Investigating maintenance operations in Industry 5.0: a cognitive-oriented tasks framework

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Abstract: The Industry 5.0 paradigm aims to improve, through a human-centric approach, the performance of cyber-physical production systems promoted by the fourth industrial revolution. If, on the one hand, the digitisation promoted by the Industry 4.0 paradigm provides many opportunities for improving the performance of production systems, on the other hand, it introduces a high level of complexity for operators in the execution of ordinary activities mainly from a cognitive point of view. The complexity of tasks and the increasing use of innovative technologies could overload the operator with numerous options and efforts to be made in a limited time, requiring decisions that lead to an excessive cognitive workload and reduce human well-being in work environments. In this context, maintenance activities are of utmost relevance; their inherent complexity and the direct dependence of the production performance on their proper and timely execution led to the development of dedicated support technologies and techniques known as Maintenance 4.0 (M4.0). Notably, M4.0 activities are strongly characterised by the above-outlined complexities, especially from a cognitive point of view. To this concern, the present research work consists of developing, through a literature search, a framework of the main M4.0 tasks aiming to identify the perceived cognitive workload according to the operator's profile (i.e., competencies, hard skills, age, etc.). This framework, as mentioned, represents the starting point for more in-depth analyses that will allow the identification of the proper operator to accomplish a high-cognitive M4.0 task by ensuring operator well-being and industrial performance.

Keywords: Industry 5.0, Maintenance activities, Industry 4.0 technologies, cognitive load, framework.

1.Introduction

Building upon the technological advancements of Industry 4.0 (I4.0), Industry 5.0 (I5.0) seeks to enhance the performance of cyber-physical production systems. This evolution is driven by a human-centric approach, emphasizing the importance of human-machine collaboration in leveraging the technologies and principles of the fourth industrial revolution (European Commission, n.d.). If, on the one hand, I4.0 drives advancements in both production efficiency and quality through the development and deployment of advanced technologies (Lucchese et al., 2022), on the other hand it has a key limitation in its neglection of industrial sustainability and worker well-being (Huang et al., 2022; Mignoni et al., 2023). Consistently with the I4.0 paradigm, the traditional view of industrial workers collaborating with automation systems has given way to the concept of the "operator 4.0." (Digiesi et al., 2020). This new paradigm emphasizes the integration of operators within cyber-physical systems, empowering them to leverage and augment their physical and cognitive skillsets (Kaasinen et al., 2020). If, on the one hand, employing technologies to enhance the inherent capabilities of the operator enhances manufacturing system flexibility, (Enrique et al., 2021), on the other hand, this introduces the challenge of managing complex human-machine systems. (Guerin et al., 2019), wherein operators are susceptible to cognitive overload because of the increased complexity of their routine tasks (MADONNA et al., 2019). To overcome this limit, I5.0 promotes social sustainability, respecting planetary boundaries and promoting talent, diversity, and empowerment (Huang et al., 2022). Abandoning a purely profit-oriented perspective, I5.0 is based on three core pillars: a human-centric approach that prioritizes human well-being within production processes, a commitment to sustainability, and the fostering of resilience (Zizic et al., 2022). Consistent with these principles, I5.0 profoundly restructures human tasks, shifting the labour from manual to cognitive (Longo et al., 2020); within the context of a fifth-generation smart factory, skilled workers are expected to perform high-value production tasks, identify and rectify deviations from standardized procedures, and possess a comprehensive understanding of the standardization and legal frameworks governing technology, societal considerations, and management practices (Maddikunta et al., 2022).

In this scenario, one of the main topics that have gained researchers' attention is the employees' attitude towards the digital transformation processes in the maintenance sector. The maintenance tasks represent one of the most expansive investments required for the current industrial transformation, where most companies are experiencing significant worker hesitation to adopt new technologies (Rathi et al., 2022). While not directly contributing to product value, maintenance tasks represent a significant cost burden for companies, ranging from 15% to 70% of their budget depending on the chosen maintenance policy (D. S. Thomas, 2018). Inefficient maintenance policies can have an adverse impact on companies. These negative effects can manifest in several ways, including reduced safety levels, increased occurrences of unplanned downtime, operational inefficiencies, shortened lifespans of assets, and ultimately, escalated costs.

