Integrated Production Planning and Stock Management in the Capsule Injection and Capping Sectors

Eduardo Mesquita Torcato David

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Supervisor at FEUP: Prof. Ana Loureiro

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

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Abstract

In an increasingly volatile and competitive industrial landscape, manufacturers face growing pressure to improve internal reliability, increase agility, and respond more effectively to demand variability. These challenges are especially acute in high-mix production environments, where limited capacity and complex changeovers can compromise operational efficiency. In response, many companies are adopting Lean principles and digital tools to optimize their internal flows and service levels.

This dissertation presents an applied industrial project developed at Amorim Top Series (ATS), a manufacturing unit of Amorim Cork, within the cork industry's value chain. The project focused on improving the internal service level between the plastic capsule injection sector and the downstream capsuling process. The research followed an action-research design, framed as a continuous improvement initiative and supported by the A3 problem-solving tool, combining quantitative methods (Kanban sizing model and constructive scheduling heuristic) with qualitative insights from direct shop-floor observation and interactions with personnel. This approach ensured that the proposed solutions were both data-driven and aligned with real operational practices.

An initial diagnosis revealed persistent coordination issues between injection and capsuling, driven by long setup times, machine eligibility constraints, and lack of production visibility. Although operating under a make-to-order logic, the injection sector was often unable to supply capsules in time, especially during peak months, resulting in delayed starts in capsuling and increased operational stress. Between January and April, the internal service level averaged only 60%, reaching a low of 48% in April, further highlighting the need for a more stable and anticipatory planning model.

To address these issues and achieve a 95% service level target, two complementary tools were developed: a Kanban system and a constructive scheduling heuristic. The Kanban system was designed to define the optimal stock levels for each plastic capsule, enabling a controlled transition from make-to-order to make-to-stock production. A robust and factory-aligned calculation model was developed, capturing key production dynamics and constraints to ensure operational feasibility. This system was integrated into a Power BI dashboard that automatically updates stock status using colour-coded alerts. A visual layout redesign based on 5S principles was also implemented to create a dedicated area for managing Kanban stock.

In parallel, a constructive heuristic was developed in Python to allocate production orders across ten injection machines, minimizing total setup time while ensuring that all capsules were ready before their due dates. The algorithm considered mold compatibility, sequence-dependent setups, engraving delays and machine eligibility. It used a slack-time-based dispatching rule and included a realistic working calendar with weekends and August as non-working periods. The output was a fully scheduled production plan, visualized through a compressed Gantt chart and exported to Excel. A total of 181 production orders were successfully scheduled, with 6 late deliveries. The simulation showed a reduction in the average setup duration between orders, decreasing from 75 minutes in the reference sequence to 18 minutes in the simulated sequence. This differ-

ence results from the sequencing logic suggested by the heuristic, which supports the planner in decision-making, and not from changes in the individual setup durations (no SMED was applied).

Together, these tools contributed to a more synchronized, agile and reliable production system. The results demonstrate the value of combining Lean principles with an action-research design and tailored data-driven solutions in complex manufacturing environments, offering a replicable framework for other industrial sectors aiming to improve internal performance and responsiveness.

Resumo

Resumo

Num ambiente industrial cada vez mais volátil e competitivo, os fabricantes enfrentam uma pressão crescente para aumentar a fiabilidade interna, reforçar a agilidade e responder de forma mais eficaz à variabilidade da procura. Estes desafios são particularmente evidentes em contextos de elevada diversidade de produtos (high-mix), onde a capacidade limitada e as trocas frequentes comprometem a eficiência operacional. Em resposta, muitas empresas têm vindo a adotar princípios Lean e ferramentas digitais para otimizar os fluxos internos e os níveis de serviço.

Esta dissertação apresenta um projeto industrial aplicado, desenvolvido na Amorim Top Series (ATS), uma unidade fabril da Amorim Cork, no seio da cadeia de valor da indústria corticeira. O trabalho centrou-se na melhoria do nível de serviço interno entre o setor de injeção de cápsulas plásticas e o processo subsequente de capsulagem. A investigação seguiu um desenho de action-research, enquadrado como uma iniciativa de melhoria contínua e suportado pela ferramenta A3 de resolução de problemas, combinando métodos quantitativos (modelo de dimensionamento Kanban e heurística construtiva de sequenciação) com contributos qualitativos obtidos através de observação direta no chão de fábrica e interações com os colaboradores. Esta abordagem garantiu que as soluções propostas fossem simultaneamente baseadas em dados e ajustadas às práticas reais da operação.

O diagnóstico inicial revelou problemas persistentes de coordenação entre injeção e capsulagem, motivados por tempos de setup elevados, restrições de elegibilidade de máquinas e falta de visibilidade sobre a produção. Embora operando sob uma lógica make-to-order, o setor de injeção frequentemente não conseguia abastecer a capsulagem atempadamente, sobretudo nos meses de pico, originando arranques tardios e maior pressão operacional. Entre janeiro e abril, o nível de serviço interno situou-se em média nos 60%, atingindo um mínimo de 48% em abril, o que evidenciou a necessidade de um modelo de planeamento mais estável e antecipatório.

Para responder a estas limitações e alcançar a meta de 95% de nível de serviço, foram desenvolvidas duas ferramentas complementares: um sistema Kanban e uma heurística construtiva de sequenciação. O Kanban foi concebido para definir os níveis ótimos de stock por cápsula, permitindo uma transição controlada de make-to-order para make-to-stock. O modelo de cálculo desenvolvido foi robusto e alinhado com a realidade fabril, incorporando dinâmicas e restrições produtivas críticas. Este sistema foi integrado num dashboard em Power BI, com atualização automática do estado dos stocks através de alertas visuais. Paralelamente, foi feita uma reorganização visual do layout, apoiada nos princípios 5S, criando uma área dedicada à gestão dos artigos regulados por Kanban.

Em simultâneo, foi desenvolvida em Python uma heurística construtiva para alocar ordens de produção em dez máquinas de injeção, minimizando o tempo total de setup e assegurando que todas as cápsulas estivessem disponíveis antes das respetivas datas-pedido. O algoritmo considerou

compatibilidade de moldes, setups dependentes da sequência, tempos adicionais de gravação e restrições de elegibilidade das máquinas. Recorreu a uma regra de prioridade baseada no slack time e integrou um calendário realista, com exclusão de fins de semana e do mês de agosto. O resultado foi um plano de produção totalmente calendarizado, visualizado num gráfico de Gantt compacto e exportado para Excel. Foram alocadas 181 ordens de produção, das quais apenas 6 ficaram fora de prazo. A simulação evidenciou uma redução do tempo médio de setup entre ordens, de 75 minutos na sequência de referência para 18 minutos na sequência simulada. Esta diferença resulta da lógica de sequenciação sugerida pela heurística, que apoia o planeador na tomada de decisão, e não de alterações na duração individual dos setups (não foi aplicada a metodologia SMED).

No conjunto, estas ferramentas contribuíram para um sistema produtivo mais sincronizado, ágil e fiável. Os resultados demonstram o valor de combinar princípios Lean com um desenho de action-research e soluções digitais customizadas em ambientes industriais complexos, oferecendo um quadro replicável para outros setores que procurem melhorar o desempenho interno e a capacidade de resposta.

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"In theory, there is no difference between theory and practice. But in practice, there is"

Yogi Berra

Contents

Acronyms and Symbols

ATC	Apparent Tardiness Cost
ATS	Amorim Top Series
CONWIP	Constant Work In Process
CP	Constraint Programming
EDD	Earliest Due Date
JIT	Just In Time
Kaizen	Continuous Improvement
KPI	Key Performance Indicator
LPT	Longest Processing time
MST	Minimum Slack Time
MTO	Make-to-Order
MTS	Make-to-Stock
NP-Hard	Non-deterministic Polynomial-time Hard
TPS	Toyota Production System
UPMSP-SE	Unrelated Parallel Machine Scheduling Problem with Sequence-Dependent Setups
WIP	Work in Process

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Chapter 1

Introduction

This project was carried out within the scope of the curricular unit Dissertation, an integral part of the Master's in Industrial Engineering and Management at the University of Porto.

The project was outlined and proposed by Amorim Cork, S.A., and was developed in a business environment, specifically at the Amorim Top Series industrial unit.

The project was conducted within the Production Planning Department, whose team provided continuous support and guidance throughout its development.

1.1 Project Framework and Motivation

The current industrial landscape is marked by uncertainty and interdependence. Global disruptions such as the COVID-19 pandemic, the war in Ukraine, and inflation have affected supply chains and procurement dynamics, exposing limitations in planning models based on long-term forecasts, extended sourcing strategies, and minimal inventory levels (Dell, 2021; Johnson, 2019). These developments have prompted a reassessment of standard operational assumptions and drawn attention to the need for more adaptable planning approaches.

At the same time, industrial production is subject to regulatory and environmental requirements. Within the European Union, instruments such as the European Green Deal, the Circular Economy Action Plan, and the Sustainable Products Initiative promote a transition towards production systems that incorporate resource efficiency, traceability, and lifecycle considerations (Nicholas, 2020). For many companies, this implies changes in internal processes and supply practices to comply with evolving guidelines and constraints.

Technological advances have also transformed industrial operations. The integration of Industry 4.0 technologies, such as the Internet of Things, data analytics, and cyber-physical systems, has improved visibility and responsiveness across production processes(Xu et al., 2021). However, these technologies introduce coordination challenges, particularly in settings with heterogeneous systems or limited integration capacity. Ensuring that available data leads to consistent and timely decisions remains a relevant concern.

This context has led to a redefinition of the role of production planning. Traditionally, planning focused on optimizing efficiency under stable conditions. More recently, it has come to serve as a buffer against uncertainty, requiring systems that are not only cost-effective but also capable of absorbing variability in demand, supply, and production availability. This change in emphasis affects both the tools adopted and the expectations placed on planning teams.

Moreover, many organizations face difficulties aligning strategic goals with day-to-day execution. While advanced planning tools can provide long-term visibility, their impact is often constrained by disconnected systems and lack of coordination across operational functions. As a result, there is increasing interest in robust planning approaches at the execution level, capable of translating high-level objectives into reliable operational routines.

In this context, there has been renewed attention to hybrid production models that account for demand variability and operational constraints. Approaches that combine MTS and MTO logic offer an alternative to rigid planning structures (Peeters & van Ooijen, 2020; Xiong et al., 2020). These models can support short-term adjustments without relying solely on capacity buffers or high inventory levels. On the shop floor, control systems such as Kanban–CONWIP have been applied to help synchronize production under demand variation (Liberopoulos & Dallery, 2014; Paksi Hartoyo & Arvitrida, 2020). Lean tools, such as visual management, pull systems, and production leveling, continue to be used to enhance coordination and maintain smooth production flow(Bicheno, 2017; M. Maarleveld, 2014).

A key operational trade-off in this environment is the balance between responsiveness and stability. On one hand, organizations must accommodate fluctuations in order volume, product mix, and customer specifications. On the other, frequent adjustments in schedules, setups, and resource allocation can undermine the consistency of production flow. Managing this balance requires planning systems that are able to anticipate variability without introducing operational volatility.

Sectors characterized by product variety, short production runs, and client specific requirements are particularly exposed to these tensions. The need to manage frequent changeovers, comply with delivery schedules, and adjust to customized specifications places constraints on planning and resource allocation. In such contexts, synchronizing production stages while maintaining stable flow and minimizing idle time becomes a central concern. The cork industry illustrates many of these conditions. It relies on raw materials that are harvested seasonally and subject to quality variation, requiring careful planning across the entire value chain. In parallel, customers increasingly demand differentiated products, both functionally and aesthetically, which leads to shorter production batches and higher variation in manufacturing routines. These characteristics reinforce the importance of planning systems that are sufficiently structured to provide stability, yet flexible enough to adapt to operational variability.

This project takes place within a dynamic industrial environment, influenced by market fluctuations, regulatory changes, technological advances, and shifting customer expectations. The emphasis on planning and coordination aims to align operational decisions with these external factors while staying consistent with Lean principles and a culture of continuous improvement

1.2 Company Profiles

This chapter presents the institutional context in which the project was developed, with a brief overview of Amorim Cork, S.A., and a focused description of the Amorim Top Series unit, where the project was carried out.

1.2.1 Amorim Cork, S.A.

Amorim Cork, S.A. is part of Corticeira Amorim, S.G.P.S., S.A., the global leader in the cork industry. Founded in 1870, the Amorim group has grown from a small cork stopper factory in northern Portugal to a multinational organization operating in over 100 countries.

Corticeira Amorim is structured into three business units:

- **Raw Materials**: Management of cork harvesting and primary transformation.
- **Cork Stoppers**: Main business unit, producing stoppers for wine, sparkling wine, and spirits.
- **Cork Solutions**: Development of innovative cork-based materials and applications for industries such as construction, design, mobility, and energy.

Amorim Cork, S.A. leads the Cork Stoppers unit and is the world's largest producer and supplier of cork stoppers, with a strong focus on quality, innovation, and sustainability.

1.2.2 Amorim Top Series

Amorim Top Series is a specialized unit within Amorim Cork, S.A., focused on the production of encapsulated cork stoppers for the premium spirits market. The unit combines cork with a variety of complementary materials to deliver tailored solutions that reflect customer requirements in terms of design, functionality, and brand identity.

Its operations are based in Portugal, with an additional industrial site in France, and it serves a global client base. The unit plays a key role in the group's strategy for high value added products, combining industrial flexibility with design precision. Because of its complex product range and the need for short lead times, the unit relies on strong planning and coordination across its production areas, especially between injection and capsuling, which is the focus of this dissertation.

1.3 Objectives

The production process at the Amorim Top Series unit involves several interconnected sectors for the manufacturing of encapsulated cork stoppers. It begins in the injection sector, where plastic capsules are produced. Some capsules are immediately ready for consumption in the capping sector, while others go through an engraving process in the same area. Cork stoppers, supplied by other units of the Amorim group, undergo several operations including mechanical finishing, washing, sorting, and final treatment before becoming available for capsuling.

Currently, the lack of coordination between the injection and capsuling sectors creates inefficiencies and material flow disruptions. The absence of regulated intermediate stock and synchronization mechanisms often results in situations where cork stoppers are ready, but capsules are not, or vice versa. This misalignment leads to stockouts, delays, and reduced process reliability.

The core challenge lies in ensuring that both sectors are aligned so that the required quantities of capsules and corks are available when needed, minimizing disruptions and optimizing resource use across the production system.

This dissertation aims to improve production planning at the Amorim Top Series unit by implementing a Kanban-based system supported by demand forecasting. The goal is to ensure continuous and efficient supply from the injection sector to the capping sector, while enhancing agility in the production flow. To address this challenge, a constructive scheduling heuristic was also developed to sequence production orders in the injection sector in a way that reduces setup times and respects delivery priorities.

The primary performance metric adopted is the service level of the injection sector towards the capsuling sector. This allowed for an objective evaluation of the planning effectiveness and its impact on the continuity of the production flow.

In addition to avoiding shortages, the project seeks to increase operational efficiency by reducing waiting times and optimizing resource usage. The system also promotes real-time visibility for planners and operators, enabling quick reactions to deviations and facilitating alignment between planning and execution.

Finally, the proposed approach is designed to be scalable and transferable, with the potential for future replication in other areas of the unit or across different sites within the Amorim group, contributing to sustained operational performance in a competitive environment.

1.4 Project Structure

This master's thesis is structured into five main chapters, following a logical and iterative methodology aligned with its practical application in the Amorim Top Series unit. The structure reflects the progression from problem framing to solution design, implementation, and evaluation, with a focus on improving planning coordination between the injection and capsuling sectors.

Chapter One, Introduction, establishes the context and motivation of the project. It presents the main challenges faced by the unit in coordinating production across sectors with different cadences and constraints. The objectives are clearly defined, including the improvement of the service level from injection to capping through better planning and synchronization.

Chapter Two, Literature Review, provides the theoretical foundation for the project. It explores key concepts from Lean and Agile production systems, with emphasis on Kanban, Just-in-Time, and forecast-based planning. It also includes a brief review of heuristic scheduling approaches relevant to short-term production planning in variable industrial environments.

Chapter Three, Initial State and Problem Overview, analyzes the current state of operations at the Amorim Top Series unit. It maps the interaction between injection and capsuling sectors, identifies inefficiencies caused by the lack of intermediate stock and synchronization, and quantifies the impact on service level. The chapter also defines the scope of the intervention and the performance indicators used to assess the proposed improvements.

Chapter Four, Methodology, details the design and implementation of the proposed planning system. It presents the development of a Kanban-based replenishment model tailored to the unit's operational conditions, including the calculation of stock levels, the number of Kanban cards, and replenishment times. In parallel, it describes the construction of a scheduling heuristic to support short-term production planning in the injection sector. The heuristic was designed to minimize setup times, reduce mold changes, and ensure on-time delivery, while accounting for engraving steps and machine constraints. The chapter also includes layout adjustments, the implementation of a Power BI dashboard for real-time monitoring, and the performance evaluation of the integrated solution.

Chapter Five, Results, presents the outcomes of the analysis and implementation carried out throughout the project. It details the performance of the proposed planning model and stock-control mechanisms, assessing their effectiveness in addressing the identified challenges. The chapter evaluates improvements in production flow, alignment between injection and capsuling, and the contribution to higher reliability and responsiveness of operations. It also highlights quantitative and qualitative results, providing evidence of the model's impact and establishing the basis for the final conclusions.

Chapter Six, Conclusions and Future Work, summarizes the project's main findings and evaluates the impact of the implemented solutions on production continuity and operational coordination. It reflects on lessons learned and discusses the potential for replicating the methodology in other units or sectors. The chapter also identifies directions for future work, emphasizing the importance of scalable planning tools and continuous improvement practices in dynamic manufacturing environments.

Chapter 2

Literature Review

This chapter provides an overview of the main concepts and methodologies relevant to modern production systems. It covers Lean and Agile principles, 5S practices, project initiation tools like the A3 methodology, inventory management, forecasting, Kanban systems, and constructive heuristics for complex scheduling. The aim is to set the theoretical foundation for the approaches discussed in the following sections.

2.1 Lean and Agile Philosophies in Manufacturing

2.1.1 Origin of Lean Philosophy

Lean manufacturing, also known as lean production, is a systematic approach to minimizing waste within manufacturing systems while simultaneously maximizing productivity. Its origins can be traced back to the post-World War II era in Japan, particularly to the Toyota Production System (TPS) developed by Toyota Motor Corporation. This system was pioneered by engineers like Taiichi Ohno and Shigeo Shingo, who sought to enhance efficiency by eliminating waste and improving processes.

The TPS introduced several key concepts, including just-in-time production, which emphasizes producing only what is needed, when it is needed, and in the amount needed, thereby reducing inventory costs and waste. Another fundamental principle is *jidoka*, or automation with a human touch, which involves stopping production when a problem occurs to prevent defects. These principles collectively aimed to create a more efficient and responsive manufacturing process.

The term "lean" itself has appear much later, in 1988, by Krafcik (1988) in his article *Triumph of the Lean Production System*. Krafcik used the term to describe a production system that uses less of everything compared to mass production: half the human effort, half the manufacturing space, half the investment in tools, and half the engineering hours to develop a new product in half the time. This concept was further popularized in 1990 by Womack et al. (1990) and Ohno (1988) in their book *The Machine That Changed the World*, which provided a comprehensive analysis of the lean production system and its advantages over traditional mass production methods.

Lean manufacturing has since been adopted worldwide across various industries beyond automotive manufacturing, including electronics, healthcare, and service industries, due to its effectiveness in improving efficiency and reducing waste (Krafcik, 1988; Ohno, 1988; Womack et al., 1990).

2.1.2 Lean Principles

Central to this philosophy are five core principles outlined by Womack and Jones (1996), which serve as the foundation for implementing lean practices.

The first principle is to define value from the perspective of the end customer. By clearly understanding what constitutes value, organizations can direct their resources toward activities that meet customer needs and eliminate those that do not. This leads to more efficient processes and greater customer satisfaction.

The second principle involves mapping the value stream, which consists of all the actions required to bring a product from concept to delivery. This mapping process allows firms to identify non-value-adding activities, also referred to as waste, and prioritize their elimination. It is through this transparency that lean organizations begin to unlock significant performance improvements.

The third principle is to create continuous flow. Once wasteful steps have been removed, the focus shifts to ensuring a smooth and uninterrupted flow of materials and information throughout the production process. Achieving flow often requires a reconfiguration of workflows, load balancing, and cross-functional training of personnel.

The fourth principle is to establish a pull system. In contrast to traditional push systems, where production is driven by forecasts, a pull system ensures that production is based on actual customer demand. The Just-in-Time (JIT) approach, a hallmark of lean manufacturing, is closely tied to this principle. JIT emphasizes producing only what is needed, when it is needed, and in the quantity needed, thereby minimizing inventory levels and reducing storage costs. This requires high levels of coordination with suppliers and well-designed scheduling systems to avoid delays or shortages.

The fifth and final principle is the pursuit of perfection. Lean manufacturing is inherently a continuous improvement process. Known as *kaizen*, this principle encourages all employees to constantly seek out inefficiencies and suggest improvements. The goal is to foster a culture of learning and incremental advancement that gradually eliminates waste and enhances quality across the organization.

Together, these principles help companies boost productivity, lower operational costs, and respond more effectively to customer needs. Empirical studies indicate that organizations applying lean principles, especially when combining technical and cultural aspects, achieve better performance compared to those relying on traditional manufacturing methods(Bortolotti et al., 2015; Ohno, 1988; Womack & Jones, 1996).

2.1.3 Agile Methodologies in Production Planning

Originally developed within the software industry, agile methodologies have progressively gained relevance in manufacturing environments, particularly in the area of production planning. These methodologies promote iterative development, responsiveness to change, and continuous improvement, offering an effective framework for companies operating under conditions of uncertainty and variability. Unlike traditional linear planning models, agile approaches allow production systems to be more adaptive, especially when facing fluctuating demand and customized production orders (Kidd, 1995).

The concept of Agile Manufacturing extends agile principles to the industrial context by focusing on rapid responsiveness to customer needs and the ability to reconfigure production processes efficiently. Agile manufacturing relies on the integration of flexible technologies, modular equipment, decentralized decision-making, and workforce empowerment to support rapid adaptation. Gunasekaran (1999) proposed a framework highlighting how agility in manufacturing enables organizations to remain competitive by responding promptly to dynamic market environments. Similarly, Sharifi and Zhang (2001) emphasized the importance of organizational culture and strategic alignment in successful agile manufacturing implementations.

