FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Resilience in Industry 4.0 Digital Infrastructures and Platforms

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WORKING VERSION

Mestrado Integrado em Engenharia Eletrotécnica e de Computadores

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June 28, 2021

Resumo

A indústria 4.0 consiste numa mudança de paradigma de produção automatizada para um conceito de produção inteligente onde todos os ativos físicos, como os produtos, componentes, estação de trabalho e máquinas, processam informação individual e fazem parte de uma rede de coisas (Internet of Things) onde podem comunicar entre si. Esses ativos são considerados sistemas cíber-físicos (CPS) e o sistema de produção, composto por vários CPS, passa a ser um sistema de produção cíber-físico (CPPS). Os CPPSs são sistemas altamente flexíveis que permitem a produção de pequenos lotes a preços competitivos e aumentar a personalização de produtos através de processos de produção adaptativos.

Consequentemente, as empresas estão a desenvolver novos sistemas de informação para ganhar visibilidade e controlo sobre os seus sistemas de produção. Um exemplo desta evolução é o investimento num Manufacturing Execution System (MES) baseado na Cloud. Embora a mudança agilize a produção, esta também aprofunda a dependência em plataformas de produção digitais e a vulnerabilidade a novas disrupções relacionadas com comunicação e informação. Neste contexto, estas novas disrupções são o novo bottleneck do sistema de produção, necessitando o desenvolvimento de novas ferramentas para antecipar e controlar os seus impactos.

Esta dissertação propõe o uso de simulação híbrida como uma ferramenta de apoio a agentes de decisão na previsão de possíveis disrupções e na avaliação dos seus impactos no sistema de produção. Assim sendo, eventos disruptivos são analisados, modelados e simulados como parte de uma metodologia desenhada para medir os impactos de disrupções nos CPPSs e ajudar a criação de uma base de dados com medidas de mitigação eficazes.

Para demonstrar e testar a metodologia, esta foi aplicada a um caso de estudo relativo a uma empresa portuguesa na indústria da cortiça. A empresa tem vindo a investir em hardware para recolher informação sobre as atividade no chão de fábrica em tempo real, e na implementação de um MES para a gestão dos processos. Apesar das vantagens, a empresa está preocupada com a dependência na infraestrutura digital instalada e a capacidade desta permanecer resiliente face a novos tipos de disrupções. Após uma análise inicial do processo de fabrico de uma das suas linhas de produção destinada a produção de rolos de tapete de cortiça e o processo de expedição dos mesmos, foram distinguidas e avaliadas duas disrupções: (1) falha de conexão entre MES e linha de produção, e (2) falha do serviço autónomo para contactar a Autoridade Tributária. Após a observação dos resultados, foram apresentados planos de mitigação possíveis.

Abstract

Industry 4.0 consists of a paradigm shift from automated production to an intelligent production concept where all physical assets such as products, components, workstations, and machines possess individual information about themselves and are part of a network with communication interfaces, where all participants can interact with each other using technologies such as the Internet of Things. These assets are now called Cyber-Physical Systems (CPS), and the manufacturing system itself a Cyber-Physical Production System (CPPS). CPPSs are highly flexible systems that allow small batches to be produced at lower prices and increase product customization through adaptive production processes.

Consequently, companies are evolving their information systems to have more visibility and control over their production systems. As an example, companies are investing in cloud-based manufacturing execution systems (MES). Although this evolution allows the production to become more agile, it also increases the dependency on digital manufacturing platforms and vulnerability to new types of information and communication disruptions. In this context, these disruptions caused by missing information or communication failures are now the new production system's bottleneck, which requires the development of new tools to manage and control them.

This thesis proposes the use of hybrid simulation as a tool to allow decision-makers to predict possible disruptions and their impacts on the production processes. Here, disruptive events are analysed, modelled, and simulated as part of a methodology designed to measure the impact of disruptions on the production system and help create a database with effective countermeasures. A use case study will be performed to test and demonstrate the application of the methodology.

Agradecimentos

A realização desta dissertação não seria possível sem o apoio de algumas pessoas, às quais gostaria de deixar uma palavra de apreço.

Em primeiro lugar, agradeço aos meus orientadores nesta dissertação, pela disponibilidade ao longo do semestre e todos os momentos de partilha de informação que tivemos.

Por último, deixo o maior agradecimento à minha família e namorada cujo o apoio foi essencial para a conclusão desta dissertação. Agradeço a presença, o carinho, e palavras que facilitaram todo o meu percurso académico. Não posso deixar de agradecer também aos meus colegas pela amizade e momentos que levarei para toda a vida. Sem todos eles, os últimos cinco anos não teriam sido tão gratificantes.

Daniel Ribeiro

*“When we are no longer able to change a situation,
we are challenged to change ourselves”*

Viktor E. Frankl

Contents

List of Figures

List of Tables

Abbreviations

i4.0	Industry 4.0
CPS	Cyber-physical system
CPPS	Cyber-physical production system
MES	Manufacturing execution system
ERP	Enterprise resource planning
UML	Unified Modeling Language
OEE	Overall equipment effectiveness
KPI	Key process indicator
PO	Porduction order

Chapter 1

Introduction

1.1 Context

Since the Industrial Revolution, we have seen incredible progress in industrial productivity through technological advances. First, the steam engine powered factories in the nineteenth century, then electrification led to mass production in the early part of the twentieth century, and lastly, the industry became automated in the 1970s. These three major steps forward in the manufacturing industry are known as the first, second, and third industrial revolutions.

Industry 4.0 or Industrie 4.0 (i4.0) is generally referred to as the fourth industrial revolution and aims to fulfill individual customer requirements in small batches [7]. It implies a paradigm shift from automated manufacturing toward an intelligent manufacturing concept. In this concept, sensors, machines, workpieces, and IT systems are connected and can interact with each other using standard Internet-based protocols and analyze data to predict failure, configure themselves, and adapt to changes [8].

The four main drivers of Industry 4.0 are the Internet of Things (IoT), Industrial Internet of Things (IIoT), cloud-based manufacturing, and smart manufacturing which help in transforming the manufacturing process into a fully digitized and intelligent one [9]. The nine pillars of Industry 4.0 (Figure 1.1) will transform isolated and optimized cell production into a fully integrated, automated, and optimized production flow. This leads to greater efficiency and change in traditional production relationships among suppliers, producers, and customers as well as between humans and machines [10].

Cyber-physical systems (CPS) are engineering systems responsible for integrating communication, control, and computing within a system governed by the laws of physics, whether natural or manufactured. In i4.0, CPSs offer the ability to increase safety, reliability, and yield in industrial production. They offer a solution to expand production capabilities that address new and advanced problems in production [9]. These systems are defined by the following characteristics [11]:

- Collect data about themselves and their environment using sensors.
- Process and evaluate the collected data.

- Connect and communicate with other systems in a global network.
- Initiate actions and interact with the physical world using actors.

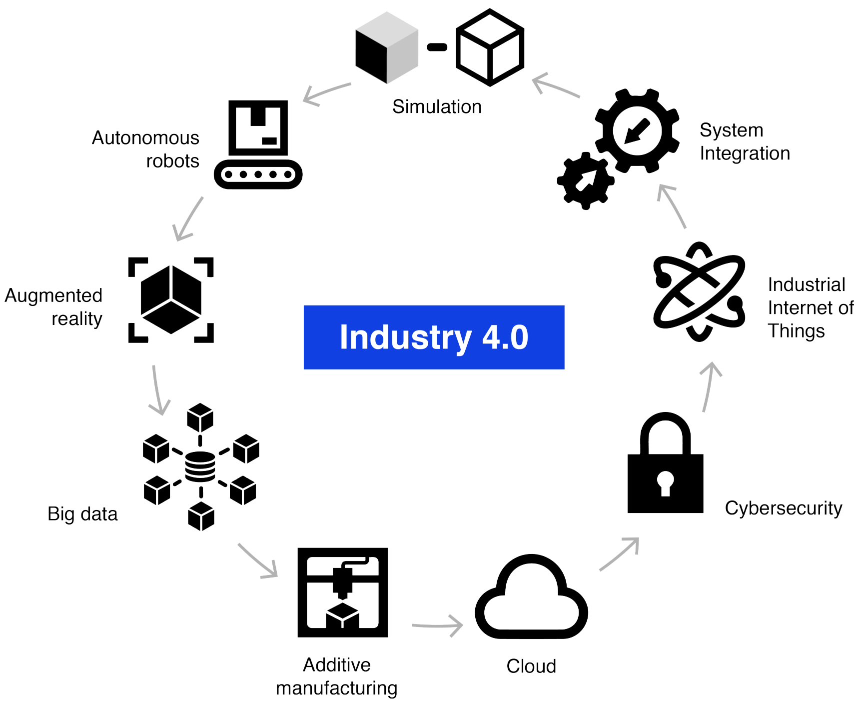

Figure 1.1: The nine pillars of Industry 4.0.

In this context, CPS can be applied in production assets, such as manufacturing stations, automation devices, machines, tools, and individual components. CPS promotes intensive connection and coordination between the physical assets and computational software providing and using data-accessing and data-processing services simultaneously [12]. The integration of CPS in the production environment leads to cyber-physical production systems (CPPS) [13]. CPPSs consist of autonomous subsystems that are connected across all levels of production, from processes, through machines, and up to production and logistics networks [14]. These are highly flexible systems that allow small batches to be produced at lower prices and increase product customization through adaptive production processes [2].

1.2 Motivation

Industry 4.0 enabled smart, efficient, specific and customized production at reasonable costs. It takes advantage of the before-mentioned nine pillars to move toward the cyber-physical production system concept and convert regular machines to self-aware and self-learning assets, thus improving their overall performance.

Although advantageous, the increasing complexity of CPPS leads to higher vulnerability to disruptions during production processes. On the other hand, the advanced connectivity between

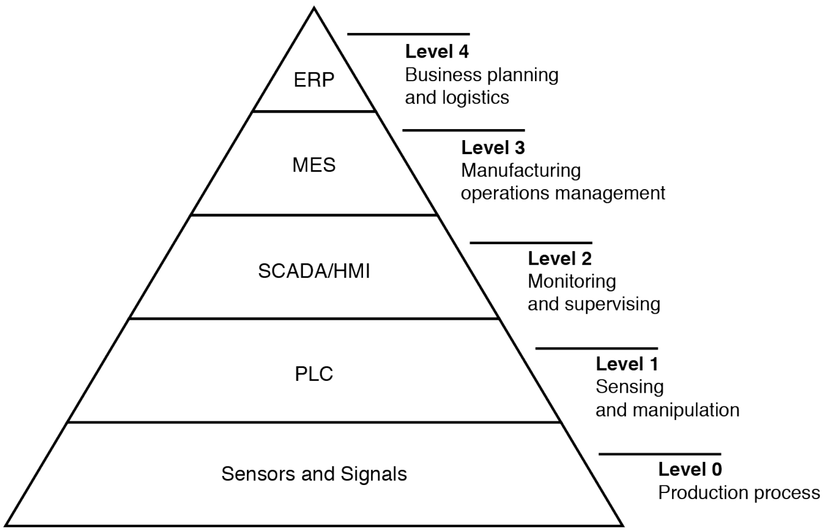

Figure 1.2: ISA-95 automation pyramid [1].

production assets, made possible by the collection and intelligent analysis of enormous amounts of data, allowed the development of tools that process data to extract information, make real-time informed decisions, and achieve adaptive process planning [15]. In the context of disruption management, simulation tools have been developed to help decision-makers respond quickly to disruptions in the production processes [16], but there are remaining gaps in the literature.

The planning and control of adaptive production processes need continuous monitoring and IT (Information Technology) support [3], leading companies to evolve their information systems. This need aligns with the necessity to better integrate the business processes with the production processes through cloud-based manufacturing execution systems (MES) and enterprise resource planning (ERP). This evolution lead to the morphing of the traditional hierarchical control architecture, or automation pyramid (Figure 1.2), into a heterarchical structure (Figure 1.3) that represents a CPS-based automation (CPPS) [2].

Heterarchical structures tend to be more resilient facing non-cascade disruptions but less resilient to cascade disruptions where a disruptive event in one system may affect other in the network [17]. They also increase the dependency on digital manufacturing platforms and vulnerability to new types of information and communication disruptions. Furthermore, these disruptions caused by missing information or communication failures are now the new production system's bottleneck, which requires developing new tools to assess their impacts and to manage them.

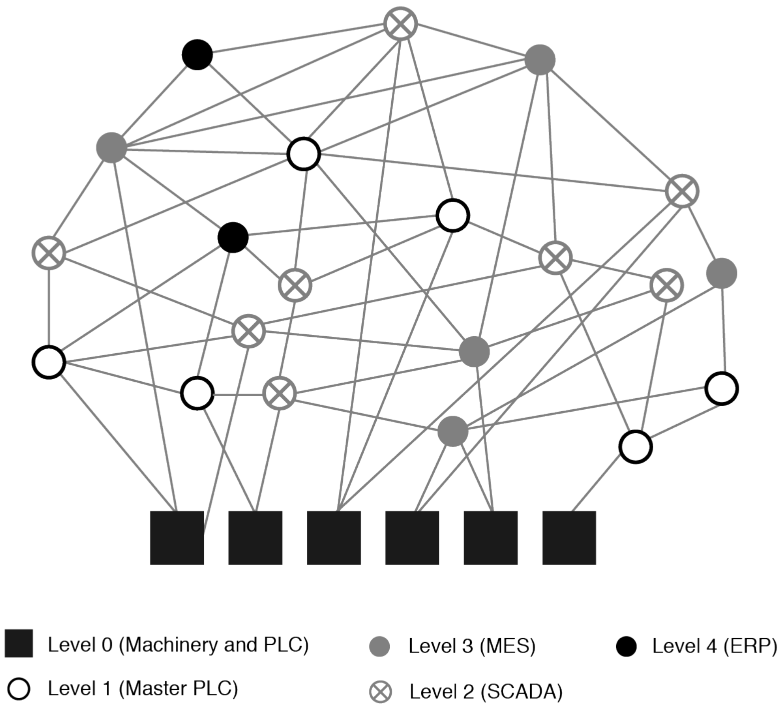

Figure 1.3: CPS-based automation [2].

1.3 Objectives

1.3.1 Research objectives

The main objective of the present work is to develop a solution capable of supporting decision-makers to predict possible disruptions and their impacts on cyber-physical production systems processes, and by doing so, contribute to the literature about resilience in i4.0 digital platforms. Due to the rising interest in simulation approaches in the area of disruption management and i4.0 in general, the proposed solution will employ simulation as a tool to achieve its goal.

