>
PREFIX VffAutoEuropaUseCase: <http://www.vff-project.eu/VffAutoEuropaUseCase.owl#>
SELECT ?ft
WHERE {?ft rdf:type VffPerformanceManagement:VffStrategicLevel.
?ft VffPerformanceManagement:hasStrategicLevel ?class.
FILTER (regex(fn:lower-case(str(?class)),fn:lower-case(\"http://www.vff-project.eu/VffPerformanceManagement.owl#Operational")))}
```

Figure 113 - SPARQL Query to Extract Individual from VffStrategicLevel

- extract the individual that represents the date '2012-08-16'

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX fn: <http://www.w3.org/2005/xpath-functions#>
PREFIX IfcDateTimeResource: <http://www.vff-project.eu/IfcDateTimeResource.owl#>
SELECT ?ft
WHERE {?ft rdf:type IfcDateTimeResource:IfcDate.
FILTER (regex(fn:lower-case(str(?ft)),fn:lower-case(\"2012-08-16$\")))}
```

Figure 114 - SPARQL Query to Extract Individual from IfcDateTimeResource

- extract the individual that represents the KPI's frequency 'Monthly'

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX fn: <http://www.w3.org/2005/xpath-functions#>
PREFIX VffCommons: <http://www.vff-project.eu/VffCommons.owl#>;
PREFIX IfcMeasureResource: <http://www.vff-project.eu/IfcMeasureResource.owl#>
SELECT ?ft
WHERE {?ft rdf:type IfcMeasureResource:IfcLabel.
?ft VffCommons:hasContent ?freq.
FILTER (regex(fn:lower-case(str(?freq)),fn:lower-case(\"^monthly$\")))}
```

Figure 115 - SPARQL Query to Extract Individual from IfcMeasureResource

- extract the individual that represents the KPI ‘HPU’

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX VffPerformanceManagement: <http://www.vff-project.eu/VffPerformanceManagement.owl#>
PREFIX fn: <http://www.w3.org/2005/xpath-functions#>
PREFIX VffCommons: <http://www.vff-project.eu/VffCommons.owl#>;
SELECT ?ft
WHERE {
                {?ft rdf:type VffPerformanceManagement:VffKpi1Plus.
                ?ft VffCommons:hasName ?name.
                ?name VffCommons:hasContent ?str
FILTER (regex(fn:lower-case(str(?str)),fn:lower-case(\"^hpu$\")))}
UNION
                {?ft rdf:type VffPerformanceManagement:VffKpi0.
                ?ft VffCommons:hasName ?name.
                ?name VffCommons:hasContent ?str
FILTER (regex(fn:lower-case(str(?str)),fn:lower-case(\"^hpu$\")))}}
```

Figure 116 - SPARQL Query to Extract Individual from VffKPI

Finally, retrieved all the necessary individuals from the VF Manager, the PME is already prepared to extract the target values for a KPI, defined in a certain Domain and for each object that is being evaluated by this KPI (in this case a type of a car). Therefore, in the following SPARQL it is intended to extract the individuals from the VffFactoryGoal class that have an initial date 2012-08-01 and final date 2012-08-31 (both information extract from the combination of the information extracted from the SPARQL described before), that are connected with an individual from VffKPI class with name ‘hpu’, classification ‘Cost’ and strategic level ‘operational’, defined in the scope of the domain ‘AutoEuropa’.

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX VffPerformanceManagement: <http://www.vff-project.eu/VffPerformanceManagement.owl#>
PREFIX VffStrategy: <http://www.vff-project.eu/VffStrategy.owl#>
PREFIX fn: <http://www.w3.org/2005/xpath-functions#>
PREFIX VffCommons: <http://www.vff-project.eu/VffCommons.owl#>
PREFIX VffAutoEuropaTestCase: <http://www.vff-project.eu/VffAutoEuropaTestCase.owl#>
PREFIX IfcKernel: <http://www.vff-project.eu/IfcKernel.owl#>
PREFIX IfcKernel: <http://www.vff-project.eu/IfcKernel.owl#>
PREFIX B2mmlResources: <http://www.vff-project.eu/B2mmlResources.owl#>
SELECT ?carname ?targetValue ?targetVal
WHERE {?ft rdf:type VffStrategy:VffFactoryGoal.
?ft VffPerformanceManagement:hasDateInit VffAutoEuropaTestCase:2012-08-01.
?ft VffPerformanceManagement:hasDateEnd VffAutoEuropaTestCase:2012-08-31.