In production planning, agile methodologies support a shift from rigid, long-term planning cycles to more dynamic, iterative approaches. Methods like Scrumban, which combines Scrum and Kanban, have been adapted for use in manufacturing planning. This hybrid model combines the structured sprint planning from Scrum with the visual management and continuous flow of Kanban, allowing teams to manage production workflows more effectively and limit work-in-progress while maintaining flexibility. Such approaches are particularly valuable in environments with frequent changes in production priorities or customer specifications.

Moreover, agile production planning encourages synchronization between demand signals and production execution. Rather than relying solely on forecasts, agile methods advocate for real-time responsiveness through tighter feedback loops and closer integration across departments. Yusuf et al. (2004) demonstrated that firms adopting agile supply chain capabilities were better equipped to meet customer requirements, manage lead time variability, and achieve higher levels of operational resilience.

Overall, the incorporation of agile principles into production planning complements lean manufacturing by adding a layer of adaptability and responsiveness. While lean focuses on the elimination of waste and optimization of flow, agile emphasizes the ability to respond to change quickly and efficiently. The combined application of both methodologies can enhance the competitiveness of manufacturing organizations in complex and volatile markets.

2.1.4 5S

The 5S is a foundational component of lean, designed to establish and maintain efficient, safe, and organized workplaces. Originating in Japan and popularized through the TPS, the term "5S" stands for five Japanese words: *Seiri* (Sort), *Seiton* (Set in Order), *Seiso* (Shine), *Seiketsu* (Standardize), and *Shitsuke* (Sustain). Each of these steps serves a specific purpose in workplace organization and collectively contributes to the elimination of waste and the enhancement of productivity (Gapp et al., 2008).

The first step, Sort (*Seiri*), involves identifying and removing all unnecessary items from the work environment, ensuring that only essential tools and materials are retained. This practice is critical for freeing up space, reducing clutter, and eliminating distractions, which in turn facilitates more efficient workflows and safer operations.

Set in Order (*Seiton*) refers to the logical arrangement of remaining items so that tools and equipment are easily accessible and located as close as possible to where they are needed. Proper implementation of this step reduces search time, minimizes motion waste, and supports standardization efforts across teams.

Shine (*Seiso*) focuses on cleanliness and regular maintenance of the workplace. Beyond aesthetic improvements, this phase serves a functional role by helping to detect abnormalities, leaks, or wear in equipment, contributing to proactive maintenance practices and reducing unexpected downtime.

The fourth step, Standardize (*Seiketsu*), involves creating routines and setting formal standards that ensure consistency in the execution of the first three steps. This includes the development of visual controls, checklists, and scheduled audits, which help integrate 5S practices into the daily habits of employees.

Finally, Sustain (*Shitsuke*) focuses on embedding a culture of discipline, continuous improvement, and commitment to the 5S methodology. This step is often the most challenging, as it requires behavioral change and long-term dedication from all organizational levels. Evidence suggests that companies that consistently reinforce 5S principles over time tend to achieve more stable and efficient operations, with positive effects on quality, safety, and employee engagement (Rahman et al., 2017).

2.1.5 Kamishibai as a Lean visual audit tool

Kamishibai is a Lean visual management device for *process confirmation* and layered audits, used to verify adherence to standards on the shop floor and trigger corrective actions. Knop and Ulewicz (2018) characterize the Kamishibai audit as a standardized, visual method to assess compliance and sustain improvements in industrial quality inspection. Beyond manufacturing, healthcare studies show Kamishibai cards sustaining front-line compliance and real-time feedback loops, reinforcing its role as a lightweight, scalable audit mechanism (Bravo et al., 2023; Corrigan & Mack, 2019). In this project, Kamishibai supports daily checks (Kamishibai cards/board), enabling exception-based control and anchoring 5S discipline.

2.1.6 Project Initiation and the A3 Problem Solving

A structured and well-defined initiation phase is essential to the success of any project, as it sets the groundwork for clear objectives, aligned expectations, and an efficient execution strategy. Within

Lean environments, the A3 methodology has emerged as a widely adopted framework for supporting structured problem-solving and project planning. Originating from the TPS, the term "A3" refers to the standardized paper size used to summarize the entire problem-solving process on a single page, promoting clarity, focus, and alignment across teams (Niemi & Fraser, 2013).

The A3 process follows the Plan-Do-Check-Act (PDCA) cycle and provides a step-by-step approach for analyzing problems and initiating improvement projects. It begins by clearly articulating the problem or opportunity, ensuring that the project's scope is aligned with organizational priorities. A detailed analysis of the current state follows, supported by factual data and visual tools such as process maps, which help to identify existing inefficiencies. Subsequently, a root cause analysis is conducted using methods like the 5 Whys or cause-effect diagrams to uncover the underlying issues rather than treating symptoms (Flumerfelt et al., 2020).

Once the root causes are identified, countermeasures are proposed and evaluated for their potential effectiveness and feasibility. This leads to the definition of a target state, which includes measurable objectives and performance indicators. An implementation plan is then developed, outlining responsibilities, timelines, and required resources to ensure successful execution. The final component of the A3 methodology includes a follow-up plan to monitor the outcomes and ensure that corrective actions are sustained over time (Pereira et al., 2019).

The advantages of using A3 thinking during project initiation are multifold. It promotes cross-functional collaboration, engages employees in continuous improvement, and provides a transparent framework for communication and decision-making. Moreover, the concise and standardized structure of A3 reports allows knowledge sharing and organizational learning, which are essential elements of a Lean culture. By integrating the A3 methodology into the project initiation phase, organizations can ensure a disciplined, evidence-based, and collaborative approach that aligns with both Lean principles and agile responsiveness.

2.2 Push vs Pull Systems and Hybrid Approach

2.2.1 Push vs Pull

In manufacturing, "push" and "pull" systems represent two distinct approaches to production and inventory management. A push system schedules production based on forecasted demand, pushing products through the supply chain to anticipated customers. This method can lead to overproduction and excess inventory if forecasts are inaccurate. Conversely, a pull system initiates production in response to actual customer demand, pulling products through the supply chain as orders are received. This approach aligns production closely with demand, reducing inventory levels but requiring flexible manufacturing processes to respond swiftly to customer needs. Each system has its advantages and challenges, and the choice between them depends on factors such as demand predictability, production flexibility, and inventory holding costs (Hopp & Spearman, 2004; Spearman & Zazanis, 1992)

2.2.2 Hybrid Production Planning: Combining Stock Regulation and Demand Responsiveness

Hybrid production planning integrates elements of both push and pull systems to balance the benefits of demand anticipation and responsiveness. According to Spearman and Zazanis (1992), this approach often involves upstream production stages operating under a push system, producing goods based on demand forecasts to capitalize on economies of scale. In contrast, downstream stages typically follow a pull system, where production aligns with actual customer demand, enhancing flexibility and reducing the risk of overproduction.

Ghrayeb et al. (2009) demonstrate that this strategy is particularly effective in assemble-to-order manufacturing environments, where high demand uncertainty coexists with significant economies of scale. By implementing a hybrid push/pull system, companies can maintain optimal inventory levels while remaining responsive to market fluctuations.

Furthermore, Lin et al. (2012) emphasize the importance of strategically positioning the Customer Order Decoupling Point (CODP) within the production process. This point defines where the transition occurs between planning based on anticipated demand and production triggered by confirmed customer orders. Proper positioning of the CODP enables organizations to benefit from both upstream efficiency and downstream responsiveness.

Overall, hybrid planning models that combine push and pull logics allow organizations to leverage the strengths of each approach, improving flow stability, production efficiency, and customer satisfaction.

2.3 ABC Analysis and Forecasting

2.3.1 Role of Forecasting in Production Planning

Forecasting plays a central role in production planning, as it provides the basis for anticipating demand, scheduling production activities, and managing inventory levels. According to Fildes et al. (2009), forecasting allows companies to determine what to produce, in what quantities, and when, which is essential to avoid both shortages and overstocking. This proactive approach enables better coordination across departments, improving responsiveness and reducing operational waste.

Tang et al. (2015) highlight that production forecasting involves estimating future demand as well as the resources required to meet it, including labor, materials, and equipment. This alignment between procurement and manufacturing with customer needs is crucial for efficient operations. Similarly, Shaul et al. (2014) emphasize that accurate forecasts are key to preventing excess inventory and enabling efficient resource utilization, particularly in complex or seasonal industries.

In a manufacturing context, forecasting also supports strategic decision-making related to capacity planning and lead time management. Fildes et al. (2009) note that it helps businesses maintain optimal inventory levels, improving service levels and reducing holding costs. Furthermore, Tang et al. (2015) argue that effective forecasting not only improves production efficiency but also strengthens a company's ability to meet fluctuating market demands.

Overall, forecasting goes beyond simple prediction; it is a key driver of efficient, demand-driven production systems. When integrated with production planning, it facilitates data-informed decision making, supports lean operations, and contributes directly to customer satisfaction and competitiveness.

2.3.2 ABC Classification for Product Prioritization

ABC classification is a widely adopted inventory management technique used to segment items according to their relative importance to the business. Ravinder and Misra (2014) state that this method allows organizations to focus their efforts and resources on the most critical items, improving control and decision-making processes.

According to Fernandes et al. (2010), items in category 'A' usually represent a small percentage of the total inventory but account for a substantial share of the inventory value. These items require tight control and frequent review. 'B' items hold intermediate importance, representing a balance between value and volume, and are managed with moderate attention. 'C' items, though they may represent the majority in quantity, contribute the least to inventory value and can therefore be managed with simpler controls.

The foundation of ABC analysis lies in the Pareto Principle, which suggests that a small proportion of items often accounts for a large share of the overall impact. As Ravinder and Misra (2014) emphasize, this approach enables companies to identify and prioritize the few items that significantly affect service levels and operational performance, reducing inventory costs while maintaining customer satisfaction.

Huang and Kusiak (1996) further argue that accurate classification requires the analysis of item-level consumption or contribution to sales or production throughput. The authors highlight that when ABC classification is correctly implemented, it provides a structured basis for differentiated inventory policies, such as order frequency and safety stock allocation.

In sum, ABC classification is an essential tool for product prioritization within inventory systems. It allows for more effective resource allocation, differentiated control strategies, and ultimately supports the efficiency and cost-effectiveness of the overall supply chain.

2.4 Kanban in Manufacturing Context

2.4.1 Origin and Principles of Kanban

The Kanban was developed at Toyota in the late 1940s by Taiichi Ohno as a means of improving manufacturing efficiency through just-in-time (JIT) production. Kanban drew inspiration from how supermarkets restock their shelves, producing only what had been consumed, creating a demand-driven system that responds to real usage rather than relying on forecasts (Ohno, 1988).

This visual control system used cards to authorize and track production, ensuring materials flowed smoothly and only as needed.

Central to the Kanban methodology is the concept of visual management, where tasks or inventory levels are made visible to all stakeholders, allowing quick identification of workflow status and potential bottlenecks. Another fundamental element is the limitation of work in progress (WIP), which helps stabilize workflows and prevent overloading of resources. Additionally, Kanban is grounded in the pull principle: each process stage requests output from the preceding one only when necessary, avoiding excess inventory and overproduction (Fujimoto, 1999).

Unlike rigid scheduling systems, Kanban supports flexibility and adaptability, allowing production systems to respond more dynamically to real-time demand. Its simplicity and visual nature make it accessible across various organizational levels, and its foundation in continuous improvement aligns with lean thinking. Rather than relying on predictive control, Kanban emphasizes responsiveness and balance in operations, contributing to more stable and efficient production environments (Monden, 2011).

2.4.2 Types of Kanban

Several types of Kanban systems have been developed to support different operational needs in manufacturing environments. All of them rely on visual signals to control production flow, synchronize processes, and minimize waste. The most common form is the production Kanban, which signals the need to manufacture a specific quantity of items. This ensures that production is based on actual consumption rather than forecasts, avoiding overproduction and aligning output with real-time demand (Fernandes et al., 2010).

Withdrawal Kanban, sometimes referred to as conveyance Kanban, authorizes the movement of materials from one location to another within the production system. It is typically used to signal the internal transfer of components between processes, enabling a smooth material flow without overstocking (Huang & Kusiak, 1996). A similar mechanism can be extended externally through supplier Kanban, which provides vendors with replenishment signals based on actual usage. This enhances supply chain coordination and reduces lead times.

In cases of unexpected demand or supply disruptions, emergency and express Kanban are employed. Emergency Kanban is activated when production is interrupted due to equipment failure or material shortages, while express Kanban is used to expedite items urgently required to maintain the flow of production (Fujimoto, 1999). Lastly, through Kanban combines the functionalities of production and withdrawal cards, authorizing both manufacturing and movement of items across stations. This simplifies communication and reduces the number of signals needed to manage operations.

Choosing the appropriate type of Kanban system depends on the complexity of the production process and the level of flexibility required. Adapting these systems effectively contributes to increased visibility, improved workflow stability, and better responsiveness to demand variability.

2.4.3 Key Formulas in Kanban

Accurately sizing a Kanban system is fundamental to ensuring material flow and production stability in lean manufacturing. Several models have been proposed in the literature, ranging from classical formulations to more elaborate structures adapted to hybrid and dynamic environments.

One of the more comprehensive approaches is presented by Salgado and Varela (n.d.), who decompose the total number of Kanbans into five distinct components, each covering a specific aspect of production variability and flow control. The total number of Kanbans is given by:

$$K = RE + LO + WI + TI + SA \tag{2.1}$$

Where: - RE: replenishment time coverage - LO: lot size coverage - WI: withdrawal peak coverage - TI: time gap coverage - SA: safety coverage

Each component is defined as follows:

$$RE = \frac{(PR \times RT_{loop})}{NPT \times SNP} \tag{2.2}$$

$$LO = \frac{LS}{SNP} - 1, \quad \text{if } LS > SNP, \text{ else } LO = 0 \tag{2.3}$$

$$WI = \frac{WA - LS}{SNP}, \quad \text{if } WA > LS, \text{ else } WI = 0 \tag{2.4}$$

$$TI = \frac{PR}{NPT \times SNP} \times |T_c - T_s| \tag{2.5}$$

$$SA = \frac{PR \times ST \times 60}{NPT \times SNP} \tag{2.6}$$

Where: - PR: requirement per period [pieces/period] - RT_{loop}: replenishment lead time [minutes] - NPT: net production time [minutes/period] - SNP: standard number of parts per Kanban [pieces] - LS: lot size [pieces] - WA: withdrawal amount [pieces/period] - T_c: shift time model of customer [minutes] - T_s: shift time model of supplier [minutes] - ST: safety time [hours]

This formulation allows for a modular and transparent calculation of Kanban quantities, considering both time and quantity-based variabilities.

2.4.4 Application of Kanban in Hybrid Production Environments

Hybrid production environments combine push and pull planning strategies to respond to both forecast-driven processes and actual demand signals. Within these contexts, Kanban systems have been adapted to support mixed production flows, where different stages of the value stream may require distinct control mechanisms.

Klug (2016) proposed a hybrid push/pull Kanban design applicable during production ramp-up phases, emphasizing that Kanban parameters such as the number of cards must be dynamically adjusted to accommodate uncertainty and variable demand. His findings demonstrate that hybrid systems can reduce lead time variability and stabilize work-in-progress levels, especially during transitions between high and low volume phases.

In addition to Klug (2016) contributions, the implementation of hybrid push/pull Kanban systems has been explored in various manufacturing contexts to address the challenges posed by demand variability and production complexities. For instance, a study by J. Maarleveld (2016) investigated a structured production planning and control approach using a push-pull hybrid system in a manufacturing environment. The research highlighted that combining push strategies for long-term planning with pull mechanisms for short-term execution can enhance responsiveness and reduce lead times. This approach allows for better alignment between production schedules and actual demand, thereby improving overall operational efficiency. Such findings underscore the versatility of hybrid Kanban systems in accommodating the dynamic nature of hybrid production environments.

2.5 Performance Measurements and Decision Support

2.5.1 KPIs in Kanban Planning

In Kanban-based production planning, monitoring key performance indicators (KPIs) is essential to ensure system efficiency and responsiveness. A primary KPI in this context is the service level, which measures the system's ability to meet customer demand within a specified timeframe. According to Jodlbauer and Huber (2008), the service level reflects the proportion of orders delivered on time, serving as a critical metric for evaluating the effectiveness of production control systems.

The service level is influenced by various factors, including inventory policies, production lead times, and demand variability. Maintaining an optimal service level requires balancing these elements to avoid both stockouts and overproduction. Altendorfer (2015) demonstrates that adjusting lot sizes and planned lead times can significantly impact service levels and inventory performance, especially in single-stage production systems with uncertain lead times and variable demand.

Other performance indicators such as cycle time, throughput, and work-in-progress (WIP) levels are also essential in Kanban planning. These KPIs interact closely with service level performance. Reducing cycle time and controlling WIP, for instance, generally leads to increased throughput and better reliability in meeting delivery expectations. As Jodlbauer (2008) explains, a customer-driven approach to production planning reinforces the importance of aligning operational parameters with customer requirements in order to maintain high service levels.

Ultimately, the service level acts as both a strategic and operational indicator, guiding planning decisions and reflecting the capability of the Kanban system to deliver value in a timely manner. Monitoring and continuously improving this KPI is essential to ensure customer satisfaction and to support lean manufacturing objectives.

2.5.2 Data Monitoring through Dashboards

In Kanban-based production planning, the utilization of dashboards for data monitoring has become integral to enhancing process transparency and decision making efficiency. Dashboards serve as visual tools that aggregate real-time data, allowing stakeholders to monitor key performance indicators (KPIs) and swiftly identify areas requiring attention.

Alaidaros et al. (2020) proposed an enhanced theoretical framework aimed at improving the progress monitoring tasks within Agile Kanban methodologies. Their study emphasizes that traditional Kanban systems often lack comprehensive monitoring capabilities, which can impede effective project management. By integrating advanced dashboard functionalities, the framework facilitates better tracking of work-in-progress, cycle times, and bottlenecks, thereby promoting more informed decision-making.

Similarly, Janes and Sillitti (2013) discussed the principles of effective dashboard design in software project management. They highlighted that well-designed dashboards should present relevant metrics in an intuitive manner, enabling teams to quickly assess project health and progress. This approach aligns with the Kanban philosophy of visual management, where transparency is key to continuous improvement.

In a practical application, Ridwan et al. (2019) developed an e-Kanban application equipped with a monitoring dashboard to measure performance in rice sourcing at the Indonesian Bureau of Logistics. The dashboard provided real-time insights into sourcing activities, allowing for timely interventions and process optimizations. This case exemplifies how dashboards can be tailored to specific industry needs, enhancing the applicability of Kanban systems in diverse contexts.

The integration of dashboards into Kanban systems not only supports real-time monitoring but also fosters a culture of accountability and continuous improvement. By providing clear visual representations of KPIs, dashboards enable teams to promptly address issues, optimize workflows, and ultimately achieve higher levels of operational efficiency.

2.6 Constructive Heuristics for Parallel-Machine Scheduling with Sequence-Dependent Set-ups

Production environments that combine unrelated parallel machines, sequence-dependent set-up times, machine eligibility constraints and order due-dates give rise to NP-hard scheduling problems. In the last two decades, *constructive heuristics* have become a mainstream tool for generating high-quality schedules within industrial time constraints (Allahverdi, 2019).

2.6.1 Definition and Classification

A constructive heuristic incrementally builds a complete schedule from scratch, selecting one job at a time and assigning it to a machine–position pair according to a deterministic rule set (Ruiz & Maroto, 2005). These heuristics are typically classified into three families:

1. **Dispatching-rule based** (e.g., EDD, ATC, LPT, MST): jobs are sorted by a priority index and placed on the earliest feasible machine (Allahverdi, 2019). The *Minimum Slack Time (MST)* rule, in particular, prioritizes jobs with the smallest margin between the due date and the time needed for processing, making it especially effective in high-mix, time-sensitive environments.
2. **Block constructive** approaches: jobs are grouped into blocks (or batches) to reduce set-up frequency before insertion (Ruiz & Maroto, 2005).
3. **Hybrid constructive seeds**: a fast deterministic schedule is built first, then refined by local search or constraint programming (Heinz et al., 2023).

2.6.2 Representative Contributions

Pérez-González et al. (2019) propose two constructive rules for the UNRELATED PARALLEL MACHINE SCHEDULING PROBLEM with machine eligibility and sequence-dependent set-ups (UPMSP-SE). Their *Earliest Feasible Completion* rule assigns each job to the compatible machine that yields the minimum completion time while satisfying the due-date, reducing total set-up hours by up to 25 % against classical dispatching rules.

Heinz et al. (2023) present a hybrid approach in which a constructive seed schedule is generated within seconds and then improved by constraint programming. The constructive phase alone achieves near-optimal makespan for large industrial instances with common secondary resources.

For identical parallel machines, Xi et al. (2015) introduce a look-ahead constructive heuristic that minimizes total weighted tardiness by evaluating the downstream impact of each assignment. Although developed for identical machines, their anticipatory mechanism is relevant whenever job due-dates are tight.

Sequence-dependent set-ups with precedence constraints are addressed by Gacias et al. (2009), who build schedules in topological order and insert each job onto the machine that minimizes cumulative set-up. Their results confirm the robustness of deterministic insertion strategies under complex technological constraints.

2.6.3 Synthesis of Findings

Table 2.1 summarizes key constructive-heuristic features reported in the literature.

Across these studies, there is agreement that constructive heuristics, sometimes combined with light improvement steps, provide a good balance between computational effort and schedule quality for industrial-scale problems with complex setups and eligibility constraints.

Table 2.1: Key constructive-heuristic features in recent studies

Reference	**Problem Context**	**Main Heuristic Mechanism**
Pérez-González et al. (2019)	UPMSP-SE with due-dates	Earliest Feasible Completion rule
Heinz et al. (2023)	UPMSP-SE + secondary resources	Constructive seed + CP improvement
Xi et al. (2015)	Identical parallel machines, tardiness	Look-ahead insertion heuristic
Gacias et al. (2009)	Precedence + sequence-dependent set-ups	Topological order + min incremental set-up

Chapter 3

Initial State and Problem Overview

This chapter presents the current state of the production system at Amorim Top Series, with a focus on the planning and operational interaction between the injection and capsuling sectors. The analysis aims to identify the main limitations and opportunities for improvement in the existing flow, which currently lacks structured planning and visibility, and to highlight the potential for further enhancement.

