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Digital twin-driven decision support system for opportunistic preventive maintenance scheduling in manufacturing

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Abstract

Preventive maintenance interventions are scheduled in industrial systems to prevent machine failures and breakdowns, which are associated with the incurrence of repair, unavailability, and quality-related costs. The execution of such interventions, however, generally represents a penalty to a manufacturing system's production throughput due to machine interruption requirements. By the use of a digital twin architecture, we develop a decision support system to schedule preventive maintenance interventions with the aim of minimizing production throughout penalties via the exploitation of real-time opportunities such as supply shortages, momentary machine idleness or machine breakdowns. The decision support system has its application demonstrated by a case in a furniture manufacturer in the State of Santa Catarina – Brazil.

Keywords: digital twin; preventive maintenance; simulation; industry 4.0

1. Introduction

The components of manufacturing machines are continuously subject to degradation as a result of environmental exposition and repetitive usage. When left unchecked, degradation effects may lead to machine failures and breakdowns, which are subsequently associated to quality, safety and productivity issues in industry. To combat degradation, industrial stakeholders may execute preventive maintenance interventions so that machines' components have their states partially or completely restored before the occurrence of failures [1].

Traditionally, the scheduling of maintenance interventions is guided by an effort to minimize costs, as managers are faced with a trade-off between the costs required to execute interventions and the costs required to run repairs if failures occur [2]. However, an additional impact of the execution of preventive maintenance consists in the loss of production throughput, as these interventions require machines to interrupt manufacturing operations before their state can be restored [3].

Since production stoppages may occur naturally due to other reasons such as supply shortages, momentary machine idleness or even machine breakdowns, a real-time scheduling of preventive maintenance interventions can be generated to exploit these opportunistic interruptions and minimize the production throughput penalties caused by maintenance activities.

In this regard, the rise of cyber-physical systems (CPS) offers a solid technological foundation towards the development of a decision support system (DSS) that provides managers with up-to-date maintenance schedules that best exploit unexpected opportunities in the shop-floor. CPS

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technologies are particularly valuable as they provide real-time connectivity between the physical and the digital worlds, as well as an array of analytic tools to enable advanced decision support [4]. One useful emerging framework to arrange these technologies is the digital twin (DT). Initially introduced by Michael Grieves in 2003 and only recently popularized in the context of the fourth industrial revolution, the DT consists of a structure in which digital models of physical assets can be created and continuously updated through the sharing of information and data [5,6]. The use of these models in the running of simulations and data analyses allows the DT to provide managers with a plethora of predictive and prescriptive insights.

In this work, a DSS for opportunistic preventive maintenance scheduling is developed based on a DT framework. A digital model of the shop-floor is developed to represent: (*i*) the stock and the flow of pieces along the manufacturing system, and (*ii*) the operational state of machines. Pieces' up-to-date positions are provided by the use of radio frequency identification (RFID) technology, while machines' up-to-date statuses are provided by the interpretation of sensor readings. The decision support service is delivered through the periodic running of short-term process simulations based on the updated model of the shop-floor and on the specific opportunity events that unfold in real-time. These simulations aim to predict time slots in which machines are not operational so that preventive maintenance interventions can be executed with minimal penalties to production throughput.

The development of the DSS is conducted following a design science research protocol, which is adequate when artifacts (e.g., information systems) have to be developed to extend organizational capabilities [7]. Furthermore, the DSS application is demonstrated by a case in a furniture manufacturer in the State of Santa Catarina – Brazil.

The relevance of this work can be highlighted from three perspectives: firstly, the work addresses the challenge of somehow integrating the planning of preventive maintenance to the reality of production scheduling, which has been a call for future research in the comprehensive literature review of Basri et al. [8]. Secondly, through the use of a design science research protocol, the work attempts to avoid the common criticism aimed at preventive maintenance research of lacking practical utility due to an excessive use of unrealistic mathematical assumptions, which is a phenomenon also highlighted by Basri et al. [8]. Thirdly, this work explores ways to use the increasingly relevant CPS technologies towards the traditional problem of maintenance planning.

