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GROUP DECISION MAKING APPROACH FOR RANKING AND SELECTING MAINTENANCE TASKS FOR JOINT SCHEDULING WITH PRODUCTION ORDERS

Abstract: *Group decision-making has captured the attention of researchers for decades but due to its importance and complexity further explorations and studies, namely for its application in industrial engineering continue to be needed in the current digital age. In this paper a group decision making approach is put forward for evaluating and selecting maintenance tasks to enable its joint scheduling with production orders, by using a collaborative management system. The proposed approach includes a two-stage collaborative assessment method, which enables a set of decision makers to rank and select maintenance tasks for being scheduled with production orders. The proposed approach uses a dynamic multi-criteria decision model that aggregates information about historical, current and provisional data about maintenance tasks. The approach is illustrated through an application example and contextualized in the state of the art. This study permits to realize that collaborative management approaches enable conducting a dynamic, integrated, distributed, intelligent, predictive, time and condition based maintenance task management in real time, based on the fusion of past, present and predicted data, and that there is still a lack of contributions regarding its use of in industrial management.*

Keywords: *group decision making; collaborative system; dynamic, integrated, distributed, parallel, and real time based industrial management.*

1. Introduction

Group decision making (GDM) is a research topic that falls within collaboration, and collaborative management domain (Kusi-Sarpong, et al., 2018; Varela, Putnik, & Romero, 2022; Varela, et al., 2022a), and is of primer relevance in the digitalization era, by promoting and enabling a sustainable development of companies (Varela, Putnik, & Romero, 2022, 2023; Varela, et al., 2022a,b, 2023).

The development of GDM approaches require the acquisition, processing and analysis of varying kind of data, which typically is expressed through Key Performance Indicators (KPI), for being monitored and controlled by using appropriate dashboards and systems (Simonov, et al. 2018).

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Over the last 20 years, the processing industries have invested heavily in automation and plant information systems such that the data is now accessible. As a result, this data should now be possible to put into productive usage. The challenge with raw data, no matter how accessible, is that it is just data, and data still requires a lot of work before it can be turned into knowledge. In most cases, the data needs to be validated, analysed and converted into a level of knowledge that is actionable, and this can still require a significant investment of time and resources.

Several kind of KPI have been frequently used to analyse companies' performance in a given context intending to reachcertain organizational goals. Every companies' functional group defines its objectives and targets, and if the raw operational data can be converted in KPI for being processed and analysed, preferably in real-time a better monitoring and control, on the processed data can be reached and thus better decision making processes can occur.

Information monitoring, based on proper DSS is fundamentalforobtaining maximum profit out of KPI through the use of suitable systems' data visualizationinterfaces, and which are currently being improved by using advanced and dynamic digital dashboards, namely through the use of power BI graphics that enable real time generated data to be analysed. Although, the real potential of a system data visualization interface relies on its interactive ability to quickly sort and display the consolidated performance metrics in order to highlight the top priority requirements and provide guidance on further actions required. This is performed through a combination of filtering, uncertainty filtering, normalization, weighting, aggregation, ranking, and selection techniques, and put available through appropriate collaborative systems and platforms (Campanella, et al., 2012; Arrais-Castro, 2015a,b, 2018; Jassbi, et al, 2016; Varela, et al., 2018; Simonov, et al., 2018).

As mentioned by Knoben, &Oerlemans (2006), inter-organizational collaboration enables to unify disparate systems and solutions in order to achieve overall strategic and operational excellence. Therefore, intra and intercompany and manufacturing environments collaboration should be intensified, and this can be accomplished by putting into use appropriate group decision support approaches. Such kind of approaches will permit to fully integrate decision-making processes among diverse manufacturing plants and resources interactions, by using suitable platforms and systems offering effective support to carry out distributed and integrated management. Such unified workflow environments will thus promote and enable collaboration and support different decision making teams to work together with an understanding of their specific requirements in the context of a general view over an extended and/or virtual enterprise, which is of upmost importance in manufacturing and management, for instance in collective maintenance and production management.

Maintenance planning plays an important role in every service and manufacturing system, as it makes them more reliable and keeps them at an optimal operational level in order to provide high quality services and products. Additionally, the proportion of maintenance costs to the total production costs, which ranges from 15% to 70% according to the type of the manufacturing firm (McCall, 1956), makes maintenance planning a critical issue. Maintenance models can be broadly classified into two types: time-based and condition-based models (Rahmati, et al., 2018). Recently, the joint optimization of production and maintenance plans has gained more attention. However, it has not been well studied compared to research on optimizing maintenance planning and production schedules independently (Pan, Liao, & Xi, 2012; Bajestani, Banjevic, & Beck, 2014; Fitouhi, et al., 2017). In addition to the above-mentioned classification of maintenance models, integrated maintenance and production scheduling models can also be classified into two types: integrated maintenance and production scheduling models with time-based maintenance activities; and integrated maintenance and production scheduling models with condition-based maintenance activities.

Maintenance operations can be classified into two main large groups: corrective maintenance (CM) and preventive maintenance (PM). CM corresponds to the actions carried out when the failure has already taken place, and PM is the action taken on a system while it is still operating. PM is carried out in order to keep the system at the desired level of operation, and several PM policies can be defined (Rahmati, Ahmadi, & Govindan, 2018; Sloan, &Shanthikumar, 2000; Taghipour, &Azimpoor, 2018), with the aim of determining when it is necessary to carry out PM operations on the machines according to different criteria used.

Besides maintenance planning, the maintenance and production scheduling is a critical decision process for the gainful management of any manufacturing system. While the first ensures reaching the production goals, besides thesatisfaction of customer demands, the second ensures that manufacturing assets are available and in the proper condition to perform their required production tasks when needed. The two decision processes are interdependent since they share a clear common issue, the manufacturing assets that are used through production and restored by maintenance actions.

Integrating production and maintenance scheduling willthus enable optimizing the joint production orders and maintenance task programming, while avoiding penalising drawbacks in companies (Ladj, et al., 2016).

Although, according to the study conducted, it is possible to realize that there is still a gap in this research domain, as insufficient work has been put forward regarding joint maintenance and production management strategies and tools.