Therefore, the study of simulation tools in the design of resilient CPPS will be carried out. For that purpose, the different types of modelling and simulation will be analysed. The next step is to define how resilience can be quantified and what types of disruptions are CPPS exposed to. The last step consists of developing a solution that will aid decision-makers to identify disruptions, assess their impacts, and establish mitigation actions.

From the main objective several others can be isolated:

- Literature review of existing solutions;
- Analysis and categorization of disruptive events in CPPS;
- State-of-the-art review on resilience, resilient CPPS architectures, and resilience metrics;

- Development of a simulation-based disruption assessment methodology for decision support;
- Experimental test and analysis in a case study.

1.3.2 Research questions

With the previous analysis in mind, the following research questions were encountered:

1. What are the main causes of process disruptions in CPPSs and how can they be categorized?

   Process disruptions are sure to occur in any production system, and with modern applications of CPS, the systems become vulnerable to new problems. This question will be answered in the literature review, which will be critical for the development of the solution.

2. How can the impacts of process disruptions in CPPSs be evaluated using simulated-based approaches?

   The simulation of expensive physical assets allows us to predict and detect failures and take control of functionality. The current state-of-the-art related to simulated-based approaches for disruption management in cyber-physical production systems will be reviewed and then a practical use case will be implemented to compare and discuss the results.

3. How can we quantify and improve the resilience of CPPSs?

   By identifying the possible process disruptions and quantifying their impacts in terms of resilience, proper mitigation actions can be taken. In the same manner as the previous questions, the resilience of CPPSs will be analysed in the literature review and in the case study.

1.4 Research methodology

An action research methodology will be used to guide this thesis. It's a methodology that uses a circular model process, described by the development of knowledge in the process and intercalating action (data collecting) with critical reflection (data analysis) [18].

The hypothesis to be tested is how simulation can be used to evaluate the impacts of process disruptions on cyber-physical production systems and suggest mitigation strategies to increase the resilience in these systems. The research started with a literature review and analysis of the state-of-the-art related to simulation-based approaches for disruption management in CPPS.

The main sources of information for the literature review will be Scopus, Engineering Village, and ResearchGate. All three of these libraries are major articles' databases in the engineering field and their access is facilitated by Universidade do Porto, which adds to the reason why they were chosen.

In a second phase the objective was to study the literature on the architectures of resilient CPPS, the main types of process disruptions caused by new digital platforms, and the metrics used

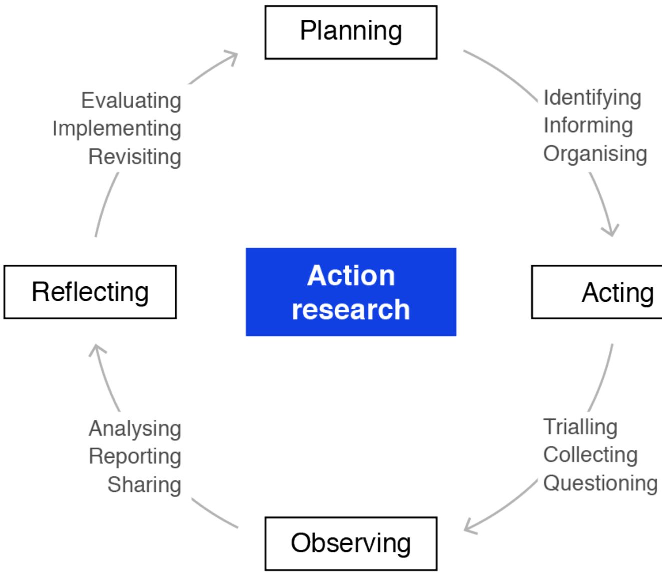

Figure 1.4: Action research model

to measure their impact in terms of resilience. The collected research will be analyzed to develop a methodology that allows, for a particular CPPS, to determine, model and simulate potential disruptive events, compare the impacts via a selected key performance indicator, and suggest effective mitigation actions.

To test and demonstrate the application of the methodology, a case study was be performed. Here, the methodology is applied, and results evaluated, based on a simulation model of the described production system and digital platforms. Following an iterative process, if the previous research determines that a new review of the literature is necessary, the process described will be repeated. Finally, using a deductive reasoning model, the initial hypothesis will be tested so that it can be validated and generalized.

The present research is an exploratory work. Thus, there was a weighted balance between the conceptual study and the use case application. Also, because the study of the impacts of disruptions caused by new digital platforms and CPS applications using simulation tools is believed to be a new potential area of research, an intermediary paper was written and published at the 18th International Conference in Manufacturing Research ICMR 2021.

1.5 Dissertation structure

This dissertation is divided in five chapters. Chapter 1 summarizes the context description, what is today's manufacturing paradigm, and the new emerging applications of cyber-physical systems and the disruptions they're exposed to. It also explains why companies need tools to assess the impact of these disruptions and how can they mitigate them to increase resilience. Lastly, the objectives are listed and the research methodology explained.

In Chapter 2, the literature on disruptions, resilience, and simulation, all in the context of cuber-physical production systems, was reviewed. Consequently, a simulation-based methodology for disruption assessment is presented in Chapter 3. The proposed methodology is then tested in a case study in Chapter 4, that pivots on a particular shop floor activity of a Portuguese company in the cork industry.

Lastly, Chapter 6 includes the conclusions made regarding the case study and the application of the methodology. Additionally, future works are suggested.

Chapter 2

Literature review

2.1 Introduction

In an industrial context, disruption management consists of dealing with unanticipated events that cause deviations in the production processes. A standard solution to handle these events is to rely on the system's robustness and deploy an untested recovery plan. This approach lacks reactivity and leaves the decision-maker with limited feasible plans, impacting the system's resilience [16]. With the increasing complexity and implementation of cyber-physical production systems (CPPS), new disruptions may occur. Thus, the decision-maker must be knowledgeable of them and their impacts on the production system. Disruption management deals with disruptions in real-time and, although the goal is not to build a disruption management system, it is aligned with the proposed solution and presents itself as a pertinent research topic.

In [16] four main classes of approaches for disruption management are distinguished: decision support, resource allocation, cooperation, and coordination. The decision support approach focuses on aiding a human decision-maker by including one or several users in the process of selecting the appropriate solution for dealing with disruptions, typically taking into account the user's objective, which in this case is to increase the system's resilience. This approach will be the focus of this research in order to assess how simulation is used to evaluate the impact of disruptions in the production system. For instance, the types of simulation and software that are being used. So, a methodical analysis of research papers on the topics of disruption events, resilience, and simulation-based decision support for developing effective countermeasures for disruptions, all in the context of CPPS, was performed.

2.2 Digital manufacturing platforms

Digital manufacturing platforms are providing services that support manufacturing in a holistic point of view. They allow the development of services responsible for collecting, storing, processing and delivering data related to either products or manufacturing assets such as material, machine, enterprises, and workers [19, 20]. Consequently, these digital platforms operate as digital extensions of capabilities for physical assets, related to the concept of cyber-physical systems [21].

The before-mentioned services, provided by platforms such as manufacturing execution systems (MES), manufacturing operations management (MOM), and enterprise resource planning (ERP) systems, aim to optimise production through improved efficiency, quality, speed, and flexibility. Therefore, they may introduce the following functionalities [22]:

- Monitoring of manufacturing processes;
- Manufacturing control and planning;
- Simulation of production processes;
- Shop floor assistance through visual interfaces;
- Predictive and automated maintenance.

Digital industrial platforms bring infrastructure, and more importantly, allow the creation of applications and value on top of this infrastructure, through their impartiality toward external complementary applications and inclusion of multiple service providers [19]. Additionally, they may be established within the factory environment or externally in cloud servers [23].

In order for digital platforms to advance in a manufacturing context, there is a need for agreements on industrial communication protocols, common data models and the semantic interoperability of data, and ultimately, platform interoperability [24]. Consequently, the mentioned interoperability, described as the ability to exchange and make use of information, leads to greater dependency on digital platforms and increases the productions system's vulnerability to new types of disruptions [25].

2.3 Disruptions

Generally, a process disruption is an unwanted event that leads to a non-executable process during the execution of the current operation, where the deviation from the plan is vast enough that the plan has to be changed considerably [26]. In this definition, disruption is the event that leads to the deviation, but not the deviation itself as seen in [27]. As such, a process deviation is defined as the effect of a disruption event.

Disruptions include both disturbances and failures since both of them can cause the process to be disrupted. A production disturbance is an unplanned or unwanted state of the system and may occur in various components of a manufacturing system [6], due to missing components, blocked manufacturing stations, absent workers, and scant resources [8]. Because of the growing advances of communication technologies in CPPSs and the importance of information transparency, disturbances can additionally be caused by missing required manufacturing information or a failure of the communication interfaces [4]. Failures are described as the non-functional state of a system.

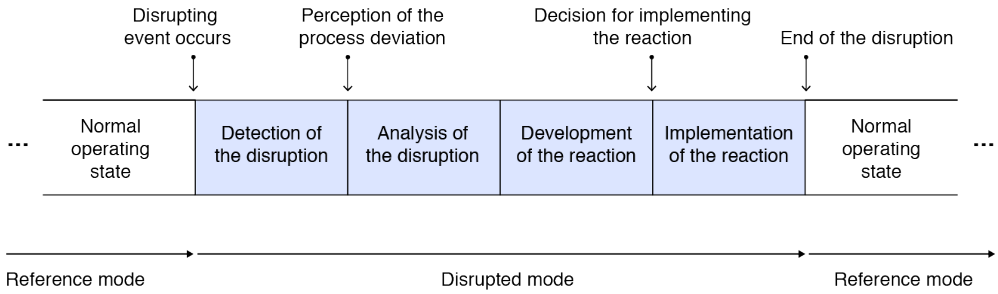

Figure 2.1: Lifecycle of a process disruption [3].

In manufacturing systems, failures may be caused by missing workforce, mechanical breakdowns, or quality problems [28].

The effects of disturbances and failures include: blocking, where the next machine in the process can no longer deliver its material; Idleness, where the machine runs out of new raw material [6]; Unsatisfied user specifications, infrastructure disruption, and risk or harm to people, machines or the environment [29].

The lifecycle of process disruption is divided into four phases [3]:

1. Detection phase: it's the time between the occurrence of the disrupting event and the time the process deviation is noticed.

2. Analysis phase: diagnose and analysis of the causes of the disruptions.

3. Development phase: develop and decide on countermeasures to solve the process deviations.

4. Implementation phase: the solution previously defined is implemented and the system should return to its normal operating state.

A similar description of the lifecycle of process disruption is presented in [30], where the detection phase is considered the latent phase, and the others the manifest phase.

2.3.1 Categorize disruptive events

The increasing complexities and dynamics of cyber-physical production processes are creating a high degree of vulnerability to anomalies arising from production processes failures and disturbances. Modeling and simulation of process disruptions are necessary to handle them in a cyber-physical production system and decide the acceptable reaction. To do that, it has to be identified what are the main disruptions events that can occur in a production system. Disruptions can be categorized according to the source of the event such as products, human resources and production equipment [28], [29]. In the case of cyber-physical production systems, the sources can be extended into information and communication [3].

In [4], an Ishikawa diagram is used to illustrate the possible causes of disruption in cyber-physical production systems. These disruptive events are divided into five categories: Material, Machine, Method, Manpower, and Milieu (environment). On the other hand, [6] proposes that information about disturbances can be obtained from a manual logbook and interviews with the personnel. This way, specific disruption events from a particular production facility can be listed, thus allowing effective countermeasures to be studied and applied.

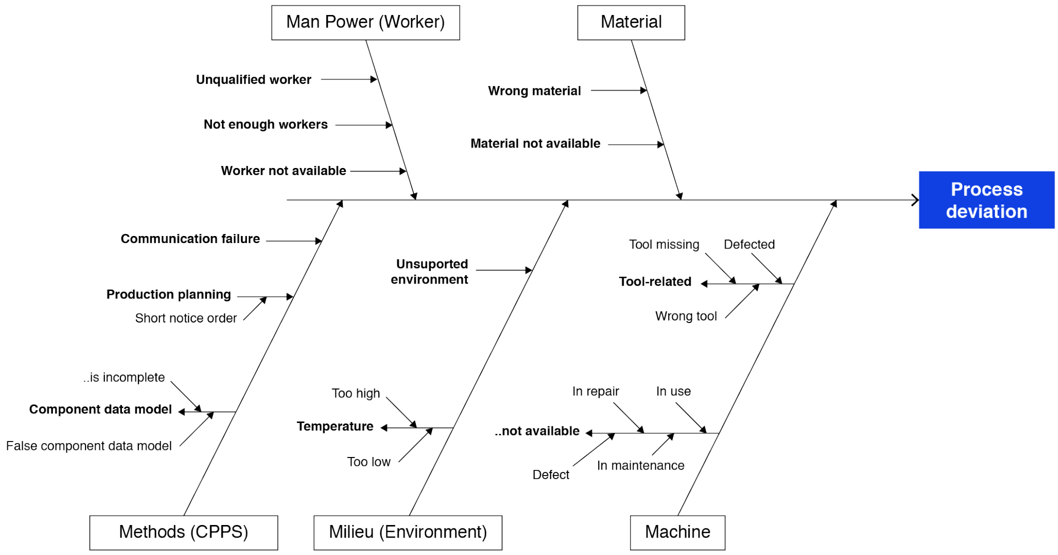

Figure 2.2: Ishikawa diagram for determining causes of process disruption in a cyber-physical production system [4].

2.4 Resilience

Resilience defines the system's behaviour when a disruption occurs during runtime. The resilience of a manufacturing system is measured by its ability to withstand disruptions through maintaining functions and structures, minimizing the time in the disruptive state, and responding to disruptive events [17]. Hence, the concept of resilience includes both the principles of robustness and agility.

2.4.1 Robustness

Robustness represents the ability of the system to deal with minor disruptions without adaptations. It is the feature of a system that allows it to resist change or external factors, maintaining its stability [30] and continuously providing the desired output [31]. Typically, robustness refers to a constructive approach that prevents uncertainty from limiting the functionality of production processes, giving resistance to anticipated changes [32].

Risk is defined as the effect of process deviations on production objectives and is closely related with the concept of robustness [33]. If the deviations have little effect, the production system is robust. So, the higher the robustness of the production system, the lower are the risks it is exposed to.