?ft VffStrategy:goalRelatedTargetValueForKPI ?target.
?ft VffPerformanceManagement:hasMeasurementObject ?car.
?ft VffPerformanceManagement:hasKPI1plus ?kpiused.
?car VffCommons:hasName ?car1.
?car1 VffCommons:hasContent ?carname.
?kpiused VffPerformanceManagement:hasDomain ?dom.
?kpiused VffPerformanceManagement:hasClassification ?class.
?kpiused VffPerformanceManagement:hasStrategicLevel ?strat.
?dom VffCommons:hasName ?domobj.
?domobj VffCommons:hasContent ?domainname.
?kpiused VffCommons:hasName ?kpiusedlabel.
?kpiusedlabel VffCommons:hasContent ?kpiusedName.
?target B2mmlResources:hasValue ?targetVal.
?targetVal VffCommons:hasContent ?targetValue.
FILTER (regex(fn:lower-case(str(?kpiusedName)),fn:lower-case(\"^hpu$\")) &&
regex(fn:lower-case(str(?domainname)),fn:lower-case(\"^AutoEuropa$\")) &&
regex(fn:lower-case(str(?class)),fn:lower-case(\"http://www.vff-project.eu/VffPerformanceManagement.owl#Cost$\")) &&
regex(fn:lower-case(str(?strat)),fn:lower-case(\"http://www.vff-project.eu/VffPerformanceManagement.owl#operational$\")))}
```

Figure 117 - SPARQL to Extract Target Values

Annex D.

Harbour Report

Oliver Wyman is one of the top five management consulting companies on a global scale, has its areas of focus strictly related with organization strategy, operations and risk management. On the other hand, Harbour Consulting is a recognized global leading in automotive manufacturing improvement, being the areas of focus mainly related with manufacturing performance improvement, the Harbour Reports for North America, Europe and South America and Benchmarking exercises. Figure 118 shows some of the main services provided by the combination of expertise of Oliver Wyman and Harbour Consulting to the key automotive manufactures.

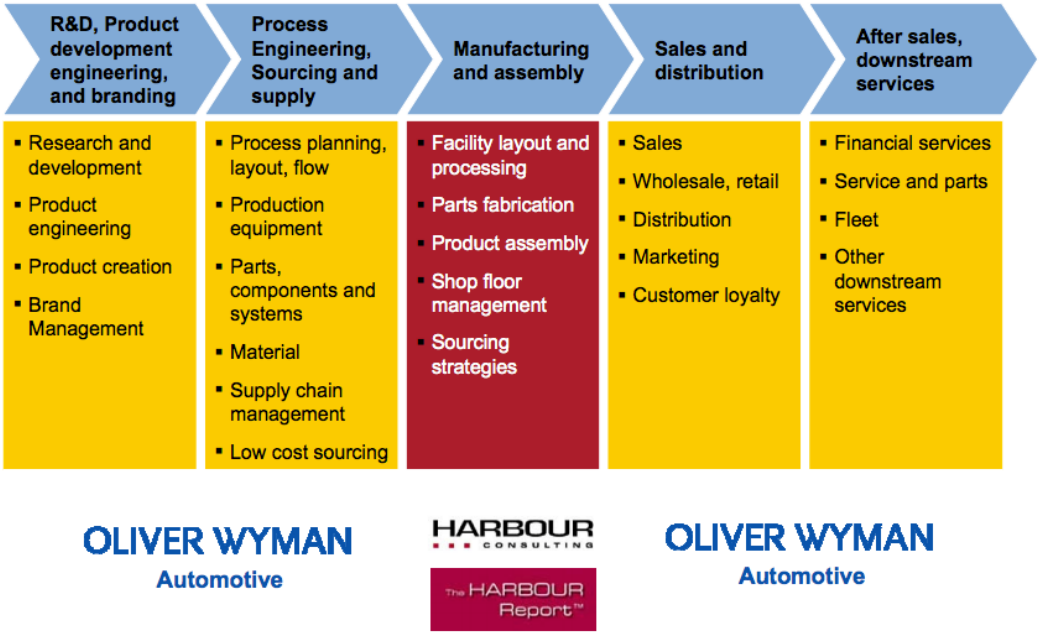

Figure 118 - Oliver Wyman and Harbour Consulting Services on Automotive Industry (extracted from The Harbour Report North America 2008)

In the scope of the Harbour Report, one of the main perspectives evaluated is the productivity related with the vehicles assembly, where each company and respective plants are detailed analysed. Here, the Key Performance Indicator used is the Hours per Vehicles, also known as HPV measure. As depicted in the following figure (Figure 119), this is a KPI oriented to the productivity perspective. Thus, its metric mainly combine information related with the manpower directly linked with the production line and the number of vehicles produced by these resources.

