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DATA-DRIVEN SMART MAINTENANCE DECISION ANALYSIS: A DRONE FACTORY DEMONSTRATOR COMBINING DIGITAL TWINS AND ADAPTED AHP

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ABSTRACT

The concept of Digital Twins has gained significant attention in recent years due to its potential for improving the performance of production systems. One promising area for Digital Twins is Smart Maintenance, enabling the simulation of different strategies without disrupting operations in the real system. This study proposes a high-level framework to integrate Digital Twins to support Smart Maintenance data-driven decision making in production lines. We implement, then, a case study of a lab scale drone factory to demonstrate how the production line performance evaluation is made under different what-if maintenance scenarios. The effects of this Smart Maintenance decision analysis approach were evaluated according to Key Performance Indicators from literature. The identified contributions are: (i) Digital Twin demonstrator focused on smart maintenance; (ii) implementation of smart maintenance data-driven decision analysis concepts; (iii) design and evaluation of what-if maintenance scenarios.

1 INTRODUCTION

Reduction of production disturbances have grown in importance in manufacturing companies and this leads to a huge effort to minimize unplanned down times and increase efficiency of production systems with a vision of failure-free production (May et al. 2018). Sub optimal maintenance decisions can lead to inefficient maintenance strategies, increased downtime, higher costs, and reduced equipment performance. Implementing a proper maintenance activity can save a company up to 20 % due to the resulting smaller production losses, improved product quality, etc. (Algabroun et al. 2022). Given this scenario, several models, methods, concepts, philosophies, and strategies have been developed in order to evaluate, quantify and predict the maintenance effects (Lundgren et al. 2018). Still there is a need to define the impact of the maintenance actions in order to have a more efficient industry (Lundgren et al. 2021).

Meanwhile, maintenance decisions are often made based on limited information or experience. Even it has been proven that maintenance plays an important role in production it still a challenge to properly quantify its benefits and justify investments (Ylipää et al. 2017). One reason for this is that the multitude of tools and methodologies make it unclear for practitioners to decide the right time and situation to apply each one. Due to this lack of practical usage to verify maintenance benefits, the investments can become harder to sustain in practice (Lundgren et al. 2018).

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Production line performance evaluation methods can help to identify the best maintenance actions and strategies, while the impact of maintenance decisions on production line performance cannot be overlooked (Lundgren et al. 2021). Given this context, Digital Twins have emerged as a powerful tool for simulating and analyzing industrial processes (van Dinter et al. 2022), this concept can be particularly useful in the context of maintenance decision making (Errandonea et al. 2020). Consequently, this paper envisions to contribute to bridge the gap of maintenance actions impact evaluation by integrating Digital Twins and data-driven decision-making concepts.

Therefore, it is imperative to enhance the utilization of Smart Maintenance decision-making strategies to optimize maintenance operations and enhance overall system performance. Specifically, the objective of this paper is to present and demonstrate a high-level framework for maintenance data-driven decision analysis, by making use of Digital Twins to simulate what-if scenarios and Analytic Hierarchy Process (AHP) to support decision making. Which means the proposed demonstrator framework integrates Digital Twins, AHP, and production line Key Performance Indicators (KPIs) to provide a quantitative approach for evaluating and comparing different maintenance scenarios and strategies.

The following sections are organized to give basis for the demonstrator structuring through a case study implementation. Section 2 provides a literature review on the theoretical background of Digital Twins, including requirements, definition and implementation road map. The Section 3, about the materials and methods, presents the basic methods and techniques used to properly perform this proof of concept implementation. Section 4 presents the results of the what-if scenarios performance evaluation, taking into account the hypothetical stakeholders, and also highlights challenges for practical implementation. In Section 5, the conclusions about this experiments are presented.

2 THEORETICAL BACKGROUND

In fact, there are at least 30 different definitions of Digital Twins that can be applied depending on the context, life cycle stage, functions needed, architecture and components/technologies (Semeraro et al. 2021). This definition let the Digital Twin concept to be interpreted in many ways, which often makes other concepts, like Digital Model and Digital Shadow, to be referred as the same thing. Nevertheless, data integration toward the physical, digital, and cyber layers differs. In one hand, a digital model does not have a real-time link to a physical thing, such as an offline simulation or mathematical model. And in the other hand, if such digital model has only a one-way real-time data communication from the physical to the digital space, it is defined as a Digital shadow, which is a significant application for monitoring in real time. These two are some of the Digital Twin architecture design patterns (Tekinerdogan and Verdouw 2020), and they both define the functions of a Digital Twin.