Through the assessment of the current situation, it becomes evident that the absence of regulated intermediate stock, combined with desynchronized production cadences and lack of performance monitoring, leads to operational challenges that affect the overall efficiency and responsiveness of the production process.

This overview provides the foundation for the development of solutions that aim to optimize the planning process, improve coordination between sectors, and ensure the reliable and timely supply of materials within the production system.

3.1 Current Production Flow between Injection and Capsuling

The production process at Amorim Top Series comprises several interconnected sectors: injection, mechanical finishing, washing, manual and electronic sorting, and, finally, capsuling. The injection sector produces plastic capsules, while cork stoppers sourced from within the Amorim Group undergo mechanical finishing, washing, manual and/or electronic selection, and a final stabilization treatment before they are ready for encapsulation. The overall flow between injection and capsuling, along with its main interactions, is illustrated in Figure 3.1.

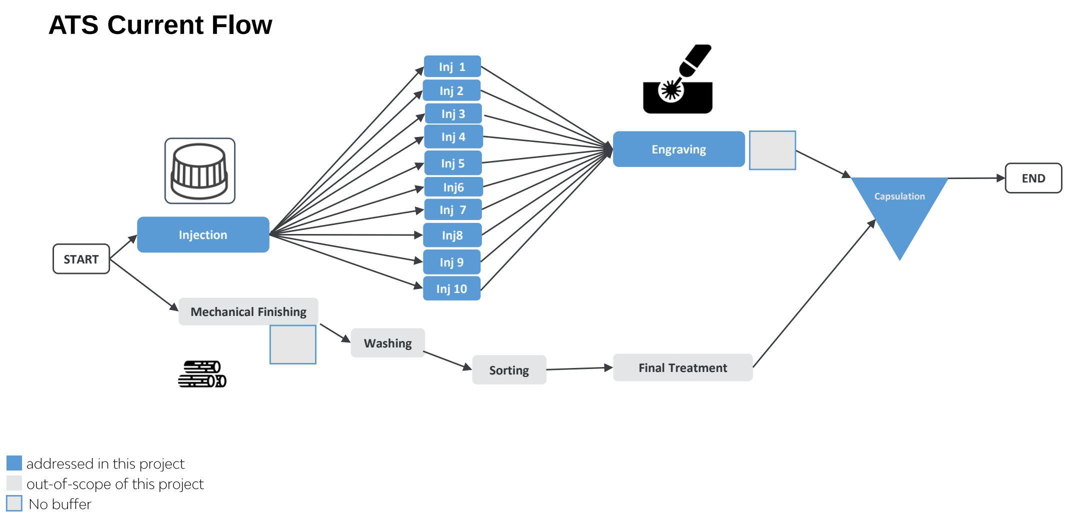

Figure 3.1: Current production flow between Injection and Capsuling at ATS, highlighting main interactions and lack of intermediate stock.

Planning is in place; however, it is predominantly short-term, reactive, and make-to-order, with limited alignment between the injection and capsuling sectors. There is no standardized, regulated intermediate stock (e.g., a supermarket or Kanban controlled buffer) between the two sectors. As a result, capsules typically flow directly from production to consumption in capsuling, which undermines continuity, encourages firefighting, and constrains the smoothness of the overall production flow.

The injection sector supplies capsules to two main destinations: direct shipment to external customers or internal consumption by capsuling, where capsules are assembled with cork stoppers to form the final product. Despite this interdependence, the absence of an integrated, medium term planning framework that is capable of anticipating capsuling demand and sizing appropriate buffers leading to operational misalignments such as delays in capsule availability, occasional excess build-up, and, most critically, the risk of starving the capsuling sector and jeopardizing on time delivery to end customers.

Operationally, injection works primarily under a make-to-order logic, driven by short-term priorities or specific order requests. In the absence of a formal mechanism for sizing and controlling an intermediate buffer, capsules are either transferred directly to capsuling or shipped. This becomes particularly critical because capsuling typically operates at a higher cadence, consuming capsules faster than they are produced in injection. Without anticipatory planning or regulated WIP, the likelihood of shortages increases, especially for high-volume SKUs.

Although each sector already has digital dashboards displaying daily production, there is no shared system that provides transparent visibility of intermediate stock levels between injection and capsuling. This gap prevents the factory from proactively regulating production flow. The current absence of a structured digital Kanban means that shortages or excess stock can only be detected reactively, often requiring urgent replanning. The aim is therefore to introduce a visual and digital stock control system, integrated into a dashboard that automatically signals whether A capsules are within defined limits. This would enable the factory to become more autonomous: after the daily kamishibai, the sector leader could verify whether stock is within both the physical space and the predefined thresholds; if not, a production order could be requested from planning immediately. This approach moves away from the traditional card Kanban and brings in a digital tool, built directly into the factory, that supports quicker decisions and strengthens both planning agility and visual management.

Furthermore, there is no designated, standardized area reserved for A products, which would typically warrant prioritization in both accessibility and control. The absence of visual management elements, such as standardized locations, clear identification, and consistent labeling leading to inefficiencies in stock handling, longer search times, and reduced planning agility. Collectively, these issues run counter to key 5S principles, particularly orderliness (Seiton), standardization (Seiketsu), and discipline (Shitsuke).

These constraints exacerbate the system's reactive behavior. With limited visibility and no regulated buffer, injection frequently has to reschedule production at short notice, straining resources and reducing machine availability for subsequent orders. The lack of dedicated areas for A items also limits the organization's ability to prioritize what matters most, thereby diminishing overall efficiency.

In summary, while planning does exist, it is insufficiently aligned and predominantly short-term and make-to-order. The absence of a regulated intermediate stock and robust visual controls further impairs the flow between injection and capsuling. These limitations underpin the challenges described in the subsequent sections and motivate the design of a structured planning model and a visual stock control system.

3.2 Identified Planning Challenges

One of the biggest challenges concerning the production planning at Amorim Top Series is the lack of regulated intermediate stock for plastic capsules, even in products with stable and high demand over the years. The injection sector now operates on the basis of short-term needs or orders of production currently, without specified stock levels or safety buffers, so on a make-to-order basis. This absence of inventory regulation causes a reactive environment of production, where capsules are produced under pressure, with less flexibility, and with excessive dependency on immediate availability of machines.

In addition, the capsuling and injection lines operate at different rhythms. At first, the injection sector operates 5 days per week, on 3 shifts of 8 hours. The capsuling sector only operates 5 days a week, on 3 shifts of 7 hours. Regarding machines, the machines in the injection sector opperate at a different cadence from the machines in the capsuling sector, usually the last opperating much faster, but not only the case, depending on the capsule. This desynchronization generates bottlenecks, inhibits optimization of resource allocation, and results in non-optimal use of machine time in the injection and capsuling sectors.

Another critical issue is the lack of real-time visibility and control of stock quantities on a simple and effective dashboard. There is not a intuitive and visual dashboard that provides production teams or planners with information on the quantity of capsules on the shop floor, and whether the stocks are too high or lacking. This gap hinders timely decision making since teams do not know current stock levels and therefore cannot anticipate when replenishment needs to be ordered. As a result, emergency production orders occur oftenly, resulting in many rescheduling orders, internal disorganization and putting pressure on resources and potential delays. Further, the planning is not guided by performance measures. The Service Level KPI of the injection sector which would allow us to monitor whether injection is delivering capsules in a timely manner to the capsuling sector is not being tracked by the company. Without this metric, it is not feasible to accurately evaluate the responsiveness and dependability of the injection department, or to observe where and when failures in the supply stream are actually occurring. The absence of such performance monitoring, allied to the lack of formal planning and stock control, results in reduced flexibility, lower agility in handling new orders, and under exploitation of the injection sector's capacity. This not only restricts production efficiency but is also a strategic risk, as the company might not be able to react to variations in demand or capitalize on opportunities for operational improvement. Short and simple, such planning issues contribute to an environment where reaction and not anticipation dominates, and control and transparency are limited. Their removal is critical to stabilize production flow, to improve the reliability of services, and to allow scalable and agile planning methods to flourish. As an antidote for this, a Service Level definition was designed in the context of this project. This KPI tracks whether capsules are received within time, against the due date set by the capsuling sector. In the event that delivery is effected earlier than or by the due date, the order is classified to be fulfilled; otherwise, as a service failure. During the internship, it was possible to start monitoring the service level of the injection sector from January to April, as illustrated in Figure 3.2.

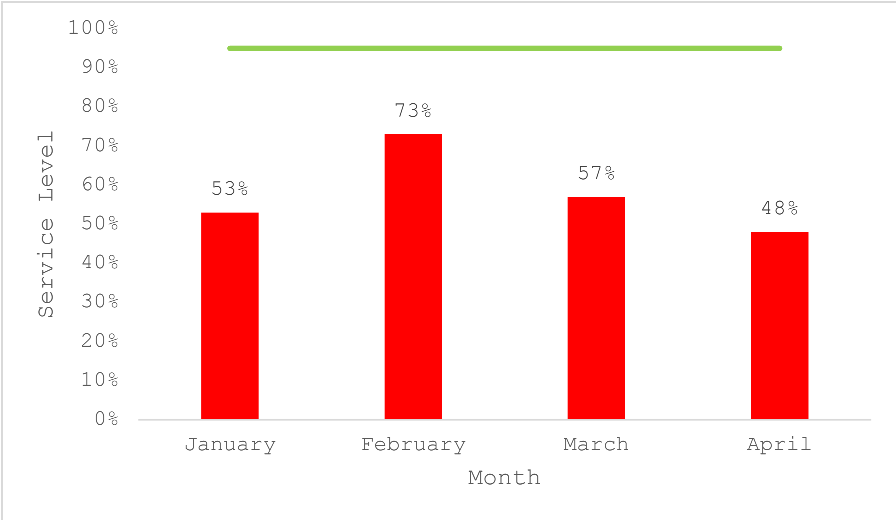

Figure 3.2: Injection Sector Service Level

In the month of January the Service Level of the injection sector was 54% with 22 orders not delivered in time on a total of 48 orders observed. In February it was 73%, with 11 orders not delivered on time on a total of 41 orders. In March 56%, with 12 orders late from 27 orders observed and last in April and the worst month observed with a Service Level of 48%, 25 orders not on time on a total of 52 orders. These values reflect the need for improvement in production planning, as the Service Level of the injection sector did not hit the target defined by the company of the 95% in any month observed.

3.3 ABC Analysis and Demand Trends

3.3.1 ABC Analysis

In order to establish a focused and effective planning strategy, it was essential to identify which plastic capsules produced internally at Amorim Top Series have the greatest impact on the production flow between the injection and capsuling sectors. This was achieved through an ABC analysis, based on the volume of capsules shipped between 2020 and 2024, on the company shipping records. Only plastic capsules produced internally in the injection sector were considered for this analysis, with all of the other capsules sourced by suppliers excluded from the scope.

The ABC classification methodology organizes products into three categories, according to their relative contribution to total production volume. Through this analysis, a set of A plastic capsules was identified, as it is possible to observe in figure 3.3:

- **A-class products**: High-volume capsules representing approximately 80% of total shipped volume;
- **B-class products**: Medium-volume, accounting for around 15%;
- **C-class products**: Low-volume, comprising the remaining 5%.

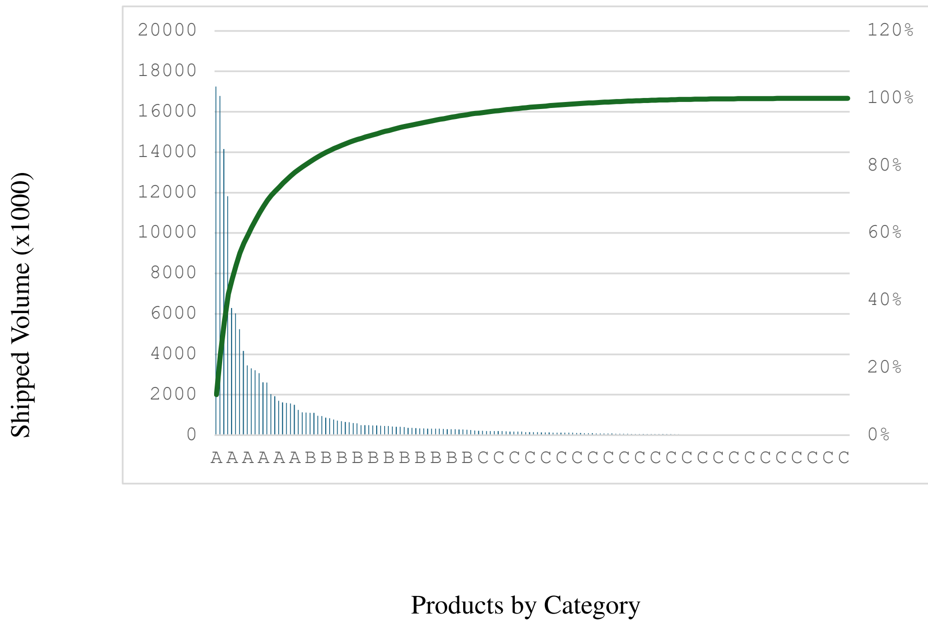

Figure 3.3: Pareto Chart - ABC Analysis

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These products, due to their high turnover and critical importance for maintaining production flow, became the exclusive focus of the planning model developed in this project. By concentrating efforts on these capsules, it is possible to maximize operational impact, as they represent the majority of material movement between the injection and capsuling sectors.

It is important to highlight that the same plastic capsule model may be used across a wide variety of cork stoppers, serving products of different categories, dimensions, and final customer specifications. A single capsule can therefore be applied to multiple final articles, depending on its compatibility with different stopper designs. However, for the purpose of this analysis, the type of final cork stopper is not considered relevant. The focus is placed solely on the plastic capsule itself, whether it is produced internally and subsequently shipped or consumed by capsuling, regardless of its downstream application. This ensures a clear and consistent evaluation of capsule flow in the injection sector, independent of final product variability.

Furthermore, it should be noted that the A products identified in 2020 remained consistent in the A category throughout the period 2020-2024. This consistency reinforces the reliability of the classification and confirms that the most critical products in terms of volume have maintained their relevance over time.

As it is possible to observe in figure 3.4, where the x-assis represents the year and the y-assis represents the number of A-Class capsules, only two new products entered the A-class group during this period, one in 2021 and another in 2024, reflecting minor shifts in demand patterns. The core group of high-volume capsules remained stable, further justifying the focus of this planning initiative on these specific products.

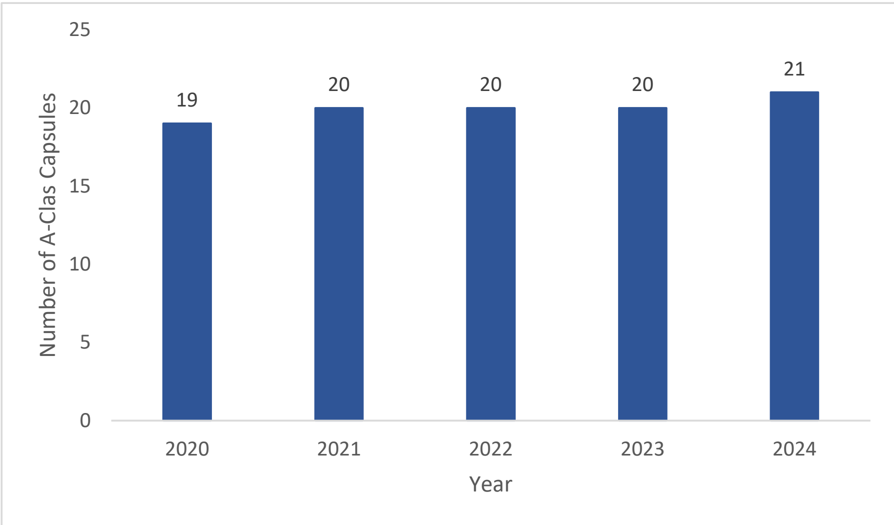

Figure 3.4: Evolution of A-class products over time

3.3.2 Demand Trends

In addition to identifying priority products, an analysis of demand trends was performed using historical data for the ABC analysis, spanning 2020 to 2024. In figure 3.5 it is presented a time series of the aggregated demand for A Capsules over the past five years (2020–2024). This analysis revealed clear seasonal patterns in the demand for A-class capsules, particularly in the months of **July** and **October/November**.

Figure 3.5: Aggregated Monthly Demand for A-Class Plastic Capsules (2020–2024).

The increase in demand during July is attributed to the need to anticipate production before the August summer shutdown, when factory activity is reduced due to holidays. Production during July is therefore intensified to ensure sufficient stock for August.

Additionally, a significant rise in demand during October and November is linked to yearend campaigns, especially in the spirits industry, where there is a peak in orders for customized cork stoppers with branded capsules. These are intended for the Christmas market, requiring advanced planning and higher stock levels to meet deadlines and customer expectations.

Also, the trend analysis of A plastic capsules, conducted using real sales and shipment data from 2020 to 2024, revealed a remarkably stable demand pattern over time. When applying a linear trendline to the monthly aggregated volume of these products, the resulting line was essentially flat, indicating no significant growth or decline in demand throughout the analyzed period.

This consistency in actual demand, sustained over multiple years, reinforces the relevance of the A products for further operational analysis. Their high volume and stability suggest that these items are strategically important within the production flow, especially considering their impact on resource allocation and production planning.

In this context, focusing on these A products is justified not only by their dominance in volume but also by the predictability of their demand, which provides a reliable basis for analyzing and improving planning and production efficiency.

The aggregated forecast demand for A products, analyzed over the past five years, confirms these seasonal peaks, reinforcing the need for a dynamic and responsive planning system that can adjust to demand fluctuations while ensuring continuity in production flow.

While aggregated demand for A plastic capsules demonstrates a stable and predictable pattern across the years analyzed, with recurring seasonal peaks in specific months, a more detailed individual product level analysis reveals a different dynamic. As shown in figure 3.6, although seasonal peaks are consistent at the aggregate level, they are not always driven by the same individual products each year. In one year, the spike in production might be attributed to a particular A product, while in the following year, the same seasonal peak could be associated with a different product in the same category.

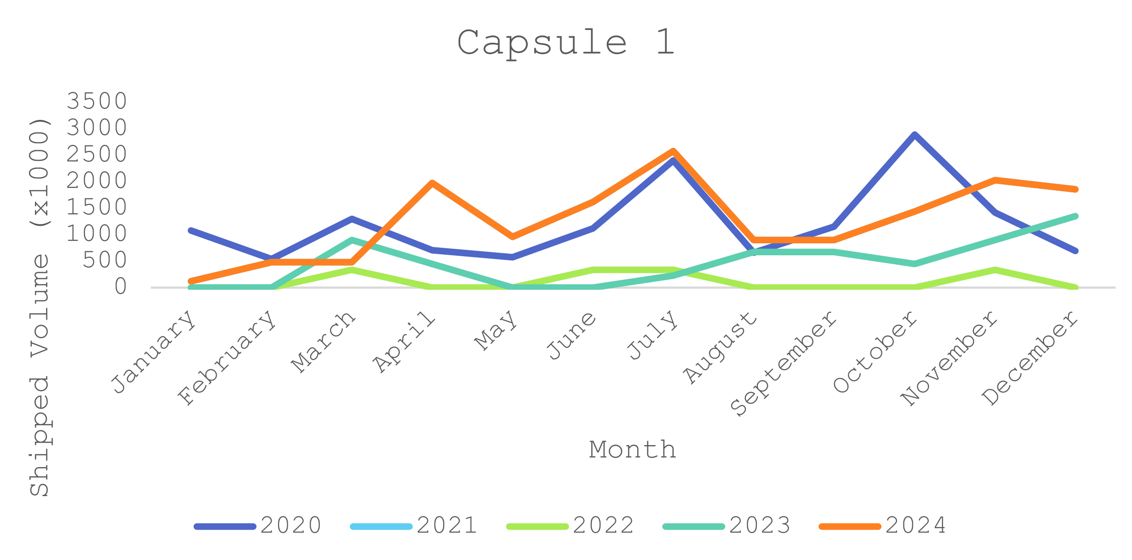

Figure 3.6: Demand for a single A-Class Plastic Capsule (2020-2024).

This observation highlights a key insight: despite global predictability, there is high variability in monthly demand at the individual product level. The distribution of demand across A products shifts annually, making it challenging to anticipate which product will drive the peak in a given period. A detailed view of the monthly demand trends for all A-class individual capsules is provided in Appendix A, supporting a more granular understanding of the variability across individual references.

As such, this variability underscores the importance of having a planning model that can accommodate demand fluctuations at the product level while ensuring responsiveness and stability in supply. A planning system that is able to buffer against variability in individual product demand, while maintaining alignment with overall demand patterns, becomes essential in such a context.

Concluding, the aggregated demand analysis of A capsules provides a valuable overview of overall production pressures throughout the year. It highlights the months where total capsule demand peaks, placing greater strain on the injection sector. However, given that these seasonal peaks are not consistently driven by the same individual products each year, it becomes clear that aggregate analysis, while useful for understanding macro-level patterns, must be complemented by product-level planning to address demand variability more effectively.

3.4 Consequences of the Current State

The current coordination between the injection and capsuling sectors reveals persistent misalignments in production planning, contributing to operational inefficiencies that undermine the overall performance of the unit. These issues are especially critical during peak demand periods, due to the specific characteristics of the products and the tight delivery timelines imposed by clients.

One of the most immediate consequences is the recurrent risk of shortages in the capsuling sector, which is entirely dependent on the timely availability of capsules from injection. In the absence of a regulated intermediate stock, any delay or deviation in injection schedules leads directly to disruptions or slowdowns in the capsuling process. This not only compromises internal delivery commitments, but also increases the risk of customer delays, with potential impacts on satisfaction levels and brand reputation.

Another relevant impact is the inefficient use of resources, particularly machine availability across both sectors. The lack of forward-looking planning leads to machines being assigned to urgent or non-prioritized orders, thereby limiting flexibility and responsiveness to new or strategically relevant demands. This reactive approach triggers frequent rescheduling and urgent setups, placing additional pressure on production teams and increasing the total number of changeovers.

In addition, the way high-volume capsules are stored and handled has become a significant source of inefficiency. In the absence of standardized storage locations and visual stock control, operators face difficulties in assessing real-time inventory levels. This results in time lost searching for materials, communication breakdowns, and, in some cases, duplicated or unnecessary production. This lack of visibility is especially problematic in a just-in-time environment, where any delay has an immediate operational consequence.