2.4.2 Agility

Represents the ability of the system to recover its original state by adapting to changes caused by severe disruptions [32]. The main advantage of an agile system is that it changes quickly and smoothly without predefined plans, meaning that not all potential disturbances need to be known since alternative mitigation actions will take place soon after disturbances occur [34]. Agility is often associated with flexibility, the difference being, flexible systems require previous knowledge of potential disruption events.

2.4.3 Measuring resilience

The analysis of production systems resilience is very important to the design stage and operations management in a dynamic global environment. Thus, it is necessary to have a basic understanding of manufacturing systems resilience, the methods and tools for optimal design, investment decisions on built-in redundancy and flexibility, and mitigation strategies [35].

2.4.3.1 Resilience indexes

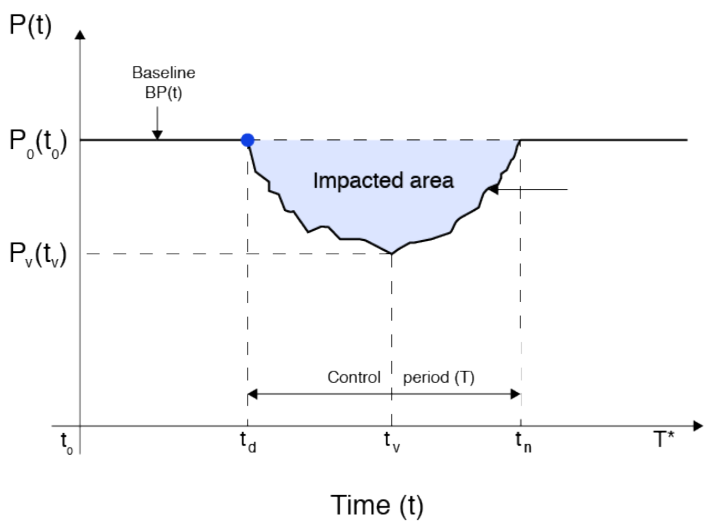

Figure 2.3: Generic resilience evaluation scenario focusing on the difference between Baseline Performance BT(t) and After Impact Performance AP(t) over a control period (T), introduced in [5].

In [36] four resilience indexes for calculating the resilience of cyber-physical systems, based on two different definitions of performance, are presented and compared. Although it was initially directed for measuring the impacts of cyberattacks, the application of these indexes is vastly wide since they are based on performance indicators.

Considering the plot in Figure 2.3, it describes a generic resilience evaluation scenario, where:

- The coordinates are Time (x-axis) and Performance (y-axis).
- BP(t) - Baseline Performance - represents the performance of the system under normal conditions.
- AP(t) - After-impact Performance - represents the performance of the system after the impact of a disruptive event.
- t_d - Disruption time - represents the time the disruption occurs.
- t_n - eturn to normality time - represents the time the disruption ends.
- $T = t_n - t_d$ - Control period.
- t_v - Lowest performance time - represents the time the system reaches the minimum level of performance after the disruption.
- T^* - Observation period - where $T^* > T$.

The first resilience index, presented in [37] is defined as:

$$\Psi_A = \int_{t_d}^{t_n} \frac{AP(t)}{T} dt \tag{2.1}$$

This index takes into consideration the area of the curve AP(t) normalized over the control period T. The higher the value, the closer to normal operating conditions, and the greater the system's resilience. This index does not need to establish a baseline and it can be applied to any performance indicator. Its major drawback is that it requires knowledge of the control period which can be difficult to estimate depending on the problem.

The second index is defined as:

$$\Psi_B = \frac{\int_{t_0}^{T^*} AP(t)dt}{\int_{t_0}^{T^*} BP(t)dt} \tag{2.2}$$

It is the ratio of the areas enclosed by the curves AP(t) and BP(t). The values range from 0 - no functionality is lost - to 1 - the limit case in which the disruptive event and the system lose its functionality. This resilience index does not require knowing the control period, but instead, a baseline performance needs to be established. Another solution that avoids knowing the control period is defined as

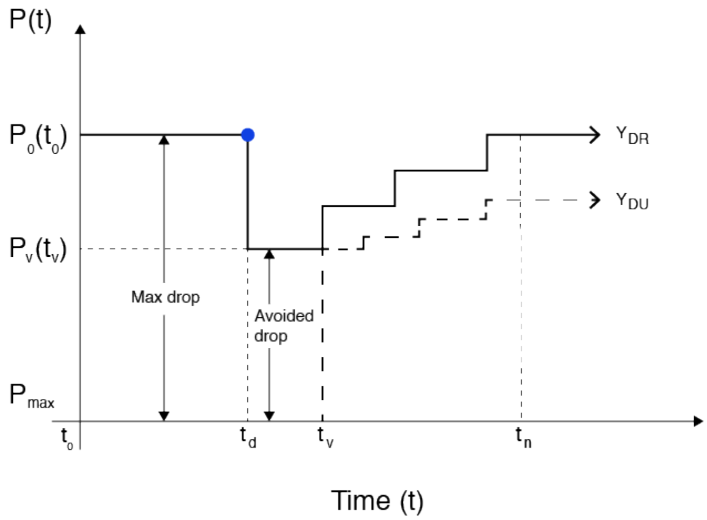

Figure 2.4: Generic resilience evaluation scenario focusing on the maximum and avoided performance drops during the disruptive event, introduced in [5].

$$\Psi_C = \int_0^{T^*} \frac{AP(t)}{T^*} dt \tag{2.3}$$

Here, the resilience index is obtained by changing the span of the integral in Ψ_A from $T = t_n - t_d$. Since the observation period T^* in a simulation scenario as in the scope of this investigation, is defined by the designers, its value is always known *a priori*. The last solution (Ψ_D) does not take into account the evolution of the system during the observation period. Instead, it uses only their extreme values.

The plot in Figure 2.4 introduces the terms:

- Maximum performance drop - Max drop - represents how much performance can be lost before the system ceases to be functional.
- Avoided performance drop - Avoided drop - which represents how much performance is left when the system reaches the minimum level of functionality after the disruption and before the recovery.

With these notions in mind, it is defined:

$$\Psi_D = \frac{P_v(t_v) - P_{max}}{P_0(t_0) - P_{max}} \tag{2.4}$$

2.4.3.2 Computing performance indicators

Since the previous indexes are based on performance indicators, these indicators will need to be computerized. What this means is that the performance of a system cannot always be directly monitored, so we must rely on process variables, which in return are mapped into the performance space [36], so that they can be used to calculate the resilience indexes presented.

The approach presented in [38] introduces the concept of Figure of Merit (FOM) functions which execute the referred mapping of variable states into performance indicators. [36] defines FOMs as:

- F:D $\rightarrow \mathbb{R}$, where D is the domain of the variable being observed, which can be restricted between 0 - minimum performance - and 1 - maximum performance.

- F(x) must increase monotonically until 1 when x, the observed variable, tends to a recommendable value, and F(x) decreases to 0 when x gets away from the recommended value and tends to an undesirable value.

No specifics are given on how to extract such a function in [38] since this is a process unique to the system. Although it's recommended that the shape of the functions should be the simplest that satisfies the defined constraints (recommend and undesirable values), where the performance decreases linearly whenever the variables shift away from the recommended value.

This approach for computing resilience indexes can be of great use since it is model-free, which means that it's not needed a detailed description of the cyber-physical system dynamics, it provides a quantitative measure for resilience, and it's general-purpose. In [35], FOMs are not used but are introduced three measures or key process indicators (KPIs) for measuring resilience, including production loss, throughput settling time, and total under production time. The advantage of using the referred measures relies on the fact that these are variables of great importance in most production systems, thus they're already being monitored, facilitating the implementation of a possible disruption management framework.

2.4.4 Resilient cyber-physical production systems

Resilience, as an emerging phenomenon, is more than the result of a single attribute of a system, but instead the result of the interactions between all of its assets [39]. Robustness - the resistance to anticipated changes - and agility - the ability to react to severe disturbances that the system's robustness cannot endure - are important requirements for a resilient CPPS, but can only be achieved by the introduction of different attributes to the system.

Regarding robustness, the system must have built-in fault-tolerant functions [40]. A fault-tolerant system is synonymous with a robust system, and can automatically accommodate faults among its components while maintaining an overall desirable performance[41].

There are two main approaches to deal with faults, either by re-organizing in real-time the remaining system elements to proceed with the necessary control functions (reconfiguration) or by making the system failure-proof for a certain number of disruptions analysed in the modeling stage [41].

A resilient architecture for CPS is discussed in [42], based on reconfiguration strategies, where the following principles can be extracted:

1. Redundancy is critical for reconfiguration. It can be implemented in the architecture of CPPS by adding machines, sensors, and any other components that can process similar operations or including flexible processes that can alternate according to the current conditions.

2. Fault detection and diagnosis should be autonomous to maintain the robustness of the system.

3. The network between controllers, sensors, and actuators should form a mesh topology. Mesh topologies are better for reconfiguration since it helps avoid concentration of load and improves the routing of communication paths.

Although critical, a system's robustness may not be able to handle unexpected severe disruptions. Thus, on the topic of agility, there is a crescent interest in the notion of self-adaptation [43], defined by the ability to adapt autonomously to environmental changes.

The CPSs' self-capabilities, such as self-adaptation, self-reconfiguration, self-optimization, and self-diagnosis, are enabled by their autonomy which in its turn is enabled by the growing exchange of information between components [44]. The before-mentioned autonomy should be appropriately designed to ensure adaptive responses to disruptions during the production processes [11], allowing the affected components to recover from localized changes.

There may be several mitigation strategies to develop solutions to a disruptive event. So, to determine the best response, a decision support system is required to run through different scenarios and help the decision-maker decide on the best action. In recent studies, simulation-aided decision support proved to be a fitting tool to analyse disruptions and determine their impact on the system, as will be analysed in the next section.

2.5 Simulation in industry 4.0

Simulation is described as the process of designing a model of a real or hypothetical system to describe and analyse its behaviours [45]. In manufacturing, modeling and simulation include a range of techniques and technical tools that allow products, processes, system design, and system performance to be tested and validated. It also aids in development cycles and reducing costs through its decision-making, education, and training abilities [46].

The high costs related to the development of experiments in physical systems, the observation of the behaviour of processes in the real world, or the building of a physical model, lead companies to rely on simulation tools [47]. In disruption assessment and management, the impacts of these experiments could be fatal for the production system components (for example machine breakdowns), leaving decision-makers almost dependent on simulation.

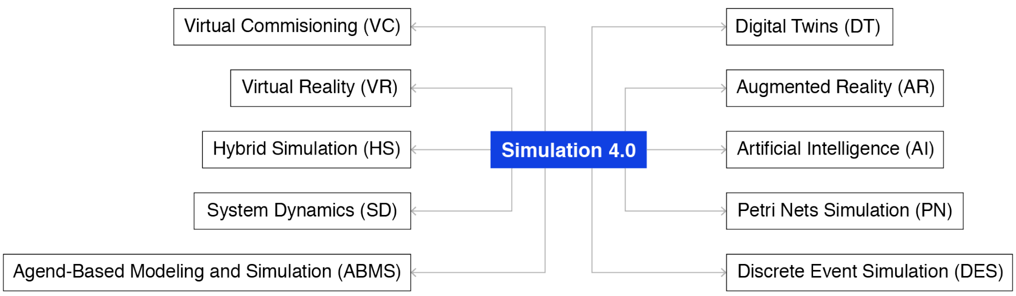

Figure 2.5: Different types of simulation-based approaches in industry 4.0.

According to [45], simulation incorporates the following key components:

- Modeling: the activity of designing a model;
- Model: an abstract and simplified description of a system, with a predetermined number of assumptions;
- System: the process that is analysed;
- Process: a set of linked elements;
- Simulation: the operation of a model over time.

Simulation makes it possible to conduct tests rapidly and cheaper in a risk-free environment, change the time window for a singular experience, and include animation to aid communication and model validation.

There are several different types of simulation discussed in the literature. The figure 2.5 gives a summary of the simulation-based approaches used in the context of Industry 4.0. According to [48], Digital Twins (DT), Agent-Based Modeling and Simulation (ABMS), and Discrete Event Simulation represent the majority of simulation-based approaches included in recent research publications regarding industry 4.0.

2.5.1 Digital Twins

Digital Twins is described as a digital representation of the physical system and seamless integration between the physical and digital spaces [49]. Digital Twins is a hybrid approach, built into four levels:

1. Geometry;
2. Physics;
3. Behaviour;

4. Rule.

The first two levels include, for the most part, kinematics and geometric simulation. It is also known as continuous simulation, which is based on computer-aided technologies, such as computer-aided design (CAD), computer-aided engineering, and computer-aided manufacturing as well as finite element analysis. The last two levels involve other simulation paradigms, such as ABMS, DES, and artificial intelligence.

Digital twins are powerful tools that should help new manufacturing systems make smart decisions through real-time communication and cooperation between humans, machines, equipment, sensor, and so forth.

2.5.2 Discrete event simulation (DES)

Discrete event simulation may be defined as “one in which the state variables change only at those discrete points in time at which events occur” [45]. The event consists of an incident that affects the state of the system, while a system’s state variable reflects all the details required at a certain point in time to describe the behavior of the system.

The use of DES enables the ability to simulate long cycles of activity of a real system in a relative shorter time, the ability to analyse a system, its different components, and their interactions, provides a risk-free environment, and also allows to monitor and control the system, solve complex problems, and aid decision-making processes [50, 51].

DES is described as the most used paradigm for simulation applications in manufacturing, material handling, and distribution systems [52]. It is also a great tool to analyse disturbances, their consequences, and propagation in a production system due to the easiness of alterations in a model, and improvement in the system can be demonstrated [6].

The use of DES in industrial settings is not new, although research shows that DES solutions should contribute to the industry 4.0 paradigm, by focusing on the following characteristics [53]:

1. Automated data exchange: Receive real data from cyber-physical systems (machines, sensors, smart products, etc..) and automatically upload it into the simulation model.

2. Automatic model generation: Aptitude to automatically build simulation models. Due to factories becoming more and more dynamic, changes in the modeled systems must be made quickly and effortlessly.

3. Visualization: The ability to visualize complex systems using virtual reality, augmented reality, 3D animation and others. 3D is still the most common type of visualization, and which benefits have been proven. According to [54], 3D animation in DES solutions can aid users spot errors, understand the system, increase model acceptability, and possibly, although not proven, provide the ability to generate ideas for improving the system.