In order to provide a contribution in this focused domain, in this paper, a group decision-making (GDM) approach for supporting maintenance tasks assessment and selection is presented, for enabling further jointmaintenance tasks and production orders scheduling, to reduce the lack of research that still prevails in this scientific domain. The proposed GDM approach is based on a Dynamic Multi-criteria Decision Model (DMCDM) (Varela, et al., 2018), implemented through a two-stage maintenance tasks processing (2SMTP) methodology, which is put available through a Collaborative Management System (CMS) that does further permit the integrated maintenance tasks and production orders scheduling.
To properly expose the developed work, this paper follows with a resumed literature review about DSS, MCDM and GDM, along with a general overview about approaches and systems for supporting maintenance and industrial operations management, in section 2. Next, the developed collaborative management system for joint maintenance tasks and production orders processing, along with the underlying group decision-making approach, and the proposed two-stage maintenance tasks assessment and selection method is briefly described, in section 3, and being further illustrated through and industrial example of application, in section 4. Follows, a final discussion and contextualization of this work within the state of the art, in section 5, and the main conclusion and proposed future work in section 6.

2. Literature review

In this section, a general overview about decision support methods and systems, along with group decision-making approaches is briefly presented next, in subsection 2.1, followed by a summarized description of maintenance and industrial operations management approaches and decision support systems, in subsection 2.2.

2.1 Methods and systems for group decision-making support

A Decision Support System (DSS) can be explained as an interactive computer-based system, which can be helpful for decision makers to use quantitative models and data for solving complex problems (Bhatt & Zaveri, 2002; Lee & Huh, 2006). A DSSenables supportingmore or less complex decision processes by using different kind of middleware and technology, and tools (Sprague & Carlson, 1982; Zarate, 1991; Vieira, et al., 2018; Vafaei, et al. 2019). Keenan (2016) referred that DSS have been developed since 1970s, and since then continuedgrowing and improving, based on new technologies, namely about databases and visual interfaces applied for properly supportingdecision-making processes. DSS mostly involve Management Science and Operations Research fields. DSS and management strategies have thus a meaningful relationship in manufacturing environments for reaching well-suited decisions (Brannback, 1994).

During recent decades, DSS have been developed in different contexts, and some contributions are summarized next.

Group Decision Support Systems (GDSS) and Executive Information Systems, which was changed to the Enterprise Information Systems (EIS), introduced to support DSS tools are becoming much improved and more effective. GDSS currently providemany useful options, includingbrainstorming, idea assessment and some other facilities for enabling communication in more or less complex problem solving scenarios (Costa, et al. 2003; Limayem & Banerjee, 2006; Varela, et al., 2021), along withother kind of the so-called Integrated Decision Support System (IDSS) that enable improving the effectiveness of classical DSS by combiningthem (Liu, et al. 2010).

More recently, DSS has applied in integrated models with Multiple Attribute Decision Making (MADM) and Multiple Objective Decision Making (MODM) in general framework of Multiple Criteria Decision Making (MCDM) for endowing a better process and environment in decision support (Jaramillo, et al. 2005; Qureshi, et al. 2017). Bakshi, et al. (2015) mentioned that when there is uncertainty indecision-makingprocesses the MCDM models will become more complicated thus requiring appropriate Multi-Criteria Decision Support Systems to present appropriate solutions in practice. The authorsmention a new decision support system established based on models, survey (literature review) and human experts interacting througha proposed framework. The main issue of their research was selecting the main criteria in MCDM models. Some other studies applied this kind of approaches in practice, and some are resumed next, to mention a fez.

Taha&Rostam (2012) applied a hybrid fuzzy AHP-PROMETHEE as main part of a decision support system for machine tool selection in flexible manufacturing cell. They mentioned that their research shows that MCDM methods can be a useful part of a DSS and that their vision would be helpful in decision making in solving complex cases.

Razmak & Aouni (2015) reviewed research related to MCDA and DSS and found out more than 100 research articles foranalysis. They categorized the articles into 9 different sections, regarding their application fields. These 9 sections were: Production and Supply Chain Management; Education; Human Resource Management; Finance and Investments; Real state and Constructions; Environmental aspects; Medical aspects; Electronic business and electronic commerce, and Multimedia.

Leyva Lopez, et al. (2016) proposed a model and system for supporting group decision-making based on a MCDM approach. The authors state that their approach was structured based on ELECTRE method and designed completely based on the web to turn the underlying process more reachable and easier applicable in practice. Theirproposed GDSS enable to put forward some advices for decision makers in order to help themmanage their priorities and preferences to allowproper decision rules with some degree of consistency and consensus.

In otherworks, namely in (Arrais-Castro, et al., 2018; Simonov, et al., 2018; Varela, et al., 2018), DSS models were proposedby using different kind of approaches, in different application contexts. According to the examples provided, it is possible to realize that DSSand approachesare applied in many different context and manufacturing and management environments, thus there is still need fornewcontributions to increase its full practical capability and usability, for instance, in the industrial context. Furthermore, decision making with uncertainty treatmentand future or prospected data processing, needs integrated and advanced DSS models and systemsto continue beingdeveloped to decrease ambiguity and vagueness of knowledge about forecasted data, which has become, especially currently, in the digital age,more urgent and necessary,for puttinginto practical use in manufacturing management (Putnik, et al., 2021).

2.2 Approaches and systems for supporting maintenance and industrial operations management

Maintenance is a crucial activity in industry, with a significant impact on costs and reliability, being immensely influential on a company's ability to be innovative, whilepermittingcosts reduction and global benefits, namely increased quality and general performance.

In the scope of maintenance management, any unplanned downtime of machinery equipment or devices does usually degrade or harm a company's core business, potentially resulting in significant penalties and unmeasurable reputation loss. According to some studies, operation and maintenance costs can range from 15% to 70% of total production cost in some companies (Bevilacqua, & Braglia, 2000; Gong, & Qiao, 2014). Therefore, it is critical for companies todevelop a well-implemented and efficient maintenance strategy to prevent unexpected drawbacks, and improve overall reliability, while reduce manufacturing systems' operating and maintenance costs.

The evolution of modern techniques, namely with the emergence of the Internet of things (IoT), along with varying kind of sensing technology, and new or improved artificial intelligence approaches and tools, among others, stimulates a transition of maintenance strategies from Reactive Maintenance (RM) to Preventive Maintenance (PM), andto Predictive Maintenance (PdM) (Jimenez, et al., 2020). RM is only executed to restore the operating state of the equipment after failure occurs, and thus tends to cause serious unproductive times, while frequently resulting in high response andreparation costs. PM is carried out according to a planned schedule based on time or process iterations to prevent breakdown, and thus may perform unnecessary maintenance, typically resulting in high prevention costs. In order to achieve the best trade-off between the RM and PM, the PdM can be performed, based on some online assessment of the conditionof manufacturing assets, and thus reach timely interventions before failure occurs, whilepreventing from high maintenance frequency, unplanned RM, and the incurrence in increased costs associated to frequent PM.