The reference integration architecture for Digital Twins consists in four concepts for the full implementation (Aheleroff et al. 2021). This four concepts are shown in Figure 1, and described as follows. Firstly, the Real System (RS) represents the physical system or process that is being monitored and analyzed, ranging from a production line to an entire manufacturing facility or transportation system. Secondly, the real-virtual communication strategy involves the transfer of data from the real system to the virtual model. This strategy must be designed and implemented with utmost care to ensure the collection and transfer of accurate and relevant data in a timely manner. Thirdly, the Virtual Model (VM) represents the selected executable model that embodies the dynamic characteristics of the real-world systems. Finally, the virtual-real communication strategy involves the transfer of data, decisions or actions from the virtual model back to the real system based on insights gained from the virtual model.

The Digital Twin, therefore, can be used to estimate the physical system's response before it is triggered by an unexpected event (Schleich et al. 2017). This functionality not only applies for one physical object. In essence, one Digital Twin can monitor multiple physical objects, and a physical object can also be monitored by multiple twins. Hence, the relationship between Digital Twin and physical object is many-to-many (Tekinerdogan and Verdouw 2020). This technology is useful when representing real systems that change over time, making a static model insufficient to adequately represent them. It is also imperative

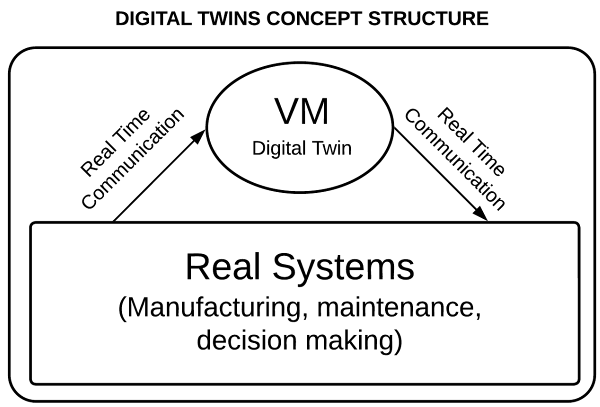


Figure 1: Digital Twin system conceptual structure.

that the Digital Twin model is capable of capturing these changes through the measurement data (Wright and Davidson 2020).

A Digital Twin model should allow the model parameters to be updated in response to measurement data, sufficiently accurate to ensure that the output values are useful in practice, and quick enough to ensure that the execution can fit the decision time window (Wright and Davidson 2020). The Digital Twin can also be built upon five different model representation categories, or as a combination of them (Semeraro et al. 2019). These five categories are: the geometrical model (i.e., defines shapes, sizes and positions), the physical model (i.e., simulates physical properties and loads), the behavior model (i.e., describes the systems reaction to disturbing factors), the collaborative information model (i.e., components interactions and collaborative behaviors), and the decision-making model (i.e., enables evaluations and validations). While the first four are descriptive in nature, the last one is an intelligent data-driven model. In this paper we implement a discrete event simulation to represent the behavior of a production line integrated with a decision making strategy focused on maintenance.

3 METHODOLOGY

By creating a discrete event Digital Twin of a production system, it becomes possible to simulate different maintenance scenarios and evaluate their impact on KPIs such as equipment availability, downtime, and costs. This allows for ”what-if” analysis (Rizzi et al. 2016) and decision making based on quantitative data. Moreover, the integration between Digital Twins and decision analysis/making methods, such as the AHP (Ishizaka and Labib 2011), enables the systematic evaluation of different maintenance strategies. Overall, Digital Twins offer a valuable tool for improving maintenance decision making in industrial contexts, helping to reduce costs and increase productivity while ensuring optimal equipment performance and reliability (Errandonea et al. 2020). In this paper, the methodology will be structured aiming the integration framework demonstration, which means that proposed scenarios are merely illustrative.

The following sections will introduce the Stena Inovation Industry Laboratory (SII Lab), where the demonstrator was developed, explain the Digital Twin model, and cover the design of experiments, including what-if scenarios, prioritization algorithm and AHP. The implementation of Digital Twins involves a systematic approach that can be resumed into five key steps (Resman et al. 2021). First, it is necessary to define the use case specifications to clearly understand the objectives of the Digital Twin (maintenance decision making). Second, the flow of processes must be defined to identify the inputs, processes, and outputs of the system (SII Lab production system). Third, it is important to define the synchronization parameters for the simulation model (what-if scenarios characterization). Fourth, when these parameters are established, the simulation model can be built and defined the synchronization strategy with the real system (here it is semi automatic). Fifth, the KPIs must be defined and calculated to support decision-making or control of the real system.

