An integrated discrete-event simulation with functional resonance analysis and work domain analysis methods for industry 4.0 implementation

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ABSTRACT

In the Industry 4.0 era, advanced analytical tools are essential for progressing with digital transformation, especially within complex socio-technical systems. However, the growing complexity of these systems in manufacturing impedes system improvement, and traditional analytical methods focusing solely on the technological aspect often fall short. To overcome this problem, this paper introduces an integrated methodology combining Discrete-Event Simulation, Functional Resonance Analysis Method, and Work Domain Analysis for analysing and enhancing manufacturing systems by considering factors like operator skill levels, demand changes, and production constraints. Implemented in two industrial case studies, this methodology effectively identifies system limitations and aids in structured data analysis, positioning it as a vital decision support system in the digital transformation of Industry 4.0.

1. Introduction

Manufacturing system's evolution is reinforcing the importance of socio-technical systems, enhancing the coexistence of human systems, machine or automated systems, and human–machine systems to maximize productivity. Researchers worldwide are putting the main efforts to model manufacturing systems that have quick responsiveness when new products are introduced, demand increases or decreases, or external conditions change [1]. For that purpose, the need for data and digitalization have been established as a necessary basic step for nowadays complex system analysis and improvement. System and continuous improvement have been critical for the evolution and success of industry. One such example is the automotive sector, which has made significant advances in waste reduction, cost reduction, and increased efficiency and resource utilization over the past few decades worldwide. Several system improvement tools, such as Lean Production, Toyota Production System, and now the paradigm of Industry 4.0 have been developed for this purpose [2].

Common problems in nowadays manufacturing are related to the trend of going from mass production to mass customization, which is commonly translated into an increased number of products and variants, and decreased production volumes. To address these problems two main considerations should be priorities in manufacturing systems: first, how to predict and deal with uncertainties, and second,

how to manage schedule or production plans, because the systems are so closely connected that the behaviours of the system could be intractable. That is the reason why the analysis of this kind of system is required from a socio-technical perspective. An example of the fragility of the new mass-customization manufacturing has been seen during the recent Covid-19 pandemic and international supply chain disruptions, highlighting the importance of national or regional backup production, safety or emergency buffers, supply chains, and suppliers, and capacity to adapt to sudden changes in production, demand, and system constraints. A cornerstone when working with system analysis and improvement considering all these factors is the availability of digital data.

Digitalization and the Internet of Things (IoT) are driving a great deal of the industrial digital transformation providing significant benefits to manufacturers of different industries to analyse systems in real-time and to try to adapt to changes in production [3]. This is usually not possible without digital data, which is becoming a requirement for nowadays manufacturing systems. Reasons for this requirement commonly are the size and complexity of the systems and the mix of socio-technical systems combining automated and manual processes and their environment; making it difficult to manage this data with traditional tools such as pen-and-paper approaches and spreadsheets. Computerized modelling tools, in this context, are usually able to

handle this complexity, commonly translated into interrelations with a high number of processes and variables associated with the different parts of the system.

Specifically, Discrete-Event Simulation (DES) has usually been a great support for this kind of operational research projects in industry. However, the integration of manual and automated processes (in some cases with a lack of digital data availability) as well as the variability of the surrounding entities, highlight a need for more qualitative approaches in combination with quantitative ones. This research project, therefore, focuses on the improvement of manufacturing systems integrating quantitative system improvement methods such as DES and more qualitative system improvement methods such as WDA and FRAM. A methodology is proposed integrating these system improvement tools considering human–machine systems in a more human-centric approach to facilitate the implementation of Industry 4.0 by integrating DES, WDA, and FRAM. The initial idea of the methodology was first introduced in a conference paper with a work-in-progress case study presented by the authors [4]. The continuation of the development of the initial case study and its application in an additional case study is presented in this paper.

A Swedish leisure boat manufacturer has been utilized as a test bed for the validation of the applicability of the proposed methodology in manufacturing systems; the additional industrial case study has followed the proposed methodology in a Japanese steel plate production line. Going through these two industrial case studies, this methodology considers quantitative and qualitative data as well as knowledge of expert and novice human resources of the system to analyse the human, machine or automated, and human–machine systems involved in production.

In the following section, a frame of reference including the main methods used in the proposed methodology is presented. The proposed methodology is presented and explained in Section 3. Section 4 presents both industrial studies and main results and Section 5 summarizes the conclusion of the research and future work

2. Complexity of Industry 4.0-based socio-technical manufacturing

Industry 4.0, commonly referred as the Fourth Industrial Revolution, pursues the integration of advanced technologies and digitization in the manufacturing and industrial sectors; the term was first introduced in Germany in 2011 and has been widely adopted worldwide [5]. The growing paradigm of Industry 4.0 (nowadays being called Industry 5.0 by including sustainability objectives), supports this required base of digitalization and self-adaptation of manufacturing systems [6,7]. In this paper, this is referred to as Industry 4.0, which involves the utilization of cutting-edge technologies such as the IoT, Artificial Intelligence (AI), machine learning, big data analytics, and Cyber–Physical Systems (CPS), aiming to establish a more interconnected and automated environment [8–11]. This can lead to enhanced flexibility, efficiency, and productivity in the production process, along with improved quality control and customization, having the potential to revolutionize the way products are manufactured and distributed [12]. For the purpose of that, researchers worldwide are putting their main efforts to model manufacturing systems that have quick responsiveness when new products are introduced, demand increase or decrease, or external conditions change [1].