The remainder of the paper is structured as follows: Section 2 presents a background regarding preventive maintenance and digital twin concepts. Section 3 describes the adopted research design. Section 4 presents the developed DSS. Section 5 demonstrates the application of the DSS in a case in industry. Section 6 outlines the paper's concluding remarks.

2. Background

In this section, we start by reviewing some of the key concepts and developments of preventive maintenance research, while also pointing out how this work differs from previous studies. Thereupon, we review the concept and main features of the DT, as its architecture supported the development of the proposed DSS.

2.1. Preventive maintenance in manufacturing

A preventive maintenance intervention can be defined in simple terms as a set of actions that can be executed to improve the condition of manufacturing systems' components before they fail [9]. Based on the level of restoration, these interventions are often classified in two distinct classes: "perfect" or "imperfect" [1], or even in as many as five distinct classes: "perfect", "minimal", "imperfect", "worse" or "worst" [10]. To plan preventive maintenance interventions, research has typically focused on either proposing methods that determine an adequate time interval to execute interventions, or on modeling machine degradation as a multi-state system, through which interventions are triggered when certain states are reached [11]. These planning methods have been generally built upon an array of techniques originated from mathematical formulations, optimization theory and artificial intelligence [8].

Regarding its goals, the planning of preventive maintenance interventions has been approached in literature as a decision problem aimed at cost minimization or availability maximization, within a context in which a plethora of factors drive costs and penalize availability from multiple perspectives. To guide maintenance policies, several authors have focused on understanding the trade-off between the cost of interventions and the costs associated with machine breakdowns. These efforts were generally enabled either by means of mathematical formulations and the use of the Weibull distribution, as observed in the work of Mijailovic [2], or by means of optimization heuristics, as seen in Wang and Lin [10]. Furthermore, a number of studies have tried to expand this trade-off analysis to achieve a more comprehensive and realistic outlook of the involved costs. Lapa et al. [12], for instance, included in their analysis other cost-related factors, such as the probability of imperfect maintenance. As another example, Ahmadi and Newby [13] refined their model so that invisible quality costs associated with machine failures could be considered when assessing the importance of preventive maintenance.

Moving closer to the context of this work, as the execution of maintenance interventions hinders production throughput due to temporary machine unavailability, some authors have highlighted that an integrated schedule of production jobs and maintenance interventions could be beneficial to balance maintenance and productivity goals. Nourelfath and Châtelet [3] and Fitouhi and Nourelfath [14], for instance, proposed to consider preventive maintenance in the production lot-sizing problem, while ensuring that customers' demands are fulfilled. Through this approach, these authors attempt to jointly optimize production jobs and maintenance intervention scheduling.

In addition to considering the scheduling of interventions as part of the production planning process at a tactical level, some authors have focused on looking at short-term opportunities to schedule interventions with a reduced penalty to availability, following a similar motivation to the one that guided this work.

Do Van et al. [15] and Iung et al. [16] proposed to opportunistically execute interventions in groups of components when machines stop due to breakdowns. Furthermore, the authors grouped components based on structural and economic dependencies to guide this opportunistic scheduling. Zhang and Zeng [17], likewise, proposed a method to execute interventions on a machine when conditions such as scheduled downtime or failure to other components in close proximity occur.

Although this work is also focused on providing an opportunistic scheduling of maintenance interventions, we attempt to follow a distinct approach through the employment of a digital twin architecture. Particularly, this allows our formulation to expand on the scope of the generally proposed opportunistic scheduling models in two ways:

- Treating machine downtime as a systemic rather than a localized opportunity: when a given machine becomes momentarily non-operational, we employ digital twin generated simulations of the shop-floor to analyze the manufacturing system in its entirety, looking at how the resulting interruption of the production flow creates opportunities to schedule interventions in any machine without hindering throughput.
- Looking for opportunities beyond machine breakdowns: we treat machine idleness generated as a result of the job scheduling process or as a result of a shortage of supplies, for instance, as opportunities to schedule interventions.