3.1 Proposed Demonstrator Framework

The increase of scientific literature on Digital Twins for Smart Maintenance indicates a necessity on understanding how to integrate these concepts properly (van Dinter et al. 2022). Industrial digitalization is a key enabler of future competitiveness and sustainability in manufacturing companies (Duan et al. 2022). While Smart Maintenance is defined as an organizational design for managing maintenance of manufacturing plants in environments with digital technologies (Bokrantz et al. 2020). Its four dimensions include data-driven decision-making, human capital resource, internal integration, and external integration. A digitised maintenance system utilizes digital technology for conducting or assisting maintenance strategies. However, Algabroun et al. (2022) argues that current challenges include the limited adoption of formal maintenance strategies and the lack of alignment between corporate strategy and maintenance strategies. It was proposed that a holistic view of the corporate situation through information visualization should address this situation (Algabroun et al. 2022).

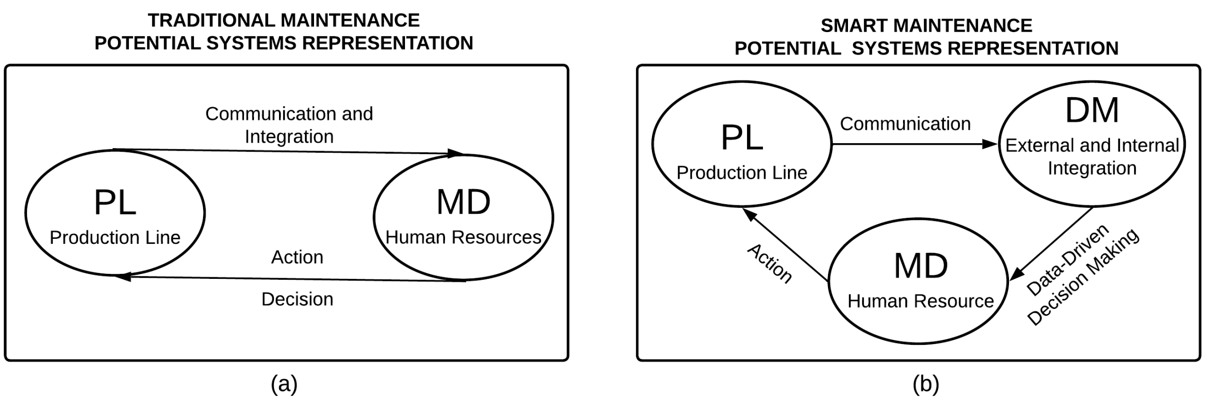


Figure 2: Potential systems representation of traditional and intelligent maintenance system instances.

Figure 2 illustrates a system representation instance including the following elements: production line (PL), decision making team (DM), and maintenance division operational personnel (MD). The objective of Figure 2 is to provide a visual representation on how the partitioning of strategic groups can facilitate the allocation of functions (communication, integration, decision making, action). For example, in a traditional maintenance system the maintenance division workers are responsible for decisions in a daily basis. However, by including a decision making group these decisions can be discussed based on data and further the maintenance operational personnel be responsible by acting in a strategic manner. This task allocation enables the integration of Digital Twins concept to serve as tool to improve communication between the production line and decision making group. This integration is presented in Figure 3, that shows how these systems can be combined to improve capabilities and assign functionalities. This integration is presented in Figure 3, that shows how these systems can be combined to improve capabilities and assign functionalities. The capabilities and functionalities we are going to test are what-if analysis, real-time communication, multi-criteria decision analysis. Moreover, we argue that the real-time data driven decision making information system is the information flow back to the real system and this combination has the potential to reduce the time to detect better maintenance strategies.