Asset management deals with the optimization of manufacturing assets usefor reducingcosts. An asset management system manages the assets over the whole life cycle, especially their reliability and efficiency. It is also responsible to optimize utilization and cost-effective maintenance of the assets. Moreover, it generates and provides information regarding the so-called "asset health" development and prognosis to support decision making of the enterprises' production management (Namur, 2009). Using the "asset health" information to generate an optimal production plan is a viable solution to better integrate a maintenance and a production planning system to increase the overall performance (e.g. in terms of costs) of manufacturing operations. Although some work was already carried out in this sense, industry is still lacking of appropriate and effective systems for supporting advanced maintenance and production management (Zhai, Gehring, & Reinhart, 2021).

Biondi and Harjunkoski (2017) proposed a joint scheduling approach for the production and maintenance of process plants that explicitly keeps track of the assets life cycle. The scheduling system includes a simple model of the asset wear that can be based on the concept of residual useful life (RUL) or of probability of failure.The authors state that the asset monitoring system is responsible of providing two types of information to the scheduling system: on the one hand, an estimation of the parameters describing the wear caused by the production on the asset. On the other hand, if an extraordinary condition of the asset isdetected, it is responsible to update a current RUL in the asset wear model of the scheduling system. Assets health information, along with the production orders, is managed by the scheduling system that takes care of the sequencing and timing of production tasks on the plant and triggers a maintenance action on the assets whenever this is required.According to the authors, their proposedmethod makes an effective use of factory units' health information to generate a feasible plan for joint production and maintenance planning (Biondi, & Harjunkoski, 2017).

Based on (Staufen, 2018), PM has not been properly explored in industry. A survey in 2020 shows that PM continues being a hot topic, for example to determine the best point in time to do maintenance tasks (Zhai, et al., 2020).

Two types of flexible PM strategies, i.e., time-based PM (TBPM) and condition-based PM (CBPM), are commonly analysed and applied (Wang, Yan, & Zhang, 2021). According to these authors, the application of TBPM is straightforward and relative ease of implementation, however, TBPM may lead to under-or over-maintenance due to inaccurate estimate of the stability of production systems. In contrast, CBPM is of more complexity, which continuously monitors and analyses the machine status to determine the implementation of the maintenance activity. The authors state that despite the complexity of computational requirement and uneven maintenance cycles, CBPM strategy can reduce the maintenance frequency to a minimum necessary level, thus improve a global production system's productivity level.

Some examples of application of TBPM in diverse kind osproduction scenarios, integrating different production scheduling strategies, are presented in (Chen, 2000; Chen, et al., 2006; Mosheiov and Sarig, 2009; Yang, et al, 2011), while CBPM has also been focused by several researchers, for instance in (Zandieh, Khatami and Rahmati, 2017; Rahmati, Ahmadi and Govindan, 2018; Sloan and Shanthikumar, 2000; and Ghaleb, et al., 2020), just to mention a few.

Prognostics and health management (PHM) is a relatively young engineering discipline that aims to enable "real-time health assessment of a system under its actual operating conditions as well as the prediction of its future state based on up-to-date information" (Kim, et al., 2017), with PdM being the underlying maintenance strategy that uses prognostics results of PHM.

The authors of (Li, Lei & Bian, 2019) state that varying operational conditions have two major effects on system degradation: Firstly, varying operational conditions influence the speed of degradation. Secondly, they lead to sudden signal changes and changepoints, which result in high variance of raw sensor readings. Thus, varying operational conditions pose an obstacle to prognostics (Zhang, et al., 2020) and are considered to be a focal point for modern PdM modelling (Aydemir, Acar, 2018).

According to (Do, Assaf, Scarf, & Iung, 2019), prognostics incorporates three tasks: 'State estimation' (estimate the current health or degradation state of the system based on historical data), 'State prediction' (predict the health or degradation state for future periods based on historical data), 'EoL' ('End of Life') or 'RUL prediction': Determine the RUL before failure or before exceeding the failure threshold for some identified degradation behaviour. The author highlights that RUL can refer to actual failure or remaining time until certain quality requirements of a product cannot be met.

Databased RUL prediction can be formulated as a supervised (Aggarwal, et al., 2018) or a semi-supervised machine learning (ML) problem (Yoon, et al., 2017). According to these authors, the high amount of required failure data to derive RUL labels for supervised prediction models is often not available in industrial practice.

Health prognostics approaches in PHM are commonly classified into physics-based, knowledge-based and data-driven approaches (Bektas, Marshall, & Jones, 2019). Physics-based models describe the phenomena of failure and degradation as physical or mathematical "white box"-model. Although physics-based models can achieve high accuracy, their development is usually costly (Bektas, Marshall, & Jones, 2019). Knowledge-based models collect identified degradation behaviors and failure events in a historic database and assess the similarity of a currently observed system state with the entries of a knowledge base (Sikorska, et al., 2011). Data-based approaches make use of the system condition monitoring (CM) data to derive transparency of the system health state and predict the RUL (Song, et al., 2018; Jia, et al., 2018; Wang, et al., 2017), further enabling to assess the uncertainty of the prediction (Benker, et al., 2020). Databased methods encourage the use of highly adaptable ML, including deep learning (DL) algorithms (Zhang, et al., 2018), in scenarios where large amounts of condition monitoring data are available and the system operation is subject to variations, partially unknown conditions or a variety of failure modes.

For an overview of knowledge-based approaches, as well as advantages and limitations of data- and knowledge-based approaches, the reader is referred to (Ran, et al., 2019), where a survey of predictive maintenancesystems purposes and approaches is presented. Next, some additional work is briefly referred.

The authors in (Malhotra, et al., 2016) propose an approach for combined health indicator (HI) estimation and RUL prediction. The publications by (Wang, 2010; Wang, et al., 2008) are among the first research works to explicitly consider the effects of time-varying operating conditions on system degradation analysis.

Li et al. (2019) model a dynamic, operation-specific degradation rate as a state transition function based on Wiener process and time-scale transformations, which capture the effect of operating conditions on the degradation curve. A measurement function smoothens the jumps in the degradation signal at operation condition changepoints by mapping each condition to a condition-specific baseline. The approach proposed by the authors is evaluated on a simulated data set of bearings, which are subject to varying rotational speeds, as well as on a data set from an accelerated degradation experimental study of rolling element bearings.