The absence of structured performance monitoring tools also hinders effective planning. In particular, the lack of a dedicated Service Level KPI between the injection and capping sectors limits the organization's ability to objectively assess planning reliability. As part of this project, this KPI was formally defined and calculated for the period between January and April, based on the percentage of orders delivered by injection before the due date requested by capping. During this period, the average service level was approximately 60%, confirming that delays in internal deliveries were frequent and often systematic.

Additionally, monthly demand variability at the individual product level adds further complexity to planning, particularly for A items. Although aggregate monthly demand remains relatively stable, the product mix fluctuates significantly from month to month. This irregularity makes it difficult to predict which capsules will experience production pressure in a given month, increasing the risk of specific stockouts.

All in all, these limitations such as reactive planning, poor stock visibility, missing performance tracking and fluctuating demand result in a fragile system that struggles to adapt to changes. This fragility becomes even more evident during critical periods such as July, when production must ramp up before the August shutdown, or during year-end campaigns in October and November, when anticipation and flexibility are key to ensuring continuity.

More broadly, the current planning limitations affect not only day-to-day operations but also constrain the company's ability to respond to market demands, seize commercial opportunities, and deliver a consistently high standard of internal service. Addressing these structural weaknesses is essential to enable a more stable, scalable and reliable production system.

Chapter 4

Methodology

4.1 Research Design

This project was developed as a continuous improvement initiative in the Amorim Top Series industrial unit. The methodological approach is practical in nature and focused on application, with the main objective of stabilizing the flow of intermmediate stock between the injection and capsulation sectors through the implementation of a pull-based production control system.

The project was initially structured using the A3 methodology, which provided a disciplined and visual framework for problem solving. This structure guided the analysis of the current situation, identification of root causes, definition of objectives, formulation of countermeasures, and monitoring of results. It ensured that each decision was based on real operational data and aligned with Lean principles.

The methodology combined both quantitative and qualitative components. On the quantitative side, two complementary tools were developed:

- A Kanban sizing model, adapted from established industrial references, to define and regulate intermediate stock levels based on demand, lot sizes and setup times;

- A constructive scheduling heuristic, developed in Python, to allocate production orders across injection machines while minimizing setup times and ensuring timely availability for the capsulation sector.

Qualitative insights were obtained through direct observation of production routines, participation in shift meetings, and informal discussions with planning and shop-floor personnel. These inputs were essential to adapt both tools to the real constraints and dynamics of the factory.

To support implementation and long term sustainability, two complementary initiatives were also included: (i) the development of a Power BI dashboard to monitor key performance indicators (KPIs) related to Kanban levels and service reliability; and (ii) a minor layout improvement supported by 5S principles, aimed at organizing the physical space used for storing and replenishing injection bags.

Finally, a sensitivity analysis was conducted to assess the impact of key parameters on the Kanban system. The results provided useful insights for decision making and reinforced the robustness of the proposed approach under different production conditions.

By following this structured and integrated methodology, the project not only introduced a Kanban system tailored to a hybrid production model, but also embedded visual management, scheduling intelligence, and workplace organization tools to improve predictability, responsiveness, and flow stability between injection and capsulation.

4.2 Forecasting - Holt Winters Additive Model

A forecasting model was developed for the demand of capsules within the A category, specifically for the capsules included in the rolling plan. Schlenkrich et al. (2024) states that capsules under a rolling plan are items whose production is scheduled based on a dynamic and continuously updated forecasting model, typically revised on a monthly basis. This approach allows production volumes to be adjusted according to the most recent demand data, helping to avoid stockouts or excessive inventory.

These capsules are generally characterized by a recurring consumption pattern with monthly fluctuations and are not linked to long-term fixed orders. The rolling plan thus serves as a decision support ensuring alignment between production capacity, available stock and demand. This strategy is particularly relevant in industrial environments with limited capacity and high product variety, as it enables prioritization of critical items with higher turnover or greater sensitivity to availability.

As previously discussed, the demand patterns for these capsules have shown a stable trend over the past years (from 2020 to 2024), without significant increases or decreases. This stability in demand, combined with clear seasonal fluctuations, makes the Holt-Winters additive model a suitable choice for forecasting. The Holt-Winters additive model was chosen because it effectively accounts for seasonality in demand, while maintaining a stable trend (Holt, 2004). Since the demand for these capsules does not show any growth or decline (as confirmed by the demand pattern analysis conducted during the study), an additive model is appropriate. In contrast, a multiplicative model would be better suited for data with growing or declining trends, which is not the case for these capsules.

The model was applied to the aggregated forecast for 10 specific capsules from the rolling plan within the A category. By using historical demand data, the forecast reflects the expected demand for the upcoming months, which helps in defining the Kanban levels for these products. This forecast is crucial for production planning, ensuring that stock levels are optimized without overproduction or underproduction. The Holt-Winters model considers both seasonal variations and the stable trend, which is why it provides a more accurate prediction for these capsules compared to simpler forecasting methods. This approach ensures that the Kanban system can be adjusted dynamically in response to the anticipated demand, while avoiding the inefficiencies associated with inaccurate or overly simplified naive forecasting models.

For the aggregated demand of A capsules, the Holt-Winters model also demonstrated a better performance than the company's tactical forecast for the year 2024. This was confirmed through the comparison of the *Sum of Squared Errors (SSE)*, where the Holt-Winters forecast achieved a lower value, indicating higher accuracy.

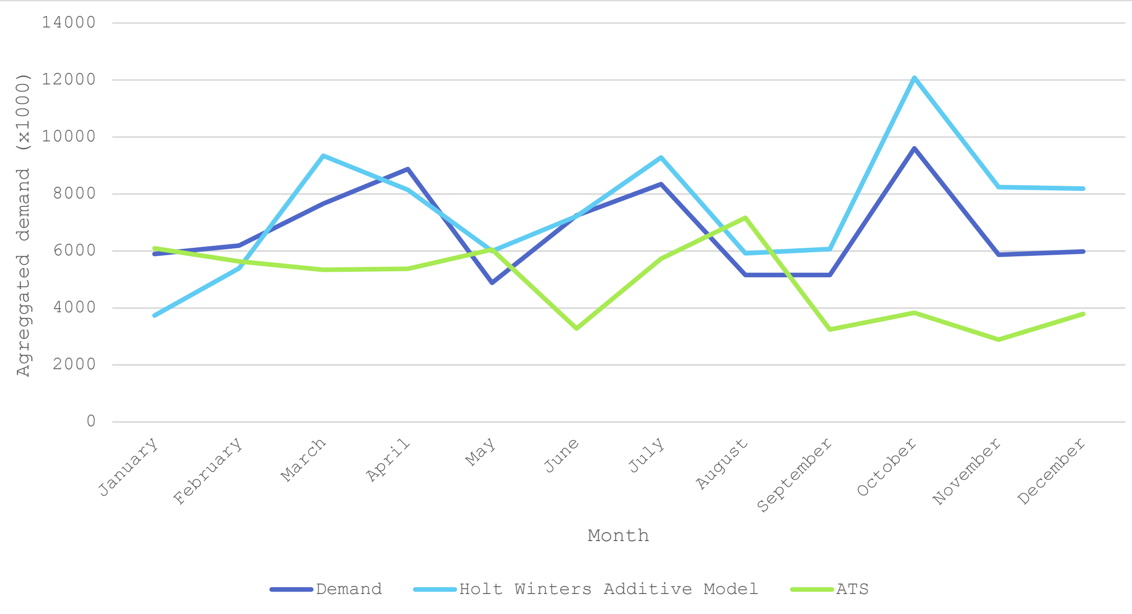

Figure 4.1: Comparison between Holt-Winters aggregated forecast and company tactical forecast for A-class capsules (2024).

However, given that the Kanban system requires a forecast per capsule, the high monthly variability from year to year for each capsule made it evident that the individual capsule forecast, generated by the Holt-Winters model, was less accurate than the forecast provided by the tactical department. Despite the higher accuracy of the aggregated forecast, the forecast by capsule was more volatile and, in some cases, provided less precise predictions. Therefore, to ensure alignment with the production reality and the tactical planning, the forecast provided by the tactical department was used for the calculation of Kanban values. This decision helped optimize the Kanban system, ensuring a more reliable forecast to adjust the production flow while aligning with the existing demand planning practices in the company.

4.3 Project Structuring Using the A3 Methodology

The present project was structured using the A3 methodology, a lean problem solving framework developed within the Toyota Production System. This approach facilitates a clear and structured analysis of problems by guiding the practitioner through a logical sequence of steps: problem identification, current state analysis, goal setting, root cause analysis, countermeasure proposal, implementation planning, and follow-up. As this academic project was developed in the context of an oriented internship and framed as a continuous improvement initiative, the A3 framework served as a robust foundation to structure objectives, analysis, and solution design.

The initial identified problem concerned instability and lack of predictability in the flow of stock between the injection and capsulation sectors. The absence of a synchronized production control mechanism resulted in inefficiencies, reactive planning, and potential service level risks.

The current state analysis included a thorough review of historical production data, an ABC classification of injected capsule references, and the identification of demand variability. The analysis revealed that a significant portion of the monthly volume was concentrated in a limited number of references (Aarticles), and that existing stock decisions were based on informal knowledge rather than structured data. In addition, the capsulation process demonstrated a higher consumption cadence than injection, further highlighting the need for better alignment between sectors.

In response, the project defined the overarching objective of stabilizing the internal flow between injection and capsulation by designing a make-to-stock replenishment system from a make-to-order system. This objective was translated into concrete subgoals, including the implementation of a Kanban model tailored to hybrid production logic, a layout reorganization based on 5S principles, and the development of a digital dashboard to monitor the system performance and support future decision making.

The A3 methodology served not only as a project structuring tool, but also as a means to ensure coherence between data driven diagnosis, solution design, and continuous improvement logic.

The complete A3 report developed during the internship is included in Appendix B, and synthesizes the project rationale and strategic alignment with Lean thinking.

4.4 Design of the Kanban System

4.4.1 Definition of the Hybrid Production Context

The current production flow follows a make-to-order logic in both the injection and capsulation sectors. Capsules are only produced after internal orders are released, based on the order portfolio. Although the planning team works with forecasts and rolling plans, this information is not translated into a structured pull system at the operational level.

In practice, the injection sector responds reactively to immediate demand, without any defined stock levels or replenishment rules. This increases the risk of disruptions in capsulation, which operates at a higher cadence and depends entirely on the timely availability of injection output. The absence of an intermediate buffer and the lack of visibility over actual stock levels often lead to urgent setups and reactivity.

To address these issues, a hybrid model is proposed: the injection sector will adopt a make-to-stock logic for A capsules, regulated by a Kanban system, while capsulation will remain make-to-order. Less critical B and C items will continue to follow a make-to-order logic, avoiding unnecessary inventory buildup. Although Kanban implies production to stock, it still follows a pull logic where replenishment is only triggered by actual consumption from downstream. This will ensure a controlled and responsive flow, decoupling the two production stages while preserving alignment with real demand.

The Kanban parameters for A items will be updated monthly based on real consumption data. While the annual forecast provides a long-term volume reference, it cannot predict the monthly distribution of demand per capsule. In fact, although total monthly demand is relatively stable, the specific capsules responsible for that demand vary significantly from month to month. This variability reinforces the need for a pull based buffer that reacts to actual consumption patterns, rather than relying solely on forecasted volumes.

In short, the proposed hybrid structure combines the responsiveness of make-to-order with the stability of pull regulated make-to-stock, focusing on A products where stock availability is most critical. This approach improves planning visibility and the internal service level between injection and capsulation, while simultaneously avoiding unnecessary inventory for lower-rotation items.

4.4.2 Kanban calculation

The Kanban system implemented in this project was dimensioned using a formula adapted from the model proposed by Bosch for production synchronization and pull flow optimization Salgado and Varela (n.d.). This approach considers five distinct components that together determine the total number of Kanban units required to stabilize the material flow:

$$K = RE + LO + WI + TI + SA$$

Where:

- RE – Replenishment time coverage
- LO – Lot size coverage
- WI – Withdrawal peak coverage
- TI – Time gap coverage
- SA – Safety coverage

Each element is defined by specific operational parameters, as follows:

$$RE = \frac{(PR \times RT_{loop})}{(NPT \times SNP)}$$

$$LO = \frac{LS}{SNP} - 1 \quad \text{if } LS > SNP$$

$$WI = \frac{WA - LS}{SNP} \quad \text{if } WA > LS$$

$$TI = \frac{PR}{NPT \times SNP} \times \left|T_{customer} - T_{supplier}\right|$$

$$SA = \frac{PR \times ST \times 60}{NPT \times SNP}$$

Where:

- PR – Requirement per period [pieces/period]
- RT_{loop} – Replenishment lead time [minutes]
- NPT – Working time [minutes/period]
- SNP – Standard number of parts per Kanban [pieces]
- LS – Lot size [pieces]
- WA – Withdrawal amount [pieces/period]
- $T_{customer}$, $T_{supplier}$ – Shift model of customer and supplier [minutes]
- ST – Safety time [hours]

For each of the A capsules selected for Kanban implementation, the sizing process was carried out individually. This was necessary due to the variability in production characteristics across different capsule types, including differences in injection speed, dimensional attributes, and post injection requirements such as engraving for client specification. These factors directly influence replenishment times, packaging capacity, and batch sizing logic, all of which are essential components in designing a reliable pull system.

The first step in the calculation was to define the Standard Number of Parts per Kanban (SNP). This was based on the number of capsules that fit into a standard plastic bag. While all bags are physically identical, the number of capsules per bag varies depending on the product's geometry and wall thickness, as they are fit in bags all of the same size and then put into pallets (32 bags). The SNP was thus determined individually for each capsule, ensuring that the Kanban loop corresponded precisely to the physical flow of materials. Regarding lot size (LS), the value adopted in this model is defined as the number of capsules contained in a single pallet. This choice is justified by the internal logistics practices observed between the injection and capsuling sectors, where material flow is governed by pallet movements rather than full production batches. Although the actual production lot on the injection machines often exceeds the capacity of a single pallet depending on demand, the transfer to capsuling is triggered as soon as a pallet is completed.

Consequently, using the full production batch as the reference for replenishment time (RT_loop) would imply that no material is available to capsuling until the entire lot is finalized, which does not reflect operational reality. In practice, the system allows for progressive transfer and consumption of pallets, ensuring a more continuous and responsive flow. Therefore, defining the lot size based on pallet quantity provides a more accurate and operationally relevant estimate of replenishment dynamics, and prevents overestimation of stock coverage time in the Kanban calculation.

The requirement per period (PR) was based either on forecast data from the tactical department or the order backlog provided by the production planning manager. However, only 11 of the all capsules classified as A capsules were included in the rolling forecast system by the tactical department. Therefore, these 11 capsules were considered for Kanban sizing, ensuring the model was supported by valid predictive data analysis. However, the calculation of the kanban was made for all of the A capsules observed, as a suggestion that they should integrate the rolling plan in order to achieve a more refine forecast by month instead of only an estimate anual budget.

The working time (NPT) was standardized across all articles, assuming continuous production at 24 hours per day, and the number of weekdays per month, depending if there are any national holidays where production stops. This assumption aligns with the company's shift model and ensures consistency in throughput calculations across all references. It is important as well to refer that the month for kanban production has only 3 weeks. This value was obtained in terms of machine availability in month terms dedicated only for kanban production. So the model considers that in a month there is only availability to produce any kanban in 3 weeks maximum. This value of 17 days (3 weeks) can even be reduced if there are any national holidays, so the NPT depends directly on the number of weekdays available for production.

The replenishment lead time ($RT_{l}oop$) was determined by analyzing injection cadence data, as registered in the company database, and validated through field observation and current data base in use. For capsules requiring engraving after injection, the $RT_{l}oop$ also included the time allocated to that process. Both injection and engraving durations were confirmed through operational data and on-site verification. Accordingly, $RT_{l}oop$ values represent the full time required to produce and release a lot to capsulation, capturing the availability window.

Safety time (ST) was calculated to guarantee that injection remains in synchronization with capsulation, preventing disruptions due to stockouts. This was achieved by analysing 2024 production records for each capsule and computing the average capsulation cadence after excluding outliers through boxplot filtering. These outliers, confirmed with team leaders, were linked to system failures, registration errors or failure in machines. The final ST was obtained by subtracting the $RT_{l}oop$ of the injection sector from the time required to process a lot in capsulation, establishing the minimum lead buffer required to maintain sector alignment. The TI component, which reflects shift model mismatches between supplying and consuming sectors, was calculated based on the shift model of the injection and capsuling sectors. Currently the injection sector operates in 3 shifts of 8 hours per day and the machines do never actually stop (only for maintenance). The capsuling sector operates as well in 3 shifts of 8 hours per day, as well as all the fabric, however, in the capsuling sector stops production for lunch time half an hour and another half an hour for cleaning every shift. So in practice, the capsuling sector is only operating 7 hours per shift, 3 shifts per day. In this component it is getting into account this diference in actual production shifts.

One component from the Bosch formula was excluded: withdrawal peak coverage (WI). WI was excluded, as capsulation never withdraws more than the available injection lot. Since the downstream process consumes only what is produced upstream, no extra withdrawal buffer is needed.

Thus, the Kanban formula applied to each capsule was reduced to:

$$K = RE + LO + SA + TI$$

Finally, the resulting Kanban quantity was rounded up to the nearest multiple of the capsulation packaging factor. This step ensures compatibility with downstream operations, simplifies storage and handling, and prevents rework in packing and labelling activities.

Overall, this methodology enabled the construction of a tailored and operationally grounded Kanban model. It incorporates all individual products specifications, mould constraints, production cadence, and forecast reliability, factors often overlooked in generic implementations, so ensures total allignement between these 2 sectores, ensuring the right value of stock actually needed every month for each capsule and ensures automation for many decisions that are actually made by the planning team in production, making this a robust model to support planning decision making. The model also integrates practical considerations from the shop floor, such as engraving time and packaging constraints, strengthening its alignment with real production conditions. By balancing flexibility and precision, the approach reinforces flow stability between injection and capsulation while preserving responsiveness to fluctuating demand.

4.4.3 5Ss and Layout Organization

As part of the methodology to support the implementation of the Kanban system, a visual and functional reorganization of the pallet storage area was proposed, based in the principles of 5S. The main objective was to create clearly delimited spaces to enhance material flow visibility, reduce ambiguity in storage, and facilitate daily operational discipline between the injection and capsuling sectors.

Given the variability in monthly demand across different capsule references, the number of pallets required per capsule fluctuates significantly. This rendered the initial idea of assigning fixed shelf positions to each capsule unfeasible. To address this, a flexible solution was developed: a specific zone was reserved exclusively for the intermediate Kanban stock, comprising a total of 12 shelf positions (equivalent to 24 pallet slots). To assist operators in correctly identifying this area and ensuring that only relevant articles are stored there, a standardised card was designed and printed. This card lists the SAP codes of all capsules regulated by the Kanban system and is visibly placed in the designated area.

Additionally, a second space was created to manage partial bags returning from the capsuling sector. These bags typically contain leftover capsules from previously opened lots and, if not properly organized, can create confusion and lead to misallocation or unnecessary reprocessing. A clearly identified zone with a total capacity of 6 pallets was defined exclusively for these leftovers.

A dedicated visual card marked "Capsule Leftovers" was affixed to the area to ensure proper segregation and operator awareness.

To reinforce daily adherence to the new layout and to the principles of standardization and discipline (Seiketsu and Shitsuke), a simple visual audit mechanism was introduced. In collaboration with the process engineering team, a Kamishibai checklist was created and implemented. Every day, the team leader performs a brief visual inspection to ensure that the designated storage rules are being followed ensuring that only Kanban capsules are stored in the reserved area, that leftover bags are properly placed, and that the defined layout is being respected.

This intervention aligns with the 5S methodology as follows:

- **Seiri (Sort):** separation between Kanban regulated stock and other materials, including leftovers, helps reduce clutter and eliminate ambiguity in pallet allocation.
- **Seiton (Set in Order):** physical delimitation and visual identification (cards) of the storage zones support correct and quick placement.
- **Seiso (Shine):** the clean and minimal layout prevents unnecessary accumulation and facilitates day-to-day monitoring.
- **Seiketsu (Standardise):** visual cards and daily Kamishibai routines create a common standard for all operators.
- **Shitsuke (Sustain):** the daily visual check reinforces discipline and ensures that the improvements are maintained over time.

In summary, this layout adjustment contributed to the physical structuring of the Kanban system by establishing a standardised, visual, and easily manageable intermediate stock area. The integration of daily routines such as Kamishibai strengthens operational discipline and ensures that the benefits of the 5S methodology are sustained in practice.

Additional visual documentation related to the implemented layout changes is provided in Appendix C. This appendix includes illustrative photographs of the injection storage area before and after the 5S intervention, highlighting the creation of a clearly marked Kanban zone and a dedicated area for partial bags. These images support the description of the layout reorganization and offer a visual reference of the improvements achieved in terms of order, standardization and visual management.

4.4.4 Power BI Dashboard for Kanban monitoring

As part of the operationalization of the Kanban system, a dedicated Power BI dashboard was developed to support real time monitoring of key production and inventory indicators within the injection sector. This dashboard is directly connected to the Excel file where all the calculation was made, ensuring that all data refreshes automatically and reflects the latest planning and production updates without requiring any manual calculation or data manipulation by the user.

The dashboard includes interactive slicers that allow filtering by individual capsule and month. If no filter is applied, the data displayed refers to the overall yearly performance; otherwise, the visualisation dynamically adjusts to reflect only the selected subset. Figure 4.2 illustrates the layout for the month of May, for a specific capsule.

- **Kanban Stock Level vs. Current Stock:** Total monthly stock requirements are compared against available stock.
- **Visual Service Level Gauge:** The central element of the dashboard shows the service level, across all capsule types in the injection sector. A green threshold is displayed at 95%, the internal target.
- **Conditional Formatting and Colour Logic:** Colours are automatically applied based on rules: red if stock is below of the minimum Kanban requirement, yellow if within a 20% margin of the target, and green if the target is met, brown if the stock is higher than the maximum kanban defined. These visual cues enable immediate identification of stock gaps or surpluses.
- **Bar Charts – Stock and Production Needs per Capsule:** Detailed individual capsule data is presented through bar charts for both current stock and production needs. This supports prioritization decisions by highlighting the most critical items, contributing to a more agile and informed decision making.
- **Forecast vs. Kanban Scatter Plot:** This chart compares the monthly production forecast to the Kanban requirements, helping evaluate the allignement of planned production relative to safety stock needs.
- **Palettes and Total Production Needs:** A summary of total palettes in stock and the production gap (in thousands of units) is displayed to contextualize the operational workload required to restore stock levels.