2.2. Digital twin in manufacturing

When first introduced, the DT could be defined as the concept of creating digital models of physical assets and establishing a link between physical and digital counterparts so that conditions and characteristics could be mirrored. Such a digital model could then be utilized as a platform for the running of tests and analyses [5,6]. With the advent of CPS and modern analytics, the DT has gained the required tools to be operationalized in practical scenarios. Within manufacturing applications, Tao and Zhang [18] drew a general architecture for the DT composed of 4 main components: a physical shop-floor connected to the digital world; a storage platform to keep all generated data; a digital model of relevant shop-floor assets; and a service layer capable of providing analytical support.

The connection between shop-floor elements and the digital world is enabled by the acquisition of real-time data from RFID devices, sensors and other internet-of-things (IoT) technologies, and subsequently by the transmission of the gathered data through wire or wireless channels (e.g., cable and Wi-Fi), guided by the use of a protocol such as the Open Platform Communications Unified Architecture (OPC UA) [19,20].

The utilized data storage platforms are generally capable of dealing with a high volume of heterogenous and multi-source data, which can be both static or subject to continuous updates, and are usually associated with "big data" storage solutions such as cloud storage [19].

According to the service requirements, different types of digital models can be developed to represent various shop-floor elements. System behavior models, designed based on the concepts of Petri nets, Markov models or discrete-event simulation models for instance, can be used on a macro scale to represent the flow and inventory of materials throughout the whole production system (examples can be seen in the works of Zhang et al. [21], Ghosn et al. [22] and Bao et al. [23]). On a micro scale, on the other hand, physical models can be used to represent the structural functionality and process status of machines (*e.g.*, the kinematic and structural model designed by Aivaliotis et al. [24] and the finite element model of a rotor system proposed by Wang et al. [25]).

Regarding its service provision capabilities, the DT can be utilized as a source of diagnostic, predictive and prescriptive analyses to support the management of manufacturing operations. It has experimented application in the areas of production, maintenance and quality management, where tasks such as the handling of flexible scheduling or the prediction of eminent faults can be addressed [20, 26]. In addition to the use of digital models to run simulations, a DT service is sometimes supported by the use of artificial intelligence (*e.g.*, the use of machine learning for anomaly detection and failure prediction in the work of Ashtari Talkhestani et al. [27]) and optimization algorithms (*e.g.*, the particle swarm optimization algorithm used to update a DT model in the work of Wang et al. [25]).

3. Research design

In this section, the design science research protocol employed in this work is detailed. The protocol was utilized to instruct the development of an information systems artifact, consisting of a DSS, based on Peffers et al. [28] guidelines. Furthermore, the developed artifact had its functionality demonstrated and performance evaluated through a single case (in the mold of a design science research 'add-on' project, as presented by Van Aken et al. [29]).

The research protocol comprised of 4 phases. Phase 1 consisted in acquiring a detailed understanding of the problem being tackled, *i.e.*, how preventive maintenance interventions are typically scheduled and which opportunities arise during production to implement a schedule that reduces penalties to the production throughput. This phase was conducted by means of two research tools that allow for the assessment of real instances of the problem: (*i*) the direct observation of both the production scheduling process and the preventive maintenance scheduling process of 3 organizations that operate within the boundaries of discrete manufacturing; and (*ii*) a round of interviews with production planning and maintenance planning staff workers, who possess practical experience regarding these subjects.

As the observation of real instances allowed for the drawing of a general research problem that could be solved by means of an artifact, phase 2 consisted in inferring the required objectives that characterize an adequate general solution, *i.e.*, which functionalities the designed artifact had to possess to successfully solve the tackled problem. This phase was validated by an additional round of interviews with production planning and maintenance planning staff workers.