Luo et al. (2019) propose a deep learning approach for health estimation and fault detection of CNC machine tools operating under time-varying conditions. In a first step, the authors use a DL model composed of stacked auto encoders (AE) and a feed forward neural network to extract impulse responses from vibrational CM data. The training and test data sets for the DL model are prepared manually by labelling whether randomly selected time windows contain an impulse response or not. In case of an impulse response, the vibration signal represents the reaction of the system to sudden forces and impacts during time-varying machining processes. After training, the DL model is used to automatically identify impulse responses in the CM data. Subsequently, the first four natural frequencies and the damping reactions of the machine tools are extracted from two different impulse responses representing two different working conditions. The authors find that the natural frequencies barely change with varying operational conditions and thus are a robust feature for HI construction. The HI is computed as the cosine similarity in the space of extracted dynamic features comparing current observations with an initial vector representing the normal state. According to the authors, since the HI is based on operation-condition invariant features, the HI is robust to different working conditions. However, the approach is not capable of performing an operation-specific prediction of system health for future loads. In contrast to most other research, the approach was evaluated on a real industrial data set, composed of vibration signals from 288 days of industrial operation.

Michau & Fink (2019) propose an unsupervised approach for system monitoring in a setting where a fleet of similar safety-critical systems is to be monitored over time. The training data for a specific system instance is enhanced by CM data from other instances of the fleet to enable CM early in a system's operational life. The authors use a variational autoencoder (VAE) architecture to model a shared latent space for the fleet, which is trained in an adversarial manner. A new loss function is designed to preserve instance-specific behaviours in the shared latent space. The health prediction is framed as a one-class classification, which aims at predicting whether the CM data is faulty or healthy. The method is evaluated using a real data set form a fleet of 112 power plants operated in different geographical locations and under different operational conditions. The authors refer that their results show that the shared latent representation and feature alignment yield an efficient and unsupervised feature representation in a setting of complex systems subject to varying conditions, which is useful for downstream PHM modelling.

The integrated optimization of production scheduling and machine maintenance has been known as a complex combinatorial optimization problem, in which heuristic or meta-heuristic approaches are commonly employed aiming to find some satisfied solutions in short time. With the advent of artificial intelligence and machine and deep learning, the application of scheduling rules-based reinforcement learning (RL) to the field of scheduling has become possible (Wang, & Usher, 2005). However, little empirical research concerning the application of RL to integrated decision making of production scheduling and machine maintenance has been conducted (Zhai, Gehring, & Reinhart, 2021).

In (Zhai, Gehring, & Reinhart, 2021) a machine degradation modelling under varying operational conditions, enabling subsequent integrated scheduling of maintenance and production ("PdM-integrated production scheduling": PdM-IPS) is introduced. The underlying model is a conditional variational autoencoder (CVAE) that is used for calculating and quantifying the change of the machine health condition after producing specific product sequences.

The gap that continues existing regarding contributions of integrated maintenance and production management approaches and systems motivated this work, in order to contribute to this scientific domain, and the proposed collaborative management system, based on a group decision-making approach is briefly described and illustrated in the next sections.

3. Collaborative management system based on a group decision making approach

Collaborative management is of upmost importance in the current digital age, enabling and promoting a sustainable development of companies (Varela, Putnik, & Romero, 2022, 2023; Varela, et al., 2022a,b, 2023). In this paper, a group decision-making architecture is proposed to enable collaborative management, and Fig 1 shows and example of its application in an industrial company that includes three work centres (WC1, WC2, and WC3), which interact with each other and with the main company's factory, through its underlying brokering service, besides communicating with clients, and maintenance technicians.

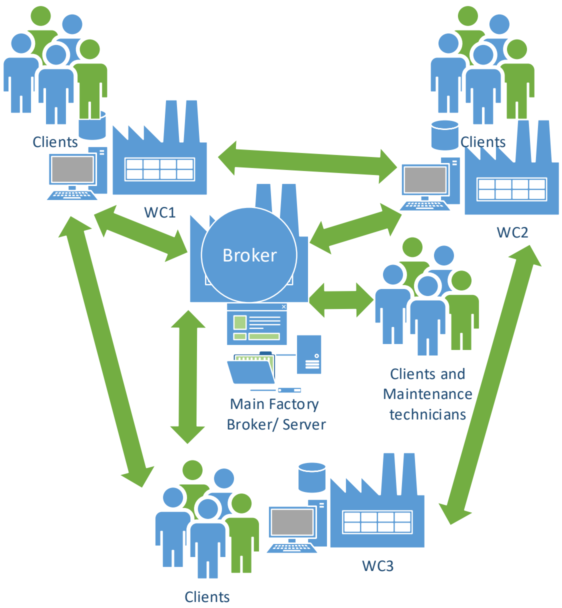

Figure 1. Group decision-making architecture

A collaborative management system (CMS) underlying the proposed group decision making architecture was developed to enable intra and inter factories and/ or work centres collaboration for jointly reaching integrated maintenance tasks and production operations scheduling, and an interface of the CMS is shown in the Figure 2, about an interface for processing a data fusion function of the DMCDM used in this work that will be further explained through an application example.

This CMS enables a wide range of diverse kind of other management functions in industrial management, namely underlying the proposedGDM approach, which is carried out by usinga maintenance tasks processing methodology with three phases, based on a two-stage assessment method, whichmakes use of a DMCDM, as expressed in the Figure 3.

The two-stage assessment method based on DMCDM was used in an industrial company, in the scope of a research project to enable the joint processing of maintenance and production orders information, and a case study is briefly described next in the section 4.

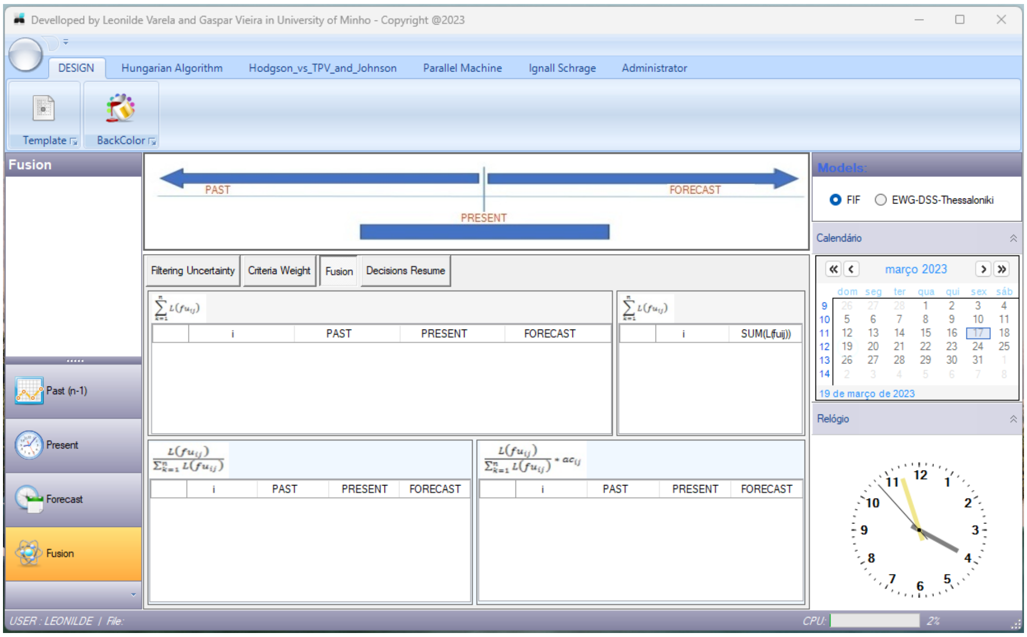

Figure 2. Collaborative management system's interface illustration: data fusion function