This dashboard exemplifies Lean principles of visual management and autonomous decision support. The automation logic, including real-time updates and dynamic colour coding allows frontline teams to monitor performance with minimal cognitive load. In the specific case of May, the system reports a service level of only 70%.

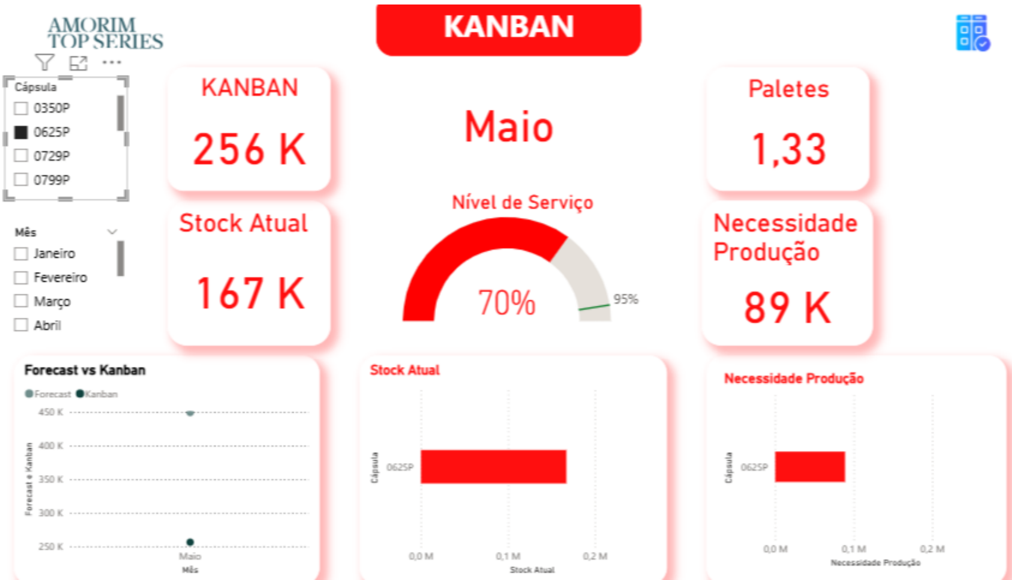

Figure 4.2: Power BI dashboard – Kanban monitoring of the injection sector (May, 0625 capsule).

4.5 Sensitivity Analysis

To evaluate the robustness of the Kanban calculation and identify the most influential parameters, a full-factorial design was performed for a single A-Class capsule, using the May production data as a reference.

Three input parameters were selected for variation:

- **Lot Size** (*LS*) – representing the batch size used in production which counts for RTLoop;
- **Average Setup Time** (*S*) – reflecting operational efficiency during changeovers;
- **Demand** (*PR*) – based on the firm customer orders for May.

Each parameter was tested at three levels: –20%, 0% (baseline), and +20%, resulting in $3^3 = 27$ possible combinations. For each scenario, the Kanban quantity was recalculated using the standard formulation.

The results are shown in Figure 4.3, which presents a heatmap of the Kanban quantity obtained for each combination of parameters.

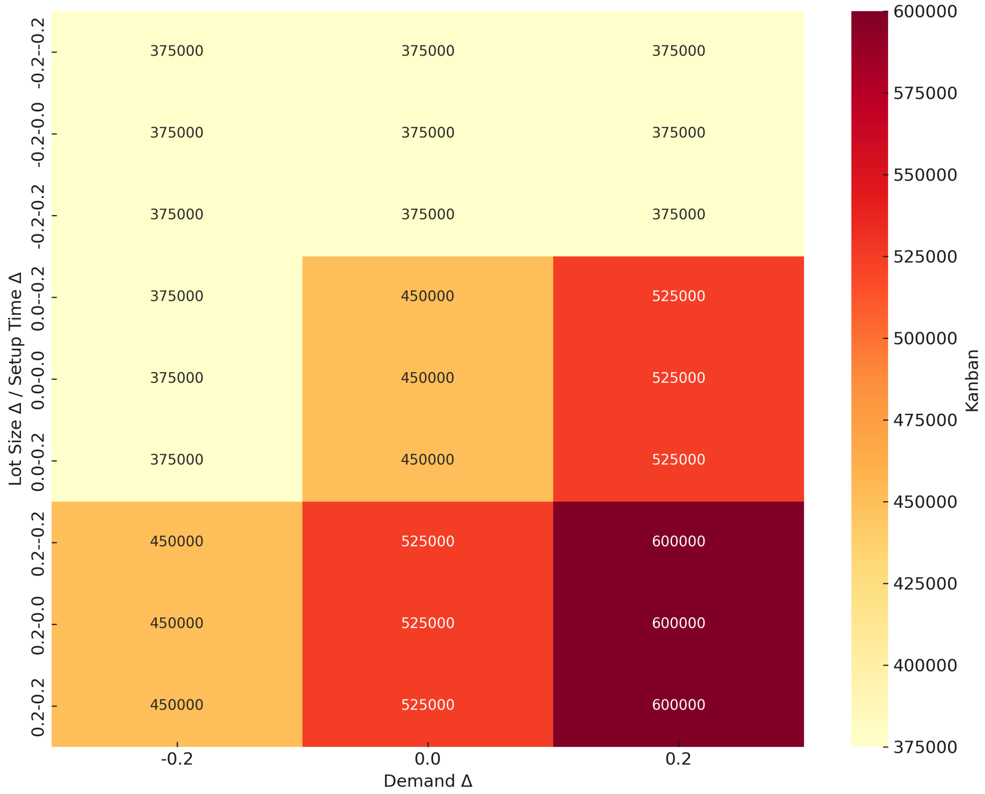

Figure 4.3: Heatmap - Kanban quantity for each combination of Lot Size, Setup Time and Demand.

The results confirm that the most influential parameter is demand. An increase of 20% in demand consistently leads to the highest Kanban values (up to 600 000 units), regardless of setup time or lot size. Lot size also plays a significant role: larger batches extend the replenishment loop and require a larger stock buffer to ensure continuity. Setup time, although less impactful in isolation, contributes to higher Kanban levels when combined with high demand or large lots. The lowest Kanban value (375 000 units) occurs in scenarios with low demand, regardless of other parameter settings.

From a business perspective, these findings reinforce the need to update the Kanban calculation regularly based on the most recent order portfolio. Since demand has the greatest impact, relying on outdated forecasts or annual averages may lead to either stockouts or excessive inventory. Although lot size also showed to be an influential parameter, in this context it is tied to the number of capsules per pallet, which is the fixed unit used in the internal logistics flow. As such, it is not commonly adjusted in operational planning. Nonetheless, in scenarios where greater responsiveness is required or stock constraints are critical, revisiting the definition of the handling unit could provide an opportunity to reduce the Kanban level, by decreasing the quantity that must be accumulated before materials are moved downstream.

While setup time showed a more limited effect in this sensitivity analysis, its influence on the replenishment loop (RT_{loop}) suggests that alternative planning strategies could be explored to reduce it indirectly.In practice, reducing the number and complexity of setups by sequencing production orders more efficiently can shorten the replenishment cycle and lower the stock needed to keep production running smoothly. This would allow for a leaner dimensioning of the Kanban without altering the structure of the system, but rather by optimizing its operational execution.

It is worth noting that this analysis focused on a subset of variables from the Kanban formula. Other relevant factors, such as the number of working days in the month, which directly influences the net production time (NPT), were held constant. Future analyses could expand on this approach by incorporating calendar variability, production cadence or machine availability, to more fully capture the operational dynamics affecting Kanban sizing.

4.6 Development of the Heuristic for Order Allocation

To support production planning in the plastic injection sector, a constructive scheduling heuristic was developed to allocate production orders to machines, with the dual objective of minimizing setup times and ensuring that each order is completed before its respective *due date*, defined as the latest possible date by which capsules must be available for the capsuling process.

The proposed solution adopts a deterministic, rule-based logic, consistent with *dispatching-rule based constructive heuristics* commonly applied in parallel-machine scheduling problems with sequence-dependent setups and eligibility constraints (Allahverdi, 2019; Ruiz & Maroto, 2005). Rather than seeking globally optimal solutions, the aim is to construct feasible and operationally robust schedules within industrial time constraints.

4.6.1 Input Data and Setup Time Modelling

The orders considered correspond to plastic capsules extracted from the company's order portfolio, including high-volume A-class items (as per ABC analysis) and lower-volume B and C-class articles. Despite their smaller lot sizes, B and C articles contribute significantly to the overall number of changeovers and are thus essential for a realistic modeling of production complexity.

All product-specific technical data, such as mould reference, number of cavities, eligible machines, dimensions, material type and colour were retrieved from the internal injection moulding database. Setup time estimation was based on direct observation of real production changeovers and includes multiple types of setups: complete mould changes, core and pin changes, and material or colour transitions. The setup model was empirically calibrated to reflect the actual dynamics observed on the shop floor.

4.6.2 Logic of the Constructive Heuristic

The main steps of the heuristic are as follows:

1. **Order prioritization based on slack time (Minimum Slack Time rule):** Orders are sorted in ascending order of slack time, defined as the difference between the order's due date and

the total time required for setup, production, and (if applicable) engraving. This follows the well-known *Minimum Slack Time* (MST) dispatching rule, which prioritizes orders with tighter margins, thus reducing the risk of late deliveries. The slack time is calculated as:

$$Slack\ Time_i = Due\ Date_i - (Setup\ Time_i + Production\ Time_i + Engraving\ Time_i)$$

2. **Machine eligibility filtering:** Each order is matched with its list of compatible machines, as specified in the technical database.

3. **Selection of a suitable machine:** For each eligible machine, the algorithm checks whether the order can be completed in time, based on current machine availability, estimated setup time, and required production and engraving durations. If multiple machines are viable, the one that avoids idleness and minimizes setup time is selected.

4. **Setup time estimation:** A composite rule is applied to estimate setup time:

   - *Mould change:* A fixed time is applied when the mould differs from the one previously used. Mould compatibility is assessed via set intersection logic (e.g., "1096" is compatible with "1096").
   - *Core and pin changes:* If only the cores or pins differ (while the mould remains unchanged), additional time is added proportionally to the number of cavities in the mould.
   - *Cleaning operations:* For machines M7 to M10, additional cleaning time is added when switching to a lighter colour or changing the material.

5. **Production time calculation:** The required production time is computed based on the order quantity and the assigned capsule injection cadence, expressed in hours.

6. **Engraving time inclusion:** For capsule types that require post-injection engraving, an additional duration is added. Although this operation does not occupy the injection machine, it delays the availability of the finished product for capsuling and is therefore included in the feasibility check.

7. **Feasibility check:** The algorithm ensures that the total duration (setup + production + engraving) does not exceed the order's due date. A strict feasibility criterion is applied, with no buffer allowed beyond the due date.

8. **Machine state update:** Once an order is assigned, the corresponding machine's availability is updated for use in subsequent iterations.

A detailed description of the algorithm's full logic, including the scheduling flow, setup decision rules, and post-processing steps, is provided in Appendix D.

4.6.3 Additional Constraints and Calendar Logic

The heuristic integrates the factory's real operating calendar. Production is assumed to be available 24 hours per day, from Monday to Friday. Saturdays, Sundays and the month of August are considered non-working periods. Setup, production and engraving times are therefore advanced or postponed as needed to avoid these non-working intervals.

Furthermore, in cases where a capsule is compatible with only a small subset of machines, the algorithm gives it allocation priority, ensuring that flexible orders are redirected to machines with broader eligibility. This strategy helps to prevent allocation deadlocks and maximizes the use of available capacity.

4.6.4 Output and Visualization

The final output includes the capsule code, assigned machine, setup start, production start, production end, and availability for capsuling. All timestamps are recorded with minute-level precision and exported to Excel for integration into production dashboards.

Figure 4.4 presents a Gantt chart focusing exclusively on the month of June, where the heuristic was applied to the current order portfolio. During this period, all ten injection machines were fully utilized, and no late deliveries were observed. The horizontal axis represents the production timeline, while the vertical axis identifies the machines. Each coloured bar corresponds to a specific capsule assigned to a machine, with scheduling logic respecting setup dependencies, due dates, and engraving constraints. This figure highlights that in June the system operated at full capacity without any service level violations.

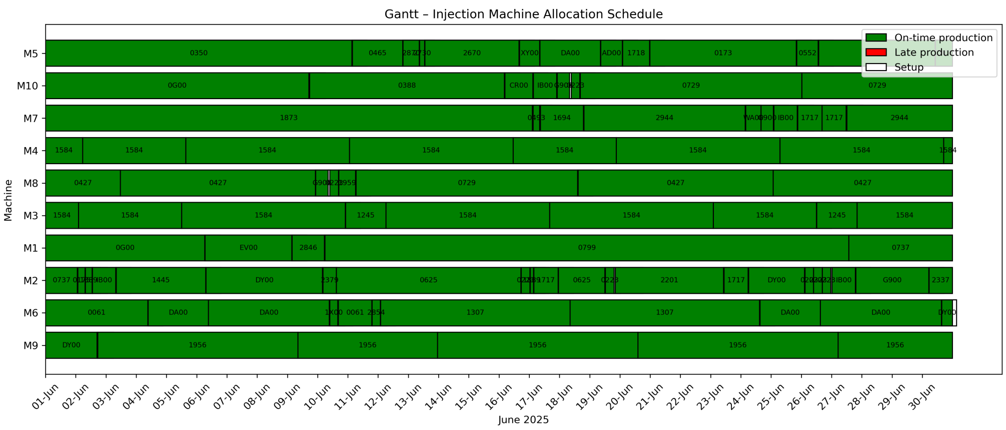

Figure 4.4: Gantt chart – Injection machine allocation schedule.

For completeness, Appendix E provides the full Gantt chart covering the entire portfolio of orders available at the time of analysis. In this broader view, a total of 186 production orders were successfully scheduled, with 6 late deliveries. The chart shows June and July with full utilization across all machines, while August appears as a deliberate scheduling gap in accordance with the factory calendar. September and later months remain largely empty, reflecting the limited visibility of customer orders during the period when the data was extracted.

Chapter 5

Results

5.1 Service Level Performance

A key performance indicator (KPI) assessed throughout this project was the internal service level of the injection sector in response to the capsuling sector.

Figure 5.1 presents the evolution of this KPI between January and June. During the first four months, which reflect the analysis of the current flow period, the average service level was approximately 60%. April showed the most significant drop, reaching a minimum of 48%, highlighting the critical inefficiencies in material flow and production prioritization. Following the implementation of the new planning system, which included a digital Kanban dashboard and the application of the constructive heuristic, a gradual improvement was observed, with the service level reaching almost 70% by the end of June.

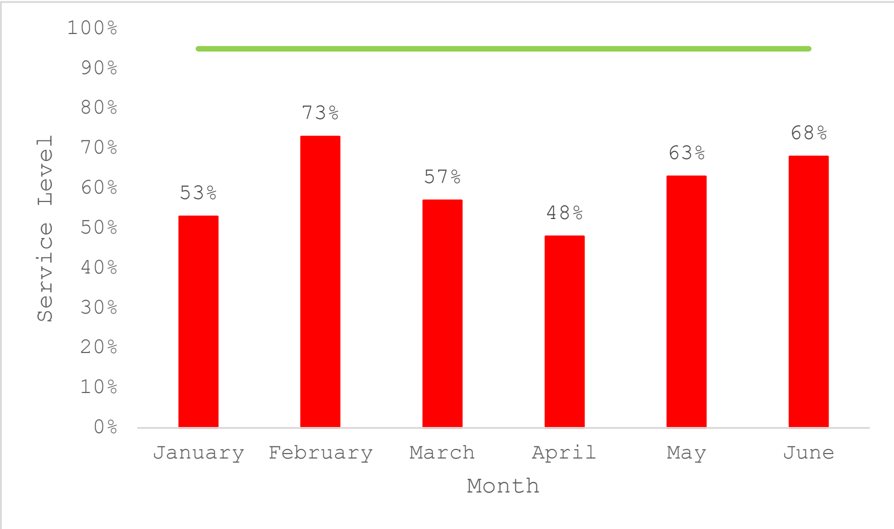

Figure 5.1: Service Level of the Injection Sector

Despite these improvements, the results remain below the ideal internal target of 95%. Two main structural limitations explain this performance gap:

- **Kanban stock levels below target:** In several instances, available inventory levels were insufficient to meet the minimum thresholds defined by the Kanban system. As a result, capsules were not produced in advance as planned, leading to unplanned setups and potential delivery delays. This mismatch is clearly illustrated in the Power BI dashboard (figure 5.2), where, for example, in May, the current stock level for several capsules was significantly below the Kanban defined target. This shortage compromised the system's ability to prevent urgent setups and contributed to a lower service level.

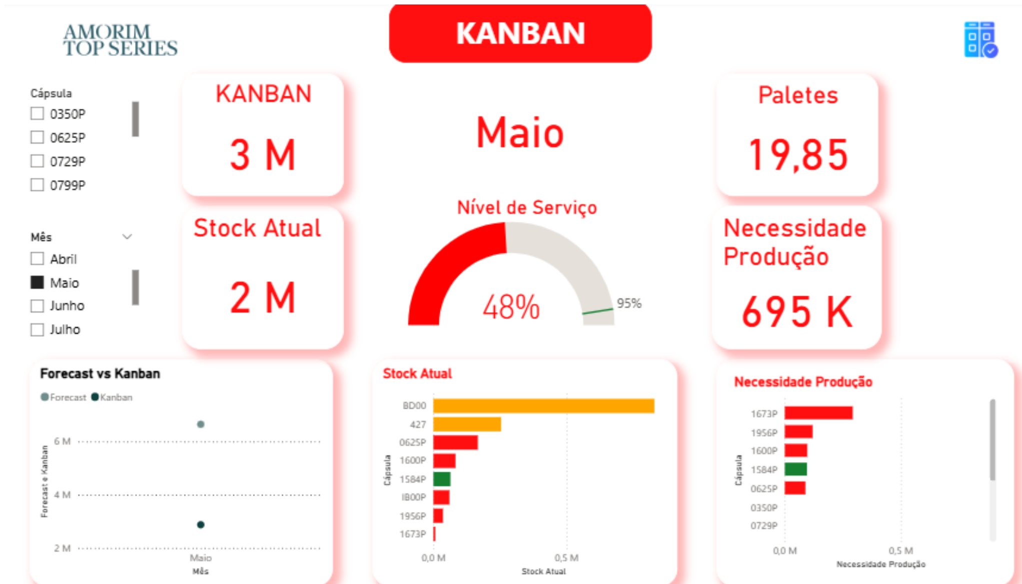

Figure 5.2: Power BI dashboard of the injection sector in May

- **Demand exceeding internal capacity:** During peak months (notably June and July), demand surpassed the productive capacity of the injection sector. In such cases, it became necessary to outsource part of the production to external suppliers, which is not compatible with maintaining ideal Kanban replenishment cycles.

These constraints highlight the need for continuous adjustment of the production planning system and reinforce the importance of anticipatory planning based on forecast integration, particularly during seasonal peaks.

5.2 Impact of the Heuristic on Setup Times

In addition to service level improvements, the constructive heuristic developed in this project suggests a significant potential for setup time reduction. A baseline measurement taken in April prior to implementation demonstrated that the average setup time was approximately 75 minutes per changeover. This value was derived from direct observation of several mold changes on the factory floor. When the same order portfolio was reallocated using the heuristic, the estimated average setup time decreased to 18 minutes. This reduction of nearly 80% is associated with the sequencing logic: grouping orders with similar technical characteristics, minimizing the number of mold or core changes, and avoiding unnecessary transitions in color or material. Additionally, the heuristic promotes continuous machine utilization as machines are only idle when setups are required, ensuring that all allocations respect predefined due dates.

These results indicate that the heuristic can support the planner by suggesting sequences that improve punctuality and efficiency, without altering the intrinsic duration of individual setups. This highlights its potential as a valuable decision-support tool for future planning cycles.

5.3 Operational Instructions Provided to the Company

As a final step of the project, two operational instruction documents were developed and delivered to the company to support the implementation and continuity of the tools created. These documents were designed to ensure that the team can autonomously use and update the Kanban model and the allocation heuristic on a regular basis.

The first set of instructions relates to the Kanban system, covering the interaction between the Excel file used for calculations and the Power BI dashboard used for visual monitoring. The second set of instructions supports the preparation of the input file required by the heuristic, allowing it to be applied to the current order portfolio in a consistent and replicable manner.

Both documents are included in the appendices of this dissertation in a simplified version (see Appendix F and Appendix G). To preserve company confidentiality, all screenshots and sensitive internal data were deliberately removed.

5.4 Alignment with Sustainable Development Goals (SDGs)

This project not only addresses operational efficiency but also contributes to broader sustainability goals aligned with the United Nations 2030 Agenda. United Nations (2015) emphasize the need to integrate sustainability principles into all areas of industrial activity, including production planning and operations.

Three Sustainable Development Goals (SDGs) are particularly supported by the work conducted:

- **SDG 8 – Decent Work and Economic Growth:** The improvement of planning logic contributes to safer, more stable working conditions. Specifically, the heuristic developed provides decision support to reduce the occurrence of unnecessary setups involving frequent changes of cores and inserts. While it does not determine the final production plan, it offers managers alternative scenarios that can lessen physically demanding tasks and promote more balanced workloads. This supports:
  - **Target 8.2** – "Achieve higher levels of economic productivity through diversification, technological upgrading and innovation, including through a focus on high-value added and labour-intensive sectors" (United Nations, 2015).
  - **Target 8.8** – "Protect labour rights and promote safe and secure working environments for all workers, including migrant workers, in particular women migrants, and those in precarious employment" (United Nations, 2015).
- **SDG 9 – Industry, Innovation and Infrastructure:** The implementation of a Python-based scheduling heuristic, a data-driven Kanban system, and Power BI dashboards reinforces the use of innovation to enhance industrial processes. This contributes to:

  - **Target 9.2** – "Promote inclusive and sustainable industrialization and, by 2030, significantly raise industry's share of employment and gross domestic product" (United Nations, 2015).
  - **Target 9.5** – "Enhance scientific research, upgrade the technological capabilities of industrial sectors in all countries" (United Nations, 2015).

- **SDG 12 – Responsible Consumption and Production:** By calculating stock levels based on actual consumption and guiding production sequencing, the tools developed help avoid overproduction tendencies and excessive setups. This provides managers with a basis for aligning production with real demand, thus contributing to resource efficiency and waste reduction. This aligns with:
  - **Target 12.2** – "By 2030, achieve the sustainable management and efficient use of natural resources" (United Nations, 2015).
  - **Target 12.6** – "Encourage companies, especially large and transnational companies, to adopt sustainable practices and to integrate sustainability information into their reporting cycle" (United Nations, 2015).