The term Industry 4.0 is accelerating this enhanced flexibility, efficiency, and productivity process among managers and stakeholders, as well as facilitating data generation, collection, and management. However, even though the definitions and possible implications of Industry 4.0 might be clear at management levels, implementations at the shop-floor level can be considered a young and growing field, and commonly are non-existent in small and mid-size companies, having tremendous potential in robotic applications [13]. System improvement implications nowadays can be considered as still quite abstract

in general, being the term used more as marketing of a system improvement paradigm to increase the sales of enhanced connectivity industrial equipment [6,12]. Additionally, the analysis and modelling of those processes as socio-technical systems (systems considering the interaction and interdependence between people, technology, and the organization of work) are not straightforward to achieve with traditional system improvement tools due to the nature and availability of digital data [4,14].

Socio-technical systems are complex systems that comprise human agents and machine agents considering the surrounding entities; they are characterized by the interaction and interdependence between people, technology, and the organization of work [15]. The social component is constituted by the individuals who operate the system, whereas the technical component includes the tools, equipment, and technology that are required to perform work tasks. The objective of socio-technical systems design is to optimize the interaction between people, technology, and the organization of work, to enhance workplace performance, safety, and well-being [16].

Computer simulation and optimization tools have conventionally been employed to facilitate the design and improvement of complex manufacturing systems to increase performance. Simulation tools, such as DES, can provide extensive support to managers and stakeholders by analysing various possible "what-if scenarios [17]". These scenarios usually analyse the performance to find bottlenecks in the system based on Key Performance Indicators (KPIs) of the simulation model [18,19]. These KPIs depend on a set of defined variables (input parameters) of the system, such as the number and type of products to be produced at every moment, the number of processes, machines, robots, operators, and transports in an assembly line. These simulation tools are typically based on quantitative data that measure resources and system performance using numeric values. However, many parameters of these complex systems cannot be measured or quantified by numbers. These parameters may include more abstract characteristics of products, processes, systems, or resources. For example, how operators with different skill levels handle unplanned situations, or how the lack of materials or personnel is addressed in the event of a logistic disruption or a pandemic situation, as recently observed. Nevertheless, for the analysis and improvement of systems with DES, available and updated digital data is required at a large scale.

DES has been frequently utilized in analysing complex manufacturing systems, especially when the complexity of the systems is considerable [20,21]. DES is usually utilized due to its ability to represent the complexity of the system over time; nevertheless, when the number of manual processes is high, the collection of data becomes more critical and tedious [22–24]. Several aspects have to be considered, such as wearable devices, sensors and cameras connected to AI systems, at the same time as sensitive issues such as the privacy of operators and workers as well as unions have to also be considered [25]. This can improve data availability and collection, however, the quality of the data might be lower due to human-related behaviours, industrial environments, and circumstances that could not often happen to a machine or robot, such as forgetting to wear or switch on a wearable device, remove it due to lack of comfort, malfunction due to lack of industrial certifications, and higher exposure to damage. The use of DES is sometimes insufficient due to the difficulty of capturing socio-technical aspects of complex systems due to the uncertainty of human behaviour [26]. Common challenges considering socio-technical systems commonly are the absence of digital and quantitative data, as well as limited data collection methods to consider safety aspects and well-being. If the systems to consider are not newly designed or adequately adapted for Industry 4.0 (considering the digital industrial transformation of human interactions), they can fail to provide digitalized performance data of resources, processes, and products even with the help of simulation and optimization tools [21].

Therefore, other methods than purely quantitative tools (such as DES tools) are required. In this study, a system improvement methodology is proposed combining DES, Work Domain Analysis (WDA),
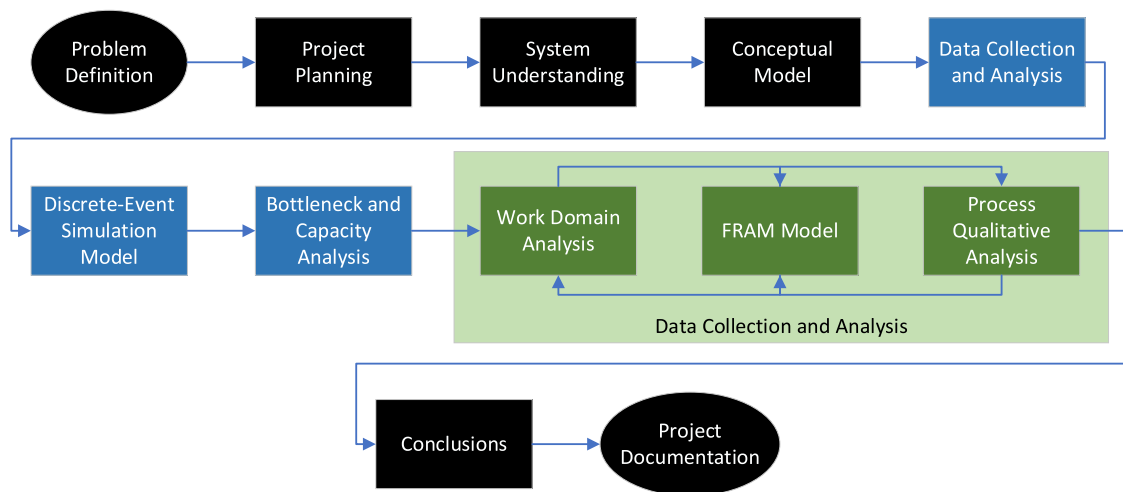
Fig. 1. Proposed system improvement DES, WDA, and FRAM methodology.