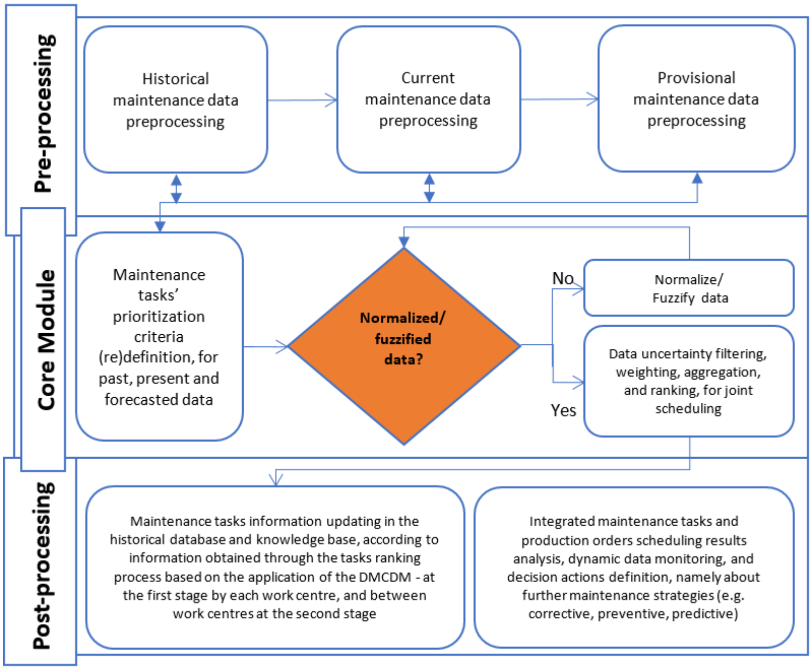

Figure 3. Proposed maintenance tasks processing methodology based on a two-stage assessment method

4. Application example

4.1 Maintenance tasks assessment methodology based on a DMDCM

The maintenance tasks assessment methodology used in this work uses a DMCDM (Jassbi, et al., 2013; Varela, Arrais-Castro, & Ribeiro, 2018), by including two stages, for intra and inter work centres tasks evaluation and selection.

1st Stage) Intra work centres evaluation: Includes 6 steps, for normalizing/ fuzzifying, weighting, uncertainty filtering, and data aggregation or fusion, for ranking and selecting the maintenance tasks (Varela, Arrais-Castro, & Ribeiro, 2018).

Step 1) Data acquisition and matrices construction: First,the definition of the evaluation criteria for processing the data about 3 moments: past, present and future, have to defined, and Figsures 4 to 6 show an example for the company's WC1, by using different kind of criteria, about: maintenance cost (MC), Lack of Production Quality (LPQ), Overall Equipment Effectiveness (OEE), Lack of Safety Indicator (LSI), Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR), and Downtime (DT), for processing past and future maintenance tasks' data; and MC, along with Service Time (ST), and Lead Time (LT), for processing current maintenance tasks' data, which were applied for ranking a set of 6 maintenance tasks (M1_1 to M1_6) of WC1.

The current or present data is acquired, in real time from the shop floor, by using appropriate communication means and devices (Vieira, et al., 2018; Varela, et al., 2021).

Maint. Task	Maint. Cost MC	Lack of Production Quality LPQ	Overall Equipment Effectiveness (100%) OEE	Lack of Safety Indicator LSI	Mean Time Between Failures MTBF	Mean Time To Repair MTTR	Downtime DT
MT1_1	630,00	28%	88	18%	28000	2	5
MT1_2	398,50	33%	79	14%	17500	4	4
MT1_3	400,00	17%	90	11%	18900	3	3
MT1_4	730,00	20%	85	13%	22400	2	3
MT1_5	490,00	15%	83	15%	15600	5	5
MT1_6	330,00	12%	92	12%	20580	1	4

Figure 4. Past data matrix

Maint. Task	Maintenance Cost MC	Service Time ST	Lead Time LT	Extended ST (EST) ST + (max(LT-d),0)
MT1_1	635,00	100	5	105
MT1_2	405,00	120	2	122
MT1_3	410,00	85	4	89
MT1_4	650,00	90	3	93
MT1_5	450,00	100	4	104
MT1_6	335,00	115	3	118

Figure 5. Present data matrix

Maint. Task	Maint. Cost MC	Overal Equipment Effectivness OEE	Downtime DT	Production Quality PQ	Mean Time To Repair MTTR	Mean Time Between Failures MTBF	Safety Indicator SI
MT1_1	640,00	85%	20	86%	5	23500	4
MT1_2	498,50	90%	35	92%	10	13000	4
MT1_3	410,00	70%	17	85%	6	25500	3
MT1_4	700,00	75%	10	73%	7	15000	3
MT1_5	395,00	73%	20	80%	9	14000	5
MT1_6	340,00	84%	18	90%	4	11000	4

Figure 6. Future data matrix

The future data can be obtained by applying some forecasting method, namely by using some machine learning approach (Putnik, et al. 2021) or be based on known real or estimated data. Prediction may also be performed using expert judgment or quantitative methods (forecasting), such as moving linear averages, quadratic averages, and other techniques.

Step 2) Normalization/ fuzzification

In the second step a normalization/ fuzzification processunderlying the DMCDM (Varela, Arrais-Castro, & Ribeiro, 2018) was performed (Figure 7), toprocess imprecision by using fuzzy logic for criterion evaluation.To guarantee that values are numerical and comparable simple triangular membership functions were used to represent the acceptable criterion values, as all expected criteria fit in the "lower is better" and "higher is better" categories (Varela, & Ribeiro, 2003). This process is essential to enable values aggregation, and the simplest method consists on dividing a value by the maximum existing one in the set (when high values are favourable to the decision) or by the minimum (when low values are favourable, such as a cost) (Jassbi, et al., 2014).