Chapter 6

Conclusion and Future Work

6.1 Conclusions

This dissertation set out to improve production planning across the two interdependent stages of injection moulding and capsuling. To achieve this, two complementary tools were developed: a Kanban sizing model and a constructive scheduling heuristic. The project was carried out in a real industrial setting, making use of operational data and close collaboration with the factory team.

The results demonstrate the feasibility and impact of the proposed tools. The scheduling heuristic was applied to the current order portfolio, successfully allocating all 181 internally produced plastic capsule orders without exceeding their respective due dates. This confirms the reliability of the heuristic in supporting a more stable and efficient production plan, with the potential to reduce emergency setups and associated operational disruptions.

In parallel, the Kanban system enabled a structured definition of stock levels per capsule, based on the order book of the company and the anual forecast and all the production variables and constraints. Despite this, the observed service level in the injection sector remains at 70%, still below the defined target of 95%. From an analytical standpoint, this is due to the fact that actual stock levels are still below the calculated Kanban thresholds. This situation is compounded by the fact that the period under analysis coincides with the peak months of production demand, during which capacity is too constrained to allow for proactive stock replenishment.

In practice, these stocks should have been built up in earlier, less loaded months. It is therefore evident that reaching the target service level depends not only on correctly sizing the Kanban levels, but also on producing stock in advance whenever capacity allows. Moreover, the systematic application of the scheduling heuristic contributes to reducing setup times and increasing the availability of resources for stock production.

Another important insight emerging from this project is the systemic impact that improvements in the injection sector can have on downstream operations. In particular, the stabilization of injection planning, through reliable Kanban stock levels and optimized sequencing, has the potential to significantly enhance the performance of the capsuling stage. By reducing variability and ensuring the timely availability of plastic capsules, the tools developed in this work help prevent bottlenecks and reactive planning in capsuling, even when multiple capsule types are involved. In this sense, the contribution of the proposed approach extends beyond local efficiency gains, supporting broader operational stability across the production flow.

Altogether, the combination of Kanban sizing and heuristic-based scheduling supports a leaner, more predictable and integrated production flow. The tools developed offer a solid foundation for reducing operational variability, improving delivery reliability, and aligning production more closely with real demand.

6.2 Future Work

Several opportunities for future research and development arise from this study. These can be divided into two main lines: the extension of the current tools to other areas of the factory, and the deepening of the technical capabilities of the tools themselves.

6.2.1 Extension to the mechanical finishing sector

A natural extension of the Kanban methodology would be its application to the mechanical finishing area, particularly for cork stoppers. This sector, although different from injection moulding in terms of process technology, also exhibits repetitive operations and recurring product families. The adoption of a pull-based replenishment system in this area could help stabilise internal workflows, reduce excess inventory, and improve material availability for downstream operations such as washing, choosing manually or eletronically, or treating.

However, such an extension must begin with a careful analysis of the product mix. As was done in the present study, it would be necessary to conduct an ABC classification of items based on order volume, frequency, and variability. The effectiveness of Kanban depends largely on having a stable group of 'A' items, products with consistent demand that make regular replenishment cycles worthwhile.

If such stability is confirmed, the parameters of the Kanban model would need to be recalibrated to reflect the specificities of the mechanical finishing processes, such as setup times, shift structures, production cadences, etc. Additionally, potential interactions between internal and external suppliers, or between semi-finished and finished products, would have to be accounted for in the replenishment logic. This work could form the basis of a broader framework for stock governance across different departments.

6.2.2 Heuristic evolution and system integration

In terms of the scheduling heuristic, several developments could increase its flexibility and operational value. A possible next step would be to add job prioritization features, letting users assign weights or urgency levels to orders depending on factors such as customer importance, delivery deadlines, or contractual penalties. This would enable the model to support more nuanced and realistic scheduling scenarios. In practice, this functionality would require coordination with key stakeholders, such as production planners, commercial teams, and logistics coordinators to define transparent rules for assigning priority levels. These could then be operationalized through a dedicated field in the dataset, which would influence the scheduling logic by adjusting the order in which jobs are considered, or by introducing weighted penalties for lateness.

Another line of improvement would be the transition from a single-objective heuristic (focused mainly on setup reduction) to a multi-objective approach that balances several key performance indicators. These could include setup time, machine utilization, stock levels, and slack time (i.e., time between production and due date), depending on the operational strategy of the company.

6.2.3 E-Kanban Integration

Building on the outcomes of this project, a promising direction for future development is the implementation of a fully integrated **E-Kanban** system within the SAP ERP used by Amorim Top Series. While the current Power BI dashboards provide visual guidance and support decision making, they rely on manual data updates and are not fully dynamic. An integrated E-Kanban would automate material flow, stock replenishment, and information updates in real time.

Key opportunities for future development include:

- **ERP Integration:** Direct connection with SAP to automatically capture consumption data, update stock levels, and trigger replenishment orders without manual intervention.
- **EDI Connectivity:** Real-time communication with suppliers and customers through Electronic Data Interchange, ensuring timely delivery of materials and reducing supply chain delays.
- **Automated Sequencing and Prioritization:** Dynamic allocation of production orders based on real-time stock availability and consumption patterns, reducing idle times and enhancing responsiveness.
- **Decision Support Enhancement:** Transforming current dashboards into a fully integrated system allows planners to focus on exceptions and strategic decisions, rather than routine monitoring.

Implementing an integrated E-Kanban system would not only extend the decision support capabilities demonstrated in this work but also provide a scalable, automated solution that aligns production and inventory management with real-time operational data. This represents a significant step towards a more agile, responsive, and efficient manufacturing environment.

6.2.4 Concluding remarks

Taken together, these developments, both strategic and operational, build on the lean philosophy that guided this work. The intention is to spread the benefits of structured, data-driven planning across different areas of production, while making the tools more autonomous, robust, and scalable. Moving in this direction could eventually provide the basis for a more integrated planning framework throughout the company.

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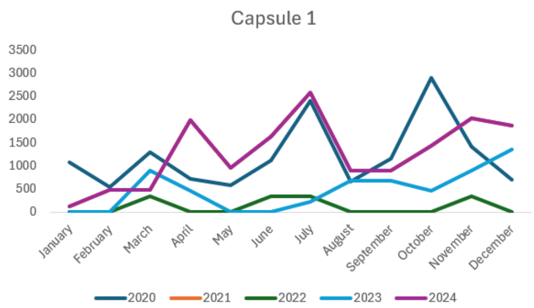
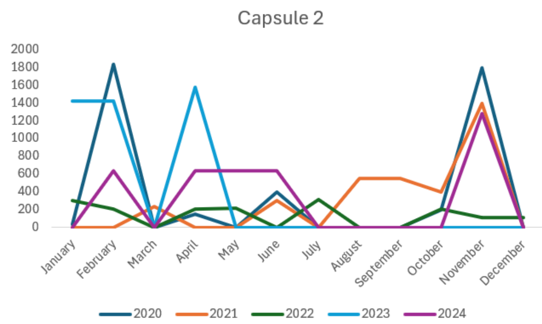
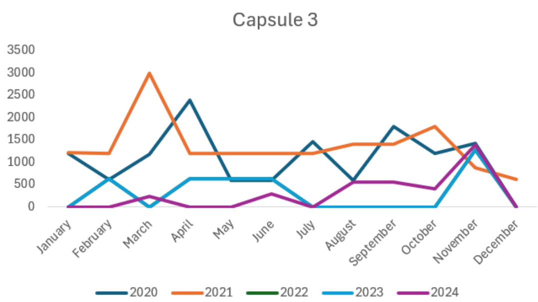
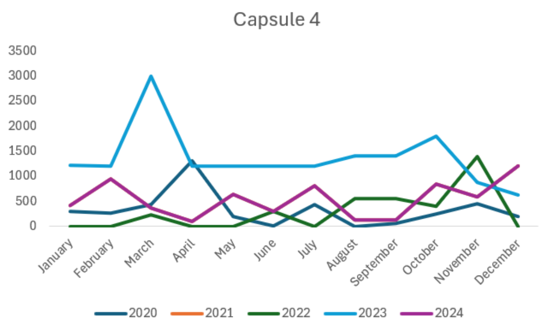
Appendix A

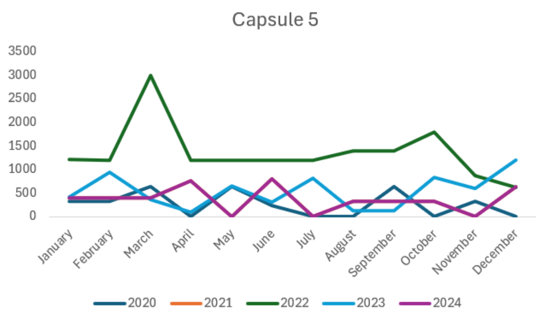
Monthly Demand Trends for A-Class Capsules

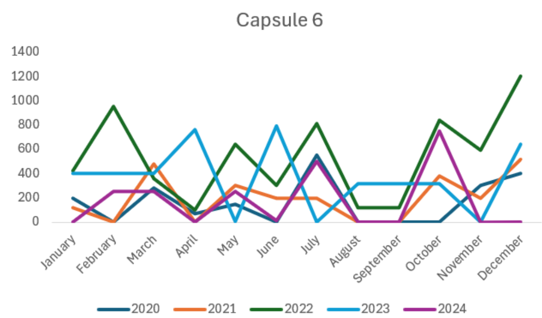


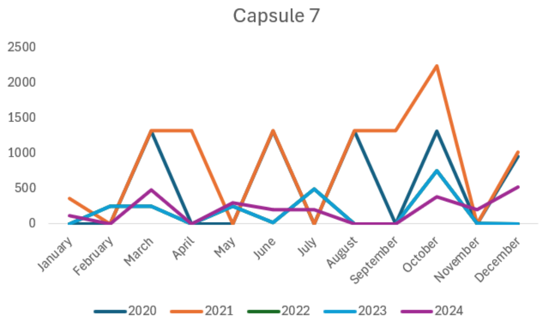








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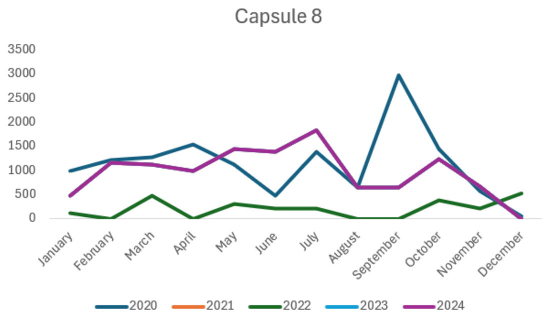
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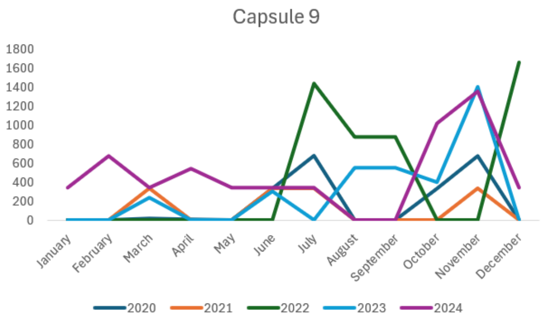
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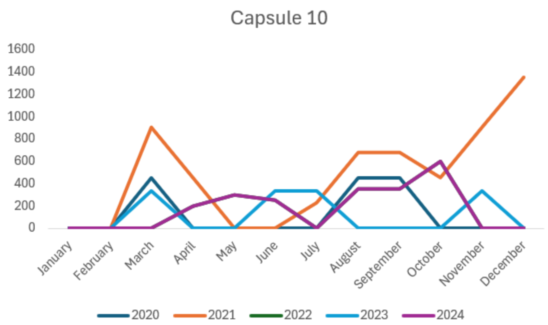
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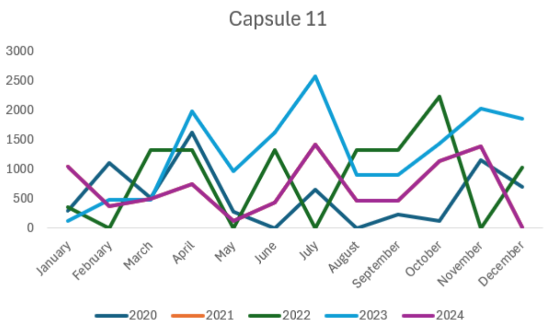
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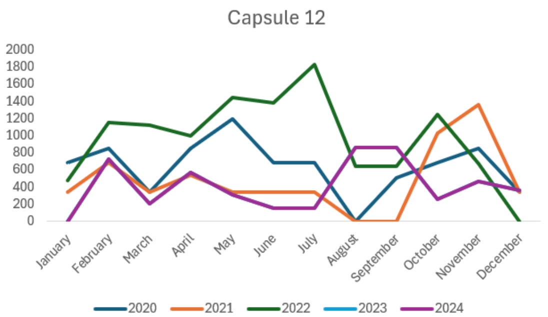
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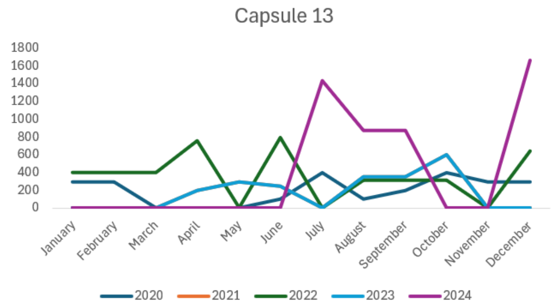
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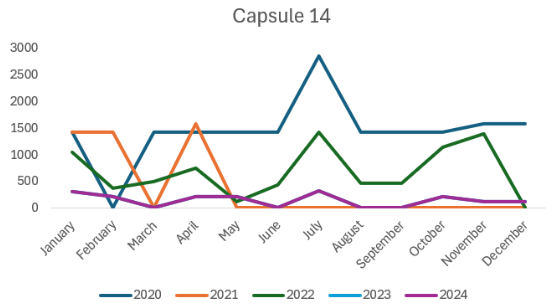
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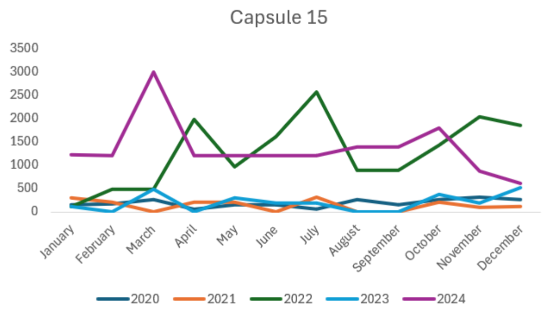
Capsule 15
3500
3000
2500
2000
1500
1000
500
0
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September
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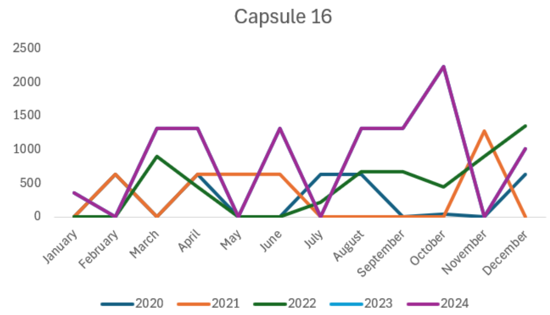
November
December
2020
2021
2022
2023
2024


Capsule 16
2500
2000
1500
1000
500
0
January
February
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May
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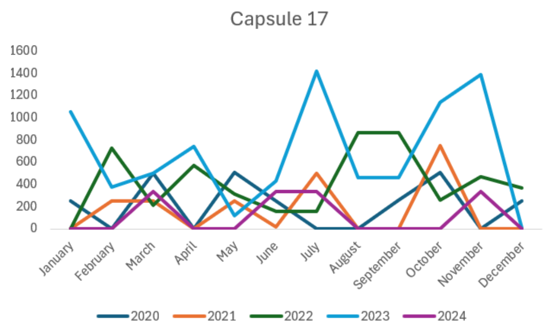
December
2020
2021
2022
2023
2024


Capsule 17
1600
1400
1200
1000
800
600
400
200
0
January
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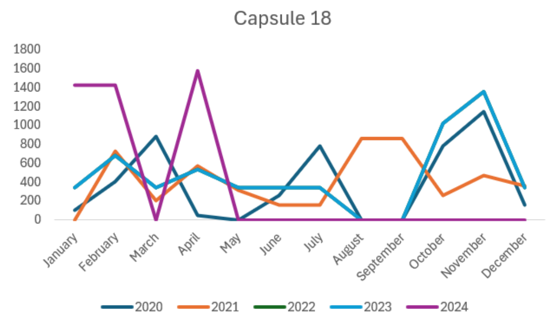
2024


Capsule 18
1800
1600
1400
1200
1000
800
600
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200
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January
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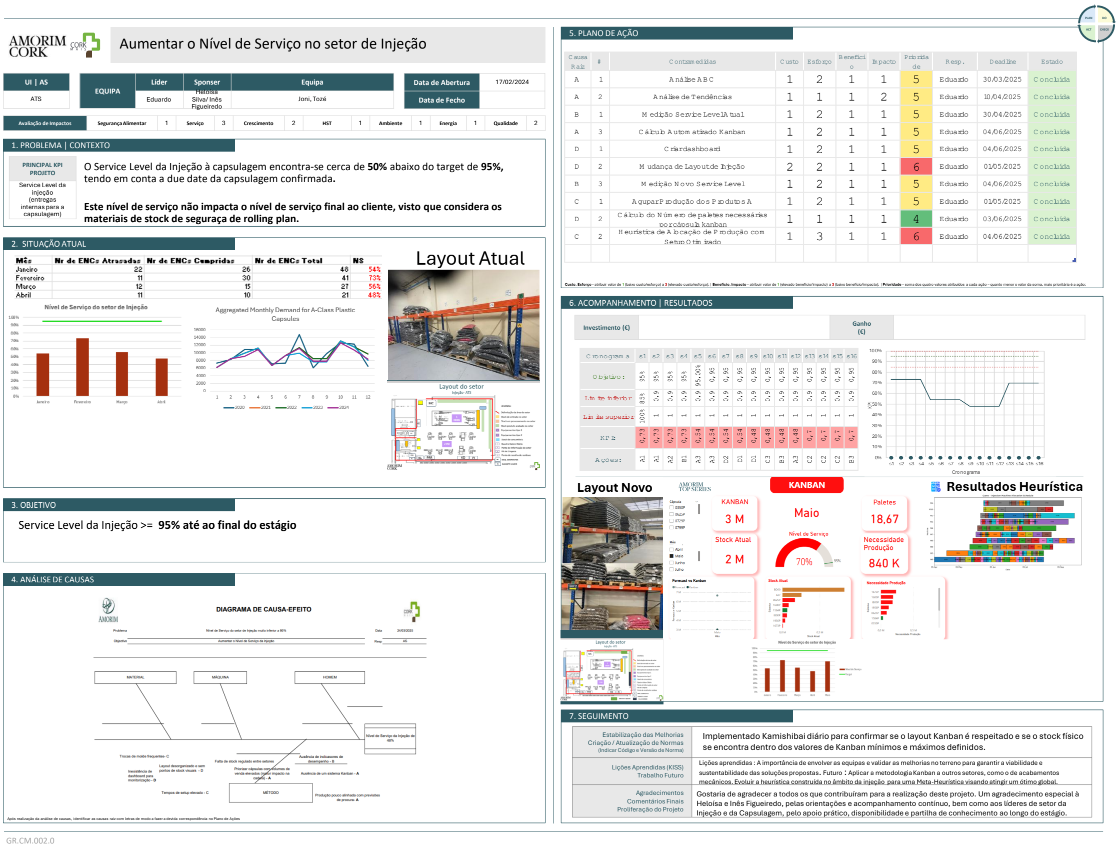
2022
2023
2024

Appendix B

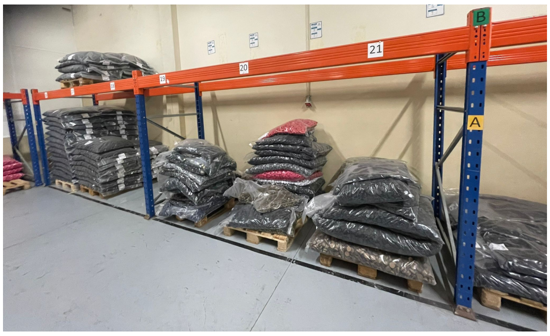
A3 Report



Appendix C

5S's – Before and After

Before – View 1



Before – View 2

After – View 1

After – View 2

Appendix D

Heuristic Pseudocode

Inputs

- Orders: capsule reference, due date, quantity, material, color, mold, machos, tacos, number of cavities, eligible machines
- Injection and engraving cadences
- Working calendar: weekdays only; weekends and August excluded

Processing Steps

1. **Preprocessing:**
   - Remove orders with missing data
   - Convert dates and prepare scheduling columns
   - Calculate production and engraving time for each order
   - Add fixed buffer time
   - Compute slack: hours remaining until due date minus required time
2. **Sort orders by ascending slack and due date**
3. **Initialize machine availability** (all machines available from earliest working day)
4. **Phase 1 – Assign orders within due date + 24h**
   (a) For each order, simulate each eligible machine with setup rules
   (b) Choose machine with best conditions (prefer idle)
   (c) Assign order, record timestamps
5. **Phase 2 – Assign remaining orders minimizing lateness**
   (a) Simulate schedule for each machine
   (b) Assign to machine with minimum lateness
   (c) Record timestamps
6. **Post-processing**