It was stated that future research of Smart Maintenance could focus on up scaling the managerial implications by developing individualized recommendations for specific manufacturing plants (Bokrantz and Skoogh 2023). As illustrated in Figure 3, we argue that the use of Digital Twins for maintenance decision-

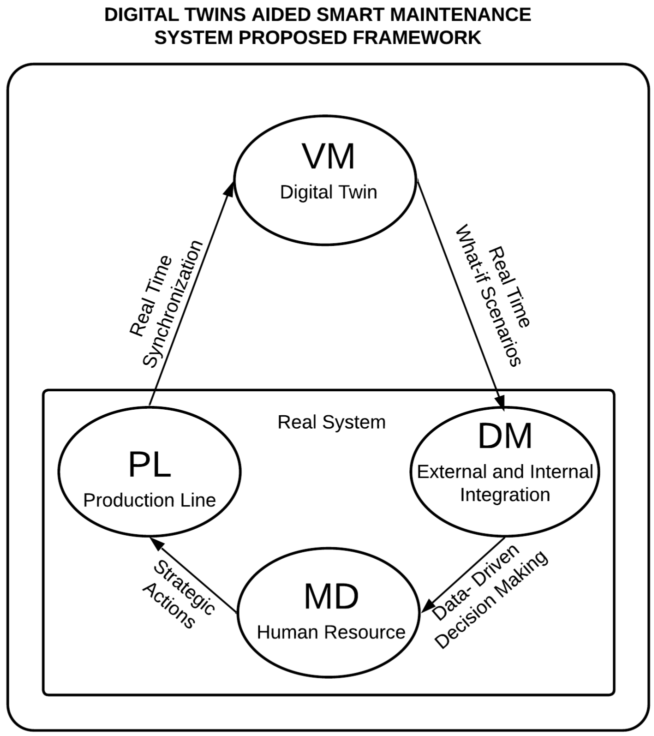


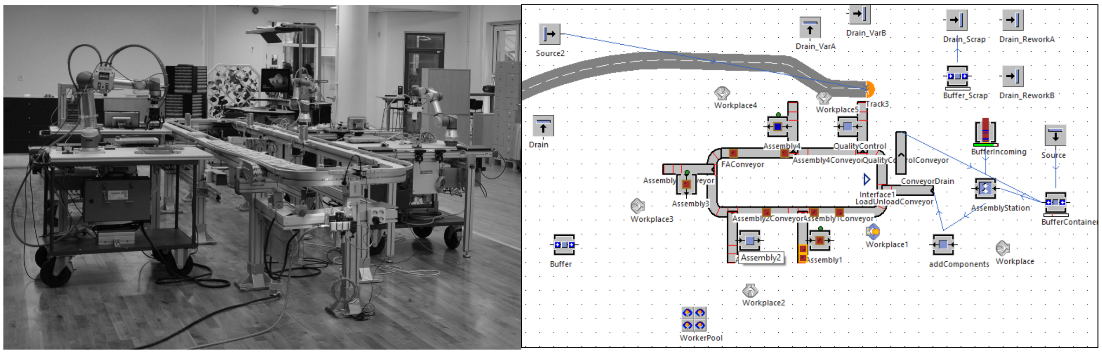
Figure 3: Digital Twin aided Smart Maintenance decision making system proposed framework for demonstrator.

making can provide valuable insights into Smart Maintenance field, leading to maintenance strategies that align with corporate goals. Moreover, the communication back to the real system is considered as the flow of information from the Digital Twins what-if scenarios and knowledge extraction to the real system using AHP. With data-driven decision-making, Digital Twins can provide a comprehensive view of the maintenance operations, enabling informed decisions based on accurate and relevant data. The human capital resource can also benefit from the use of Digital Twins as it provides employees with the necessary tools and resources to make data-driven decisions real-time. In terms of internal integration, Digital Twins can improve the synchronization of maintenance functions with other plant operations by providing a holistic view of the entire system. Lastly, external integration can also be enhanced by Digital Twins as they can facilitate collaboration and communication with external parties, resulting in more efficient and effective maintenance operations.

3.2 Real System and Synchronization Strategy

The methodology of this paper will be conducted at the SII-Lab in Lindholmen, Gothenburg, which serves as a Swedish national test bed for industrial digitization. The SII-Lab consists in a production line that specifically focuses on the assembly of drones, with five branch-assembly stations and one main final assembly station, represented in Figure 4. Additionally, each assembly station comes equipped with a designated maintenance workplace to facilitate efficient maintenance operations. The lab also utilizes in-house logistics to transport both internal and external subcontractors to the main conveyor.