Phase 3 consisted in the development of the artifact: a DSS for opportunistic preventive maintenance scheduling, which serves as a general design to solve the research problem. This phase encompasses the theoretical contribution of this work and is supported by means of a literature review regarding the use of the DT in manufacturing applications.

Lastly, phase 4 consisted in the demonstration of the artifact's use by means of a case in industry. This instantiation of the general design provides knowledge regarding the way in which the developed artifact can be deployed.

This 4-phase protocol was implemented following an iterative process, as the artifact's development (phase 3) was subject to a conceptual validation and improvements suggestion, and the artifact's implementation (phase 4) was subject to a practical validation and improvements suggestion. Both validation processes consisted in the running of an evaluation conducted by subject-matter experts. This research protocol is presented in Fig. 1.

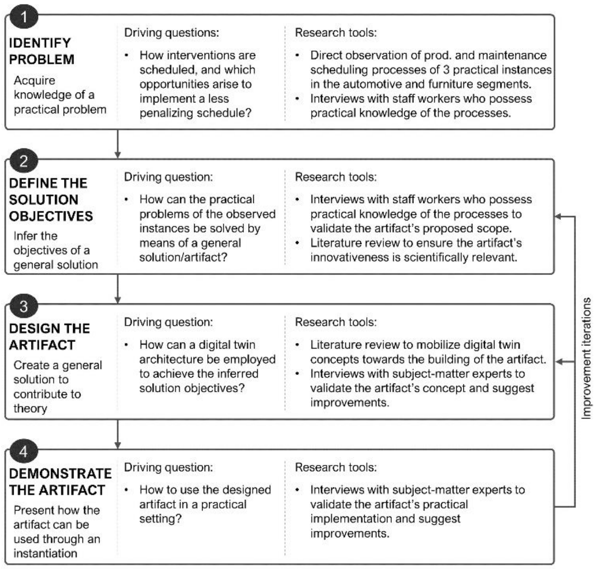

Fig. 1. Design science research protocol.

4. Decision support system design

We present the artifact design in 2 parts. Firstly, we describe the overall scope of the DSS, which was drafted based on the observation of practical instances and the execution of interviews. Secondly, we present the digital twin architecture, created to support the DSS operation.

4.1. Decision support system scope

To formulate the DSS scope, we consider a production system in which preventive maintenance interventions, for all machine components, are periodically planned according to manufacturer best practices guidelines. We consider a set $P = [p_i \ \forall \ i = 1, \ldots, l]$ of the l preventive maintenance interventions that are planned to be executed in the future up until a given period of time T (*e.g.*, all interventions that are currently planned for any date during the upcoming month). Each intervention should possess the following properties: a specific component to which it refers, a planned date to occur, a duration of time required to execute it, and a specific know-how required to execute it (*e.g.*, some interventions have to be executed specifically by workers specialized in dealing with electrical systems).

In addition to this maintenance-related information, we consider the production system has a short-term production schedule, covering a given future period of time, limited by a time parameter t, in which the sequence of part numbers to be launched into the process, as well as all planned shutdowns of production are known. Furthermore, we consider that a maintenance workers' availability schedule is provided for the duration of time limited by t, in order to inform when workers with specific know-hows will be available to be called upon.

Based on these premises, the DSS works as follows: periodically, or as a result of a manual request, the DSS accesses an updated digital model of the shop-floor and runs a short-term simulation of the production flow according to the production schedule available for the time period limited by t (this schedule includes any planned shutdown, including stoppages to execute preventive maintenance interventions that are due and could not be opportunistically scheduled). An updated model of the shop-floor is used so that: pieces positions along the system are up-to-date; and any non-operational machine is correctly indicated, along with its predicted time of repair.