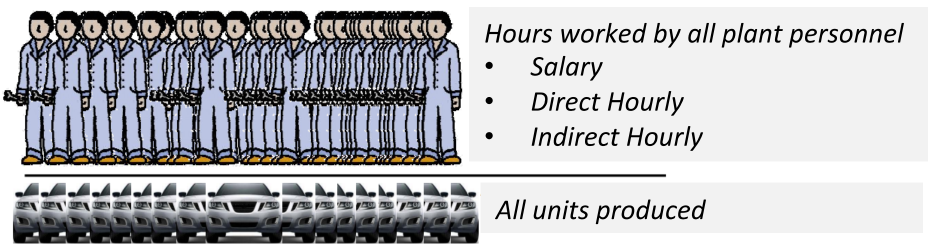

Figure 119 - Hours per Vehicle Metrics Scope (extracted from The Harbour Report North America 2008)

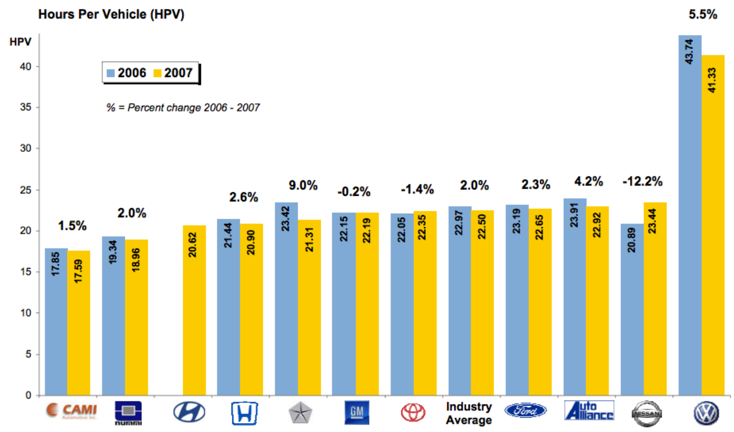

Figure 120 - Example of a companies Benchmarking chart in terms of productivity perspective (extracted from The Harbour Report North America 2008)

As an example of the outcome obtained from the benchmarking exercise provided by the Harbour Report, Figure 120 shows the ranking of companies in terms of productivity observed at 2007 at North America. On the other hand, Figure 121 shows the same benchmarking exercise but divided per plants and types of vehicles. If it is true that Figure 120 provides an interesting view of automotive companies performance, in terms of operational management, Figure 121 use more detailed information, delivering, because of that, a reliable picture of the reality once production lines are compared per car segment.

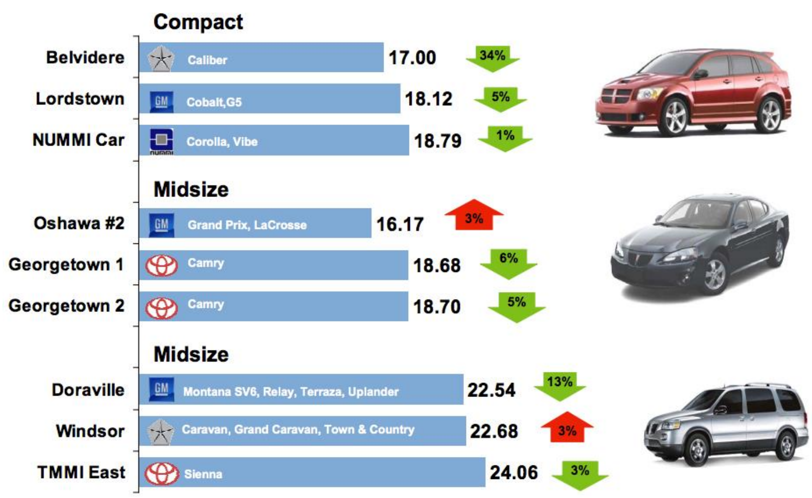

Figure 121 - Example of plants benchmarking in terms of productivity perspective (extracted from The Harbour Report North America 2008)

Annex E.