MC

	x	u(x)
1,1	630,00	0,250
2,1	398,50	0,829
3,1	400,00	0,825
4,1	730,00	0,000
5,1	490,00	0,600
6,1	330,00	1,000

bi	330	
pi	400	(730-330)

Figure 7. Normalization and fuzzification example for the MC criterion

In order to filter uncertainty a method underlying the DMCDM referred in (Varela, Arrais-Castro, & Ribeiro, 2018) is used, which considers two parameters, accuracy and confidence to "filter" the membership function values. The accuracy parameter expresses deviations from nominal values and the confidence expresses the degree of trust on the data gathered.

The logic of this filtering process is that if we do not trust an input source (e.g. confidence on data is only 80%) then the initial value must decrease proportionally (e.g. a value 10 would be reduced to 8), Thus accommodating deviations in the value, for example +3 or -3 from a value of 10.

Let a_{ij}be the accuracy associated with criterion j for MTi, representing a left or right deviation from the original value; when a_{ij} is zero it means we accept the gathered value without deviation errors.

The confidence, wc_j, is a percentage, as for example, we trust with 90% the values for "Maintenance Cost, MC".

Additionally, λ ∈ [0,1], is a parameter that reflects the decision maker's attitude. Values close to zero indicate an optimistic attitude; higher values indicate a pessimist attitude.

The accuracy rate, expressing the allowed deviation from the base values, is defined for each criterion, based on the associated data quality. The value also reflects the imprecision associated with the data gathering process. Based on the criteria and its associated confidence rates, the filtered imprecision values, fu_{ij} (e.g. acij), were calculated, as illustrated next for the MC criterion.

Step 3) Uncertainty filtering

Hence, the adjusted membership value is calculated using the following formula (Varela, Arrais-Castro, & Ribeiro, 2018):

$$fu_{ij} = wc_j * (1 - \lambda * \max_{x \in [a,b]}\left\{\left|\mu(x) - \mu\left(x_{ij}\right)\right|\right\} * \mu(x_{ij})) \quad (1)$$

Where [a,b] is the inaccuracy interval:

$$a = \begin{cases} min(D), & if\ x_{ij} - a_{ij} \le min(D) \end{cases} \quad (2)$$

$$b = \begin{cases} x_{ij} + a_{ij}, & if\ x_{ij} + a_{ij} \le max(D) \end{cases} \quad (3)$$

Using the function (1), along with (2) and (3), we are able to penalize input values, which display any of the two types of uncertainty, i.e. inaccuracies or lack of confidence on data, within an optimist or pessimist view from the decision maker.

MC

wc_j	100%	λj	1	(in)acuracy int.	0%	pi	400	
i,j	u(xij)	xij	aij	a	u(a)	b	u(b)	acij
1,1	0,250	630	0	630	0,250	630	0,250	0,250
2,1	0,829	399	0	399	0,829	399	0,829	0,829
3,1	0,825	400	0	400	0,825	400	0,825	0,825
4,1	0,000	730	0	730	0,000	730	0,000	0,000
5,1	0,600	490	0	490	0,600	490	0,600	0,600
6,1	1,000	330	0	330	1,000	330	1,000	1,000

Figure 8. Uncertainty filtering example for the MC criterion.

Step 4) Weighting

The step 4 enables to allow different weights for different temporal stages or criterion. Here we will use linear weighting functions to express the relative importance of criteria. These functions allow penalizing or rewarding bad or good levels of criteria satisfaction, i.e., instead of assigning single weights, we represent them using a function that depends on criteria satisfaction (eq. 4):

$$L\,(fu_{ij}) = \alpha * \frac{1 + \beta\, fu_{ij}}{1 + \beta}\;, 0 \leq \alpha,\, \beta \leq 1 \quad (4)$$

where α defines the semantic importance of criteria ('1' – very important, … '0' - ignored), and the β parameter defines the slope for the weighting function (a higher value or slope means a steeper function, thus a higher penalty, e.g. '1', and '0' – null penalization) to penalize, more or less, badly satisfied criteria. For example, if we assign to criterion Maintenance Cost, MC the values α=1 and β=0.67, we are defining this cost as a "very important" evaluation parameter with an average slope decrease. In this case, we want to reward the best quotes and penalize the bad ones (i.e. we want to reward lower costs).

j=1 (MC)

i,j	fuij	alfa	beta	L(fuij)
1,1	0,250	1	0,670	0,699
2,1	0,829	1	0,670	0,931
3,1	0,825	1	0,670	0,930
4,1	0,000	1	0,670	0,599
5,1	0,600	1	0,670	0,840
6,1	1,000	1	0,670	1,000

Figure 9. Weighting example for the MC. criterion

Step 5) Aggregation

After the four previous steps, we have a weighted vector for each criterion. The step five is to determine the score (rating) for each time period, past, current and future, by using an approach that is illustrated for the past values about the MC criterion. The following results were obtained for historic information, using the data fusion equation 5:

$$r_i = sum\left(\frac{L\left(fu_{ij}\right)}{\sum_{k=1}^{n} L\left(fu_{ij}\right)} * fu_{ij}\right) \quad (5)$$

i	MC	OEE	DT	LPQ	MTTR	MTBF	LSI
1	0,699	0,669	0,643	0,799	0,479	0,593	0,889
2	0,931	0,736	0,931	0,628	0,668	0,650	0,772
3	0,930	0,539	0,605	0,509	0,642	0,622	0,677
4	0,599	0,575	0,700	0,589	0,578	0,593	0,677
5	0,840	0,515	0,742	0,668	0,720	0,685	0,889
6	1,000	0,479	0,569	0,549	0,611	0,564	0,772

i	r_i	Maint. Task
1	0,485	MT1_1
2	0,656	MT1_2
3	0,320	MT1_3
4	0,191	MT1_4
5	0,601	MT1_5
6	0,362	MT1_6

Figure 10. Aggregation example for the MC criterion in the past data matrix.

Step 6) Decision

Once applying the steps underlying the DMCDM: normalization/ fuzzification, weighing, uncertainty filtering, and aggregation or data fusion to the past information of the WC1, it is possible to obtain the following rankings of the corresponding 6 maintenance tasks considered in this example:

Maint. Task	Score	Position
MT1_2	0,65644141	1
MT1_5	0,6009151	2
MT1_1	0,48491111	3
MT1_6	0,36222612	4
MT1_3	0,31985451	5
MT1_4	0,19085262	6

Figure 11. Decision matrices example for the MC criterion

Next, we repeat the process underlying the DMCDM for future information, and in this case study the same criteria that have been used for past information evaluation were used for future data processing. Once having calculated the historical and prediction (future) scores for each alternative, we also need to evaluate the present status (present data).