Several factors contribute to the complexity of a maintenance task. These include working within running production processes, facing time constraints, and dealing with complex machinery comprised of several components, each necessitating a distinct understanding of specific methods and procedures (Alhaag et al., 2022). The inherent complexity and criticality of maintenance tasks led to the development of a paradigm known as Maintenance 4.0 (M4.0). According to this paradigm, advanced monitoring systems enable the application of predictive maintenance policies. By minimizing both the cost of maintenance activities and the risk of plant downtime, these policies promote enhanced production efficiency (Zonta et al., 2020). Moreover, the integration of different I4.0 enabling technologies is being explored to improve the effectiveness and management of maintenance operations. The implementation of Augmented Reality (AR) technologies to support the operator in performing maintenance activities is the most significant example in this context (Psarommatis et al., 2023; Zonta et al., 2020). AR can support maintenance tasks, offering step-by-step guidance for diagnostics, inspection, and training operations (Gattullo et al., 2019; Roy et al., 2016).

While I4.0 technologies offer potential to empower operators in handling novel maintenance tasks, their complexity and the integration of innovative technologies can present challenges. Operators may indeed face information overload due to the multitude of options and time constraints, leading to excessive Cognitive Workload (CWL). This aligns with the human-centric focus of the I5.0 paradigm, which necessitates considering CWL during the design of maintenance tasks. Calibrating CWL for maintenance operators during their routine activities can improve working conditions, reduce error rates associated with high CWL, and ultimately contribute to enhanced production performance. However, to achieve this goal, it is necessary to know the characteristics of the main M4.0 tasks, as well as those of the operators that most influence their proper performance. To this concern, the objective of the present work consists of building a framework of the main M4.0 activities. To achieve this, a Systematic Literature Review (SLR) has been conducted to understand, in addition to the tasks reported in the literature, also the characteristics of each task and the contexts in which they have been considered. In this way, it will be possible to develop models and tools that are effective in supporting the assignment of maintenance operations at the industrial scale.

The rest of the paper is organised as follows: in the second section, the research methodology adopted to carry out the SLR and to analyse the obtained results is illustrated. Then, in Section 3, the M4.0 tasks framework is presented and the obtained results are illustrated and discussed. Finally, in section 4, the conclusions of the present work with insights for future studies are provided.

2. Research Methodology

To achieve the objective of this work, i.e., to identify a framework of the main M4.0 tasks, a SLR has been conducted. It effectively gathers all available evidence in the literature to address a specific research question in a thorough and unbiased manner, thereby providing results from which conclusions can be drawn and decisions made (OXMAN & GUYATT, 1993). For carrying out the SLR, the steps recommended by the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) statement have been followed. According to the PRISMA methodology, the phases of which a systematic review process is composed are four, i.e., identification, screening, eligibility, and inclusion (Moher et al., 2009). Two authors have independently read, selected, and analysed the articles to minimize interpretation biases. They have compared their results and harmonized them under the supervision of another author. The combined findings are presented in the current and subsequent sections. Figure 1 provides an overview of the review phases conducted.