If all machines are operational, the DSS runs the simulation with r replications and temporarily stores all time slots in which each machine was observed to be idle during the running of a given simulation replication. The possibility of running a simulation with multiple replications was considered due to the high variability that sometimes characterizes machines' cycle times in manufacturing. Since the results of a single simulation replication may be heavily affected by highly variable input parameters, the running of multiple replications can be used as a countermeasure against the effect of this variability on the DSS's performance and assertiveness. This variability management feature is enabled by the execution of a trimming process to adjust the obtained idleness time slots after the conclusion of all requested simulation replications. Such a process is done by only keeping time slots that were observed to indicate machine idleness in all simulation replications. An example of this trimming process can be given for a hypothetical case in which $r = 2$ replications are executed. If a machine is observed to be idle from: 09:00:00 to 11:00:00 during the first replication; and 08:00:00 to 10:00:00 during the second replication, a trimmed time slot of idleness from 09:00:00 to 10:00:00 is kept after the running of the replications, so that the upper and lower bounds of the obtained time slots are excluded to account for the effects of variability, ensuring that the final time slot delivers a more assertive indication of machine idleness.

The acquired idleness time slots are used to opportunistically schedule the execution of preventive maintenance interventions that are planned to happen in the future, up until the planning period limit, indicated by T. A way to optimize the setting of parameter T is not addressed in this work, but we highlight the trade-offs that encompass such a decision. The value of T determines how far into the future the DSS will look into, when trying to place planned interventions into opportunistic time slots it finds in the short-term. The higher the value, therefore, the greater the possibilities of matching an available time slot with a planned intervention. However, designating interventions that are only due in the long-term to time slots in the short-term also means incurring maintenance costs more frequently.

To schedule the execution of a preventive maintenance intervention into a machine idle time slot, the DSS checks all the following compatibility criteria: (*i*) whether there is any intervention that targets the components of the idle machine; (*ii*) whether these components are in conditions to receive an intervention; (*iii*) whether the time duration requirements of the intervention fit into the available time slot; (*iv*) whether there is any available specialized maintenance worker to execute the intervention during the available time slot. If these criteria are verified, the DSS informs management about the opportunity to execute the intervention. If multiple interventions can be scheduled at the same time, the DSS informs management about all possibilities and requests a manual selection. After the management's validation, any intervention that is opportunistically scheduled in this way is interpreted as a "planned shutdown" in subsequent simulations.

If there are non-operational machines as the simulation replications begin, a few steps are added to the core functionalities presented above. From the perspective of the DSS, the non-operational machines are treated as "idle" until a predicted time of repair has passed, *i.e.*, preventive maintenance interventions can be scheduled to exploit their non-operational status. In case of a breakdown, failed components that are waiting or are under corrective maintenance are flagged as "not in condition to receive an intervention". This particular flag is visualized when the DSS is checking its compatibility criteria.

4.2. Digital twin architecture

The DSS functions as a service provided by a DT architecture. The utilized architecture design is presented in Fig. 2. The core of the DT consists in its digital model layer. To achieve its intended functionality, the DT shapes a digital picture of the shop-floor by means of a production system model focused on the representation of pieces' positions and movements, as well as machines' status. The model's outline can be comprehended as a simple graph structure, in which a set of vertices $V = [v_j \ \forall\, j = 1, \ldots, m]$ is used to represent the m locations in which pieces can be temporarily stored to either wait or be subject to processing, *i.e.*, inventory buffers and machines; and a set of edges $E = [e_k \ \forall\, k = 1, \ldots, n]$ is used to represent the n utilized transportation routes to move pieces along buffers and machines. The graph structure is built during a pre-operational stage of the DSS, based on the processing requirements of each manufactured part number.

The created shop-floor model is utilized by the DSS in two ways: firstly, it is continuously subject to an update routine, in which each vertex's dynamic properties (current level of inventory, current operational status, list of current pieces IDs, and time spent since the arrival of each piece ID) and each edge's dynamic property (current level of inventory in transport) are updated to reflect real-time status; secondly, it is subject to short-term simulations (periodically or due to a manual trigger) to provide the DSS's decision support service. Vertices' static properties (processing/waiting time distribution parameters, setup parameters, minimum batch to start processing, and maximum allowed quantity of pieces in inventory) and edges' static parameters (transportation time distribution parameters, and minimum batch to start transport) are employed to enable accurate simulations.