In order to build the Digital Twin demonstrator, the model was implemented in the Tecnomatix Plant Simulation software (Siemens 2023). It was not a trivial task to ensure that the model could be updated in real-time with high frequency data. In this sense, worth it to note that the integration of Digital Twin and high-level decision making systems is not a high-frequency process. Real-time synchronization refers



(a) SII Lab Real System. (b) Tecnomatix PlantSimulation Virtual Model

Figure 4: Real and virtual system used in this demonstrator proposal.

to the ability of a system to update its status or data in real-time or near real-time, as events occur. For example, in control systems, real-time synchronization requires that the system be able to respond to events in milliseconds or less. In shop floor operations, real-time synchronization may require that certain information be delivered in minutes or seconds. However, in the context of strategic management decisions, real-time synchronization may take hours, days or even months. Therefore, in the context of maintenance decision-making, it makes sense to synchronize data at a lower frequency. This allows for the efficient use of resources and the optimization of maintenance activities without compromising on the quality of decision-making.

3.3 Discrete Event Simulation Model

The simulation was formulated based on the conceptual model derived from the drone factory's production, ensuring the accuracy and precision of its representation. The simulation model function is to represent the real system behaviour in situations that did not occur yet, in our case maintenance scenario. In order to express these behaviours we define synchronization parameters and KPIs to serve as the input and output measures for further analysis. In this study we took into consideration 3 input synchronization parameters for scenario characterization, and 10 output KPIs for decision making analysis. The input parameters are (i) availability rate for individual machines, (ii) production mix percentages, and (ii) prioritization for maintenance in each machine.

Algorithm 1 Maintenance Prioritization Algorithm

```
procedure PRIORITIZE(stations left to prioritize)
    while stations left to prioritize > 1 do
        for i in stations left to prioritize do
            prioritize maintenance actions in station i
            run simulation model
            calculate the KPIs
            return objective function value
        end for
        rank stations priority according to the throughput
        return the station with highest priority
    end while
    return stations priority rank
end procedure
```

We implemented a production mix of two drone characteristics, three assembly stations, a quality check place, a main conveyor, inventories and pallets that travel with the pieces to assembly. The represented assembly stations are connected as follows: the first and second ones are responsible for drone A assembly, the third one is responsible for drone B assembly, and all the pallets go through a quality check place that can accept or reject the quality of drone. When the drone is rejected it goes back for a rework queue that will wait for empty pallets and new pieces.

The Digital Twin demonstrator is built upon SII Lab previous baseline models from experiments, master thesis and research papers (Chávez et al. 2022). The main modifications we propose are the output KPIs, failure functions, a broker that can perform personnel dispatching to reactive maintenance service orders and a prioritization strategy for repairs. The prioritization function shown in Algorithm 1 is designed by following a generalization of the theory of constraints method (GPOOGI) (Wu et al. 2019). After running this iterative prioritization procedure, an optimal priority for maintenance operation for each scenario is decided. This prioritization algorithm is added to the original model so we can compare different maintenance strategies, however, it will not necessarily be the optimum among all the scenarios. This happens because even if we prioritize the maintenance actions, there are other parameters that influence more the final production line performance, for example the production mix.

3.4 Knowledge Extraction Strategy: Adapted AHP

In this section, we present an approach to demonstrate the decision making element depicted in Figure 2.b and, further, in Figure 3. To do so, the prioritization of KPIs was carried out through a workshop held at the Industry and Materials Science Department at Chalmers University of Technology. This workshop was attended by 15 manufacturing professionals, including PhD students, Senior Lecturers and Professors from three different research groups.

The prioritization process involved a 0 to 5 scale questionnaire for the evaluation of KPIs and their potential impact on the system performance. Through this workshop, the team had the objective of providing valuable information for decision-making purposes, as stakeholders in real world should do. The intention of this approach is to extract knowledge from these hypothetical stakeholders who provided insights and perspectives on the selected KPIs for this specific proof of concept case study. This knowledge extraction strategy aims to contribute to the alignment between hypothetical stakeholders and maintenance strategies, since each stakeholder had a different perspective and we applied a structured way of measuring it.

AHP involves the creation of a relative importance or preference through the calculation of overall scores to determine the best option (Forman and Gass 2001). Usually, the relative importance of these criteria is based on pairwise comparison from the AHP fundamental scale (Saaty 2004). But, we adapted this fundamental scale to a questionnaire that evaluates the group of criteria, and each KPI inside the criteria separately. Then, the pairwise comparison values were calculated through the ratio between the stakeholders evaluation scores. For example, imagine that OEE is evaluated as a 5 importance KPI (in a 0 to 5 scale) and the Throughput is evaluated as 2. The pairwise comparison value of OEE compared to the Throughput is $5/2 = 2.5$.