Evaluating the present or current data means to evaluate the proposals/ quotes that have been received and then fusion the respective information. For that purpose, the following criteria were used to evaluate present data: MC (Maintenance Cost), ST (Service Time), and LT (Lead Time), as previously shown. Summarizing, the final ratings of the maintenance tasks regarding past, future and present data, for the WC1, along with the final ratings, after final data weighting and fusion, for the WC1 are the following, correspondingly:

WC1 - past

Maint. Task	Score	Position
MT1_2	0,65644141	1
MT1_5	0,6009151	2
MT1_1	0,48491111	3
MT1_6	0,36222612	4
MT1_3	0,31985451	5
MT1_4	0,19085262	6

WC1 - future

Maint. Task	Score	Position
MT1_6	0,26894646	1
MT1_3	0,20261408	2
MT1_2	0,19190658	3
MT1_5	0,18941079	4
MT1_1	0,17917192	5
MT1_4	0,08739849	6

WC1 - present

Maint. Task	Score	Position
MT1_3	0,87521921	1
MT1_6	0,70014439	2
MT1_5	0,64948589	3
MT1_4	0,59392525	4
MT1_2	0,50540424	5
MT1_1	0,30551333	6

WC1 – final scores

Maint. Task	Score	Position
MT1_3	0,5652022	1
MT1_5	0,5343635	2
MT1_6	0,4947301	3
MT1_2	0,4929897	4
MT1_4	0,3549720	5
MT1_1	0,3428058	6

Figure 12. Past, future, present and final scores matrices examples for all the criteria in WC1

After the application of the same procedure that has been used for processing the information related to WC1 to the other two work centres (WC2, and WC3), by accomplishing the same main 5 steps of the DMCDM, the following final maintenance tasks' rankings have been obtained for these WC2 and WC3.

Next, the two maintenance tasks, out of each WC, with the higher ratings shown next are selected for further processing in the 2nd stage of the maintenance data processing method.

It is important to notice that despite M1_3 not having good rankings in terms of historical data evaluation, it benefits from the greater importance that has been given in WC1 to the present or current data.

WC2 – final scores

Maint. Task	Score	Position
MT2_2	0,5699688	1
MT2_6	0,5284007	2
MT2_5	0,4882188	3
MT2_4	0,3952934	4
MT2_3	0,3838716	5
MT2_1	0,3742694	6

WC3 – final scores

Maint. Task	Score	Position
MT3_1	0,6617229	1
MT3_2	0,5652877	2
MT3_5	0,4242146	3
MT3_3	0,4114283	4
MT3_6	0,3966577	5
MT3_4	0,3958268	6

Figure 13. Final scores matrices examples for all criteria underlying past, present and future fused data about WC2 and WC3

Although, regarding the MT1_5, it reaches a higher rating than MT1_6, besides being a little worse positioned in terms of present data ratings, and with considerably worse position regarding future data, as the past data has an higher impact in the final rating than the provisional of future data, which in this case this favours MT1_5.

2nd stage) Inter work centres evaluation

In the 2ndstage, the DMCDN is repeated for the best rankings obtained in the 1st stage. Thus, follows the application of the same approach to the six maintenance tasks from the 1st stage with a higher ranking to be further processed based on the application of the same DMCDM by the whole set of decision makers underlying the WC1, WC2, and WC3, to obtain the final list of the three maintenance tasks with higher priority for being jointly scheduled with the production orders, by repeating the application of the same main 5 steps that were previously applied on each WC.

In this 2nd stage of the method, a higher importance has been given to the past data, followed by present and less importance to the future data, to obtain the final overall rankings.

Thus, the 3 maintenance tasks with better ratings - out of the set of the six maintenance tasks list including the two of each WC with a higher priority - that were reached for being jointly scheduled with the production orders are the following: MT2_2 (being redefined as simply M2, the M3_2, redefined as M3, and M1_5, redefined as M1).

It is important to notice that eventually other criteria and importance could be defined for accomplishing this second stage of the decision method.

(a) Final scores of MTi from 1st stage

i	Score	Maint. Task
1	0,5652022	MT1_3
2	0,5343635	MT1_5
3	0,5699688	MT2_2
4	0,5284007	MT2_6
5	0,6617229	MT3_1
6	0,5652877	MT3_2

(b) Final rankings of MTi from 2nd stage

Maint. Task	Score	Position
MT2_2	0,6463834	1
MT3_2	0,5581164	2
MT1_5	0,4785514	3
MT3_1	0,4774147	4
MT2_6	0,4337532	5
MT1_3	0,1708652	6

Figure 14. (a) Aggregated final scores' matrices about WC1, WC2, and WC2 from the application of the 1st stage and (b) the 2nd stage of the maintenance tasks assessment methodology

4.2 Collaborative scheduling: joint selected maintenance tasks and production orders programming

The joint collaborative scheduling is performed next, based on the model presented in (Varela, et al., 2022b), to jointly program a current set of companies' production orders, along with the previously selected set of the three maintenance tasks with higher scores: MT2_2 that will now be defined simply as M2, MT3_2 as M3, and M1_5 as M1, related to the workcentres WC1, WC2, and WC3, correspondingly, and alternative possible solutions are shown in the Figs 15 to 17 below.

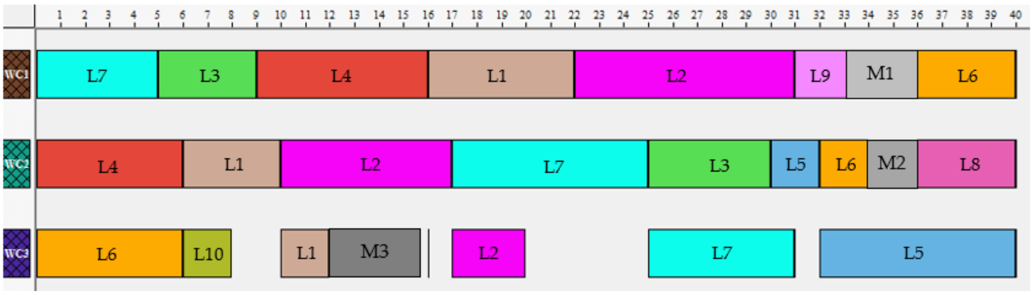

Figure 15. Gantt chart about the best solution found for scenario 1 (about the minimization of the internal performance measure, makespan, Cmax) (adapted from, (Varela, et al., 2022b))