and Functional Resonance Analysis Methods (FRAM). The WDA is a method utilized for assessing human work, which aids in identifying the functional structure of independent controlled systems and interfaces [27–29]. WDA has been used in manufacturing applications for logistics and predictive maintenance design involving human factors [30–32]. WDA has also been implemented in manufacturing for system design and development in manufacturing considering human factors and safety standards [33–36]. This technique enables the identification and analysis of functions, variables, and interrelations that are associated with the performance of a system, with a focus on the human-centric approach [37]. WDA involves identifying the goals, tasks, and activities that are required to achieve the system's objectives, as well as the constraints and resources that impact the work domain. It is used to understand the cognitive or manual task designs of systems that are compatible with the characteristics of the work domain and to identify potential sources of variability and risk within the system [28,30,38]. FRAM and WDA are both methods commonly used in the field of Human Factors and Ergonomics to analyse complex socio-technical systems and interactions with the work environment [39,40].

On the other hand, FRAM is a method employed for analysing complex socio-technical systems. It was developed by Hollnagel and colleagues to address the limitations of conventional risk assessment methods that primarily concentrate on identifying and mitigating individual failures or errors [41]. FRAM involves identifying the system functions and their interrelationships, as well as the variability and performance conditions that affect the system's overall behaviour [42, 43]. The technique employs an abstract representation of the system, which facilitates the analysis of system functioning. FRAM should not be considered as a model itself, it should be considered as a prospective risk assessment method. It is based on a non-linear, dynamic systems approach, and it is particularly useful for understanding the behaviour of complex systems that are subject to variability and uncertainty [43, 44]. FRAM considers the role of human operators and their interactions with the system and it can be used to identify potential areas of risk mainly related to variability and human factors [45–47].

Both FRAM and WDA are qualitative methods that rely on expert judgment and analysis to understand the behaviour and characteristics of complex socio-technical systems and they have been usually used for safety and risk analysis applications [37,48–50]. The closest applications combining WDA and FRAM have been analysed [37,42,50,51]. Its integration with DES has not been further found in the literature, hence, the proposed methodology is presented in the following section.

3. Methodology

This project proposes a system improvement methodology combining quantitate and qualitative methods including simulation tools. The

proposed methodology, shown in Fig. 1, considers systems with a high number of interrelations including human–machine interactions. The methodology is based on the mentioned DES, WDA, and FRAM and the main objective is its application for complex manufacturing system design, analysis, and improvement.

The upper row of the figure, the analysis stage, focuses on establishing the start-up of the project, defining the objectives, project planning, understanding the system and doing a conceptual model of the main processes of the system at different abstraction levels [52]. It can be useful in this step to define several conceptual models, for example going from the most strategical or abstract/wide perspective, to a more tactical or even operational abstraction level, in which the level of detail of different processes, subprocesses, and what happens between process is also analysed.

Usually, two or three abstraction levels are enough to understand the magnitude of the problem and the processes that should be in focus, the required data, and therefore suitable data collection methods. Black-coloured blocks represent trivial project steps focusing on general start-up or wrap-up functions, while blue-coloured functions are focused on the simulation part of the project, based on quantitative data and capacity analysis. Green-coloured blocks represent the qualitative approaches based on WDA and FRAM, usually with more focus on quality, skills, and qualitative performance aspects.

The second part of the methodology, the core of the methodology, (second row of blocks in Fig. 1), focuses first on the simulation approach, trying to identify bottlenecks and weaknesses of the system if enough digital quantitative data are available or can be collected. A deep analysis of required and available data should be done at the beginning of the project to ensure there is enough time allocated for the data collection process which might be time-consuming if too detailed and diverse or collected manually. Once the main weaknesses or bottlenecks of the system are found with simulation, a deeper analysis of those identified processes can be done with WDA (an example of this simulation analysis is presented in the first case study in Fig. 4). For the WDA, the quantitative factors or variables related to the bottleneck or weaknesses of the system have to be identified. This can be done through interviews, documentation analysis, and Gemba, paying attention to small details that are not usually written in manuals or instructions of the processes in question but that might affect the performance of the system, This can be the performance of different people working with the same process (such as skills level, qualification, expertise, age, and personality), personal and professional relations between employees, malfunctioning of equipment, material delivery delays, and interruptions. Then a WDA is built, usually following a set of steps: Establish the purpose and use of the WDA, establish

abstraction levels (abstraction–decomposition space) and boundaries, identify the nature of constraints and potential sources of information, iteratively work on the abstraction–decomposition space with several iterations, and finally validate the abstraction–decomposition space and WDA [28,29].

Usually, the different abstraction levels answer the question "how" going down in the WDA from their upper abstraction level, and "why", going up from the lower abstraction levels [50]. The upper part of the WDA is usually the "Functional Purpose", which commonly is related to the aim, problem, or objectives of the study; for example, to reduce quality defects, and the lower layer. On the other hand, the lowest part of the WDA, "Physical Function", usually represents the detailed steps that contribute to the process or its improvement. Some authors recommend the use of nouns for abstraction levels and others recommend the use of verbs; in this case, the verbs option could clarify the nature of the tasks or processes represented in the WDA, hence, verbs have commonly been predominant [28,53].