Using the workshop results, a comparison matrix is built, then calculated the weights representing the relative importance of the criteria. To ensure the consistency of the pairwise comparisons, a consistency analysis is performed. The consistency index (CI) and the consistency ratio (CR) are calculated using the eigenvalue vector c of the normalized comparison matrix. According to Saaty (Saaty 2004), the CR must have a maximum value of 10%, which indicates that the matrix inconsistency is not relevant.

4 RESULTS

In this section, we present the results and discussions of the experiments conducted to evaluate the proposed framework's fundamental capabilities, including: simulation of what-if scenarios with a Digital Twin model, knowledge extraction from stakeholders, evaluation of these scenarios. The main objectives of the experiments were (i) to characterize the hypothetical stakeholders' decisions based on the AHP results, (ii) evaluate the what-if scenarios according to the the parameters previously defined, and (iii) perform data-driven decision analysis to determine the best and worst scenarios. The experiments were designed to demonstrate the framework's potential to assist in Smart Maintenance decision-making processes by providing a structured approach to analyze and evaluate scenarios. In the following subsections, we will present and discuss each of the experiment's results in order to provide insights on their significance and implications.

4.1 Experiments Design

In this paper, we aim to explore the impact of maintenance strategies into different production system scenarios. One of the principal applications of the Digital Twins aiming to increase the industry competitiveness is the capability of performing what-if scenarios. What-if scenarios experiments can be considered different simulation model executions that are directly related to the practical problems faced (Resman et al. 2021). These experiments results are stored in KPI database that will be fundamental for the further data-driven decision analysis.

Table 1: What-if scenarios description.

Id	Scenario Description
Sc 0	Machine availability of 95%, a balanced production mix.
Sc 1.1	Machine availability of 95%, an unbalanced production mix (75% d.A / 25% dB).
Sc 1.2	Machine availability of 95%, an unbalanced production mix (25% d.A / 75% dB).
Sc 2.1	Machine availability of 98%, a balanced production mix, reactive maintenance.
Sc 2.2	Machine availability of 92% and 95% to quality check, a balanced production mix.
Sc 3.1	Machine availability of 95%, a balanced production mix, prioritised maintenance actions.
Sc 3.2	Machine availability of 92%, a balanced production mix, prioritised maintenance actions.
Sc 3.3	Machine availability of 92% and 95% to quality check, a balanced production mix, prioritised maintenance actions.
Obs:	Simulation time: 1 week, with 5 days and 8 hours per day. Ideal cycle time of 4.5 minutes. All the time related KPIs are measured in minutes.

The scenarios description is presented in Table 2 and were obtained by running what-if scenarios on the Tecnomatix Plant Simulation model. Three groups of experiments were defined to evaluate the impact of machine availability, different production mixes, and prioritization in maintenance tasks. The first group of scenarios considers machine availability and a balanced production mix, and variations of an unbalanced production mix. The second group of scenarios evaluates the impact of machine availability on quality check and reactive maintenance. Finally, the third group of scenarios explores the effect of prioritized maintenance actions on machine availability and a balanced production mix. These scenarios are intended to represent a range of options analogous to which stakeholders would need to evaluate. However, this scenario design is hypothetical and the goal is not to calculate generalized KPIs or practical recommendations. Instead, these scenarios serve as a comparison basis for the proposed high-level framework, which means in a real world case the scenarios need to be designed again according to the context.

4.2 What-if Scenarios Characterization

The output KPIs are divided in two main criteria: the Productivity Criteria (C1) and the Maintenance Performance Criteria (C2). C1 is composed of 5 KPIs, namely total throughput (C1K1), equipment availability (C1K2), production cycle time (C1K3), equipment downtime (C1K4), and overall equipment efficiency (C1K5). On the other hand, C2 is made up of the number of rework activities (C2K1), number of machine failures (C2K2), mean time between failure (C2K3), number of unplanned tasks (C2K4), and time spent for unplanned maintenance tasks (C2K5). The KPIs were defined according to the data availability and relevance for the case study from a extensive list of indicators to measure the effects of Smart Maintenance (Lundgren et al. 2021). Still, it is important to remember that in a real application of data-driven smart maintenance other relevant criteria must be considered, as costs, scrap rate, return on investment, etc.