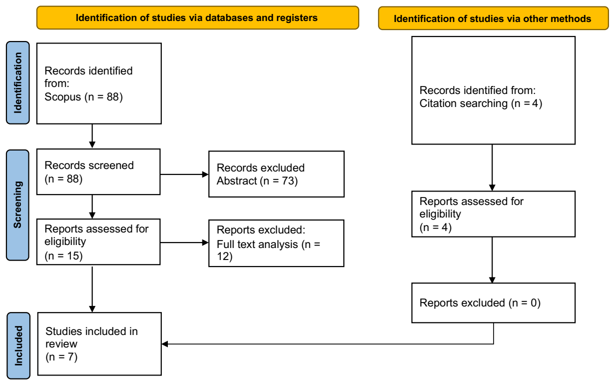

Figure 1: PRSIMA 2020 flow diagram employed for carrying out the SLR. Adapted from (Page et al., 2021)**.**

As it can be observed from Figure 1, in the context of the first phase, a search has been performed on Scopus, due to its broader coverage for industrial engineering (Ren et al., 2019). To this concern, the query "maintenance" AND "task" OR "activity" AND "Industry 4.0" OR "Industry 5.0" AND "description" OR "classification" OR "taxonomy" OR "type" has been employed to conduct the research on documents' title, abstract and keywords. Including all available records without time restrictions, 88 documents have been identified as the sample for the screening phase (i.e., the second step of the PRISMA methodology). The documents have been screened by analyzing their titles and abstracts and have been selected for full-text reading if they met one eligibility criterion., i.e., if they mentioned the description of maintenance procedures, routines, activities or tasks. At the end of the screening phase, 15 papers have been found that meet the eligibility criterion and have been fully read. Subsequently, 12 papers have been excluded for non-conformity with the research conducted, resulting in a sample of 3 papers. Moreover, 4 papers identified through the snowballing approach (Wohlin, 2014) have been added to the final sample of documents (Figure 1). Finally, 7 studies have been included (i.e., the last step of the review process according to the PRISMA methodology) in the final sample of studies on which a descriptive and thematic analysis have been conducted, whose results are illustrated in the following section. Thus, the descriptive analysis has investigated the composition of the sample in terms of publication type and research type, as well as the trend over the years of the papers considered. Moreover, the thematic analysis has been conducted to identify the main themes, findings and gaps described by the selected works, thus interpreting the qualitative results obtained (J. Thomas & Harden, 2008). In accordance with the objective of the present study, selected papers have therefore been analysed based on specific criteria. It is noteworthy that, in the context of the present work, a task has been defined as a sub-component of a maintenance activity. First, the maintenance tasks detailed in each paper have been highlighted. Furthermore, the maintenance policies under which these tasks were recorded have been considered. It is indeed possible to observe a higher occurrence of specific types of tasks depending on the policy adopted (Keith Mobley, 2002). To this concern, the Predictive (Pd), Preventive (Pv) and Corrective (Co) maintenance policies have been considered, being the most widespread both at industrial and academic levels (Molęda et al., 2023). The identified tasks have been moreover classified by their physical or cognitive nature, being this issue of great interest in the context of the present analysis. Additionally, the mention of specific I4.0 technologies has been assessed to understand their correlation with increased CWL on operators (Carvalho et al., 2020). Finally, each maintenance task has been categorized according to the taxonomy proposed by the European technical reference standard EN 13306:2017 (European Committee for Standardization, 2017). Specifically, tasks have been identified that can be considered as Condition Monitoring (CM), Inspection (Ins), Routine Maintenance (RM), and Compliance test (CT).