For the construction of the WDA, in these cases, visits to the production sites, analysis of company documentation, meetings with engineering teams and system responsible persons, as well as interviews with expert and novice operators were performed to collect the data, construct the WDA, and receive feedback to verify and validate it by the company. The WDAs developed in this project are presented in the following section. Once the WDA was defined, it was time to start working with FRAM representations.

To build a FRAM representation, the WDA was analysed from the perspective of the problem description of every case study. Then the aim and objectives were double-checked and the main functions, usually related to the same hierarchical level of the WDA, were selected to be included in the FRAM [50]. The hierarchy levers often used as reference are the generalized function, object-related function, physical function, or a combination of them [50]. This process of FRAM construction can become an iterative process. When analysing the FRAM representation, it might be difficult to draw ideas or conclusions considering the objectives of the projects and data obtained from documentation, meeting, and interviews. In some cases, some additional processes or functions have to be added to the WDA, further data collected, and then translated into the FRAM until it represents the functions, key aspects or factors, and key interrelations of the system being analysed [50].

Once the WDA and FRAM are built, some boundaries of the FRAM can be added to limit the focus of the system improvement process, and the variability of key functions affecting the performance or related to the aim and objectives of the project is added. A workshop with brainstorming and the collected data by hand can be useful to draw some conclusions, to then be presented and discussed with the management team of the system analysed. The methodology has been demonstrated to serve as a guideline for managers and stakeholders and provide a decision-support tool for system improvement in manufacturing systems. The explanation of the methodology and potential results are summarized by going through two industrial application case studies in the following section.

4. Industrial case studies

In this section, two industrial case studies are presented. In these case studies, the steps of the methodology presented in Section 3 were applied. The first case study, case study A, a capacity analysis of a Swedish leisure-boat manufacturer, has a stronger focus on simulation at the initial stage of the project to find the main bottleneck or limitation of the system: the sensitive painting process mainly based on manual tasks and experience. The second case study, case study B, considering a Japanese manufacturer of steel plates, aims to identify potential improvements of the key bottleneck process of the factory, the coiling process of the metal plates, requiring expert skills for the good development of the process.

4.1. Case study A

This industrial case study aimed to perform a production capacity and reconfigurability assessment of a leisure-boat manufacturer. The main objective was to increase the flexibility and resilience of the production including different levels of abstraction (strategical, tactical, and operational), two main stages of the manufacture (composite production and assembly), and considering the main constraints of space, operators skill levels, product moulds, and internal logistics transports.

Following the methodology, after having a clear definition of the aim, objectives, scope and boundaries of the project, DES was considered one of the main tools for the initial improvement process, since quantitative data were available for the different processing times, buffers, product mix, and transports at a tactical level (considering just processing times of main processes).

First, the required data were collected by analysing documentation provided by engineers and team leaders of different departments and processes to start defining a conceptual model of the system at a strategic level. Working with simulation at a strategic level resulted in what looked a bit useless due to the high level of abstraction and lack of data at that level. For example, the processing times (of the entire department as a whole) had never been collected or analysed. Therefore, the construction of the conceptual model focused on the tactical level, collecting the data of the different processing times and main resources needed for each process. The data regarding the different processing times of automated processes and machining centres were available. Nevertheless, when translating this conceptual model at a tactical level, the information regarding times between processes was missing, such as transport and waiting times and several manual processes. Hence, a step down to the operational level was done and more detailed data were collected to update the conceptual model and simulation model.

An operational level of abstraction included the level of detail of different departments, transports, and processes required to manufacture each family of products. Siemens Plant Simulation was chosen as the simulation software tool due to its customization capabilities, which allowed for the programming of predefined objects or processes in the simulation model. This is useful for representing the complex characteristics, behaviours, and interrelationships of the system. As can be appreciated in Fig. 2, the layout of the factory is represented in the DES model, the production or machining areas are represented in the middle and right parts of the layout, while the assembly area is represented on the left. Each grey squared object represents a process, such as trimming, painting, engine connection, transport, or storage.

The majority of the entities represented in the model have quantitative data associated with them, such as capacity, delivery rate, and fixed or variable processing times. Real stochastic behaviour is represented using different statistical distributions. When building the simulation model, for some of the processes additional data collection and analysis may be required during the model-building process, and assumptions can be made if necessary. For example, operators and people in charge of the processes may be interviewed to develop triangular statistical distributions including minimum, most common, and maximum process times, when further data are not available. These distributions must be validated before being programmed into the simulation model by verifying them with the real system and discussing them with the staff in charge of the processes.