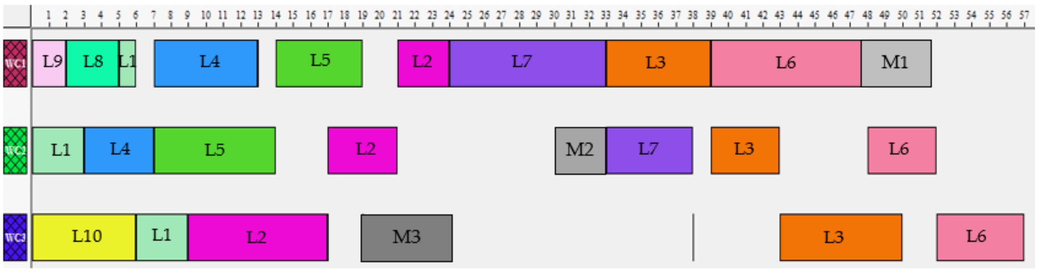

Figure 16. Gantt chart about the best solution found scenario 2 (about the minimization of external measures, tardy jobs, Nt, and maximum tardiness, Tmax) (adapted from, (Varela, et al., 2022b))

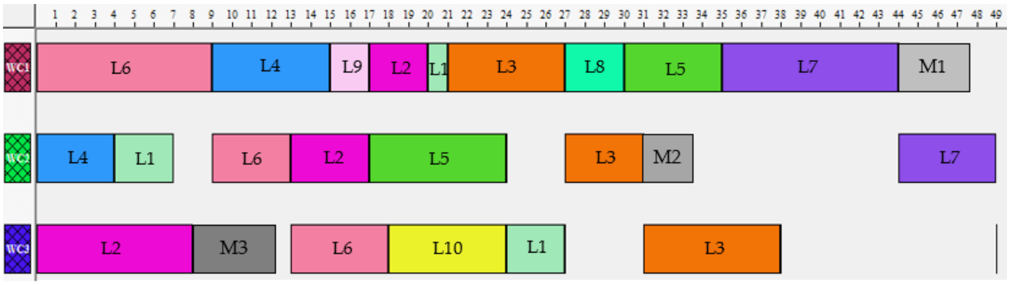

Figure 17. Gantt chart about the best solution found for scenario 3 (about the combined (50%-50%) minimization of both kind of measures, Cmax, and Nt) (adapted from, (Varela, et al., 2022b))

These Gantt charts express possible alternative solutions for jointly scheduling the maintenance tasks and a set of ten lots of production orders (L1 to L10), based on the preference that is given by the decision making team regarding internal oriented performance measures (makespan) (Fig. 15) or external oriented ones (tardiness and tardy tasks) (Fig. 16) or a combination of internal and external measures (makespan and tardy tasks) (Fig. 17). Thus, the developed CMS provides additional flexibility by enabling tochoose the best suited application scenario, by using appropriate scheduling algorithms put available for processing the joints maintenance and production tasks,according to a given industrial context and management preferences or goals of the decision team.

5. Final Discussion

According to a study conducted, and by analysing a set of twenty publications about maintenance and production management a resume of main contributions from the literature were analysed, considering a set of seven main dimensions underlying this study about: dynamic, integrated, real-time, distributed, and predictivemanagement strategies (Varela, et al., 2023), along with time and condition based maintenance,as synthetized in the Table 1.

Table 1. Resume of main dimensions of literature contributions and proposed approach

Dimension / Contribution	Dynamic	Integrated	Real time based	Distributed	Predictive	Time based	Condition based
(Aggarwal, et al., 2018)	X		X		X	X	X
(Do, Assaf, Scarf, & Iung, 2019)	X					X	X
(Aydemir, Acar, 2020)	X		X		X		X
(Bektas, Marshall, & Jones, 2020)	X		X		X		
(Benker, et al., 2021)			X		X		
(Biondi, &Harjunkoski, 2017)	X	X	X		X	X	X
(Lee, &Chen, 2000)		X				X	

Dimension Contribution	Dynamic	Integrated	Real time based	Distributed	Predictive	Time based	Condition based
(Ghaleb, Taghipour, Sharifi, & Zolfagharinia, 2020)		X				X	X
(Kim N-H, An D, & Choi J-H, 2017)			X		X	X	X
(Li, et al., 2019)	X		X		X	X	X
(Luo, et al., 2019)	X		X		X	X	X
(Malhotra, et al., 2016)			X		X	X	X
(Michau & Fink, 2019)	X		X	X	X	X	X
(Mosheiov, & Sarig, 2009)		X				X	
(Rahmati, Ahmadi, & Govindan, 2018)	X	X	X				X
(Sloan, & Shanthikumar, 2000)		X				X	X
(Wang, & Yu, 2010)		X				X	
(Yang, Ma, Xu, & Yang, 2011)	X	X				X	
(Zandieh, Khatami, & Rahmati, 2017)		X					X
(Zhai, B. Gehring, & Reinhart, 2021)	X	X	X		X	X	X
This work	X	X	X	X	X	X	X

The analysed publications listed in the Table 1 show that, on average, 3 to 4 of the dimensions proposed for carrying out the collaborative maintenance and production management are considered. Therefore, it is noticeable that this work is novel and that there is still a gap regarding this kind of contributions in the focused scientific and technological domain.

6. Conclusion

In this paper a group decision making (GDM) approach for maintenance tasks ranking and selection for being jointly scheduled with production orders was put forward. The proposed approach was implemented based on a two-stage assessment method, which makes use of a dynamic multi-criteria decision method (DMCDM). The DMCDM enables to merge and jointly process and analyse maintenance information regarding historical, current and provisional data, based on corresponding subsets of criteria, which are defined according to a group of decision makers that interact on its definition and application of the proposed underlying maintenance tasks processing methodology, which is accessible through a developed collaborative management system (CMS), accessible by a set of entities for enabling joint decision-making. The utilization of the proposed GDM approach was illustrated through an industrial example of application and it revealed to be promising in supporting joint maintenance and manufacturing orders processing, once permitting to rank and select a set of maintenance tasks with highest scores for being jointlyscheduled with production orders by using other functionalities included in the CMS. This is a novel contribution, as far as our knowledge, and based on the study conducted there are no similar contributions in the literature that enable a distributed and dynamic maintenance tasks assessment and selection, based on a DMCDM, for being further jointly programmed with production orders, through the CMS.Besides, the CMSincludes other functionality, namely for predicting maintenance key performance indicators, which are considered through criteria included in the prognostic data processed using the DMCDM, such as mean time before failure. Thus, this works contributes to the maintenance and production orders management scientific domain, which continues lacking of contributions that enable collaborative decision-making, which is considered of upmost importance to promote a sustainable development of companies, and is supported by new technologies underlying the current digital age, being still necessary further developments and industrial applications to be explored.

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