Painting Process

Following, for each activity represented within the painting process, a detailed description was performed:

Phosphate Coating: Initially, the car body that enters at the Paint line from the Body area needs to be submitted to different cleaning stages (car body pre-treatment) in order to remove the impurities originated in the previous section. This is the reason why the phosphate coating is the first main activity of the painting process.

This activity is performed on steel parts for corrosion resistance and used as a foundation for subsequent coatings or painting. It works as a conversion coating in which a diluted solution of phosphoric acid and phosphate salts is applied via immersion and chemically reacts with the surface of the part being coated to form a layer of insoluble and crystalline phosphates, capable of increasing the porosity and enhance the ink penetration.

E-Coat: Following, the car body needs to be submitted to an E-coat process. This industrial process, also known as Electrophoretic deposition (EPD), enables that colloidal particles suspended in a liquid medium migrate under the influence of an electric field (electrophoresis) and are deposited onto an electrode.

In other words, after the car body finished its cleaning process, the body parts are submerged in an E-Coat tank where the body, full of negative charge (--) is in contact with the ink with opposite charge (++). With this process, the ink particles are attracted to the body car forming a uniform film, with a specific density, over the entire vehicle.

This activity ends when the car is introduced within an E-Coat Oven aiming to cure the paint film, making it hard and durable to assure maximum performance properties. The temperature can range between 80ºC and 200ºC.

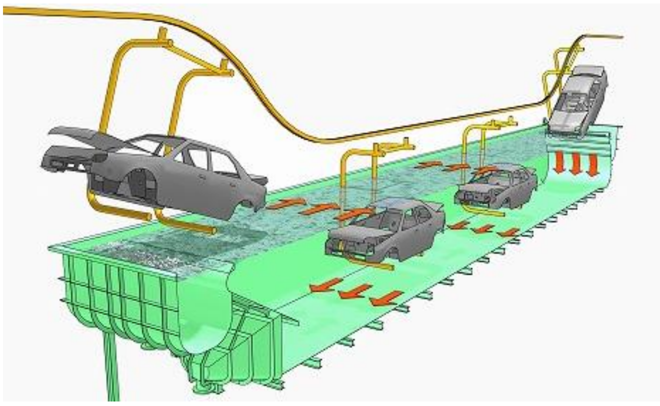

Figure 122 - Example of E-Coat Bath

Sealer Line: The third main activity developed during the Autoeuropa painting line is the Sealing stage. Typically, a sealant, which is a viscous material with little or no flow characteristics, is used to close small openings that are difficult to shut with other materials, offering important properties such as insolubility, corrosion resistance, and adhesion.

Therefore, from this activity, it is expected to be provided the following three basic functions.

1. Fill a gap between two or more parts of the car body.
2. Form a barrier through the physical properties of the sealant itself and by adhesion to the body parts.
3. Maintain sealing properties for the expected lifetime, service conditions and environments.

Nowadays, the application of the sealant is done automatically with robotic arms, following a Flat-Stream approach, and manually where specialized operators apply sealant in specific/critical points of the body. As explained before, the sealer is applied using a Flat-Stream approach, as presented in the figure below. In this figure, it is also possible to depict other different sealer application approaches such as the full cone and the hollow cone.

This activity ends when the car is introduced within a Sealer Oven aiming to cure the sealant applied at this stage, making it hard and durable to assure maximum performance properties.

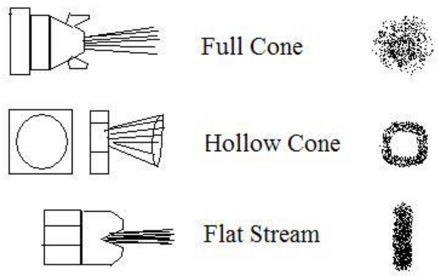

Figure 123 - Sealer Application Techniques

Primer Coat: After sealing all the main junctions of the body, the following activity of this complex industrial process is the primer coat. A primer or undercoat is a preparatory coating that ensures not only a better adhesion of the ink to the surface, but also increases the paint durability, providing additional protection to the body.

This main activity is divided into two main sub-activities: Primer Preparation and Primer Coat. While the first one is mainly performed by humans, the second one is performed by robotic arms for big areas and humans for small areas and details.

The application of the primer must be performed within a proper kiln called ARP (Air Replacement Plant). The ARPs use the atmospheric air from outside, refines the air, and supplies it to the Paint booth, thus creating a constant flow of dust free air into the paint booth, helping to maintain a positive pressure.