3. Results and discussions

This section details the results obtained from the literature search conducted in the context of the present work. As far as concerns the composition of the selected sample, it has been observed that the papers cover a period from 2014 to 2022, with a higher frequency in 2017 and 2022 (i.e., 28.57%). This result confirms the timeliness of the topic. Moreover, as for the composition of the sample in terms of type of paper and research conducted, it has emerged that the majority of the selected works are journal papers (i.e., 71.42%) and that in 57.14% of the cases, analytical evaluations applied to real case studies have been considered. In general, however, it can be stated that the findings of this work are of practical relevance, as the rest of the works considered are case studies and application cases. As for the content of the selected papers, their tracked characteristics are reported in Table 1. First, (Gatta et al., 2022) proposed a Deep Learning approach for extracting wind turbine features in order to implement Pd maintenance. Indeed, the authors confirm that the advent of I4.0 technologies (e.g. IoT) and artificial intelligence has increased the interest of both academics and practitioners in predictive maintenance practices as a cost-saving strategy. The authors, consistent with the main objectives of preventive maintenance, have highlighted as a key maintenance task the observation and control of variables that describe the state of the system. (Aust & Pons, 2022) moreover addressed a topical issue, i.e. the evaluation of the improvement offered to aircraft maintenance inspection operations by different advanced technologies. Specifically, the authors considered the inspection activities of engine blades and compared the operator's performance with those of image processing software, artificial intelligence software and 3D scanning. They considered three inspection tasks, which have been included in the proposed framework: inspection based on sample image processing, inspection based on detected image processing and inspection based on physical component analysis. From the statistical analysis conducted on the data obtained from several experiments, the authors found that the operator outperforms advanced technologies in screen-based inspection due to its cognitive abilities, decision-making capabilities, versatility and adaptability to changing conditions, while it performs worse than 3D scanning in part-based inspections. (Salonen et al., 2020) instead developed a case study to demonstrate the relevance of analysing historical data collected in computerised maintenance management systems (CMMSs) for improving the performance of the company's maintenance system. The possession of a high-level basic maintenance system is indeed identified by the authors as a fundamental requirement for the development of an effective predictive maintenance system. In the context of the case study analysed, the authors considered different basic maintenance activities, including fault repair and machine condition monitoring, as shown in Table 1. (Islam et al., 2017) developed a methodology for assessing human error probability in maritime on-board maintenance operations, acknowledging its utmost relevance for safety. Specifically, the authors considered two maintenance routines for proving the proposed methodology, i.e., the maintenance of a marine engine exhaust gas turbocharger and the maintenance of a condensate pump. For each routine, all the tasks to be accomplished were reported, and all of them have been included in the present work. Similarly, (Noroozi et al., 2014) employed the Human Error Assessment and Reduction Technique, i.e., one of the most widespread human error probability estimation techniques, to assess the criticality of pre- and post-maintenance operations. As part of this work, the authors considered two maintenance routines to remove process equipment from service and to return components to service (Table 1). (Shou et al., 2019) developed a methodology to distinguish value added from non-value-added turnaround maintenance activities in a lean manufacturing perspective. To test the developed methodology, they considered the turnaround maintenance activities of a gas plant. Finally, (Senra et al., 2017) developed a scheduling algorithm to be integrated into the CMMSs to assign preventive maintenance tasks to available technicians to minimise global delays. Within the scope of the present work, preventive maintenance activities conducted in a company operating in the automotive sector were included, which were considered by the authors to test the algorithm developed.

Table 1. Framework of the identified M4.0 tasks (Legend: Pd: Predictive, Pv: Preventive, Co: Corrective, Cg: Cognitive, Ph: Physical, CM: Condition Monitoring, Ins: Inspection, RM: Routine Maintenance)