2.5.3 Agent-based modeling and simulation (ABMS)

ABMS or Multi-Agent Systems (MAS) can be defined as "a set of elements (agents) characterized by some attributes, that interact with each other through the definition of appropriate rules in a given environment" [55].

Agents are defined as components with their own behaviour and rules, where the modeller can decide when the rules shall be triggered [56]. It may represent either material or non-material components such as sensors, machines, products, people, and innovation. In the context of i4.0, AMBS can act as a modelling paradigm for cyber-physical systems. Thus, agents can be considered as decision-makers with some level of learning and adaptation [57].

In most instances, the behaviour of the agent can be modelled using a discrete event approach or system dynamics. Moreover, the dynamics of the environment where the agents live are often modelled using traditional simulation methods [47]. In these circumstances, a process flowchart or a flow diagram may be used as an agent's internal behaviour, hence why several agent-based models are, in reality, hybrid (or multi-method) models.

2.5.4 Simulation-based approaches for disruption management

As process disruptions have a negative impact on the performance of a manufacturing system, reducing the effect of disruptions is the most important step to achieve resilience in the affected processes. Disruption management aims to reduce the overall time of the system in disrupted mode, which can be achieved by an effective decision-making process for developing countermeasures [16].

Ingemansson et. al. (2004) developed a method suitable for reducing the impacts of disturbances in a general manufacturing system. The objective was to use a combination of a DES scenario and the actual implementation to achieve increased efficiency in a production system. The methodology consisted of three main functions: (1) collect the data necessary to study the causes of disturbances in the production system; (2) test different alternatives to detect the differences in output; (3) lastly, apply necessary techniques to eliminate or minimise disturbances. The methodology is to then be combined with the steps of a discrete-event simulation process presented by [45] as seen in Figure 2.6. The continuous application of the methodology gives companies an increasing knowledge of disturbance reduction in their production systems [6].

Cauvin et. al (2009) present a general framework for disruption management aiming at supporting decision-making in a disrupted and distributed environment. The decision support approach proposes to minimize the consequences of disrupting events on the production planning of distributed industrial systems. The general frame of the Decision support approach is decomposed in two steps. The first step includes the system analysis phase where effective recovering actions are identified and characterized. The second step is focused on the validation of the recovering process through its simulation and evaluation of its impacts on the distributed system. This solution proposes to improve the reactivity of a system by aiding the design of decision-making processes which allow the actors of these systems to quickly answer disturbances [16].

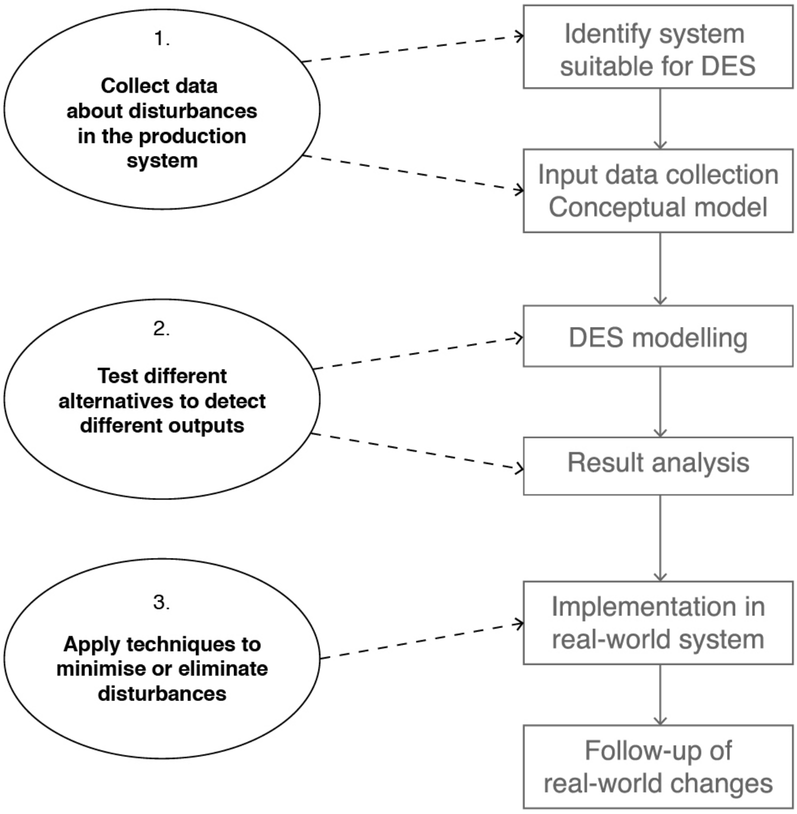

Figure 2.6: Methodology for disturbance reduction [6].

The research published by Galaske et. al. (2015) proclaimed to serve as the foundation in process deviation management. It presents a deviation management system to support the decision-making process in cyber-physical production systems (CPPS). Here, process deviations are defined, analysed, and modeled. The authors focused on the concept of smart components, which are intelligent manufacturing and assembly objects equipped with CPS (sensors, actors, and a communication interface) and a component data model that stores information about production processes, and other components. Smart components can communicate with each other, machines, and manufacturing stations, store information about process deviations and adjust the originally planned process sequence in the presence of a disruptive event. In this context, the paper exemplifies the development of logical models that accurately describe CPPSs and their behaviour during a process deviation scenario, using UML activity diagrams. The modeled concept is then implemented in a simulation model using discrete-event simulation software, used for the definition of the best possible reaction [4].

Galaske et. al. (2016) proposed a simulation-based decision support system for supporting the disruption management process in cyber-physical production systems. It introduces an approach for analysing disruptions and determining the recommended mitigation strategy, similar to those studied previously. First, disruption events are categorized and clustered by similarity. Then, for each event, possible mitigation strategies are derived and stored in a database to be accessed by the decision support system. The best mitigation strategy is later determined in the disruption management process by comparing the simulation results using selected key performance indicators (KPI) to measure resilience. The research differentiates its disruption management process by focusing on the communication between the decision support system and the DES. This communication simulates the information exchange and the autonomous decision-making process between intelligent production assets (CPS). The biggest takeaway is the importance of having a dynamic disruption database that feeds a decision support system with effective countermeasures in case disruptive events occur [3].

2.6 Conclusions

The research of disruptions in CPPS has been ever-present since the concept was introduced in the literature and its intrinsically connected with the design of resilient CPPS architectures. These resilient architectures include both robust and agile attributes. The first is implemented by introducing fault-tolerant features such as redundancy, autonomous fault detection, and a decentralized network of controllers, sensors, and actuators. On the other hand, the system's agility is defined by its ability to adapt to changes. It expresses reactive strategies that meet environmental changes with corresponding organization actions by rapidly re-configuring the operating states of a production system.

To accommodate new types of disruptions, resilient CPPS should also leverage their autonomy, provided by the connectivity of production assets and the amounts of data exchanged between them, to achieve adaptive process planning. Consequently, it is possible to conclude that a decision support system where different disruption scenarios can be run through is needed to develop effective countermeasures and that DES has proven to be the most common tool to achieve that. These scenarios are then compared using selected KPI or by computing state variables into the performance realm.

Chapter 3

Simulation-based disruption impact assessment for decision support

3.1 Introduction

As introduced before, new applications of cyber-physical systems are coming to use, companies are adopting technologies such as the Internet of Things (IoT) and Cloud-based manufacturing, services and platforms, which lead to new types of disruption events. In addition, the growing autonomy and cooperation between components and platforms, supported by Big Data, and the morphing from a hierarchical to a heterarchical automation architecture, introduce greater vulnerability to cascading disruptions that extend their effects to other elements of the cyber-physical production system.

Due to its novelty, disruption events must be analysed to ensure the CPPS's resilience. For that purpose, this chapter introduces a methodology, based on the research around disruption management presented in the last chapter, that proposes hybrid simulation as a tool to allow decision-makers to measure the impacts of disruptions on the production processes and possibly create a database with effective countermeasures. The methodology is composed of four steps (Figure 3.1):

1. Identify and categorize disruption events
2. Model and simulate the disruption scenarios
3. Evaluate the impact using selected KPI
4. Identify possible mitigation actions

3.2 Identify and categorize disruption events

Before starting to model disruption scenarios, the kind of disruptions that can occur in a production system must be established as the starting point. Improved identification of the causes of

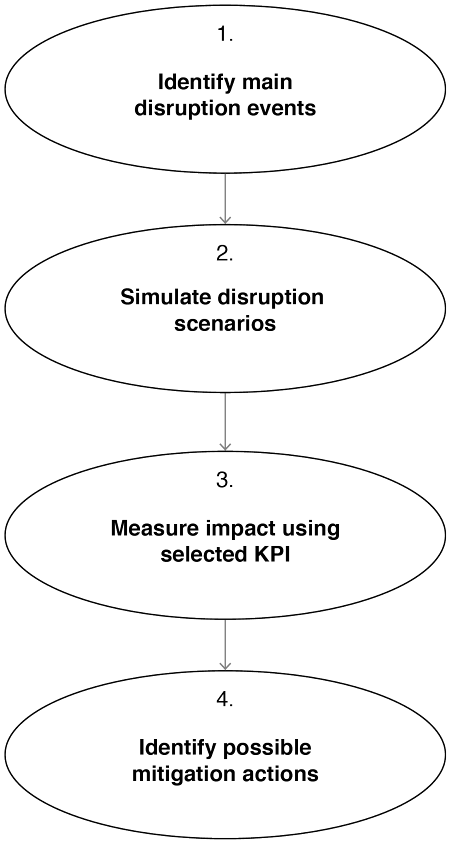

Figure 3.1: Methodology steps.

failures and disturbances in cyber-physical production systems should offer substantial opportunities to solve them in the long term. It is particularly useful if the system is still in the development phase, and for that, the Ishikawa diagram in Figure 2.2 is a great tool. In the case of a production system already in use, it's feasible to obtain information about disruptions from a manual logbook and interviews with the automation personnel. This way, specific disruption events from a particular production facility can be listed, therefore, allowing effective mitigation plans to be studied and applied. Although they can be similar across the manufacturing industry, the possible scenarios upon a disruptive event are bounded by each particular manufacturing system, hampering the implementation of a general countermeasures database. Thus, the importance of gathering knowledge within the facility.

Once identified, it is recommended that the disruptions are categorized (Figure 3.1), firstly, according to their cause. The causes are divided into manpower, material, environment, machine, and methods (communication and information) [4]. Secondly, it should be defined the location in which the observed disruption occurred. The different locations can be production, design, inventory, supplier, logistics, assembly, production control, quality management, and sales [28]. Lastly, to aid the modelling phase and better understand the behavior of the CPPS and the synchronous interactions between its elements, the platforms involved in the affected process should also be identified.

Table 3.1: Disruption categorization

Description	**Cause**	**Location**	**Involved system elements/platforms**
General description of the disruptive event	Manpower	Production	Specific to the affected processes
	Material	Design	
	Environment	Inventory	
	Machine	Supplier	
	Methods	Logistics	
		Assembly	
		Production control	
		Quality management	
		Sales	

In addition, the categorization of a disruption should include its predicted impact and likelihood. The predicted impact refers both to the literal consequence of the disruptive event and a qualitative quantification of the predicted impact - low, medium, or high (see Table 3.2). The later qualitative approach is also used to classify the foreseen likelihood of the disruption to occur. By gauging these two aspects in an initial phase, it is possible to prioritize analysis and later make comparisons between the perceived versus the simulated impact, much like a risk analysis.

Table 3.2: Disruption categorization - perceived impact and likelihood

Expected impact		**Likelihood**
General description of the expected impact	Low	Low
	Medium	Medium
	High	High

3.3 Model and simulate the disruption scenarios

To better understand the behaviour of a cyber-physical production system and its elements during a disruptive event, it must be represented by models. A model is a simplified duplicate of a system, including its characteristics and processes. By simplifying it in terms of abstraction in modelling methods, the complexity of the observed problems in the modelled system can be reduced, which makes it easier to find a solution.

The modelling and simulation step is further divided into four stages (Figure 3.2):

1. Design conceptual model
2. Develop software model
3. Validate model

4. Run simulation model

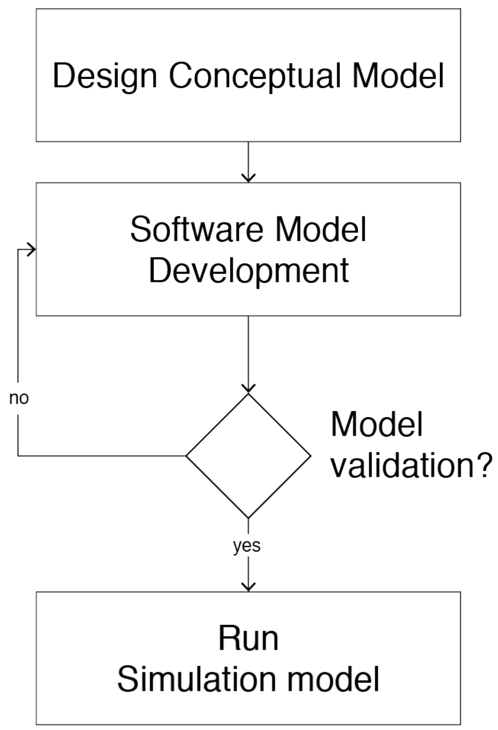

Figure 3.2: Modelling and simulation stages.

Once the disruptions are identified and categorized, the next stage is to design a conceptual model that describes the system's behaviour during the disruptive scenario. The conceptual model takes into consideration the system specifications to graphically represent its elements, their actions, and interaction with each other. Therefore, the disruptions previously identified and categorized are used as starting points, helping to the modeller gather all of the relevant information about the to be modelled processes.

Between the graphic languages used to design conceptual models, it's recommended to opt for Unified Modelling Language (UML) activity diagrams. Activity diagrams are graphical descriptions of workflows of gradual activities and actions that support multiple-choice decisions, iteration, and parallel flows. Regarding UML, these diagrams intend to model both computational and organizational processes, as well as the data-flows intersecting with the related activities. In case the modelled process involves multiple elements (actors), swimlanes can group activities performed by the same actor facilitating the visualization of interactions between them. An example of a UML activity diagram application can be seen in Figure 3.3.