In sum, these units are responsible for creating an enclosed environment safer for workers by facilitating the elimination of toxic fumes and providing the right environment capable to enhance the painting process.

This activity ends when the car is introduced within a Primer Oven aiming to cure the primer applied at this stage, making it hard and durable to assure maximum performance properties.

Enamel: After the application of the primer, the body is prepared to be painted with the desired colour, which is the Enamel activity. This step is mainly divided into two main sub-activities: Base Coat and Clear Coat.

The Base Coat is, in a simple way, the application of the desired colour without any strengtheners or hardeners and it is not glossy. That's the reason why, afterwards it is necessary to apply some sort of clear coat or urethane base coat in order to stay protected from the elements and to make it shine. In line with this, the Clear coat paint activity should be performed.

Similarly to the previous activity, the enamel activity must be performed within a proper kiln called ARP (Air Replacement Plant). Thus, also in this activity, these units are responsible for creating an enclosed environment which is safer for workers by facilitating the elimination of toxic fumes and providing the right environment capable of enhancing the painting process.

This activity ends when the car is introduced within a Primer Oven aiming to cure the primer applied at this stage, making it hard and durable to assure maximum performance properties.

Buy off: Following, the body is ready to be sold to the final area of the production line (Assembly Line). Thus, the car goes to a section of the line called Buy Off where quality checks are performed by both Paint and Assembly line experts. Here, three different scenarios can happen: a) the paint doesn't present any problem so it is ready to go the RAS; b) the paint presents minor problems that can be solved at the Storage Repair; c) or the paint/body present major problems that force this car to go again to the Enamel stage.

Wax Cavity Coat: Finally, when all the quality procedures were performed and the special painting line transportation supports were extracted, the car goes to a final section where the wax is applied as a sealer of the cavities under the body, by a proper machine inside of an oven that should be at a specific temperature. In the same line, the wax must be maintained at a specific temperature in order to be at a liquid state.

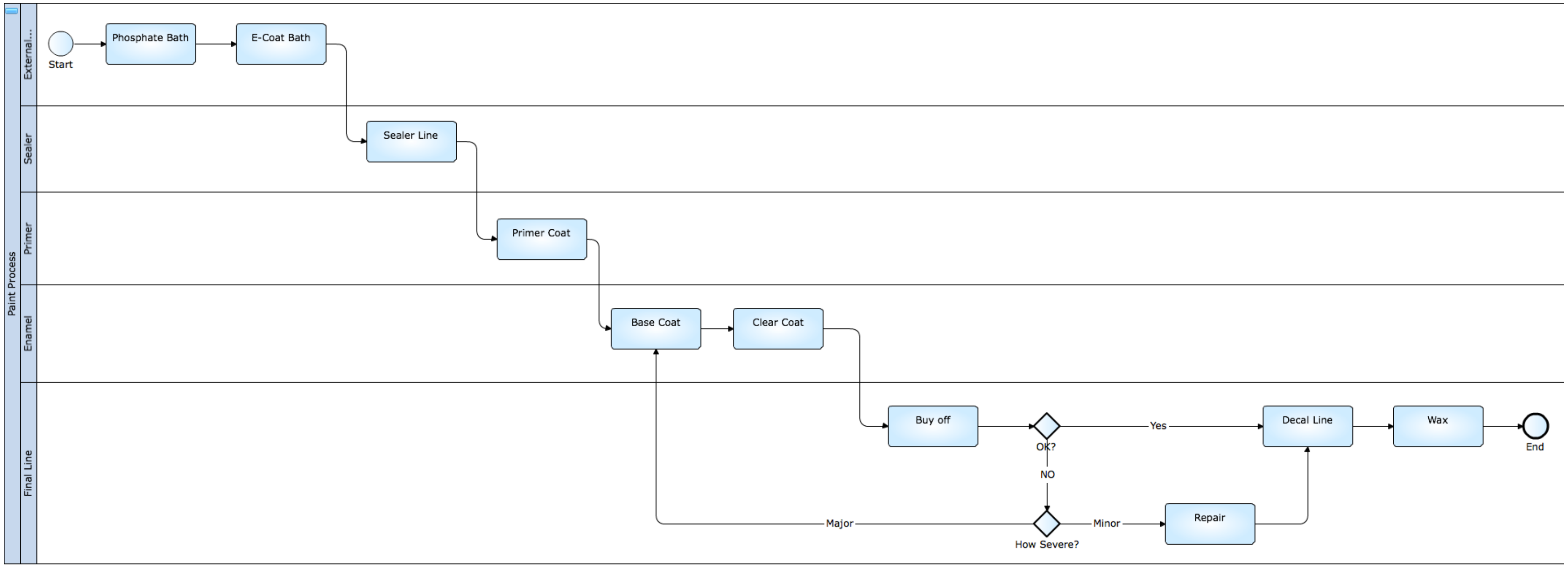

Figure 124 - Painting Process in Business Process Notation

Annex F.