Ref.	Industry	Maintenance activity	Task description	Maintenance policy	Task type	I4.0	EN 13306:2017
(Gatta et al., 2022)	Oil & Gas	Offshore oil wells maintenance	Observation and trend interpretation of controlled variables	Pd	Cg	Machine learning	CM
(Aust & Pons, 2022)	Aircraft	Engine blade inspection	Visual inspection based on the interpretation of images of individual parts (sample images)	Pv	Cg		Ins
			Visual inspection based on interpretation of images of installed parts (images captured within the machine through specific instruments)	Pv	Cg		Ins
			Visual inspection directly conducted on the part	Pv	Ph/Cg		Ins
(Salonen et al., 2020)	Metalworking	Maintenance activities on driveline components for heavy construction vehicles manufacturing machines	Repairing faults	Co	Ph		Rep
			Checking the measured value of system vibrations	Pv	Cg	Sensors	CM
			Checking the measured value of system temperature	Pv	Cg	Sensors	CM
			Checking the measured value for system compressed air leakage	Pv	Cg	Sensors	CM
			Checking the system component geometry measurements	Pv	Cg	Sensors	CM
			Checking the electrical effects measures of the system	Pv	Cg	Sensors	CM
			Checking the thermal characteristics of the system	Pv	Cg	Sensors	CM
(Islam et al., 2017)	Maritime	Preventive maintenance on marine engine exhaust gas turbocharger	Air filter cleaning	Pv	Ph		CM
			Water cooling spaces in the turbine casings cleaning	Pv	Ph		RM
			Bearings and bearing housings cleaning	Pv	Ph		RM
			Turbine side cleaning	Pv	Ph		RM
			Blower side air duct cleaning	Pv	Ph		RM
			Removing and replacing the bearing units	Pv	Ph		RM
			Removing and replacing the rotor	Pv	Ph		RM
			Dismantling the rotor	Pv	Ph		RM
			Reassembling the rotor	Pv	Ph		RM
			Removing the nozzle ring	Pv	Ph		RM
			Nozzle ring replacement	Pv	Ph		RM
			Sealing bushes replacement	Pv	Ph		RM
			Gland strips replacement	Pv	Ph		RM
			Turbine blades replacement	Pv	Ph		RM
			Anti-corrosion plugs and baffles replacement	Pv	Ph		RM
			Ball and roller bearings replacement	Pv	Ph		RM
			Oil pumps with integral lubricating system replacement	Pv	Ph		RM
			Checking the clearances after an overhaul	Pv	Ph/Cg		RM
(Noroozi et al., 2014)	Oil & Gas	Isolating condensate pump on an offshore oil and gas facility	Check lines for fluid and pressure	Pv	Ph/Cg		RM
			Check bleeds/vents for obstruction	Pv	Ph		RM
			Close isolation valves	Pv	Ph		CM
			Lock and tag isolation valves	Pv	Ph		CM

		before maintenance	Depressurize lines	Pv	Ph	CM
			Drain lines	Pv	Ph	CM
			Purge lines	Pv	Ph	CM
			Perform pressure test and isolation leak test	Pv	Ph/Cg	CT
			Open all drains of affected equipment	Pv	Ph	CM
			Perform mechanical isolation (fit slip plates, disconnect lines, etc.)	Pv	Ph	CM
			Re-pressurize lines	Pv	Phy	CM
			Isolate, lock and tag motor from control centre	Pv	Ph	CM
			Test motor for power	Pv	Ph/Cg	CT
			Revalidate permit	Pv	Cg	CM
			Break containment	Pv	Ph	CM
			Testing pressure and isolation at intervals	Pv	Ph/Cg	CT
(Noroozi et al., 2014)	Oil & Gas	Reconnecting condensate pump on an offshore oil and gas facility after maintenance	Check lines and equipment for obstructions	Pv	Ph	CM
			Remove mechanical isolation/connect lines to pump	Pv	Ph	CM
			Remove locks and tags from valves, leaving valves closed	Pv	Ph	CM
(Shou et al., 2019)	Oil & Gas	Major turnaround maintenance of a gas plant	Turbine hot gas path inspection	Pv	Ph/Cg	Ins
			Compressor bearing & seal inspection	Pv	Ph/Cg	Ins
			Compressor major inspection	Pv	Ph/Cg	Ins
			Valve repairs & replacement	Pv	Ph	RM
			Vessel inspections	Pv	Ph/Cg	Ins
			Turbine major inspection	Pv	Ph/Cg	Ins
			Statutory vessel inspection	Pv	Ph/Cg	Ins
			Bearing & seal inspection	Pv	Ph/Cg	Ins
			Valve overhauls, upgrades and replacement	Pv	Ph	RM
			Line and vessel repairs	Pv	Ph	Rep
(Senra et al., 2017)	Automotive	Maintenance activities on automotive production lines	Replacing the Stator and Rotor of the Dispensing Pump	Pv	Ph	RM
			Cleaning the flow tank	Pv	Ph	RM
			Check flow quantity	Pv	Cg	RM
			Replacing Vacuum Pumps	Pv	Ph	RM
			Replace interface needles	Pv	Ph	RM
			O-ring replacement	Pv	Ph	RM
			Cleaning the oven glasses	Pv	Ph	RM