The second stage puts the attention on converting the conceptual model into a functional software model. Consequently, the appropriate simulation modelling approach must be defined. From

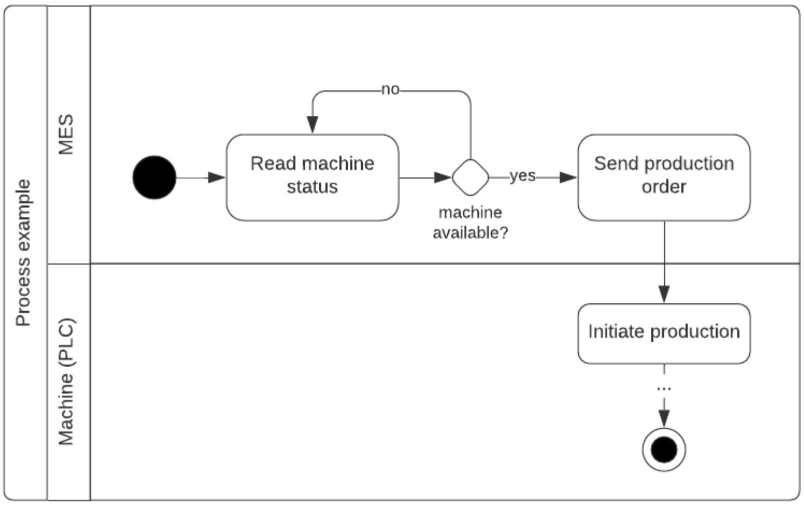

Figure 3.3: Conceptual model of a process example.

the literature, it was possible to conclude that descrete event simualtion (DES) has been the most generally accepted approach for simulation applications in manufacturing, material handling, and distribution systems. It also proved to be an efficient tool to understand the propagation of disruption in production systems. However, it is not a suitable approach to visualize the interactions between different elements of a CPPS, such as a manufacturing station and the digital platforms (e.g. MES and ERP). For that purpose, the different elements of the system should be modelled as agents, that is, defined as individuals with their own behaviour and rules. Agent's are a model's building blocks and represent its different logical sections. In agent-based modelling, a system can be decomposed into different agents, with different levels of detail, that can interact with each other and influence their behaviours. The behaviour of each agent is then defined through DES, forming a hybrid approach. To build and run the model the simulation software to be used is Anylogic. Anylogic is a hybrid (or multimethod) simulation modeling tool that supports the integration of different modeling paradigms, namely discrete event and agent-based, facilitating the implementation of the proposed methodology.

The model validation stage is crucial to determine its credibility, determining whether or not it is a valid representation of an actual system. Despite it being abstractive and with simplified actions and activities, a simulation model should remain reliable. Otherwise, its development over time will not draw the required results and, for this reason, it should be redesigned. Whereas if approved, the modeller may proceed to the last stage and run the model.

3.4 Evaluate the impact using selected KPI

The simulation models should have the ability to store information about production metrics and key process indicators (KPI). This way it is attainable to track information during the simulation and later export the data to be analysed. To evaluate the impact of disruptions in the system, the data should include indicators related to resilience. Aiming to fulfil this need, the indicator suggested to assess the resilience of the system and the impact of the disruption events is the overall equipment effectiveness (OEE).

The overall equipment effectiveness metric depends on three factors; availability, performance and quality.

$$OEE = Availability \times Performance \times Quality \tag{3.1}$$

Availability is defined by the ratio of the time spent concluding a task to the scheduled time. The system's availability is the primary reason why the OEE is a good metric for resilience. Resource availability is a random factor that is affected by disruptions. Thus, a lack of availability leads to a decline in efficiency and therefore indicating a lack of resilience. Furthermore, by tracking the availability of, for example, a manufacturing station, it is possible to identify the moments where a disruption in a different location prompted the station to be unavailable.

$$Availability = \frac{available\ time - failure\ time}{scheduled\ time} \tag{3.2}$$

Performance is the ratio of the time to complete a task during ideal conditions compared to the realization in real conditions. Much like availability, performance is also reduced by disruptive events. Particularly, disturbances that lead to a decreased production rate, in most instances related to manpower or machine problems, such as worker errors or defected machine tools.

$$Performance = \frac{ideal\ time\ spent}{real\ time\ spent} \tag{3.3}$$

Quality can be assessed by measuring the ratio of the number of good products and the total number of products. Defining quality as meeting customer requirements means that a product is rejected if not within specifications. That being said, any disruption related to material, manpower, environment and machine, that does not immediately stop the production process, will, in theory, increase variability within products and consequently the number of rejected products as well.

$$Quality = \frac{good\ products}{overall\ products} \tag{3.4}$$

Resilience in manufacturing is the ability to withstand and adapt to disruptions, and can be improved by reducing the time in the disruptive state. As discussed, the more frequent and longer disruptions become, the more it is expected to reduce the OEE. Furthermore, no matter the cause, disruptions will most likely impact at least one of the OEE's factors. Therefore, little variation in the OEE during disrupted mode translates to a higher resilience, and significant changes the contrary. Besides, the fact that it is a widely used indicator in the industry, means that most companies are already tracking it, facilitating the implementation of the methodology.

3.5 Identify possible mitigation actions

After the simulation and evaluation of the disruptions' impacts on the OEE, the decision-maker should be able to identify the affected areas and what can be changed to increase the resilience in the system. If identified and feasible, the mitigation actions can be implemented in new models and simulated to test their effectiveness in improving the system's resilience. Afterwards, these mitigation actions should be ranked according to the results.

Although the effectiveness of the mitigation actions is the main outcome of the simulation, the most effective measure may not be the most appropriate. For example, a recurrent machine breakdown disruption that is slowing down the production process might be best solved by introducing redundancy to the system, which requires buying a new machine to divide the load. While effective, other criteria must be analysed and weighed before prioritizing the action. In this case, the company's budget, shop floor space, worker's availability, and others should be factored in. Ultimately, for equally appropriated mitigation actions, the simulation results dictate the best solution.

3.6 Conclusions

In this chapter a methodology to support the decision-maker evaluate the impact of disruptions in the production system and identify possible mitigation actions was presented. The methodology obeys the following steps:

1. **Identify and categorize disruption events**

   The identification of causes of disruptions in CPPS is the first step to solve them in the long term. These can be identified using a general-purpose diagram like the on in Figure 2.2 or by gathering information from log books and interviews with the automation personnel. Once identified disruptions should be categorized by its cause, location, and involved system's elements.

2. **Model and simulate the disruption scenarios**

   The modelling step consists in designing a conceptual model, developing a software model, validating the model, and lastly simulate it to extract the results. A hybrid simulation paradigm is used to describe the system behaviour, where the involved elements are modelled as agents and their behaviour as discrete events, using the Anylogic software.

3. **Evaluate the impacts using selected KPI**

The simulation model must be able to measure the production system's availability, performance, and quality, to then calculate the OEE. The OEE is affected by a multitude of disruptions, thus, a lack in resilience will result in a lower OEE and vice versa.

4. **Identify possible mitigation actions**

   The simulation and the results evaluation should allow the decision-maker to identify mitigation actions. If feasible, the methodology can be iterated, starting from the modelling and simulation step, including the mitigation plan in the model to measure the gains in resilience and decide on the best action.

Chapter 4

Case study analysis

4.1 Introduction

This research hypothesises that hybrid simulation can be used as a tool to evaluate the impacts of disruption events. For that purpose, the methodology presented in the last chapter was developed with the intent to be tested in a use case study. The selected case study is a Portuguese company in the cork industry that dedicates itself to the production of various cork products, including stoppers, sheets and sheets rolls.

In order to align the industrial automation system with the i4.0 concept, the company has been increasing the level of digitization of its factories with the introduction of hardware to collect information and data from the shop floor and the installation of a manufacturing execution system (MES) for the management of its production processes. Furthermore, they've also moved the MES and enterprise resource planning (ERP) systems to cloud servers to better integrate business and production processes, and move toward a heterarchical architecture.

Despite the advantages of this digital transition, the company is concerned with the dependence on the digital infrastructure that has been set up and its ability to stay resilient in the event of disruptions. Now, disruptions related to information and communication issues are a new bottleneck of the production processes.

To understand the behaviour of the production system, a section of the shop floor activity will be considered. This activity is performed by a production line responsible for the manufacturing of cork sheet rolls. The block diagram of Figure 4.1 shows the referred production line, which is composed by a double belt press with three steps linked through a material handling system (MES), where processing begins after a production order is sent by the MES to the PLC Master through OPC protocols. Afterwards, the production line begins the mixture of glue and cork grain and conveys the mixed composite to the press that continuously creates a sheet that is at the end re-winded to form a prescribed amount of rolls.

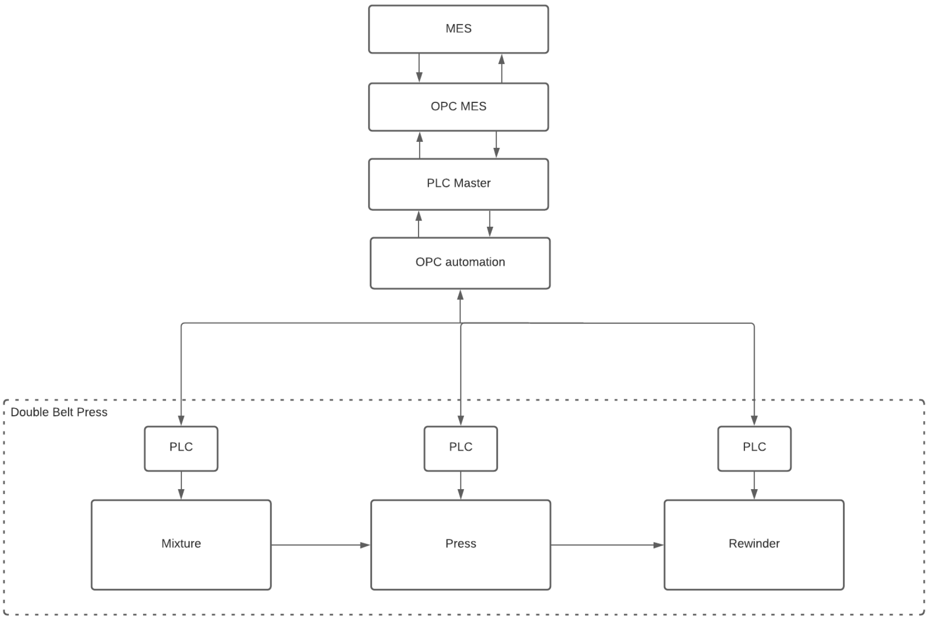

Figure 4.1: Block diagram of the double belt press production line.

4.2 Modelling of the normal scenario

The normal production scenario, without any occurrence of disruptive events, is represented in Figure 4.2 where each system element, the production line and MES, is represented as a swim lane containing the respective actions. For the purpose of simplifying the double belt press activity, its three operations - mix, press and rewind - are considered as just one where the cork sheet is produced at the fixed rate of seven meters per minute.

Regarding the conceptual mode of Figure 4.2, the first step begins with the production line ready to start, triggering the MES to send a new production order (PO). The MES reads the status of the required parameters (e.g. inventory space) and authorizes the start of the PO if every thing is normal. In the second step, the production line detects the authorization, stores the recipe in local memory, and either turns on setup mode if requested or begins producing the batches. Each batch represents a sheet roll, and there are, typically, more than one per PO. At the end of every roll produced, the production line signals the MES and waits for confirmation before moving to the next batch or removing the production cycle, in case it was the last one. For the last step, the MES notices the end of the production cycle and signals the production line by removing the PO authorization so that it can clear the non-cumulative variables and start a new production order. It is also at this point that a new expedition order for the just-finished production order is created.

The analysis of the system was extended to incorporate the expedition or shipping process. Figure 4.3 illustrates the behaviour of the involved elements, starting with the creation of a new expedition order that triggers the contact with the carrier to schedule the shipment, followed by the autonomous process of contacting the tax authority. Only then can the warehouse prepare the

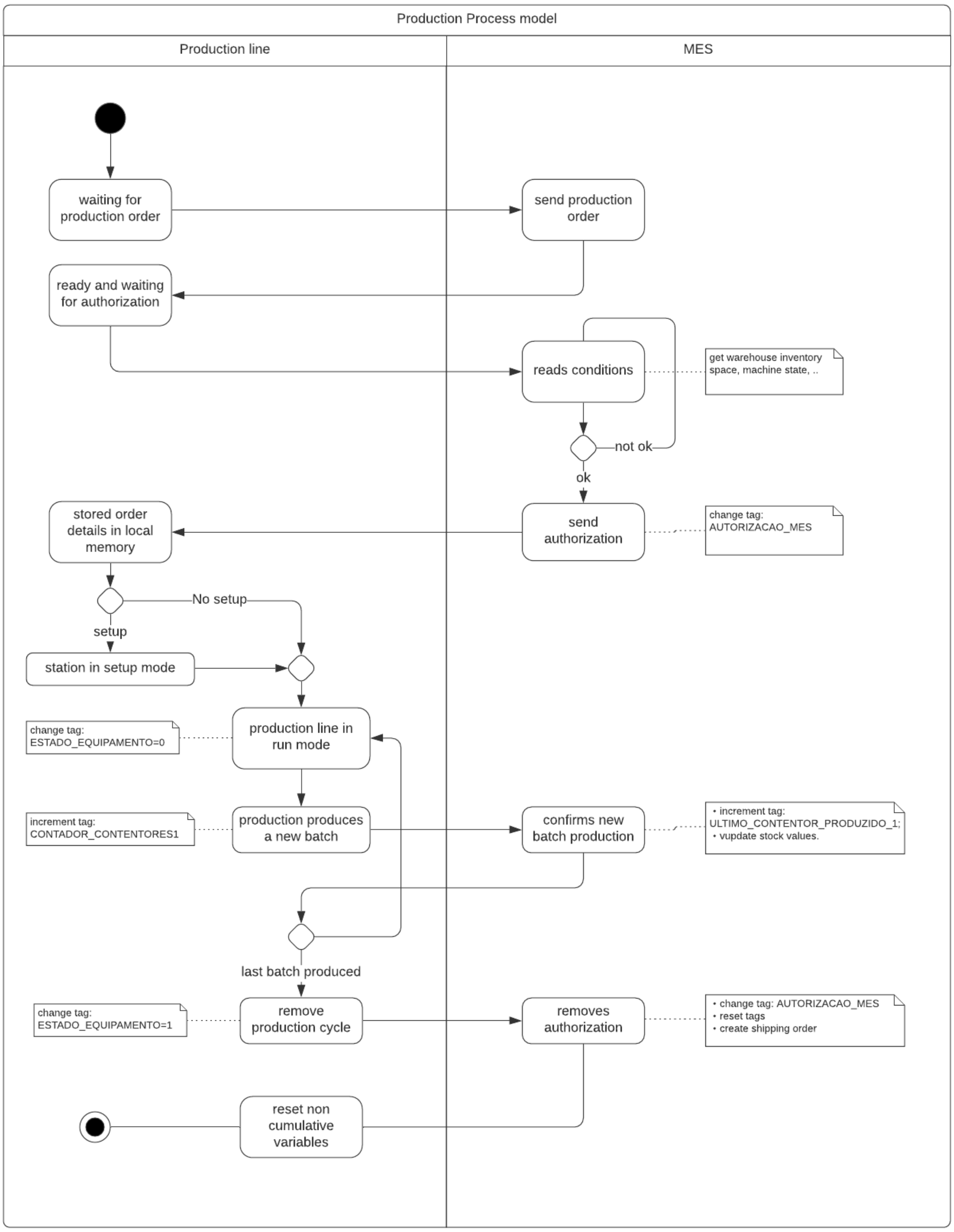

Figure 4.2: Production process conceptual model - UML activity diagram.

order for shipping. In the interest of simplifying the behaviour, it is considered that order's batches leave the warehouse six hours after preparations begin. Once shipped, the MES is updated with the current inventory space.