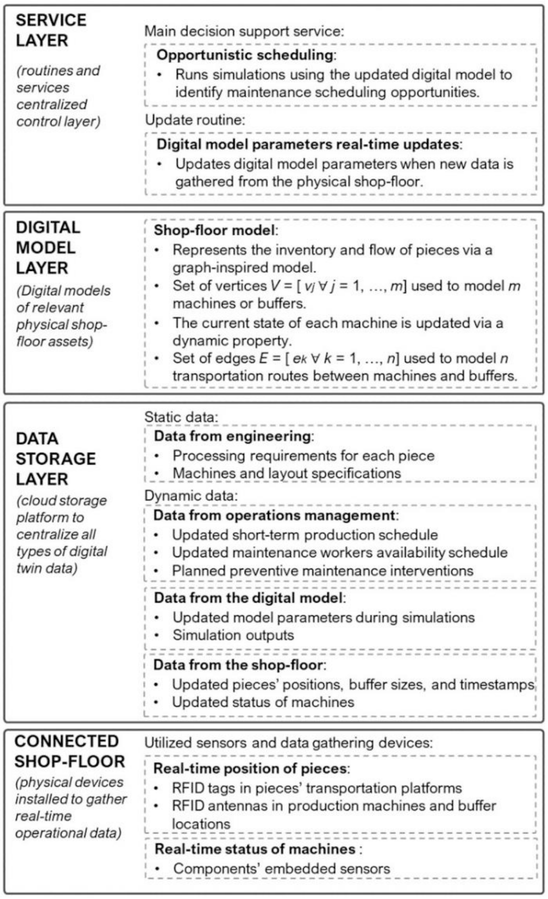

Fig. 2. Digital twin architecture.

The running of simulations follows a discrete-event simulation logic. Firstly, an initializing procedure is run so that: (*i*) the planned production stoppages within the simulation time limit t are read; (*ii*) the upcoming production schedule is read; and (*iii*) the expected time of completion for pieces under process is computed. Thereupon, the simulation enters an iterative loop. A simulation clock is advanced by a scheduling function, which moves time forward towards the moment when an event that changes the model's state occurs, as well as calls the adequate support function to implement the necessary state changes. The simulation reaches its ending either when the clock hits the time limit t, or when all production jobs that were scheduled are completed. The simulation is based on the occurrence of several different types of events: the launching of production jobs, the beginning and the ending of processing/waiting times, the beginning and the ending of transportation times, the beginning and the ending of planned production shutdowns, and the predicted moments broken machines get repaired. The processing requirements data for each part number is used to guide pieces' movement along the designed network of machines, buffers and transportation routes.

After the simulation reaches its conclusion, idleness time slots for all machines are gathered and, in case of multiple replications, adjusted according to the trimming process presented in Section 4.1. Lastly, a preventive maintenance intervention designation routine is run so that the compatibility of the obtained idleness time slots is checked, and potential opportunities to schedule maintenance interventions are returned to the users of the DSS.

As the DT's service layer runs its model update routine or its main decision support service, a data storage layer is responsible for centralizing all data that is either used or generated by DT components. Processing requirements, machine specifications and layout specifications data are static and utilized mostly during the pre-operational stage of the DSS to allow for the creation of the shop-floor digital model. The short-term production schedule, the maintenance workers availability schedule and the planned preventive maintenance interventions are data elements that are subject to change due to managerial level modifications, and have their use in the running of simulations to provide the DSS's decision support service. As simulations are run, the data storage layer is also responsible for storing simulation data, as well as simulation outputs that are returned to managers in the form of a maintenance schedule proposal. Lastly, up-to-date pieces' positional data, movement timestamps and machine status are all dynamic data gathered from the shop-floor to allow for the digital model parameters update routine.