Table 2: What-if scenarios description and normalization parameters.

Parameter	C1K1	C1K2	C1K3	C1K4	C1K5	C2K1	C2K2	C2K3	C2K4	C2K5
Average	797.13	0.72	8.38	677.63	0.52	23.13	143.63	22.56	117.63	595.73
Minimum	315.00	0.57	4.77	257.49	0.12	9.00	47.00	12.31	42.00	216.16
Maximum	1,005.00	0.89	27.77	1,022.06	0.82	30.00	221.00	51.06	170.00	862.26

The simulation model results were obtained by running what-if scenarios based on different maintenance strategies. The basic simulation parameters were adopted according to the usual parameters in 98 Swedish companies between 2006 and 2012 (Ylipää et al. 2017) and the standard failure distribution functions in the software Tecnomatix PlantSimulation. The KPIs were calculated for each scenario and are presented in Table 2. We ensured that the minimum and maximum values are feasible when compared to the same OEE benchmark reference. To enable the comparison between the scenarios, the KPIs were normalized using the parameters shown in Table 2. These parameters can also be used to understand the statistical description of the KPIs. The normalization allows to compare the performance of different maintenance strategies through the AHP strategy.

4.3 Hypothetical Stakeholders Decisions Characterization

The analysis of hypothetical stakeholder decisions can yield valuable insights into the decision-making process and its impact on the performance of the system. The characterization of stakeholders' decisions allows the identification of the KPIs that influence at most their decisions. The KPIs were discussed in the workshop, and the AHP was applied to calculate the average weight coefficients. In the meanwhile, each of these KPIs were calculated and normalized using the min max strategy to evaluate the scenarios within the Digital Twin context, these min max values are available in Table 2. The normalized coefficients are presented in Figure 5 in a box plot format median, minimum, maximum, quartiles and outliers are emphasized.

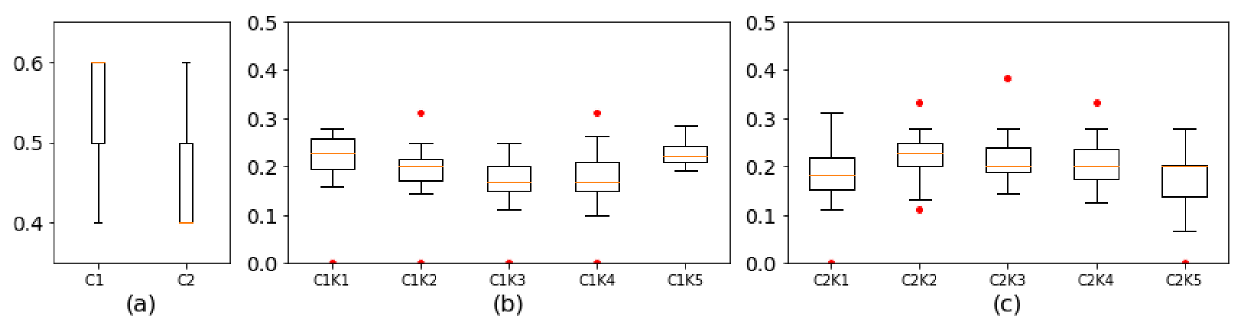


Figure 5: (a) Box plot of the Criteria weights from AHP evaluation, (b) Box plot of KPI weights inside Criteria 1, (c) Box plot of KPI weights inside Criteria 2.

Upon analyzing the graphic, it is noteworthy that the mean value for C1 in the criteria evaluation was 0.6 and for C2 it was 0.4, indicating that C1 was slightly considered more important than C2. Among the KPIs inside C1 criteria, OEE (C1K5) was the only KPI without outliers and lower range, while C1K4 showed the highest variability. The KPIs with the most relevance inside C1 were final throughput and OEE. On the other hand, the variability of answers was greater in C2 than in C1, as evidenced by the range of boxes. The two KPIs with higher range in the box plots were number of rework activities (C2K1) and time spent to unplanned maintenance tasks (C2K5), which is a sign of different perspectives among the decision makers. For a more detailed stakeholder characterization, additional methods such as cluster analysis or statistical descriptions could be performed, although they were not within the scope of the present study.