The weekly production plan in Table 4.1 displays the scheduling of the orders for the week considered in the present case study. It specifies, for each PO, the order reference, total quantity (in meters), production sequence and daily expected quantity. The working week starts at 11 PM

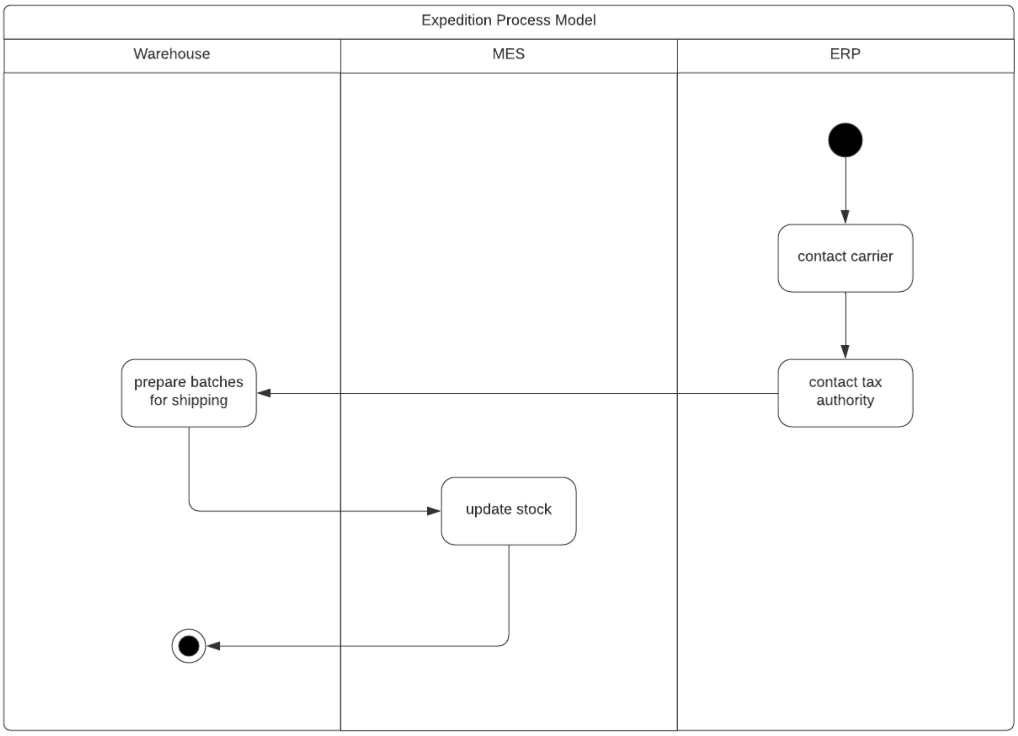

Figure 4.3: Expedition process conceptual model - UML activity diagram.

on Sunday and lasts until 10:59 PM of the next Sunday.

4.3 Simulation model

This section describes the process of developing the simulation model of the normal scenario. Consequently, an agent-based model of the production system was built, in which the production line, MES, production orders, and expedition orders are agents. Agents are a model's building blocks and represent its logical sections. Hence, the model is decomposed into different levels of detail that can interact with each other.

By default, Anylogic has one agent called Main that acts as the environment for the other agents. The Main is the top-level agent that defines the network and communication used by the remaining agents. For that reason, the Main agent is going to represent the MES, responsible for sending the POs to the production line, monitoring stocks and production, and displaying data graphically in real-time.

4.3.1 MES

The behaviour of the MES agent is defined using statecharts which are advanced constructs for describing event and time-driven behaviours, formed by states and transitions. The statechart's states

Table 4.1: Weekly production plan

Ref.	Quantity	Sequence	M	T	W	T	F	S	S
P 0094	18000	2	420,00	10080,00	7497,42				
P 0052	30400	3			2158,8	10080	10080	8080,8	
P 0055	10400	4						1579,2	10080
P 0094	8400	1	8400						

are alternative, which indicates that there can only be one state active at a time, although the agent may have multiple statecharts running simultaneously. Regarding transitions, when triggered, they may lead to a state change that makes a new set of transitions active. The MES is represented by three statecharts (Figure 4.4): *MES_order* for order execution, *MES_stock* for managing warehouse space, and *MES_productionLine* responsible for data collection of the production line and synchronous communication.

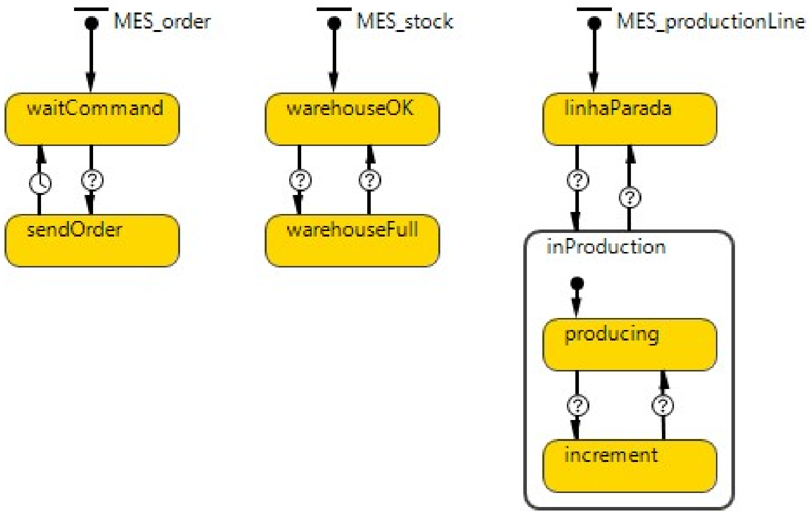

Figure 4.4: MES agent statecharts

The MES is able to detect state and variable changes in the production line by including event listeners. Events can trigger cyclic actions that mirror the production line variables, allowing the MES agent to check whenever a new batch is produced. Accordingly, the production line agent, after producing a batch, waits and listens the MES for the acknowledgment signal. Whenever a new batch is produced, the MES collects shop floor information that can be later exported and analysed, such as current PO, batches produced, total cork sheet produced, and current machine state.

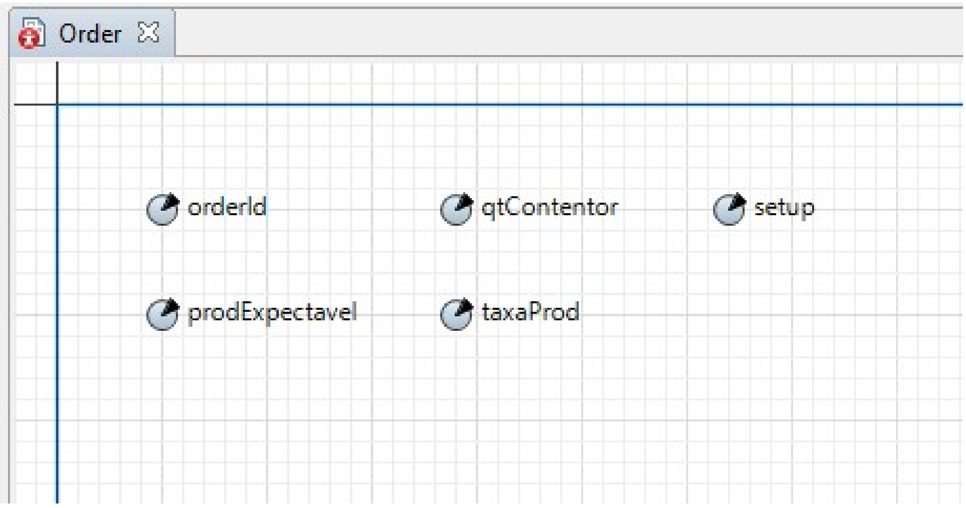

Figure 4.5: Production order agent parameters

4.3.2 Production order agent population

The communication between the MES and production line is defined through a complete and complex protocol. The protocol defines the information that is shared from the MES to the production line and vice versa. For non-disclosure purposes, the protocol will not be published in this publication. Either way, due to the level of abstraction selected, the protocol is simplified to a minimal selected amount of data crucial for the implementation of the model, including the production order information.

The production order is modelled as an agent population containing the four production orders discussed previously. These agents represent the array type data structures passed from the MES to the production line, containing the following information as parameters: reference (orderId), quantity (prodExpectavel), roll size (qtContentor), production rate (taxaProd), and whether or not there's setup (setup). As mentioned previously, the production rate is fixed and equals seven meters per hour for every production order. Regarding the setup, it will only be apllied to the first production order.

4.3.3 Production line

The production line agent uses blocks from Anylogic's process modeling library to receive the PO agent and store the recipe information in local variables. Secondarily, the behaviour of the production line during the manufacturing process is modelled using a statechart. As seen in Figure 4.6, the initial state marks the production line as waiting and ready for the PO. As soon as the the agent receives the PO and it enters in the delay block *produceOrder*, the statechart is prompted to transition to the next state where the production process may begin. At the end of the production cycle, the PO agent leaves the *produceOrder* block, removing it from the flow and allowing for a new order to start.

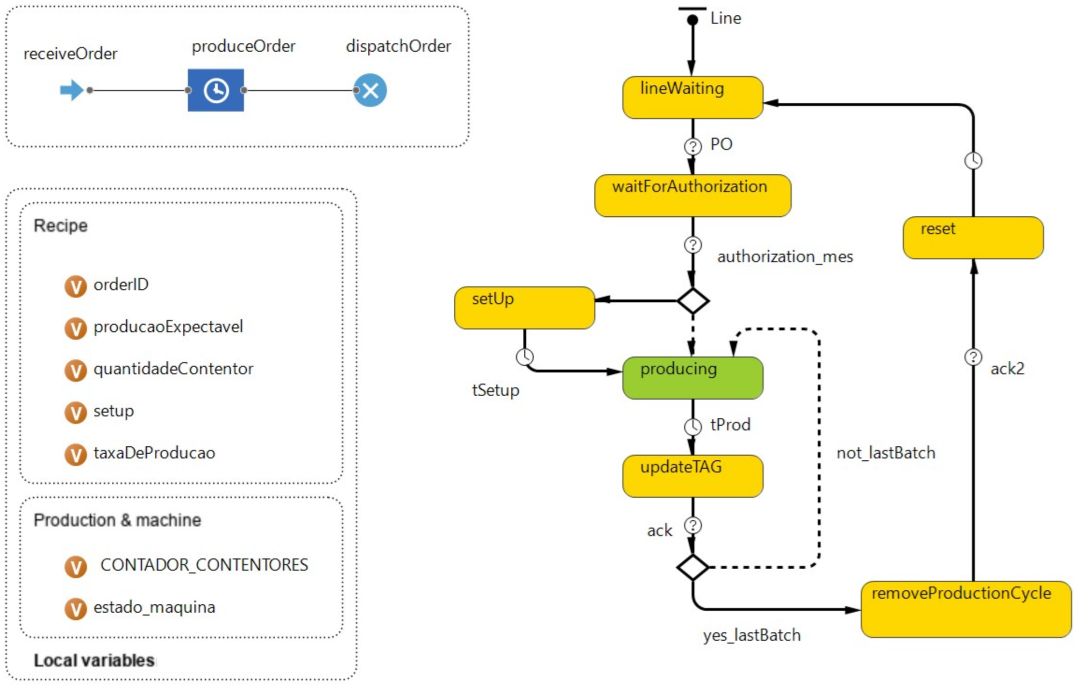

Figure 4.6: Production line agent behaviour and variables

Concerning the system's OEE, measured by its availability, performance and quality as in 3.1, only the availability will be taken into account. The performance and quality are assumed to be constant. Firstly, because the production rate is considered to be fixed, thus the performance remains the same during the entire week. Lastly, because the disruptions to be tested are not machine or worker related, and do not interfere with the product's quality, as seen in the next sections. As for the value, both factors are regarded as good and equal to 0,9.

Consequently, to measure the production line's availability, it is required knowledge of the available time - effective time spent on the manufacturing process - which is given by the time spent on the green *producing* state in Figure 4.6, and failure time, translated by the unnecessary and unexpected time spent not producing due to disruptions, with the exception of the set up mode.

4.3.4 Expedition process and order agent population

Similarly to the production order agent population, the agents of the expedition order population represent data that flows from the MES to the digital platform responsible for the shipping process. Thus, the *expeditionOrder* agents (Figure 4.7) do not have their own behaviour, but rather three parameters: a distinct reference (eOrderId), the matching production order reference (PO_Id), and the batches that it contains (nr_rolos).

Upon creation, these orders enter the *expeditionProcess* agent process flow depicted in Figure

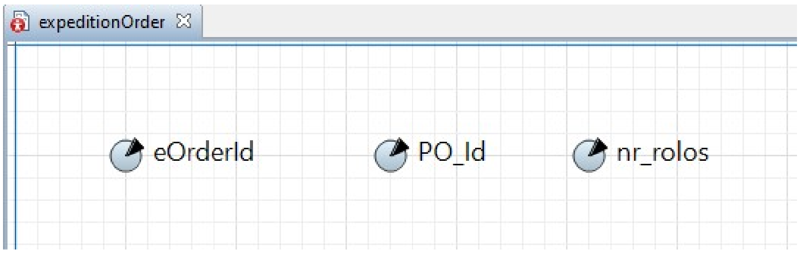

Figure 4.7: Expedition order agent parameters

4.8, that models the different activities described in Figure 4.3. Here, the delay blocks *contactCarrier* and *contactTaxAuthority* simulate the connection with external platforms responsible for the described services.