Verification involves checking that the system accurately represents reality, while validation ensures that the behaviour and performance of the simulation model accurately represent the real system [54]. This is typically done in coordination with experts and managers from the different areas of the system represented in the simulation model. The validation process involves comparing the output variables of the simulation model with the main parameters of the real system, such as throughput, lead time, and work-in-progress. Fine-tuning of the input parameters of the simulation model is done until the comparison is accurate enough for the purpose of the study. A verified and validated
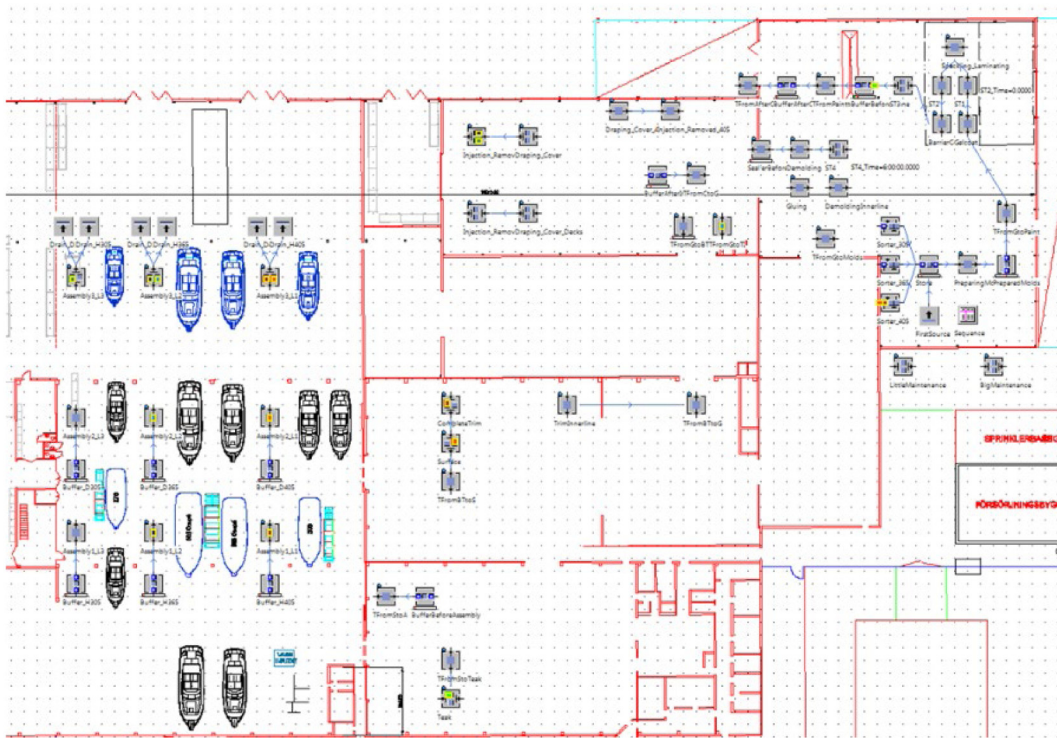
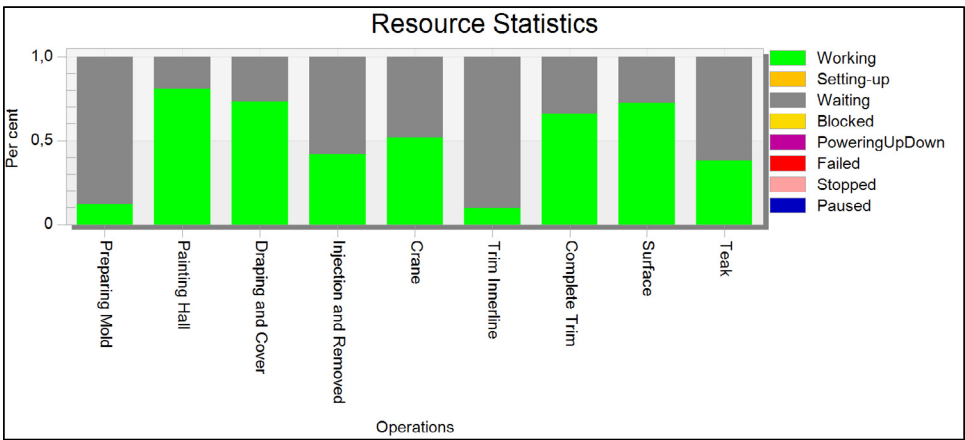**Fig. 2.** Shop-floor layout represented in the DES model.

Fig. 3. Bottleneck analysis of the main manufacturing processes of the production site.

DES simulation model of the system can then be used to test different scenarios for system improvement and to perform a bottleneck analysis, one of the main strengths of DES. An example is shown in the following Fig. 3:

This chart shows the different processes to produce the main parts of the boat, the deck and the hull represented, in the X axis. The Y axis represents the occupation of the time they are working. Ideally, a balanced production should have similar occupation levels so there is not much waiting time and buffers between processes. However, in this chart, it is possible to appreciate the highlight of the occupation of the painting hall. After double-checking this information with the managers and stakeholders of the factory to ensure the results obtained from the DES model were in line with reality, it was decided to focus this study in the painting hall as indicated by the bottleneck analysis. Additional experiments of "what-if scenarios" were defined to evaluate changes in the design or performance of the system. The scenarios contributed to the investigation of different product mix margins and bottleneck analyses to identify the primary limitations of the system.

When examining the painting hall, it became apparent that the bottleneck was not in the painting processes themselves. Quantitative data were unavailable, and performance was influenced by several factors that were not directly related to the painting process. Furthermore, due to the strict quality standards required for painting, processing times could not be reduced, and adding another painting cabin was not feasible due to space limitations. As a result, the focus shifted from quantitative analysis of the painting process to qualitative analyses using FRAM and WDA. The WDA obtained by documentation analysis, meetings with managers and production responsible persons, as well as interviews with novice operators is presented in Fig. 4.