As can be observed from Table 1, a total of 65 maintenance tasks have been identified through the conducted SLR. The first finding concerns the industrial sector to which the tasks belong. In particular, it has been observed that the majority of the tasks (i.e., 46%) belong to maintenance routines carried out in the Oil & Gas sector, followed by routines carried out in the maritime sector (i.e., 28%). This result is in line with what is generally highlighted in the literature. According to (Telford et al., 2011), indeed, Oil & Gas infrastructures, both inshore and offshore, are highly capital intensive, and any failures could lead to significant economic and environmental damage. In this regard, the need for an effective and economically efficient maintenance system is imperative. Furthermore, this study has allowed to understand that Pd maintenance activities are not yet widely considered in the literature. In this regard, it has emerged that only 1.6% of the identified tasks are conducted within the framework of a Pd maintenance policy. This data support what has been previously reported in the literature, i.e., that to effectively and efficiently implement Pd maintenance activities, it is first necessary to possess an organic data collection and monitoring system, and that most companies globally are still working to implement such systems (Lee et al., 2017). Instead, it has emerged that the majority of the identified tasks are carried out within the framework of Pv maintenance policies (i.e., 97% of the total identified tasks, of which 31.8% are CM tasks, 47.7% RM tasks, and 15.9% Ins tasks). From the observation of this result, it is therefore possible to state that it is currently advisable to focus on this type of tasks when developing a tool that finds immediate applicability in the industrial context. Another relevant finding that has been observed in the present study concerns the absolute lack of evaluation of the impact that I4.0 technologies have on the performance of tasks, in terms of support or increase in the level of difficulty, especially from the cognitive point of view. The use of machine learning algorithms and sensors has been indeed mentioned only in the case of two maintenance routines. As regards, instead, the nature of the identified maintenance tasks, it has been possible to observe that 63% of the tasks are of a physical nature, that 20% are of a physical/cognitive nature and that only 17% are of a completely cognitive nature. Although this result might apparently seem to contrast with what is generally stated in the literature, i.e., that in the context of I4.0 tasks are becoming mainly cognitive (Zonta et al., 2020), it is possible to understand how the observed data depends because in almost none of the analyzed cases, as mentioned above, the impact of I4.0 technologies on the performance of maintenance operations has been considered.

4. Conclusions

The objective of this study was to identify a framework of the main M4.0 tasks. A SLR has been indeed conducted to achieve this goal. It led to the overall identification of 65 maintenance tasks, primarily identified in the Oil & Gas sector. However, this study has mainly allowed to understand how Pv maintenance activities are currently the most considered in the literature and how there is a systematic lack of evaluation of the impact that I4.0 technologies have on the improvement or worsening of operator performance in carrying out maintenance tasks. These results offer significant contributions both from a knowledge and a practical point of view.

First, the proposed framework has allowed for a preliminary rationalization of knowledge on the analysed topic. If appropriately integrated, it could constitute a reference point for the development of models and the evaluation of methodologies. The developed framework can also constitute a starting point for practitioners, who could use it to carry out internal analyses, for example.

While this study offers different contributions, it also presents some limitations. First, a very limited number of papers have been selected within the framework of this work, and the results obtained have been analysed according to a limited number of categories. Finally, it is necessary to highlight the lack of the practitioners' point of view for the proposed framework to have global relevance and be validated. In this regard, future studies could focus on integrating the proposed methodology with semi-structured interviews with a sample of practitioners, mainly from the industrial sectors identified as critical. In addition to identifying further maintenance tasks, they could offer a significant contribution, especially regarding the use of I4.0 technologies to support maintenance and could offer insights regarding the change offered by the use of such technologies on operator performance.

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