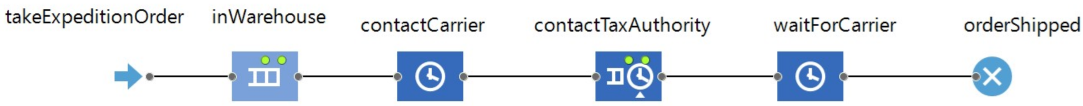

Figure 4.8: Expedition process model

4.3.5 Disruption modelling

Availability is related to planned work time and unplanned events such as disruptions, including working disturbances and component failures. These unplanned events lead to unavailable production lines and a decrease in efficiency, which in return point to a lack in resilience. In this context, reliability can be defined as the probability that a component (e.g. machine, sensors, etc) will work flawlessly for a given time under certain predefined conditions, and is directly connected with the component's estimated failure-free and repair time.

Reliability can be described by the component's mean time to failure (MTTF) or failure rate. If the component is fixable, then the MTTF can be further decomposed into the parameters: mean time between failures (MTBF) and mean time to repair (MTTR).

$$MTTF = MTBF - MTTR \tag{4.1}$$

Both the MTBF and MTTR parameters are estimations that can be described stochastically with normal, exponential and triangular distributions, or with constant values. By changing the parameters, it is possible to assess the impacts of disruptions under different conditions.

After analysing both the production and expedition processes, two different disruption scenarios were identified and will be analysed in the following sections: (1) connection failure scenario, and (2) tax authority service unavailable scenario. It will only be addressed the impacts of short-term disruptions, because the simulation was performed only for the presented weekly plan. Therefore, these disruptions will be analysed individually and with poor reliability parameters.

4.4 Connection failure scenario

4.4.1 Introduction

Throughout the manufacturing process there are synchronous moments where the production line must wait for the MES acknowledgment before moving on to the next action, the exception being the batch production confirmation during run mode, because the double belt press is a bulky machine that cannot stop until the order is complete. These moments are then vulnerable to disruptions that intercept the communication between elements. Realizing that, the first disruption to be analysed is a network connection failure (Table 4.2). Although the likelihood of the disruption is low, it is expected medium impacts on the production line's availability as a result.

Table 4.2: Connection failure

Description	Cause	Location	Involved elements
Connection failure	Methods (communication)	Production	MES and Production Line

4.4.2 Modelling

Due to the machine's design and structure, it cannot stop once a production order is being processed. Consequently, for each bath produced, the production line will continue without updating the MES and will instead save the information on a buffer within the facility. On the other hand, if the failure remains after removing the production cycle, the production line cannot signal the MES and will stay unavailable until the connection is reestablished.

Therefore, three different bottlenecks are identified (see Figure 4.2):

- Waiting for production order;
- Waiting for authorization;
- Removing production cycle.

Note that the process steps of waiting for a new PO and removing the production cycle are virtually consecutive, considering that the step for resetting the variables takes place immediately after the MES removes the authorization. In this context, it is assumed that the disruption does not occur until the first PO is sent, making the first and third bottleneck mentioned above the same.

The production line ensures that the communication is active with a heartbeat variable that is gradually incremented. If the heartbeat stops for a predefined amount of seconds, then it is considered that the connection to the MES is lost. In this model, all connected elements are notified of the connection failure, which is triggered by a cyclic event, by the means of the Anylogic built-in feature *connections* that enables messaging through the network. For that purpose, a new state called *conState* (Figure 4.9) was implemented in the production line agent, that receives the failure notification and triggers the transition to the *connectionFail* state. Consequently, the *connectionFail* state suspends the event listener that mirrored the MES variables. Additionally, Figure 4.9 illustrates the two bottlenecks in red. The unavailable (or failure) time is the result of the sum of the time spent in these states while the connection is down.

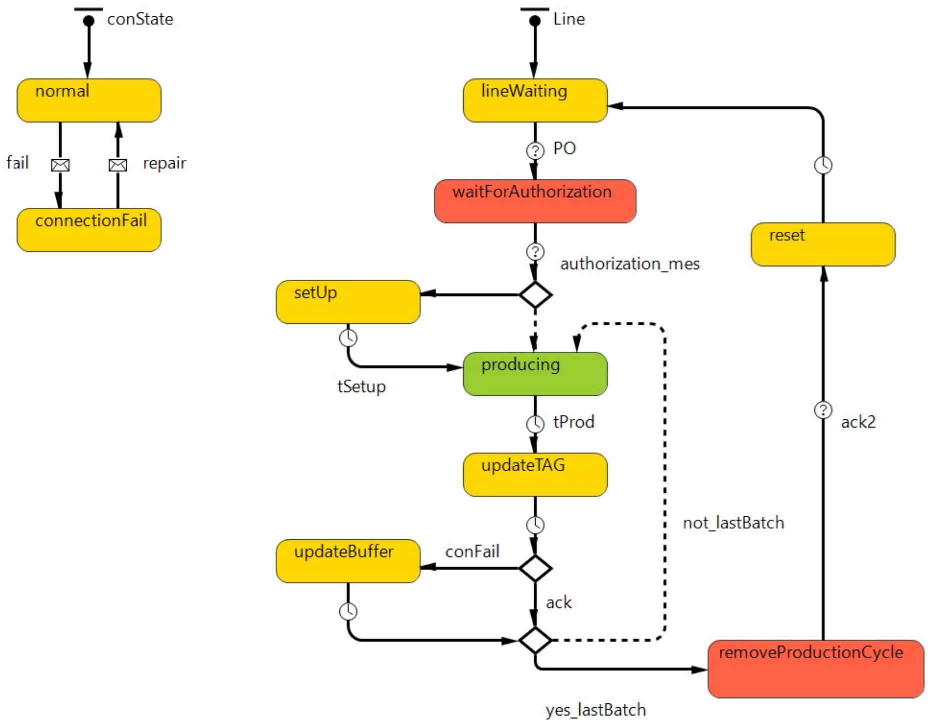

Figure 4.9: Production line model - Connection failure scenario

4.4.3 Results and conclusions

To assess the impact of the described disruption on the OEE, the connection was cyclically severed, with different MTBF and MTTR values. The normal scenario (run 0) was also simulated to compare the results. Table 4.3 shows the simulation results for the different disruption scenarios. It is possible to conclude that the simulated disruptive events do not have a direct impact on the batch manufacturing process. Additionally, they may not even interfere with the entire production process if the connection fails and recovers during the manufacturing of the same production order (run 1, 2 and 3).

The biggest bottleneck is then at the end of the production cycle where, although the current production order just finished, the system cannot begin the next one. Also, the impact is more evident in the runs with longer recovery times, as seen in Table 4.3, where the impact is only visible starting from the fourth run, in which the recovery time is equal to or bigger than 16 hours. Despite being evident in this case, it is difficult to predict that this will stay true every time since it is conditioned by the weekly production plan sequence. Regardless, it is expected that a longer recovery time leads to a greater decrease in the system's availability.

Finally, to reduce the disruption impacts, it is necessary a manual action for order execution. This way, the bottlenecks are eliminated, the production line's availability increases, and the system becomes more resilient to this kind of disruptions. However, this application may impact different indicators and would need an in-depth analysis before implementing it.

Table 4.3: Connection failure simulation runs and impact on OEE

Run	**MTBF (hours)**	**MTTR (hours)**	**Availability**	**OEE**
0	-	-	0.984	0.797
1	24	2	0.984	0.797
2	24	6	0.984	0.797
3	24	12	0.984	0.797
4	48	16	0.983	0.796
5	48	24	0.598	0.483
6	48	30	0.555	0.450

4.5 Tax authority service unavailable scenario

4.5.1 Introduction

At the end of the production cycle an expedition order for the completed PO is created. The two main activities include contacting the carrier for shipping scheduling and contacting the tax authority for registering the order/sale. The tax authority contact operation is autonomous and thus susceptible to disruptions such as connection failure, delayed or unavailable service due to software malfunctioning, among others. If such disruptions were to happen and the expedition process was delayed, the warehouse might get overloaded. Without any warehouse space left for the incoming production orders, the production line will not proceed and waits for the delayed expedition orders to leave the warehouse. Aware of this possibility, the disruption on Table 4.4 will be modelled and tested. Once again, the likelihood of the disruption to occur is low, based on the experience up to date. The expected impacts are similar to the connection disruption scenario.

Table 4.4: Tax authority service unavailable

Description	Cause	Location	Involved elements
Tax authority service unavailable due to software error	Methods (communication)	Inventory	MES, ERP and warehouse

4.5.2 Modelling

The normal behaviour of the MES and production line are already dependent on the warehouse space. The MES agent is able to track the stock by summing the total amount of rolls of the expedition order agent that were not shipped yet. Once the warehouse maximum capacity of eighty rolls is exceeded, the *warehouseFull* state is activated (see Figure 4.4), not allowing the *MES_productionLine* state to leave its original state and therefore not giving authorization to the production line to move on.

Figure 4.10 depicts the expedition process model during the disruptive event. The resource pool unit *digitalForm*, responsible for the *contactTaxAuthority* service, allows for failure and repair events to be scheduled and to define the agent behaviour upon these events. Hence, it is programmed to trigger the *serviceUnavailable* block, stopping the expedition orders from moving forward until the service is repaired and operating again.

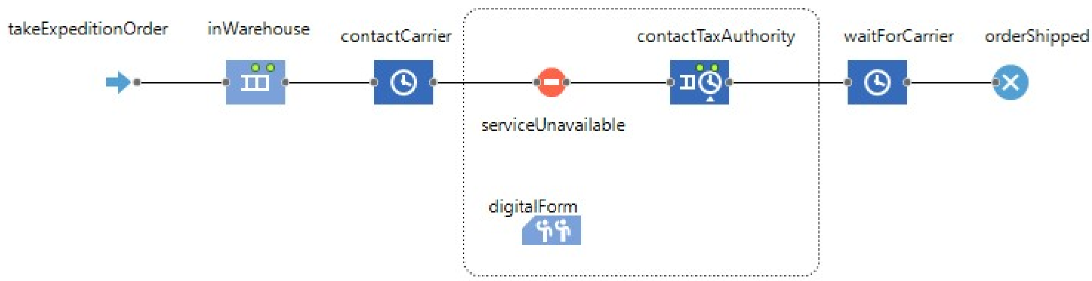

Figure 4.10: Expedition process model - Service unavailable scenario

4.5.3 Results and conclusions

The software component's mean time between failures (MTBF) is large comparing to the working week. This means that it will not impact the production line's availability, as concluded from initial analysis. Therefore, the impact of sporadic failures was assessed.

Table 4.5 depicts three of the experiments made. Experiment 0 is related to the normal scenario, where no disruptions occur. From here, the optimum values of the availability and OEE are deduced. Regarding experiment 1, it differs from experiment 2 in the mean time to repair value used in the simulation runs. In the first experiment, the disruption is assumed to take 72 hours to repair, while in the second one, it takes 96 hours. In both experiments, the following runs were performed:

- **Run 1:** the disruption occurs moments before the first production order in the weekly plan sequence (Table 4.1) is completed.

- **Run 2:** the disruption occurs moments before the second production order in the weekly plan sequence is completed.

- **Run 3:** the disruption occurs moments before the third production order in the weekly plan sequence is completed.

Table 4.5: Tax authority service unavailable simulation run and impact on OEE

	Experiment 0 Normal scenario	**Experiment 1** **MTTR=72 hours**			**Experiment 2** **MTTR=96 hours**		
		Run 1	**Run 2**	**Run 3**	**Run 1**	**Run 2**	**Run 3**
Availability	0.984	0.984	0.958	0.984	0.984	0.709	0.984
OEE	0.797	0.797	0.776	0.797	0.797	0.574	0.797

The results confirm that for Experiment 1, with shorter repair times, the system's availability is barely affected since, by the time the service is back to normal, the production line is yet to finish the order and the warehouse space remains acceptable. As for experiment 2, with a longer recovery time, the availability remains unaffected except for the second run where the availability dropped from 0.984 to 0.709. In this case, the number of roles in the warehouse exceeds the limit and do not allow the manufacturing process to continue. Then, it is concluded that the impact is directly related to the number of roles produced in the production orders following the disruption. Consequently, considering once again that the disruption is identified before the current order is completed, it is possible to reschedule future orders and reduce downtime, by executing the ones with less quantity first.

Additionally, to respond to the disruption, the system should notify a human decision-maker of the malfunction, and a manual action for the tax authority contact should be deployed, leveraging the system's agility. Regarding robustness, the company could prevent this disruption by expanding the warehouse to accommodate more rolls, although it would be a costly and undesirable scenario.

Chapter 5

Conclusions and future work

Nowadays, companies in the manufacturing field are adopting new technologies such as the Internet of Things, cloud manufacturing, and Big Data, shifting toward the industry 4.0 paradigm. This shift promotes smart, efficient, and customized production at reasonable costs through the implementation of cyber-physical systems (CPS). CPSs collect and evaluate data, and communicate with other systems to make realtime decisions. In this context, CPS can be applied in production assets leading to the concept of cyber-physical production systems (CPPS). Although advantageous, the increasing complexity of CPPS causes greater dependency on the digital platforms, making them vulnerable to new types of communication and information related disruptions. Hence, companies that adhere to i4.0 enabling technologies must be aware of these problems and their impacts. Therefore, a simulation-based methodology for disruption assessment was developed. It focuses on aiding decision-makers to predict disruptions and their impacts on the production system processes.

5.1 Main conclusions

Research question 1 was addressed in Chapter 2, where the literature on disruptions was reviewed to grasp the main types of disturbances and failures in CPPS. The research found that disruptions are categorized by their cause and include familiar sources of problems as in any production system, such as manpower (e.g. absent worker), material (e.g. wrong material), machine (e.g. machine breakdown), and environment (e.g. temperature too high). Regarding, cyber-physical production systems, the sources extend to information (e.g. incomplete data) and communication (e.g. connection failure).

Research question 2 was first tackled in Chapter 2. The literature reviewed suggested that there has been a rising interest in the development of simulation tools that aid the disruption management process, by simulating different recovery scenarios and comparing results to ensure the best mitigation actions are deployed. Furthermore, it described discrete-event simulation (DES) as the most common in manufacturing applications, including disruptions evaluation. From Chapter 2, it is concluded that there is a need for companies to have a database with effective mitigation actions, which can be obtained using simulation. On that note, a simulation-based methodology for disruption assessment was presented in Chapter 3. It focuses on aiding decision-makers to evaluate the impact of disruptions on the production system's overall equipment effectiveness (OEE) and develop adequate mitigation strategies. To further expand the literature, the methodology is based on a hybrid simulation paradigm, where the involved elements of the system (production and digital platforms) are modelled as agents that can interact with each other, and their behaviours as discrete events, using the multi-method modelling Anylogic software.