This WDA is represented in five abstraction levels, starting with the "Functional Purpose", wider and more abstract, and finishing at the "Physical Function", usually determined by more specific tasks. Some key functions that could have a significant impact limiting the performance of the system were identified by first adding the upper and lower layers, and then by asking "why" (upstream) and "how" (downstream), the layers in between were built. After an analysis of
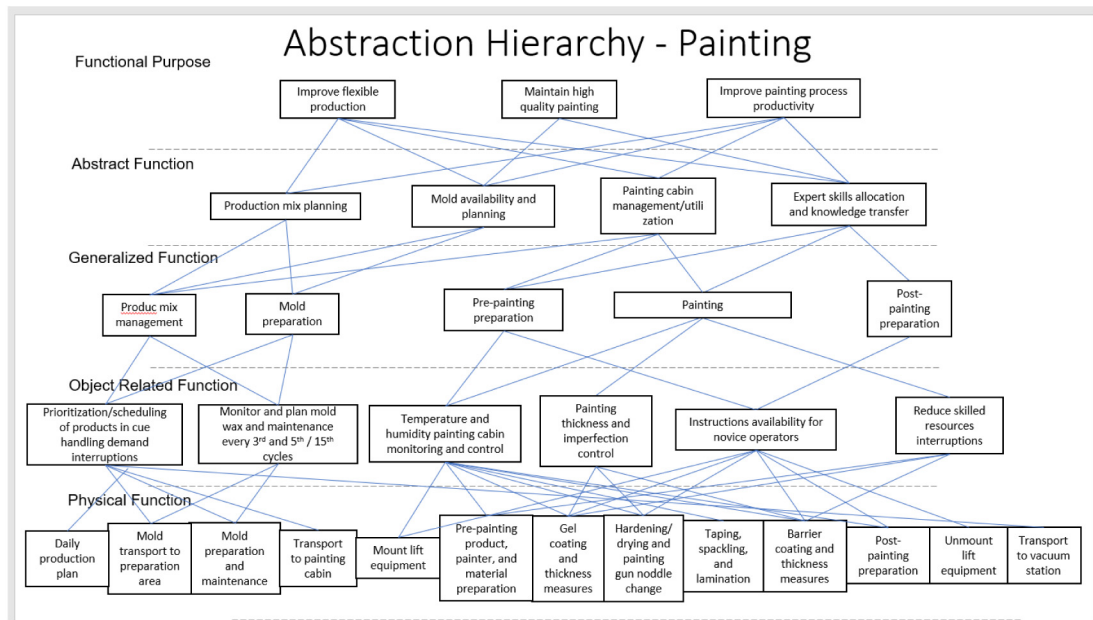
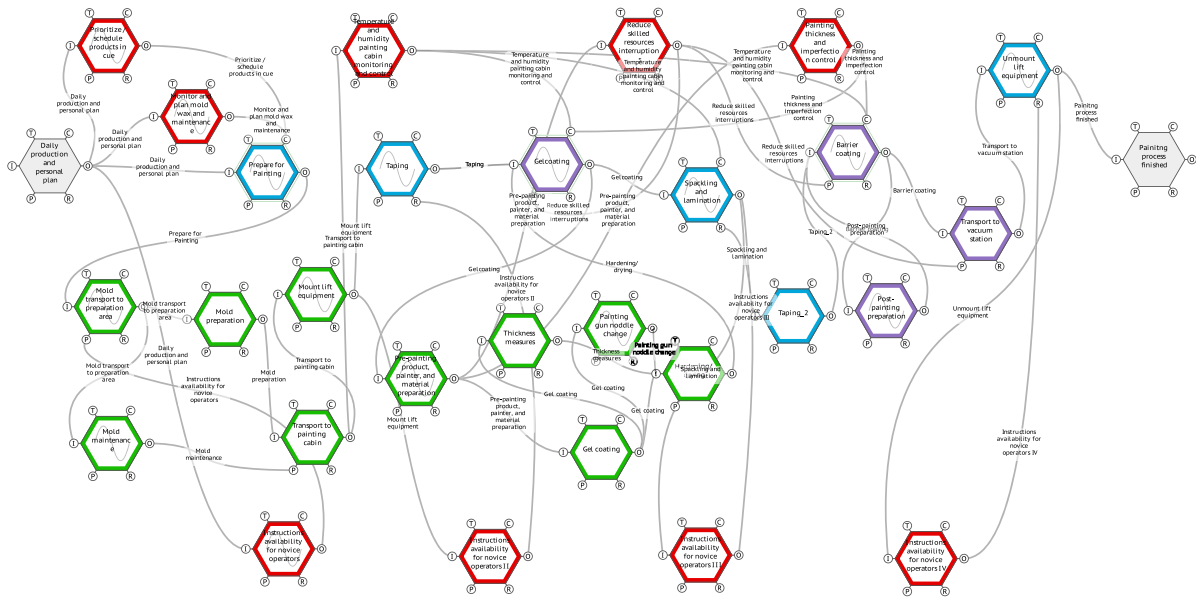**Fig. 4.** Work Domain Analysis of the painting process.

Fig. 5. FRAM representation of the bottleneck found in the system.

the implication of the functions in the physical processes and limiting the performance of the system, key functions, mostly represented in the "Object Related Function", were considered. These functions are the prioritization or scheduling of the products in the cue for the painting hall, the maintenance and preparation of the moulds, the control of the thickness and imperfections of the paint, the availability of instructions to novice operators, and the interruptions of expert operators. Therefore, these were the functions to be represented with FRAM, as presented in Fig. 5.