Body Process

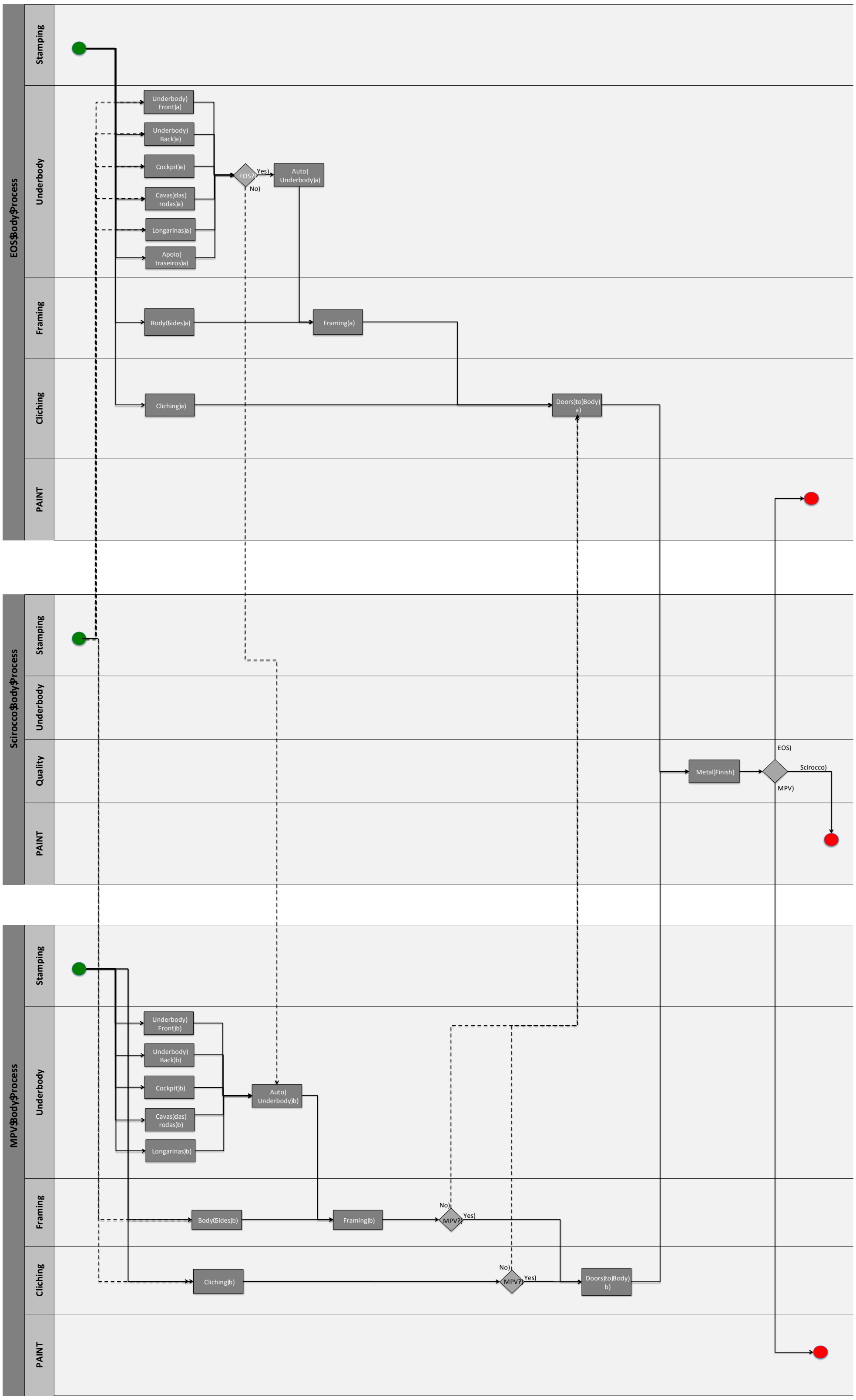

Figure 125 - Industrial Processes at Body Shop