4.4 Data-Driven Decision Analysis

The decision function is a mathematical formula that measures the performance of the system. Let D be the decision function, identified by Equation 1. This decision function takes into account the importance of each KPI based on the AHP results and the normalized KPI values from the simulation model.

$$D = \sum_{j=1}^{2} wc_j \cdot \sum_{i=1}^{5} w_i \cdot KPI_i j \tag{1}$$

Where KPI_{ij} represents each normalized KPI i position inside each criteria j, and w_i represent the weights assigned to each KPI based on their relative importance from AHP analysis. This function is used to evaluate, rank and decide which scenarios are the best or worse ones.

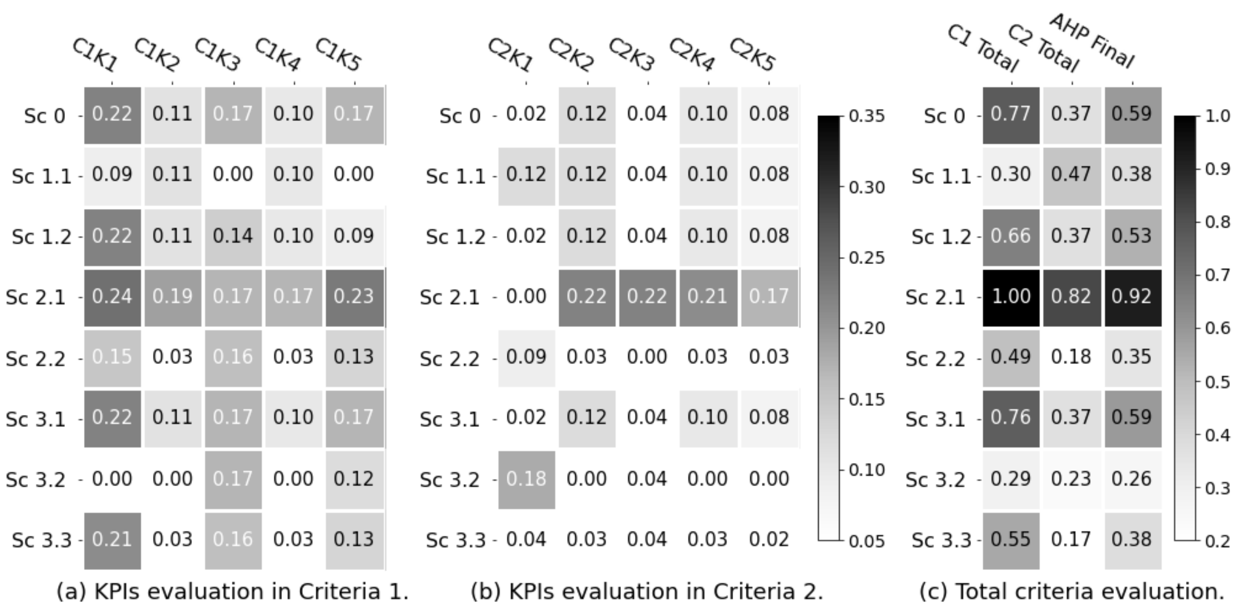


Figure 6: (a) AHP evaluation of criteria 1 KPIs; (b) AHP evaluation of criteria 2 KPIs; (c) final AHP criteria evaluation.

As expected, the best scenario was the one with higher machine availability (lower machine failure rate) input parameter and the worst scenarios were the ones where the availability was the smallest value (highest failure rate). The prioritization of the KPIs proved to be particularly useful when the failure rate was not uniform between the machines. Furthermore, changes in production mix impacted the performance of the system, causing bottleneck machines to raise. The Digital Twin aided Smart Maintenance Decision Support System is able to effectively evaluate the productivity and maintenance performance. However, this work is a first step for a full implementation of the framework. The authors argue that next steps should focus on: a) the data synchronization strategy improvement; b) data-driven decision making strategy validation; c) run the scenarios in real-time.

5 CONCLUSION

The findings of this paper reveal that the proposed framework can be implemented, although it still requires more manual effort than initially expected. The framework has been demonstrated through the implementation of Digital Twins, the extraction of stakeholders' knowledge, and data-driven decision analysis. In a real-world context, this framework would be deployed in an work environment to facilitate discussions among relevant stakeholders. It is essential to have the right people participating, i.e. the maintenance manager and plant manager, to conduct the workshop. It should be noted, however, that high-level decision making is not a high-frequency process, and proper planning is essential for successful implementation. In the future, this study could be expanded by gathering condition monitoring data to access predictive maintenance strategies. Still, this demonstrator is a first step to achieve the full potential of a Digital Twin aided smart maintenance system.

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