Although sensor specificities vary according to the requirements of each distinct industrial segment, we preconize general guidelines to build a data acquisition structure that is compatible with the type of information required to run this particular DSS. The use of RFID tags in any platform utilized as a means of piece transportation, in conjunction with the use of RFID antennas in every utilized machine or buffer, enable the identification of parts entering and leaving the locations modeled as vertices in the digital model, as the tags move within radiation range. The real-time status of machines, on the other hand, can be drawn from application-dependent embedded sensors. Lastly, predicted repair times for non-operational machines can be uploaded manually by the maintenance staff when breakdowns occur, or can be estimated based on historical values or by means of data analytics. An algorithm capable of providing such as information, however, is not addressed in this work.

5. Decision support system demonstration

We demonstrate the designed artifact's use in a practical scenario. Firstly, a description of the organization used as a case is provided. Secondly, the operation of the DSS is demonstrated by the running of a test scenario, in which opportunities for the scheduling of preventive maintenance interventions are presented.

5.1. Case description

The manufacturer utilized as a case to demonstrate the application of the developed DSS consists in an organization of the furniture industry which possesses a production plant with approximately 120 employees in the State of Santa Catarina - Brazil. The plant specializes in the manufacturing of wooden bed frames to international customers. Specifically, the wood preparation sector has been chosen to run a pilot project to implement and demonstrate the DSS. An illustration of the sector's layout and its supported part number routes can be observed in Fig. 3.

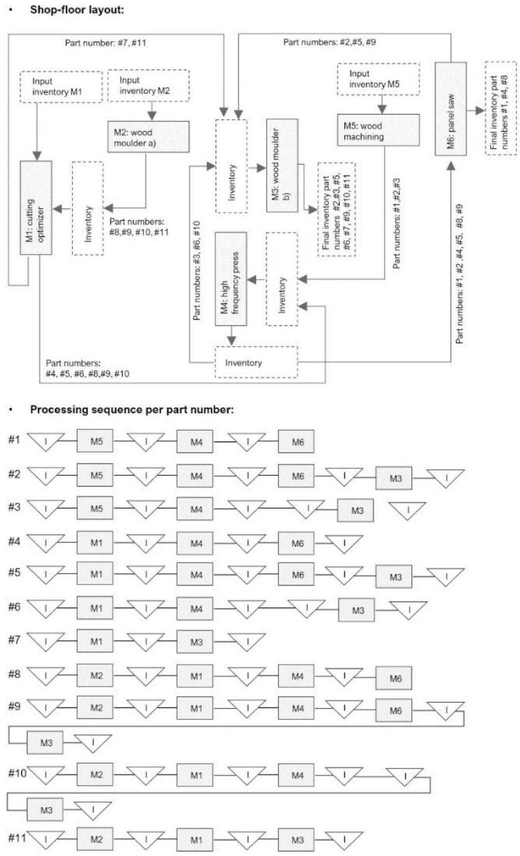

Fig. 3. Wood preparation sector layout and part routes.

The preparation sector is composed of 6 machines: a cutting optimizer, 2 wood moulders (addressed as moulder "a" and moulder "b"), each one used in distinct parts of the process, a high frequency press, a machining center and a panel saw machine. Along the sector, 11 different part numbers are produced following different routes.

Production planning is executed following a 2-stage process. Firstly, a monthly planning is drafted jointly by the commercial and manufacturing departments according to an analysis of customer demand and finished products inventory. This tactical level plan is used to adjust the material requirement planning and the production staff capacity. Subsequently, based on a daily goal of production for each part number, a short-term production schedule is created by line supervisors. Lastly, preventive maintenance interventions are executed periodically for all machine components, according to deadlines computed based on the machines' manufacturers best-practice guidelines.

5.2. Decision support system application

For this application example, the DT architecture conceptualized in Section 4 was computationally implemented through the use of the Python 3.7 programming language. The DSS operation can then be demonstrated by the running of a test scenario, utilizing the manufacturer case's data as input parameters. Particularly, we consider that a set of 5 preventive maintenance interventions are planned to be executed by the end of the month, according to the specifications presented on Table 1.