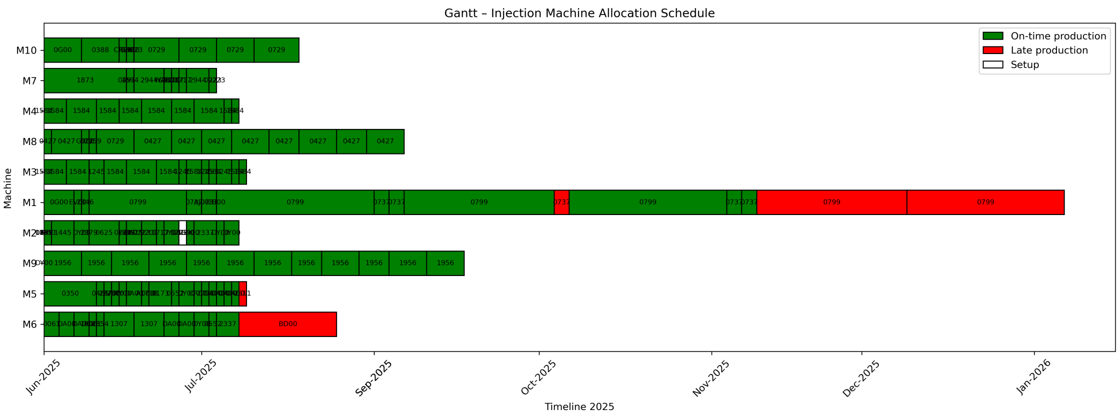
- Compute setup times
- Average setup time
- Count late orders
- Export Excel schedule
- Generate Gantt chart

Outputs

- Assigned machine for each capsule
- Start time of setup
- Start and end time of production
- Date when capsule ready for capping
- Setup time per order and average setup time
- Number of late orders
- Gantt chart

Appendix E

Gantt Chart - Allocation for All Capsules



Appendix F

Work Instruction – Kanban System

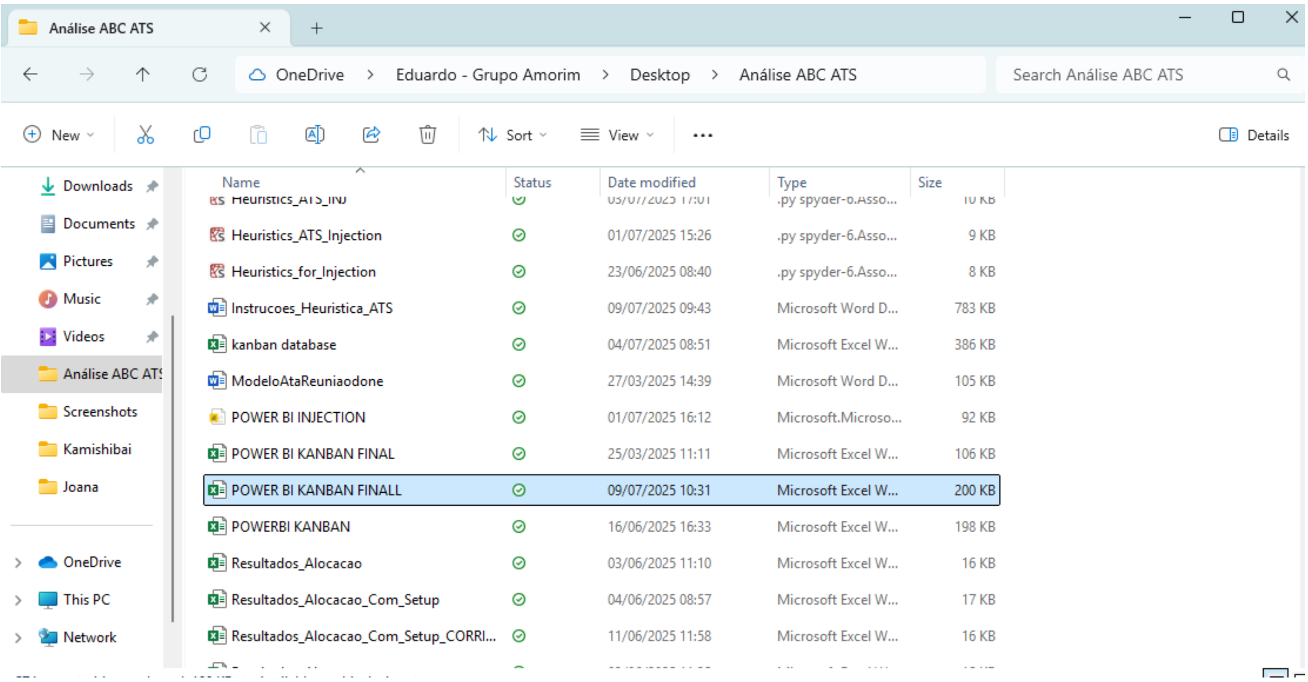
INSTRUÇÕES DE TRABALHO

Gestão do ficheiro de base de dados para o Power BI – Kanban

Grupo Amorim
ATS

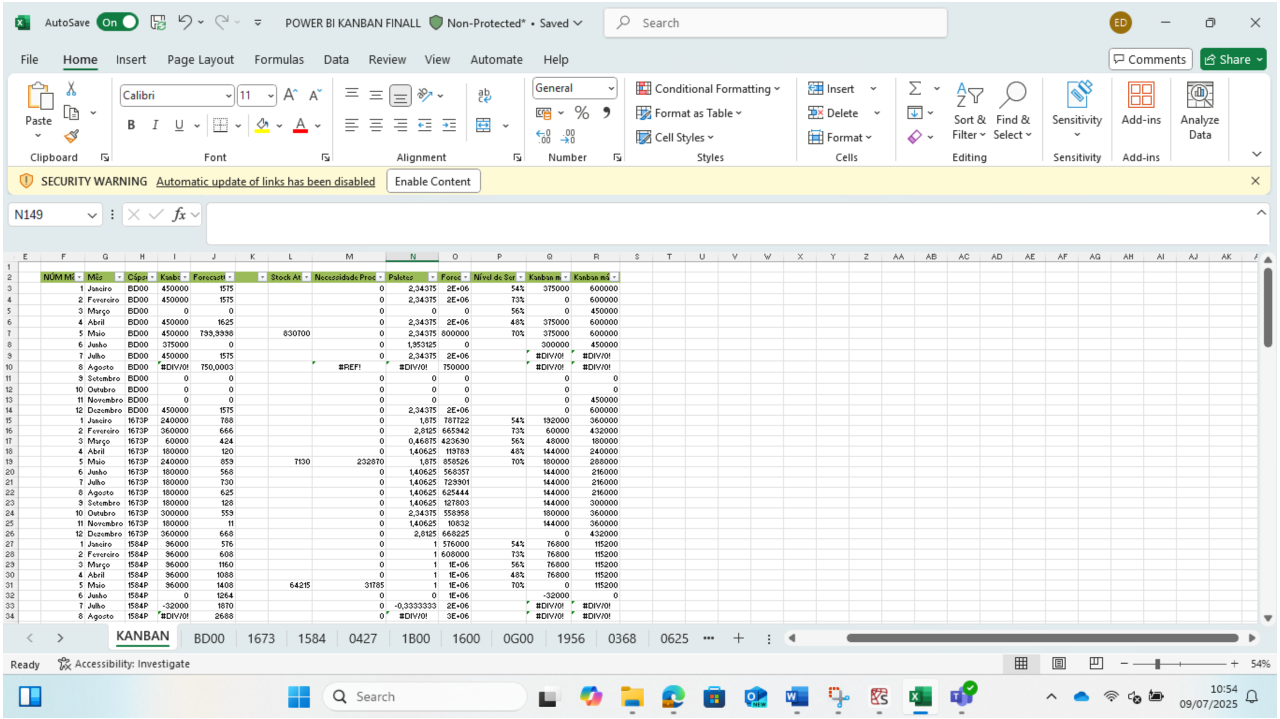
1. Objetivo

O presente documento estabelece as diretrizes para a correta utilização e atualização do ficheiro "POWER BI KANBAN FINALL.xlsx", que serve de base de dados para o dashboard "POWER BI INJECTION". Este procedimento assegura que os dados de cálculo de Kanban sejam atualizados corretamente por cápsula, impactando diretamente os indicadores visuais no Power BI.



2. Estrutura do ficheiro "POWER BI KANBAN FINALL.xlsx"

O ficheiro contém uma aba principal denominada "KANBAN", que agrega e consolida os dados relevantes de todas as abas individuais (cada uma correspondente a uma cápsula específica). Esta aba alimenta diretamente o Power BI.



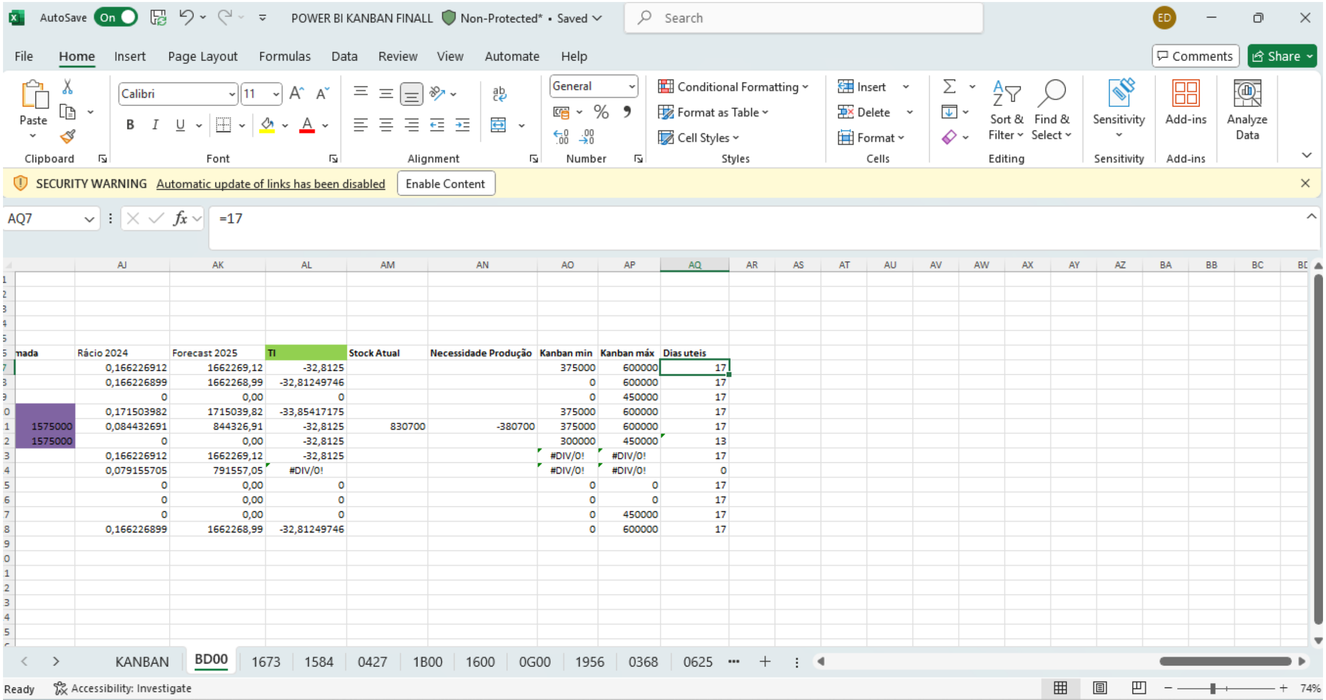
Não é necessário realizar alterações diretas na aba "KANBAN", pois esta recolhe automaticamente os dados provenientes das outras abas. Contudo, importa referir que apenas cápsulas com materiais do tipo "rolling plan" são incluídas no Power BI. As restantes, embora com cálculo de Kanban efetuado, não são carregadas para o dashboard nesta fase da implementação.

3. Atualização das abas individuais por cápsula

Cada aba individual segue a mesma estrutura, mas os dados variam consoante a cápsula em análise.

3.1 Coluna "Dias Úteis"

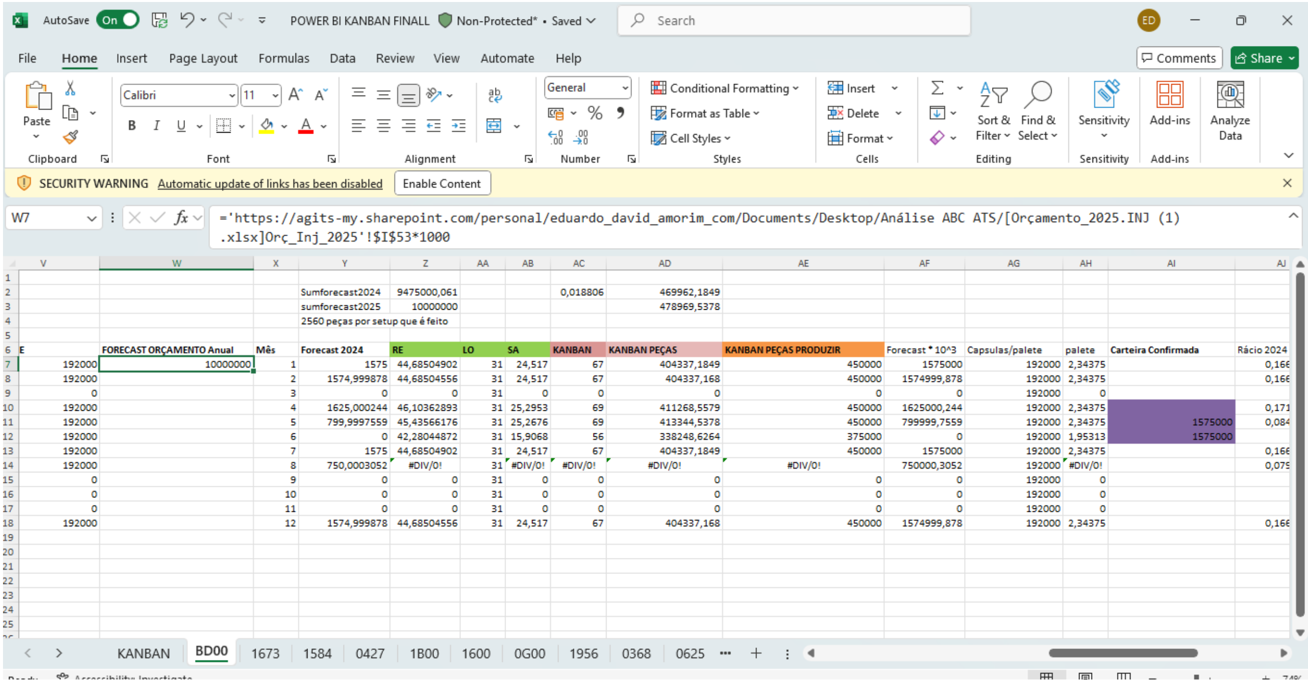
Esta coluna apresenta 12 linhas (uma por mês) e deve ser atualizada manualmente para refletir o número de dias úteis do mês em vigor. Este valor influencia diretamente o "Net Production Time" (NPT), afetando de forma imediata o cálculo do Kanban.



3.2 Forecast anual (SumForecast)

A extrapolação do forecast mensal é feita automaticamente com base nos dados do forecast anual por cápsula, que provém do excel “Orçamento_2025.INJ.xlsx”.

Para cada novo ano (ex: 2026), deve-se substituir o valor de "SumForecast2025" por "SumForecast2026", conforme definido no orçamento anual da empresa no excel “Orçamento_2025.INJ.xlsx”.



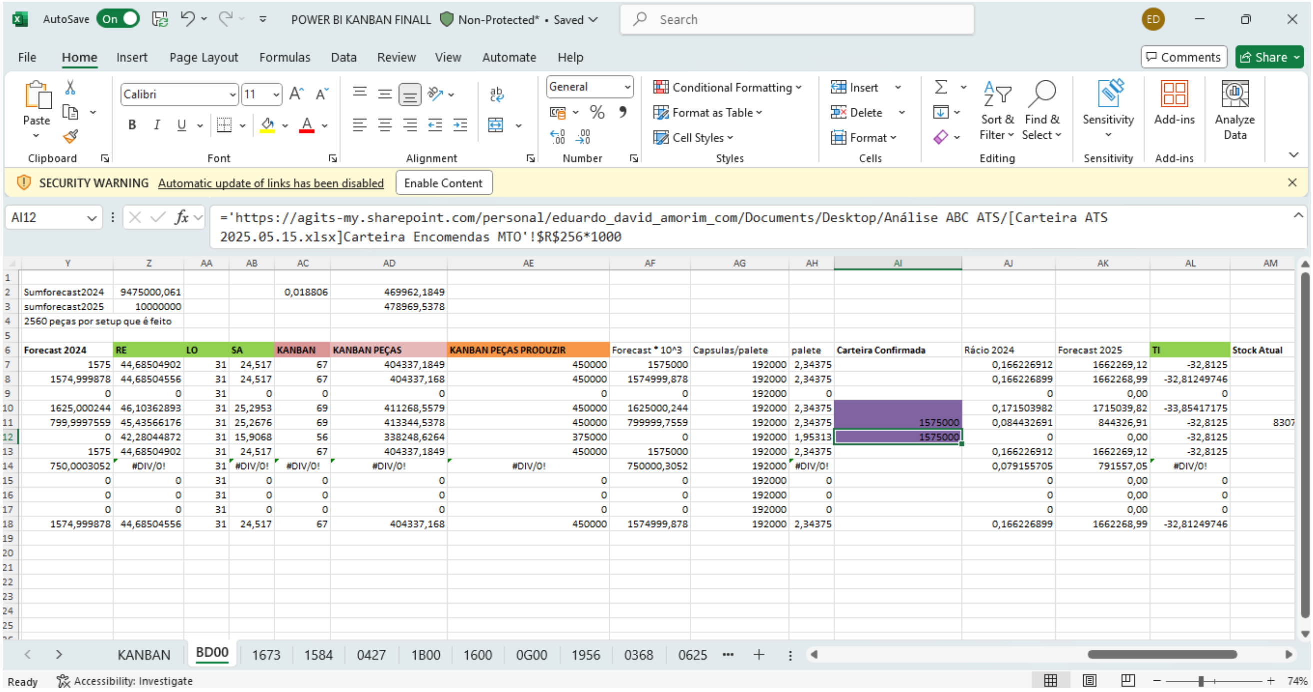
Há que neste excel filtrar a cápsula que se quer trabalhar no excel do Kanban e copiar o forecast definido para essa cápsula.

3.3 Coluna "Carteira de Encomendas"

Esta coluna deve ser atualizada com a soma das quantidades encomendadas para o mês em causa. Importa referir que se devem considerar todas as ordens do mês e não apenas uma em específico, de forma a refletir corretamente a procura real no cálculo do Kanban.

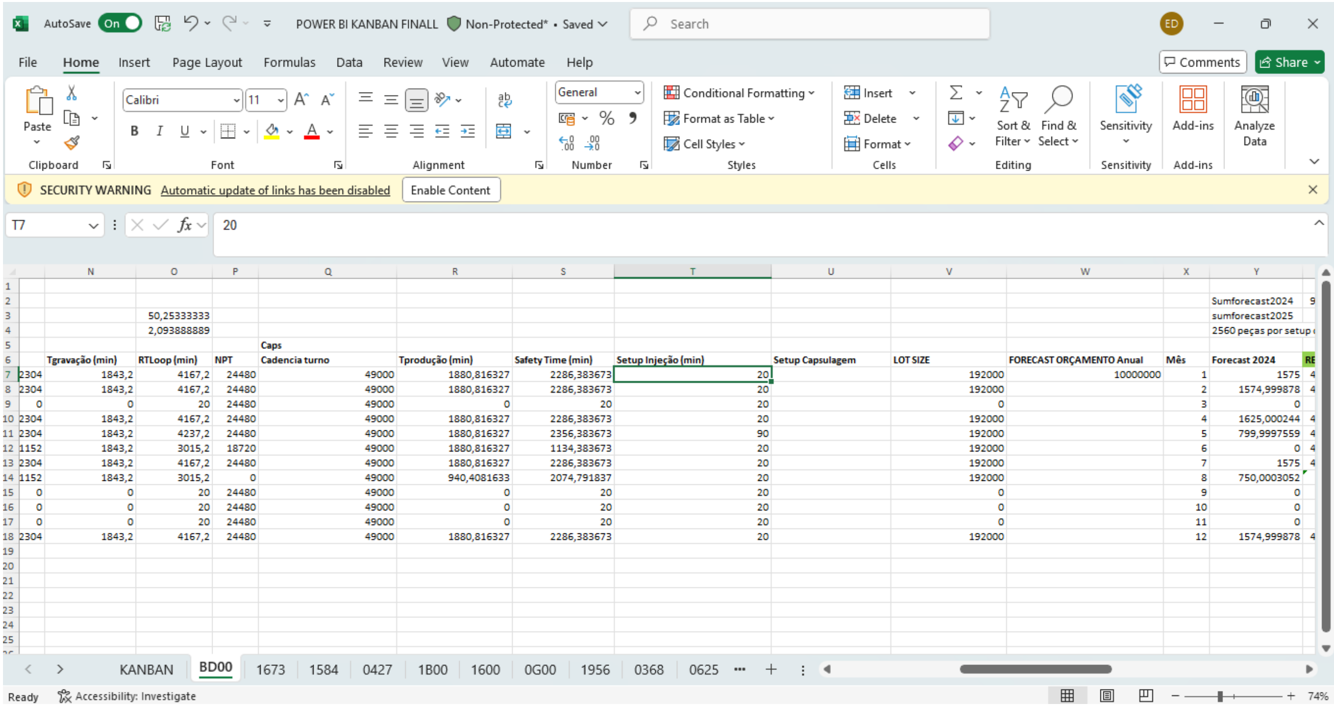
Inicialmente na coluna "Cáps.", do excel da Carteira de encomendas deverá ser feito um filtro apenas da cápsula que se quer verificar.

De seguida, para o mês específico igualar o valor da carteira de encomendas referente no excel do kanban e multiplicar por 1000 (*1000). Segue um exemplo para o mês 6 referente à cápsula BD00 (isto é feito de igual forma para cada cápsula).



3.4 Setup Injeção (min)

Caso sejam ajustados os tempos de setup referentes à injeção, esse valor deve ser inserido na coluna "Setup Injeção (min)". Este parâmetro influencia diretamente o valor de "RTLoop", sendo por isso essencial garantir que está corretamente refletido. É de realçar de como o lot size representa o número de cápsulas que é possível acomodar por palete, uma vez que se trata da unidade de movimentação entre os 2 setores, o setup base de 20 minutos foi considerado por cada palete produzida. Caso os valores dos setup se alterem no chão de fábrica há a necessidade de alterar este valor.