The figure shows the FRAM representation of the bottleneck identified in the previous DES model. The human-centric approach of the socio-technical system is represented using functions in the form of hexagons. These functions represent key processes, variables, and preconditions necessary for improving performance in the bottlenecked environment. Qualitative data obtained from the WDA, further observations, system analysis, and expert and novice operator interviews are reflected in these functions. This representation offers the advantage of variability analysis to identify which functions can constrain the system under different performance or demand circumstances.

In this FRAM representation, it is possible to appreciate the processes with higher variability and potential cause of delays (purple and blue hexagons in addition to the key red processes of "prioritize/schedule products in cue", "Monitor and plan mould wax and maintenance", and "Instruction available for novice operators" (key processes due to high impact in the performance of the system due to their number of interdependences with other processes in the system and relation to human processes.

Considering these key processes after identifying the bottleneck area or department with DES and collecting and analysing the socio-technical data with WDA, the study has highlighted the importance of several key constraints affecting the performance of the system,
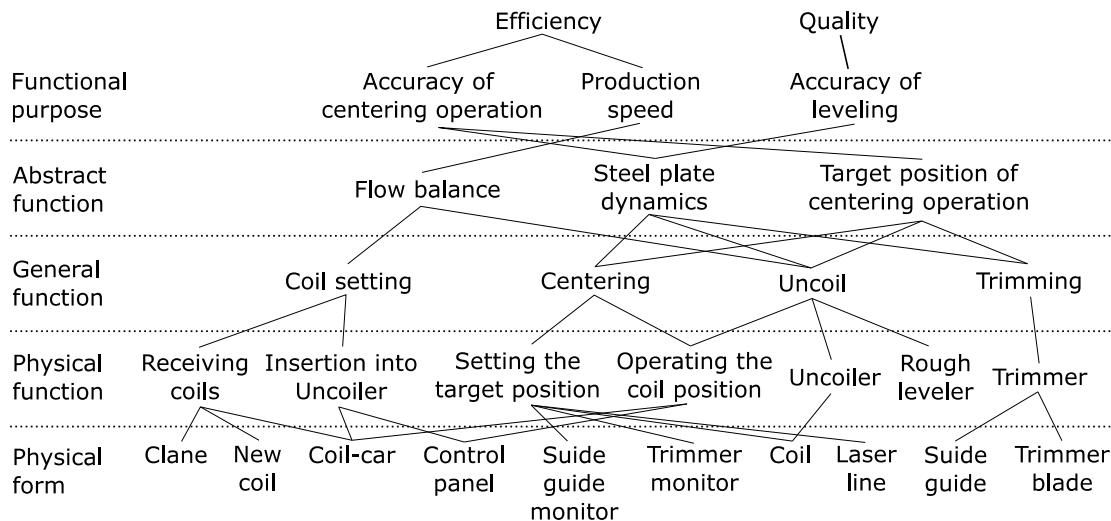
Efficiency   Quality

Functional purpose   Accuracy of centering operation   Production speed   Accuracy of leveling

Abstract function   Flow balance   Steel plate dynamics   Target position of centering operation

General function   Coil setting   Centering   Uncoil   Trimming

Physical function   Receiving coils   Insertion into Uncoiler   Setting the target position   Operating the coil position   Uncoiler   Rough leveler   Trimmer

Physical form   Clane   New coil   Coil-car   Control panel   Suide guide monitor   Trimmer monitor   Coil   Laser line   Suide guide   Trimmer blade

Fig. 6. Work Domain Analysis of the coiling process [50].

including the main production bottleneck, lack of space at the painting cabin (especially for novice operators), and a limited number of transports, moulds, and expert personnel, especially during lower production periods (such as summer, Christmas, or pandemic times). Additionally, the study identified several key variables, such as thickness quality control, room and humidity parameters, and lack of specific process instructions for novice operators which are potential sources of delays due to creating interruptions for expert skill persons assigned to other tasks. Future work considers the construction of a DES model of the improved system to analyse the metrics improvement of the KPI of throughput, work-in-progress, and lead time of the system.

4.2. Case study B

The focus of this study was on the production process of flat steel plates from coiled steel plates. The centring operation, which ensures accurate cutting of the steel plate, was the target of the study. An operator near the uncoiling machine must control the position of the steel plate during processing, while another worker occasionally carries a new coil into the process. This requires multitasking and a high level of skill. The study compared the attention allocation features between expert and mid-level workers during single-task and multitasking situations. The study used eye-tracking experiments and interviews to collect and compare gaze behaviours and responses between the two groups.

Data collection methods were based on interviews with expert and novice operators, as well as eye tracking devices to record where the operators pay more attention performing different tasks and comparing the data with expert and novice operators. Eye-tracking experiments were conducted during the operation using "Tobii Pro Glasses 2", and interviews were conducted afterwards, where the worker could recognize where they were looking. The interviews included the same questions for both participants and gaze behaviours and responses were collected and compared between the expert and mid-level workers. In a similar way to case study A, after defining the objectives of the project, designing a conceptual system to understand the system and guide the data collection, processing data was collected together with interviews and eye-tracking methods. In this case, the bottleneck of the system was defined from the beginning, therefore, even if quantitative data of most of the process was available, a DES model was not necessary to identify the bottleneck, the centring operation of steel plates [50]. Then, once the data were collected and the system understood, the project focused on a WDA diagram at different abstraction levels and its translation to FRAM. This WDA diagram is shown in the following Fig. 6.