Table 1. Planned preventive maintenance interventions.

ID	Machine:	Component:	Duration:	Technical area:
1	M4: high frequency press	Command panel	120 mins	Electrical
2	M4: high frequency press	Hydraulic	50 mins	Mechanical
3	M6: panel saw	Command panel	120 mins	Electrical
4	M6: panel saw	Hydraulic	50 mins	Mechanical
5	M6: panel saw	Saw (lubrication)	20 mins	Mechanical

Furthermore, we consider that in the beginning of a production shift, after an hour of normal operation, the DSS is triggered to verify preventive maintenance scheduling opportunities for the next 2 hours, as the machine 4 – high frequency press, has suffered a failure with predicted repair time of 2h. The daily production schedule is consequently adjusted so that the production of part numbers #7 and #11 is prioritized as they do not require processing in machine 4. We present in Fig. 4 an illustration of the identified idleness time slots, and the proposed preventive maintenance intervention scheduling, considering a single simulation replication. For the sake of this application test, we consider that maintenance workers of all technical domains are available to be called to action.

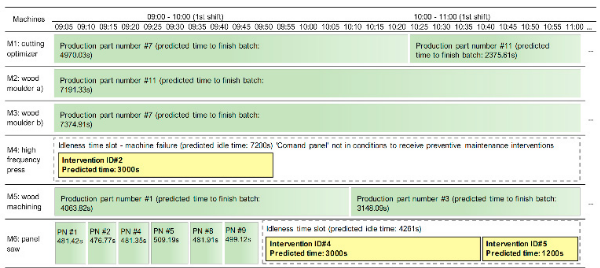

Fig. 4. Idle time slots and intervention scheduling.

According to the updated scheduling, the DSS predicts the completion times of production jobs for each machine, as well as the movement of jobs downstream. Dynamic properties of the model enable the computation of updated buffer levels, which allow the DSS to visualize, for instance, that M6 will have input buffer to function for a while, despite the lack of supply from the non-operational M4. Furthermore, static properties of the model (e.g., processing/waiting time distribution parameters) allow the DSS to verify that M6 will stay approximately 2939s in activity (according to the executed simulation replication), before becoming idle due to lack of input inventory.

Due to idleness as a result of failure, the DSS has identified that intervention ID 2 can be scheduled to be executed in M4. More interestingly, the DSS managed to capture the systemic consequences of M4's breakdown within the short-term (2 hours) production plan provided by management, predicting in which moment the lack of supply enables the scheduling of interventions ID 4 and ID 5, both to be executed in M6. Due to the stochastic nature of processing times in several manufacturing applications, more simulation replications may be run, as discussed in Section 4, to achieve time slots predictions that possess greater assertiveness.

6. Conclusion

In this work, we employed a DT architecture to enable the use of short-term simulations based on a dynamically updated digital model of the shop-floor. Such an architecture can be employed to provide maintenance managers with up-to-date schedules of preventive maintenance interventions that best exploit machines idleness or downtime, with the aim of minimizing production throughput penalties.

Our approach is restricted to applications set within the boundaries of discrete manufacturing, as well as to production control strategies capable of generating a reliable short-term schedule of production jobs. On its current settings, the DSS takes as input a pre-determined production scheduling and works to minimize throughput penalties generated by preventive maintenance interventions.

Future research may be directed, therefore, towards the expansion of the DSS scope, so that the production and maintenance intervention scheduling activities are addressed at the same time, with the unifying goal of maximizing production throughput.

CRediT author statement

Anis Assad Neto: Conceptualization, Methodology, Writing -Original Draft, Software, Visualization. Bruna Sprea Carrijo: Software. João Guilherme Romanzini Brock: Software. Fernando Deschamps: Conceptualization, Writing -Review & Editing, Supervision, Project administration. Edson Pinheiro de Lima: Project administration, Funding acquisition.

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