POWER BI KANBAN FINALL • Non-Protected* • Saved

SECURITY WARNING Automatic update of links has been disabled Enable Content

T7 20

	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
1														
2													Sumforecast2024	9
3			50,25333333										sumforecast2025	
4			2,093888889										2560 peças por setup	
5					Caps									
6		Tgravação (min)	RTLoop (min)	NPT	Cadencia turno	Tprodução (min)	Safety Time (min)	Setup Injeção (min)	Setup Capsulagem	LOT SIZE	FORECAST ORÇAMENTO Anual	Mês	Forecast 2024	RE
7	2304	1843,2	4167,2	24480	49000	1880,816327	2286,383673	20		192000	10000000	1	1575	4
8	2304	1843,2	4167,2	24480	49000	1880,816327	2286,383673	20		192000		2	1574,999878	4
9	0	0	20	24480	49000	0	20	20		0		3	0	
10	2304	1843,2	4167,2	24480	49000	1880,816327	2286,383673	20		192000		4	1625,000244	4
11	2304	1843,2	4237,2	24480	49000	1880,816327	2356,383673	90		192000		5	799,9997559	4
12	1152	1843,2	3015,2	18720	49000	1880,816327	1134,383673	20		192000		6	0	4
13	2304	1843,2	4167,2	24480	49000	1880,816327	2286,383673	20		192000		7	1575	4
14	1152	1843,2	3015,2	0	49000	940,4081633	2074,791837	20		192000		8	750,0003052	
15	0	0	20	24480	49000	0	20	20		0		9	0	
16	0	0	20	24480	49000	0	20	20		0		10	0	
17	0	0	20	24480	49000	0	20	20		0		11	0	
18	2304	1843,2	4167,2	24480	49000	1880,816327	2286,383673	20		192000		12	1574,999878	4

KANBAN BD00 1673 1584 0427 1B00 1600 0G00 1956 0368 0625

3.5 Validações Finais

Antes de guardar o ficheiro e permitir a atualização no Power BI, verificar o seguinte:

- A coluna "Dias Úteis" está atualizada com base no calendário do mês em vigor;
- A coluna "Carteira de Encomendas" reflete todas as ordens do mês;
- O forecast anual está correto e corresponde ao ano atual em análise;
- O valor do setup está ajustado, caso aplicável;
- O ficheiro mantém o nome original e está guardado na pasta correta.

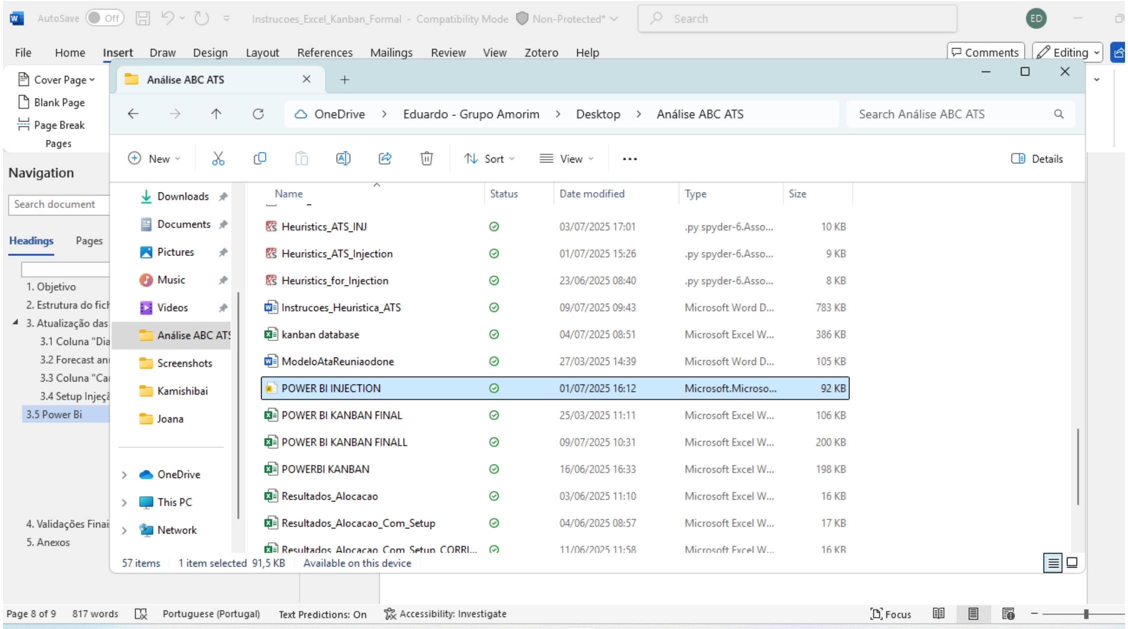
3.5 Power Bi

A análise dos dados calculados no ficheiro POWER BI KANBAN FINALL.xlsx é realizada através do dashboard desenvolvido em Power BI, com o nome **"POWER BI INJECTION"**.

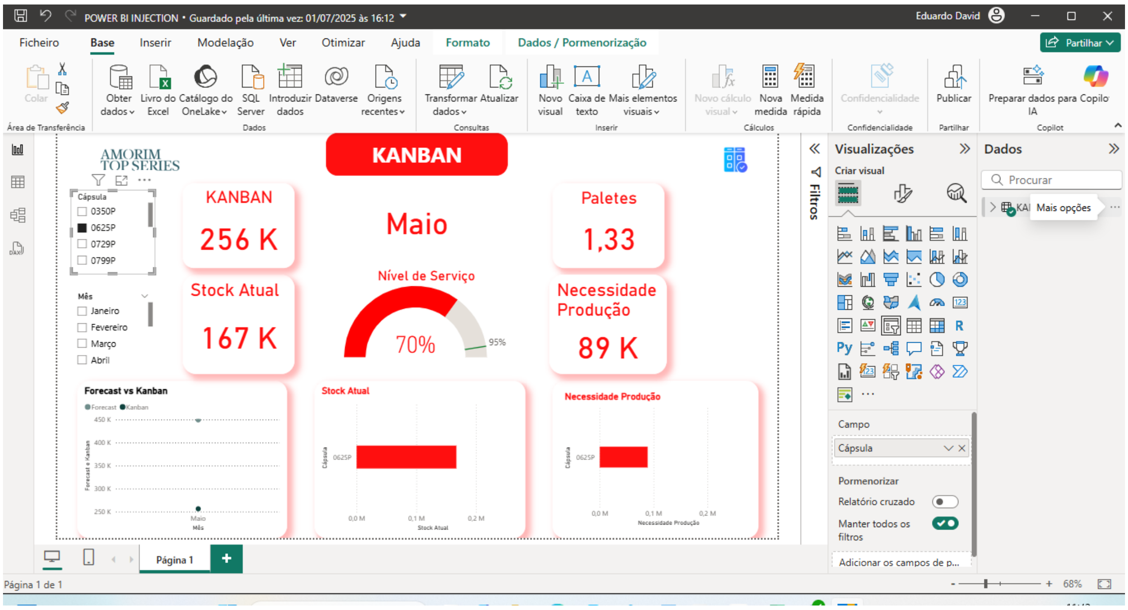
3.5.1 Atualização dos dados

Para garantir que o Power BI reflete os dados mais recentes:

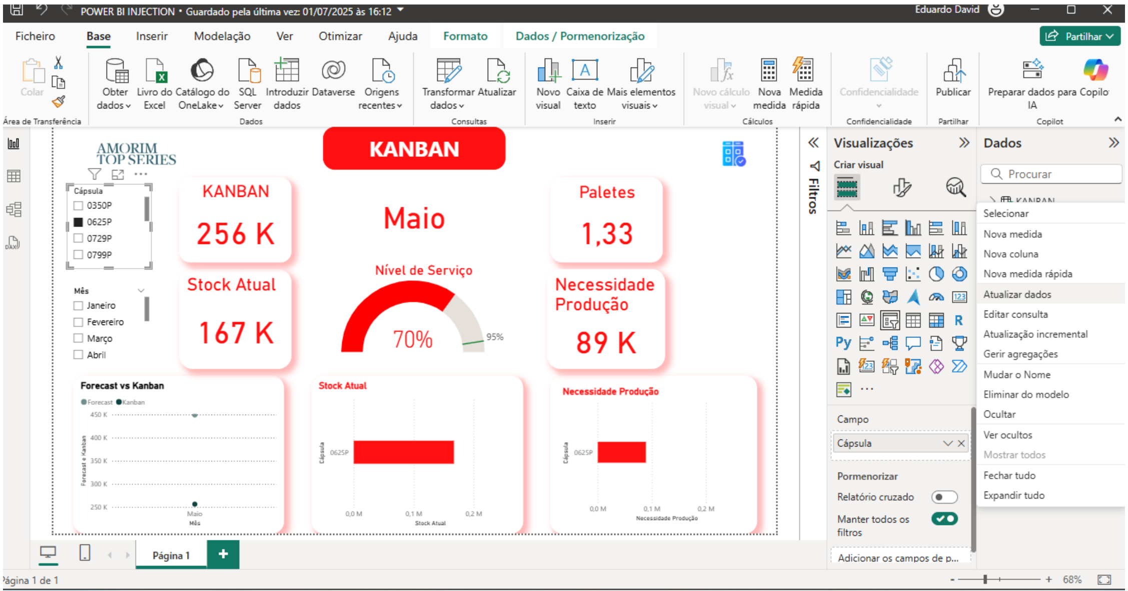
1. Abrir o ficheiro do dashboard POWER BI INJECTION.pbix.



2. No momento da abertura, abrir a aba referente a "Dados", como o conjunto de dados proveniente do excel se denomina de KANBAN, clicar nos 3 pontos que aparecem à direita.



3. Confirmar a atualização, clicando em “Atualizar dados”. O programa irá buscar os dados atualizados ao ficheiro de Excel POWER BI KANBAN FINALL.xlsx.



4. Após a atualização, todos os gráficos e indicadores são automaticamente recalculados com base na nova informação.

Nota: É fundamental que o ficheiro de Excel esteja previamente atualizado e guardado com o mesmo nome e que não esteja aberto no PC antes de efetuar a atualização. Caso contrário, poderá surgir erro de ligação.

3.5.2 Interpretação dos gráficos

Todos os elementos visuais presentes no dashboard são automáticos e interativos. O utilizador não precisa de efetuar qualquer tipo de cálculo ou tratamento adicional — o Power BI processa os dados diretamente a partir da folha "KANBAN" do Excel.

O objetivo principal é permitir uma visualização clara e rápida de indicadores-chave relacionados com o sistema Kanban.

Filtros disponíveis

No painel lateral esquerdo, estão disponíveis dois filtros principais:

- **Filtro de Mês**: permite selecionar um mês específico (ex. Maio) e visualizar todos os dados correspondentes apenas a esse período. Caso nenhum mês seja selecionado, os dados apresentados correspondem ao total acumulado anual.

- **Filtro de Cápsula**: ao selecionar uma cápsula específica (ex. 0350P), os gráficos e indicadores exibem dados apenas dessa cápsula. Se nenhum filtro for aplicado, os valores apresentados serão agregados para todas as cápsulas com plano rolling.

Estes filtros podem ser usados isoladamente ou em combinação para uma análise mais segmentada.

Indicadores e gráficos apresentados

Na imagem fornecida, observa-se a seguinte disposição dos elementos gráficos:

- **Indicadores principais (parte superior central):**
  - **KANBAN**: valor calculado total (ou da cápsula filtrada) para o mês selecionado.
  - **Stock Atual**: quantidade disponível em stock no momento da análise.
  - **Paletes**: conversão da quantidade de stock para número estimado de paletes ocupadas.
  - **Necessidade de Produção**: diferença entre necessidade estimada segundo o Kanban e stock atual.
  - **Nível de Serviço**: representado por um gráfico semicircular, indica a percentagem de cobertura de stock face ao valor de Kanban (ex.: 70%).
- **Gráficos comparativos (parte inferior):**
  - **Forecast vs Kanban**: gráfico de linhas que compara a previsão de consumo com o valor de Kanban, por cápsula.

- **Stock Atual (gráfico horizontal)**: ranking visual do stock atual por cápsula (ou para a cápsula selecionada).
- **Necessidade Produção (gráfico horizontal)**: exibe, por cápsula, o valor necessário de produção para atingir o nível de Kanban.

Todos os gráficos são **automáticos** e atualizam-se dinamicamente com base nos filtros selecionados.

Appendix G

Work Instruction – Scheduling Heuristic

Instruções de Trabalho

Alimentação da base de dados “Data_for_Heuristics.xlsx” para execução da heurística de alocação de produção

Grupo Amorim
ATS

1. Objetivo

O presente documento estabelece o procedimento formal para o preenchimento correto da folha de Excel `DATANEWPYTHON` no ficheiro `Data_for_Heuristics.xlsx`. Esta folha constitui a base de dados necessária à execução do algoritmo de alocação de produção no setor de injeção de cápsulas plásticas.

2. Documentos de origem

Para realizar este procedimento, devem ser utilizados os seguintes ficheiros de suporte:

- Carteira de Encomendas (todas as Ordens de Produção registadas)

- Joana 2025.xlsx (referência das cápsulas do setor de injeção)

- BaseDadosInjeção_CarteiraEncomendas24022025.xlsx (base com dados técnicos complementares)

3. Procedimento

3.1 Identificação das cápsulas relevantes

1. Abrir a Carteira de Encomendas.

Aplicar a função VLOOKUP para cruzar os códigos de cápsulas com os ficheiros "Joana 2025.xlsx" e "BaseDadosInjeção_CarteiraEncomendas24022025.xlsx", de forma a identificar apenas as cápsulas produzidas no setor de injeção.

2. Após o cruzamento, aplicar um filtro na coluna do VLOOKUP e manter apenas as cápsulas válidas.

3. Copiar os dados relevantes para a folha "DATANEWPYTHON" do ficheiro "Data_for_Heuristics.xlsx".

3.2 Preenchimento da folha DATANEWPYTHON

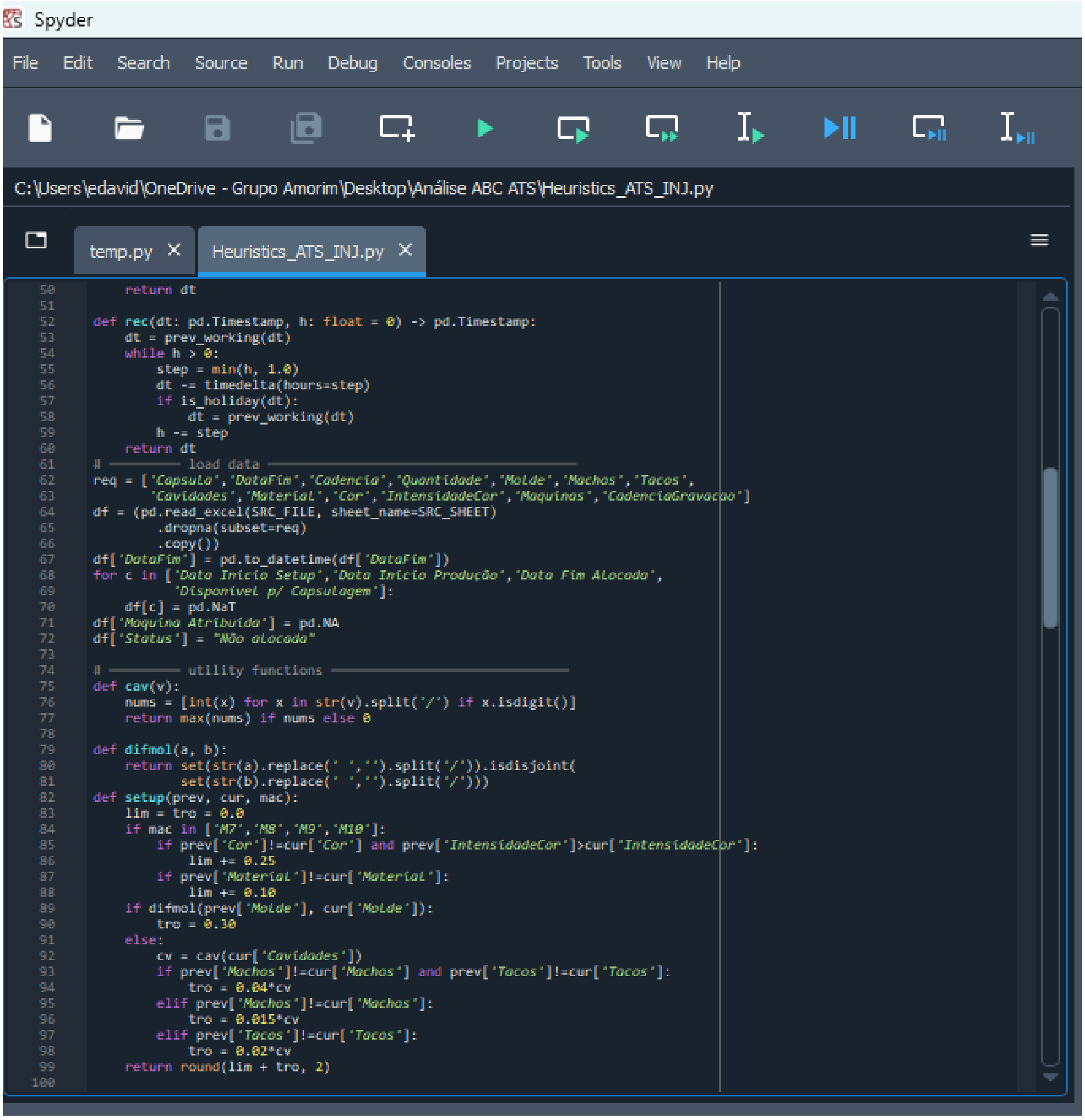
As seguintes colunas devem ser preenchidas com base nas fórmulas indicadas ou na informação extraída dos ficheiros:

Coluna	Fonte / Fórmula
Capsula	Código da cápsula (copiar da carteira de encomendas)
DataFim	Data de entrega da encomenda
Quantidade	Quantidade da encomenda multiplicada por 1000
Cadencia	=IFNA(VLOOKUP(A2;'[BaseDadosInjeção_CarteiraEncomendas24022025.xlsx]Base de dados'!$D$5:$H$307;5;FALSE);30000)
Molde	=IFNA(VLOOKUP(A2;'[BaseDadosInjeção_CarteiraEncomendas24022025.xlsx]Base de dados'!$D$5:$E$307;2;FALSE); VLOOKUP(A2;'[Joana 2025.xlsx]mp cápsulas'!$K$2:$R$4629;8;FALSE))
Cavidades	=IFNA(VLOOKUP(A2;'[BaseDadosInjeção_CarteiraEncomendas24022025.xlsx]Base de dados'!$D$5:$F$307;3;FALSE); VLOOKUP(F2;'[Joana 2025.xlsx]Inventário Moldes '!$B$2:$C$185;2;FALSE))
Máquinas	=IFNA(VLOOKUP(A2;'[BaseDadosInjeção_CarteiraEncomendas24022025.xlsx]Base de dados'!$D$5:$G$307;4;FALSE);"1;2;3;4;5;6;7;8;9;10")
Descrição	Copiar da carteira (exemplo: "CP PL AC PRT 31,5X19,3X12X7 AR CMP")
Tacos	=TEXTBEFORE(TEXTAFTER(I2;" ";4);"X")
Machos	=INDEX(TEXTSPLIT(TEXTAFTER(I2;" ";4);"X");2)
Cor	=INDEX(TEXTSPLIT(I2;" ");4)
IntensidadeCor	Após coluna auxiliar com =UNIQUE(L2:L229;FALSE), aplicar =VLOOKUP(L2;$P$2:$Q$14;2;FALSE)
Material	=INDEX(TEXTSPLIT(I2;" ");3)
CadenciaGravacao	Atribuir 25000 apenas se a descrição da cápsula indicar que há gravação

4. Validações Finais

Antes de guardar e executar o algoritmo, devem ser realizadas as seguintes validações:
- Verificar se todas as colunas obrigatórias estão corretamente preenchidas;
- Confirmar o arrastamento das fórmulas para todas as linhas preenchidas;
- Não há necessidade de eliminar quaisquer erros de referência ou células com #N/A, isso já é tratado pelo código. Apenas se nas bases de dados não existirem dados relativos a uma cápsula específica o valor que aparecerá na coluna será o #N/A mas não há necessidade do remover.
- Garantir que o ficheiro mantém o nome original: "Data_for_Heuristics.xlsx".

-Não trocar o nome das colunas referentes à aba DATANEWPYTHON do excel "Data_for_Heuristics.xlsx". Caso se altere haverá necessidade também de alterar no código. Este pequeno trecho de código seguinte demonstra claramente que se as colunas forem alteradas todo o código terá de sofrer alterações praticamente.



Spyder
File Edit Search Source Run Debug Consoles Projects Tools View Help
C:\Users\edavid\OneDrive - Grupo Amorim\Desktop\Análise ABC ATS\Heuristics_ATS_INJ.py
temp.py
Heuristics_ATS_INJ.py
    return dt

def rec(dt: pd.Timestamp, h: float = 0) -> pd.Timestamp:
    dt = prev_working(dt)
    while h > 0:
        step = min(h, 1.0)
        dt -= timedelta(hours=step)
        if is_holiday(dt):
            dt = prev_working(dt)
        h -= step
    return dt
# ──────── load data ────────────────────────
req = ['Capsula','DataFim','Cadencia','Quantidade','Molde','Machos','Tacos',
       'Cavidades','Material','Cor','IntensidadeCor','Maquinas','CadenciaGravacao']
df = (pd.read_excel(SRC_FILE, sheet_name=SRC_SHEET)
        .dropna(subset=req)
        .copy())
df['DataFim'] = pd.to_datetime(df['DataFim'])
for c in ['Data Inicio Setup','Data Inicio Produção','Data Fim Alocada',
          'Disponivel p/ Capsulagem']:
    df[c] = pd.NaT
df['Maquina Atribuida'] = pd.NA
df['Status'] = "Não alocado"

# ──────── utility functions ────────────────
def cav(v):
    nums = [int(x) for x in str(v).split('/') if x.isdigit()]
    return max(nums) if nums else 0

def difmol(a, b):
    return set(str(a).replace(' ','').split('/')).isdisjoint(
           set(str(b).replace(' ','').split('/')))
def setup(prev, cur, mac):
    lim = tro = 0.0
    if mac in ['M7','M8','M9','M10']:
        if prev['Cor']!=cur['Cor'] and prev['IntensidadeCor']>cur['IntensidadeCor']:
            lim += 0.25
        if prev['Material']!=cur['Material']:
            lim += 0.10
    if difmol(prev['Molde'], cur['Molde']):
        tro = 0.30
    else:
        cv = cav(cur['Cavidades'])
        if prev['Machos']!=cur['Machos'] and prev['Tacos']!=cur['Tacos']:
            tro = 0.04*cv
        elif prev['Machos']!=cur['Machos']:
            tro = 0.015*cv
        elif prev['Tacos']!=cur['Tacos']:
            tro = 0.02*cv
    return round(lim + tro, 2)