This WDA diagram represents five levels of abstraction visualizing the functional structure of the system and links representing means-purpose relationships of different processes of the system obtained from the interviews of expert and mid-level workers. This facilitated the understanding of the system and performance of different operators in different situations as well as facilitated the construction of a FRAM representation to analyse the variability if the of the systems and multitasking potential performance of operators with different skill levels.

FRAM enables the analysis of variabilities that impact the system, causing unexpected situations. Variability is defined as factors that affect the system's state, such as fluctuations in the performance of human workers or automated machines. Again, the hexagon represents each function with six aspects in FRAM, including input, output, pre-condition, resource, control, and time. The FRAM representation so presented in the following figure (see Fig. 7).

This FRAM represents the monitoring processes performed by operators (hexagons in blue), the processes to estimate the state of the steel plate and evaluate own operation of the operator (hexagons in green), and the responding actions to centre the coil and operate a new coil (hexagons in red). Hirose et al. developed a simulation method based on FRAM that quantitatively supports the analysis process by calculating the propagation of variabilities. Common Performance Conditions (CPCs) are proposed in the Cognitive Reliability and Error Analysis Method (CREAM), which defines factors that affect the performance of human workers or automated machines [15]. The simulation method allows the investigation of the propagation of variabilities and their impact on the entire system. Variabilities such as "Availability of resources" or "Number of goals" can be assumed in the target operation. The simulation study envisioned the effect of operators' attention allocation characteristics represented by the FRAM model on the propagation of these variabilities, which can be numerically represented by the CPC score or Probability of Action Failure (PAF).

The results of this study suggest that the expert worker possesses superior attention allocation features; the expert can effectively identify where to look and allocate attention, even during multitasking, highlighting that the expert has a deep understanding of the abstract relationships between components of the working environment [50]. This conclusion of how the expert operator's attention management affects work performance was derived from the FRAM simulation results.

Based on these findings, it is hypothesized that the expert can adapt to multitasking situations by predicting where attention should be directed based on the relationships among elements. In contrast, mid-level worker appears to struggle with multitasking, as they tend to focus only on individual elements. However, since this conclusion

Fig. 7. FRAM representation of the coiling process [50].

is based on data from only one person in each group, the study examined whether this is a universal feature of experts using a model-constructive approach. The most representative operator of each group was selected to represent the sample. Utilizing the WDA and FRAM this hypothesis has been demonstrated and extended to expert and mid-level operators. The simulation results, further detailed in the related conference publication, showed that the expert's attention management represented by the FRAM model structure contributed to maintaining the work performance against the variability of the CPC "Number of goals" [50].

5. Results and conclusions

This paper proposes a decision-support methodology combining DES, WDA, and FRAM for socio-technical systems in manufacturing systems when quantitative data system improvement methods are not enough to fully support decision-making. The main objective has been the improvement of complex manufacturing systems considering a mix of human and automated processes, different abstraction levels of the systems, and different skill levels of operators involved in the manufacturing processes. The project uses DES, WDA, and FRAM to develop a methodology for system design, verification, and improvement. The methodology focuses on a human-centric approach to improve human–machine systems, using DES to identify the bottleneck or limitations of the system when quantitative data is available, WDA to structure the data collection of qualitative data of the identified limiting areas of the system, and FRAM to represent and analyse key processes and factors as well as their interrelations limiting performance.

As it can be appreciated going through both case studies, first the identification of the key or bottleneck process is the starting point for the improvement of the entire system applying the proposed methodology. In both cases, the behaviour of the operators was analysed and summarized with a set of interviews and additional data collection methods such as observations, documentation analysis, and eye-tracking experiments. In case study A, DES play a vital role here, while in case study B, the focus from the beginning was on the bottlenecked process, therefore the use of simulation for the identification of the bottleneck process was not relevant in this case. On the other hand, for the analysis of the main limiting processes, the painting and the coil rolling, the WDA was a key approach to understanding and analysing the requirement of the human and automated workforce in every step of the process. Going through the interviews with operations in both cases, it was crucial to identify the needs of expert skills in specific tasks, analyse performance, and the implication that interruptions or lack of expert skills can have in the system. In both cases, WDA and FRAM have facilitated to capture socio-technical aspects of complex systems considering human behaviour uncertainty.

Considering machine or automated process performance, digital data through the digital industrial transformation is facilitating the use of advanced analytical tools. Nevertheless, even if data from automated processes are starting to be generated, collected, and analysed, there is significant room for the increase of concrete applications and their integration with manual operations and human factors. There is still a need for complex system improvement in systems with large numbers of interrelated entities combining automated and manual processes as well as quantitative and qualitative data. In particular, socio-technical

systems can be challenging to analyse and model due to the nature of the data, the impossibility to collect it, or the lack of it.

It has been demonstrated that a combination of WDA, FRAM, and DES is an appropriate approach for identifying system weaknesses and bottlenecks. This combination enables a more in-depth analysis of the system's interrelationships at various abstraction levels, facilitating the identification of potential solutions from both quantitative and qualitative perspectives. The results of the study have contributed to a better understanding capacity increase of the industrial partners. As future work, further data collection, additional interviews with operators and different skill levels, and further case studies are being analysed. Additional simulation models of the presented case studies are being considered to quantitatively analyse and compare the performance of the improved scenarios with KPI. Furthermore, the application of the methodology outside manufacturing, for example in healthcare systems, could generate an interesting discussion about handling similar problems in different sectors.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used chat.chatgptdemo.net to improve readability, keyword selection, and grammar check. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Declaration of competing interest

Data availability

The data that has been used is confidential.

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