The proposed methodology is then tested in a case study in Chapter 4. It pivots on the production and expedition processes of a single production line responsible for manufacturing cork sheet rolls. The involved elements in these processes include the production line, the manufacturing execution system, and the enterprise resource planning system. Each element was modelled as an agent, including the production and expedition orders that are exchanged as data flows. Here, it was verified that once identified, the disruption scenarios, described as the behaviour of the system and its elements during the disrupted mode, can be modelled and simulated to evaluate the impacts on the overall equipment effectiveness (OEE).

Similarly, research question 3 was addressed in Chapter 2, 3 and 4. From the literature it is concluded that resilience is directly related with the system's performance, and describes its ability to maintain functions during disruptive events. Therefore, resilience can be assessed with key performance indicators, including the OEE. Although the OEE does not exactly quantify the system's resilience, it has proven to be a coherent indicator of either a lack or improvement of resilience. Additionally, because the simulation results can show the system's availability, quality and performance, it is possible to identify mitigation actions that directly serve the most affected factor. In the case study analysed, even though the availability was the only factor assessed, it was possible to observe where and when was the system's availability impacted and suggest response actions to increase its resilience.

5.2 Case study conclusions

Regarding the case study analysis, the connection failure scenarios simulated manifested a great impact on the production line's availability. It was possible to illustrate how the time in disruptive mode tends to lead to higher unavailability times, as expected. The same can be concluded for the tax authority service disruption, where a disruption in a digital platform related to expedition process could have an impact on the production line's availability.

The use of agents to model data arrays was found to be a potential way to represent communication protocols. A few points support this decision: they're easy to create, Anylogic allows for agent populations which in return allow for multiple identical arrays to be created, and the ability to exchange them among other agents. For example, the production line agent can receive and handle different agents within its environment and be influenced by them. Nevertheless, this application was limited in the case study since only two agent populations representing data were used, four production orders and four expedition orders. Thus, it is difficult to predict the behaviour of the system if the use of agents as communication protocols were to exponentially grow.

Statecharts proved to be a simple and efficient way to model the MES and production line behaviours. However, agents cannot detect statechart transitions in different agents, which might be crucial for agents from which one's behaviour can influence the other. Consequently, Anylogic's event blocks were used as event listeners that cyclically mirrored a different agent's local variables, giving access to real-time data. The cycle time should be in the millisecond mark, otherwise, the expected result might not be achieved. Although functional, this method, together with the great sum of condition (or event) triggered transitions in the statecharts, significantly increases the computational load during the simulation runs. Mostly because of the event logs that are stored in the simulation database. In this case, the event logging capability should be deactivated, improving the simulation run time.

5.3 Future work

The expansion of experiments in different case studies, with different disruption scenarios and lower levels of abstraction, is key to further validate the proposed methodology. One of the limitations of the current case study was only having access to one weekly production plan, which did not allow for long-term disruptions to be addressed. Thus, they should be addressed in the future, with relevant reliability parameters that are more closely aligned with reality. Additionally, further adjustments to the simulation models should be made to be able to receive real data from cyber-physical systems and incorporate 3D animation for a better understanding of the system's behaviour.

Having a disruption management system that autonomously diagnosis and triggers the simulation of possible mitigation actions to decide on the best one will increase the production system's agility. Further developments should see the current methodology adapted to integrate the mentioned autonomous process to aid the decision-maker in real-time.

Appendix A

Research paper

The following pages compose an intermediary paper that was written and published at the 18th International Conference in Manufacturing Research ICMR 2021.

Resilience in Industry 4.0 Digital Infrastructures and Platforms

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Abstract. We live in a world where companies are shifting toward the industry 4.0 paradigm. One of the pillars of Industry 4.0 is the digitalization of physical assets and manufacturing processes, moving towards the Cyber-Physical Production Systems concept (CPPS). In these systems, every component of the production process - machines, tools, workstations, etc. - is equipped with sensors, possesses information about itself, and can interact with each other, allowing the production of smaller batches at lower prices and increase product customization through adaptative processes. Consequently, companies are evolving their information systems to have more visibility and control over their production systems. This change increases both the production system's agility and its vulnerability to communication and information related disruptions. Hence, companies that adhere to Industry 4.0 enabling technologies must adopt new methodologies and tools to become aware of the new risks that arise by the introduction of new digital platforms, their impacts in the production systems, and how they may react to remain resilient. In this paper, disruption events and adequate mitigation strategies are analyzed, modeled, and simulated as part of a methodology designed to measure the impacts of disruptive events on the production system.

Keywords. Industry 4.0, Cyber-Physical Production System (CPPS), disruption management, hybrid simulation.

1. Introduction

Industry 4.0 consists of a paradigm shift from automated production to an intelligent production concept where all physical assets such as products, components, workstations, and machines possess individual information about themselves and are part of a network with communication interfaces, where all participants can interact with each other using technologies such as the Internet of Things. These assets are now called Cyber-Physical Systems (CPS), and the manufacturing system itself a Cyber-Physical Production System (CPPS). CPPSs are highly flexible systems that allow small batches to be produced at lower prices and increase product customization through adaptive production processes [1].

Consequently, companies are evolving their information systems to have more visibility and control over their production systems. As an example, companies are

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investing in cloud-based manufacturing execution systems (MES). Although this evolution allows the production to become more agile, it also increases the dependency on digital manufacturing platforms and vulnerability to new types of information and communication disruptions [2]. In this sense, these disruptions caused by missing information or communication failures are now the new production system's bottleneck, which requires the development of new tools to manage and control them.

This paper proposes the use of simulation as a tool to allow decision-makers to predict possible disruptions, their impacts on the production processes and to create a database with effective countermeasures. Thus, this paper aims to answer the following questions: (1) What are the main process disruptions in CPPSs? (2) How can the impacts of process disruptions in CPPSs be evaluated using simulated-based approaches? (3) How can we quantify and improve the resilience of CPPSs? Using action research methodology, disruption events and adequate mitigation strategies are analyzed, modeled, and simulated as part of a methodology designed to measure the impacts of disruptive events on the production system. A use case study will be performed to test and demonstrate the application of the methodology.

2. Literature Review

2.1. Disruptions

Generally, a process disruption is an unwanted event that leads to a non-executable process during the execution of the current operation, where the deviation from the plan is sufficiently large that the plan has to be changed substantially [3]. In this definition, disruption is the event that leads to the deviation, but not the deviation itself as seen in [4]. As such, a process deviation is defined as the effect of a disruption event.

Disruptions include both disturbances and failures since both of them can cause the process to be disrupted. A production disturbance is an unplanned or undesirable state or function of the system and can occur in different parts of a manufacturing system [5], due to missing components, blocked manufacturing stations, missing workforces, manufacturing stations, resources, and workers. Failures are described as the non-functional state of a system. Because of the increasing use of communication technologies in cyber-physical production systems and the importance of information transparency, disturbances can also be caused by missing required manufacturing information or a failure of the communication interfaces [2]. Failures in manufacturing systems may be caused by the missing workforce, mechanical breakdowns, or quality problems [6].

The lifecycle of process disruptions is divided into four phases [7]. The first phase is the detection phase. This is the time between the occurrence of the disrupting event from a normal operating state and the time the process deviation is noticed. The second phase is the analysis phase that comprises the diagnose and analysis of the causes of the disruptions. The third is the development phase, where the countermeasures to solve the process deviations are identified and tested. The fourth phase is the implementation phase where the solution previously defined is implemented and the system should return to its normal operating state.

2.2. Resilience

Resilience describes the system's behavior when a disrupting event occurs during runtime. The resilience of a production system can be measured by the ability of a production system to withstand disruptions through maintaining functions and structures, reducing the time in the disruptive state, and responding to disruptive events [8]. In this context, the concept of resilience incorporates both the principles of robustness and agility.

Robustness describes the ability of the system to cope with minor disruptions without adaptations. It is the feature of a system that allows it to resist change or external factors, maintaining its stability [9] and continuously providing the desired output [10]. Typically, robustness refers to a constructive approach that prevents uncertainty from limiting the functionality of production processes, giving resistance to anticipated changes [11]. On the other hand, agility describes the ability of the system to regain its original state by adapting to changes caused by severe disruptions. The main advantage of an agile system is that it converts quickly and smoothly without predefined adaptation plans, meaning that not all potential disturbances need to be known since alternative response actions will take place soon after disturbances occur [12].

2.3. Simulation-based disruption management systems

As process disruptions have a negative impact on the performance of a manufacturing system, reducing the effect of disruptions is the most important step to achieve resilience in the affected processes. Disruption management aims to reduce the overall time of the system in disrupted mode [7], which can be achieved by an effective decision-making process for developing countermeasures [13].

As seen in [2], [5], [7], a disruption management methodology can be divided in four stages (Figure 2). In the first stage are identified the main causes for process deviation in the manufacturing system, and for each cause, possible response actions are listed in the second stage. In the last stages, the response actions are simulated and the gains in resilience of the system are measured so that the best action can be identified.

Disruptions are bound to happen and to better respond to them, they need to be organized into categories. In the context of Industry 4.0, disruptions can be categorized according to the source of the event: products, human resources, production equipment, communication, and information [6], [7], [14].

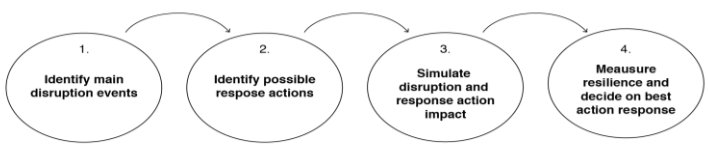

Figure 2. Stages of a disruption management methodology

A. Ingemansson et. al. [5] proposes that information about disruptions can be obtained from a manual logbook and interviews with the personnel. This way, specific disruption events from a particular production facility can be listed, thus allowing effective countermeasures to be studied and applied. The possible scenarios upon a disruption are bounded by the particular manufacturing center limitations, so it would be difficult to implement a general countermeasures database. Thus, the importance of gathering knowledge within the facility.

The response actions for a given disruption event are simulated to illustrate their impact on the production processes. The impact will be measured using key performance indicators (KPIs), which in turn are used to compare the different scenarios. For measuring resilience, indicators such as production loss, throughput settling time, total under production time [15], and overall equipment efficiency (OEE) are widely used. For a general-purpose approach, state variables can also be mapped into the performance space [16].

3. Concept proposal

The research's purpose is to create a solution that allows companies to assess the impact of disruptions in production systems and the support information systems for industrial processes. As introduced before, new applications of cyber-physical systems are coming to use, companies are adopting technologies such as the Internet of Things (IoT) and Cloud-based manufacturing, which lead to new types of disruption events. Disruptions that occur in a particular system may have impacts in the others and that's what the solution seeks to answer with the use of simulation tools.

The methodology is in line a disruption management system and will follow the four steps discussed in the previous chapter. First disruptions are categorized according to the source (Methods, Machine, Material, Man power and Milieu) [2] and location (production, logistics, supplier, production control,..). Then, possible scenarios are gathered and simulated. Due to its wide use in the industry, the key performance indicator to be used for comparison is the OEE.

We hypothesize that a hybrid simulation-based solution is able to carry out the defined objectives. Hybrid simulations refers to the modeling approach that combines multiple simulation methods. In this case, agent-based simulation to model the different systems as agents, discrete event simulation (DES) to model the processes, and system dynamics (SD) for the production (production rate/time).

4. Case Study Analysis

The selected case study is a Portuguese company in the cork industry. This company has been increasing the level of digitization of its factories with the introduction of hardware to collect information and data from the shop floor and the installation of a manufacturing execution system (MES) for the management of its production processes. Despite the advantages of this digital transition, the company is concerned with the dependence on the digital infrastructure that has been set up and its ability to stay resilient in the event of disruptions.

With their concerns in mind, the methodology previously described was applied. In the interest of time, a single production station was implemented consisting of a double belt press responsible for the production of cork sheet rolls. The production system receives orders from the MES, stores them in queue and proceeds with the scheduled production cycle. During a process, the cyber-physical production system is assumed to possess the ability to self-diagnose, that is, if a disruption event occurs, it can signal the MES about the event. In order to demonstrate the concept, the communication failure between MES and production system disruption will be introduced in the system.

In this case the production cannot proceed without storing data in the MES database, so two different scenarios are originated: (1) Production finishes current order and waits for the connection to be reestablished, or (2) the production data is stored in a buffer within the facility and the orders follow the normal scheduling. The MES database is later updated. To measure the impact of the disruption in the system, the reference state, where no disruption occurs, will also be simulated.

5. Results and Discussion

The simulation was executed in the hybrid simulation software Anylogic. The simulation corresponds to a full working week since the station doesn't stop until all the scheduled orders are complete. The disruption will have a cyclic reoccurrence time of 5 hours, and two different durations, one longer than the other.

Table 2. Simulation results

	Long disruption		Short disruption	
Reference state	**Scenario 1**	**Scenario 2**	**Scenario 1**	**Scenario 2**
0.751	0.725	0.751	0.732	0.751

The results are as expected. In the second scenario the OEE was the same as the reference state since the production maintained the normal schedule. But it is expected that it will affect other indicators because the data will later have to be asynchronously updated in the MES database. In the first scenario the production had to wait for the disruption to be solved, thus affecting the indicator. The impact is greater if the disruption lasts longer since, for shorter events, the connection is re-established before the current order is finished, causing no harm to the availability of the station. This observation shows that there are certain time intervals where the normal connection to the support system may be lost without affecting the OOE, which can be useful for maintenance purposes.

This paper presents a simulation-based methodology capable of evaluating the impacts of disruption events and finding suitable response actions to increase resilience in Cyber-Physical Production Systems processes. The methodology's focus is the use of a simulation tool to model the production system and the information systems, which simulates the communication between the two agents, the data flow, and the behaviour of the system during the disruptive event. For future research, the modelling of the communication between the manufacturing system and its information system should be more detailed and closer to a real OPC server.

Acknowledgements

This work is financed by National Funds through the Portuguese funding agency, FCT - Fundação para a Ciência e a Tecnologia, within project UIDB/50014/2020.

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