Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 55-10 (2022) 2318–2323

Maintenance-Free Factory: A Holistic Approach for Enabling Sustainable Production Management

Robert Glawar, Fazel Ansari, Luisa Reichsthaler*, Wilfried Sihn*, Daniel Toth, ***

* *Fraunhofer Austria Research GmbH, Theresianumgasse 7, 1040 Vienna, Austria (Tel: +43 676 888 616 07; e-mail: robert.glawar@fraunhofer.at)*

** *TU Wien, Research Group of Smart and Knowledge-Based Maintenance, Vienna, Austria*

Abstract: For decades, different approaches have been designed and implemented for optimizing maintenance management systems in manufacturing. Especially advancing digitalization is leading to novel data-driven maintenance methods and strategies. However, the envisaged value-added implementation of novel solutions faces several challenges in the industrial context. Despite plausible advantages for manufacturing enterprises, maintenance is not yet considered as an enabler and driver of sustainable and resilient production management. Maintenance-Free Factory (M2F), thereby, is to investigate unexhausted potentials for transforming maintenance to an enabler rather than cost-driven system along manufacturing. Pursuing this line of research, this position paper reflects the perspective of the authors on maintenance management, based on experiences gained from research and practice over the past years. It aims to trigger thoughts on the vision of M2F considering i) profound change in maintenance organization and processes, ii) value-driven application of diagnostics, predictive and prescriptive methods, iii) significant change in the competence profile of maintenance engineers, and iv) a reorientation in strategic mind-set of managers and chief production planners. A key element is exemplary discussed in detail, i.e., the need for a flexible maintenance shift model, which may lead to a significant increase in performance of production systems and increase of overall equipment effectiveness.

Keywords: Digital transformation; maintenance; planning; production management; shift model; industrial data science.

1. INTRODUCTION

What ways can make a difference in the future of industrial maintenance? To answer this question, the term “maintenance-free factory” (M2F) has been addressed by the academic community, especially by the national academy of science and engineering in Germany (Acatech). M2F aims at planning and optimizing production processes with the highest resilience to external and internal disturbances, thus enabling sustainable production management (Henke et al., 2019). However, M2F has not been yet sufficiently explored in the body of knowledge in maintenance and operations management. It is in fact a quite vague and industry-oriented concept that requires scientific foundation. Yet, there is room to critically investigate how this concept can be defined and how it can contribute to the state of the art in maintenance and operations management. This position paper reflects the perspective of the authors on M2F towards laying the ground for future research. In this paper, the concept of M2F emphasizes that maintenance is an integral part of production systems throughout the entire product life cycle, including original equipment manufacturers (OEMs) and machine users.

Manufacturing enterprises, especially asset-intensive industries, aim at increasing the reliability, availability, maintainability and safety of industrial machines, while keeping maintenance costs under control (Bousdekis et. al., 2015 & Golpîra and Tirkolaee, 2019). An increase in product individualization and market volatility while shortening lead times results in increasing complexity in production and maintenance planning. For decades, production and maintenance planning have been mostly considered separately. This lack of a communication channel and integrative modeling and analysis is also evident in the literature of production, maintenance and operations management (Ansari et.al., 2019 & Liu et.al.,2018). For this purpose, it is necessary to consider the relation between maintenance and production planning in strategic, tactical and operative levels. In many cases, production units need to be shut down for maintenance activities, which may lead to a tension between the production and factory maintenance of a company and most importantly affects lead times. On the one hand, a sustainable and resilient production system needs maintenance. On the other it leads to shutting down the operations and therefore causes the loss of production margins, i.e. reduced overall equipment effectiveness (OEE). When planning maintenance, one needs to take production into account and vice versa. Maintenance is often seen as a subsidiary of production processes in the literature (Glawar et.al., 2021 & Budai et.al., 2008). Further, maintenance attempts to impose constraints on the production that it deems necessary to achieve complete equipment reliability. Consequently, the implementation of an optimal maintenance policy is constrained by the demands of production. Focusing on M2F, maintenance should become an enabler and driver of sustainable production management, i.e. integral part of the overall business strategy, and should be coordinated and scheduled within manufacturing activities. Thus, maintenance

10.1016/j.ifacol.2022.10.054

itself should become more robust and flexibly adaptable to production planning (Gyulai et. al., 2018).
To overcome these challenges and to achieve an essential added-value for operation, production and maintenance management, industrial companies mostly rely on the use of data-driven methods and strategies. Especially advancing digitalization is led to novel data-driven and AI-enhanced maintenance methods and strategies (Glawar et.al., 2019; Jasiulewicz et.al., 2020 and Neri et.al., 2018). Using digital tools and advanced-analytics capabilities alongside traditional lean and reliability-centered techniques, they aim to predict and prevent equipment failures, increase productivity, and streamline the management of external contractors (Bousdekis et. al., 2015). However, the value-added implementation of these new solutions has not sufficiently triggered a breakthrough in the industrial context yet. In particular, the large investment, especially on predictive maintenance as e.g. reported in (IOT-Analytics, 2021) has not resulted in major improvements comparing to maintenance strategies without sensing and computing technologies. Considering the above discussion, this position paper examines maintenance from a different, critical point of view. It encompasses thoughts and incorporates practical experiences of the authors on maintenance management specified by introducing the vision of M2F. It paves the way for the optimization of the maintenance management system as a flexible working time model, acting as an integral part of manufacturing systems with the use of data-driven maintenance methods and strategies.

2. MAINTENANCE MANAGEMENT IN RESEARCH AND PRACTICE: WHAT IS YET MISSING?

2.1 Maintenance Management from a scientific perspective

Over the last decades, manufacturing enterprises increased the degree of system and process automation towards meeting competitive market trends, shorter product life cycles and rapid technological and industrial developments. This has been emphasized by the introduction and integration of cyber-physical systems into production and logistic networks (aka cyber physical production systems, CPPS) (Monostori et. al., 2016). To stay in a competitive edge, organizations seek to improve efficiency and effectiveness of production systems, inter alia, by increasing their automation levels, which in turn lead to a greater number of resource consumptions that need to be monitored and maintained. These well-intentioned optimizations result in an increased importance of maintenance to secure the availability of manufacturing system resources and ensure sustainable production management. However, the role of maintenance and its major contribution to the economic success of manufacturing enterprises is commonly underestimated and is mainly characterized as an auxiliary function (Schreiber et. al., 2020). the literature of maintenance and operations management, there are several maintenance strategies with and without sensing and computing technologies, which have been employed and tested throughout the years. These strategies include, inter alia, optimization methods for eliminating the root causes of failures and thus minimizing maintenance requirements. The focus is on improving equipment reliability, while reducing cost of ownership. The chosen strategy can be considered effective when maximizing equipment uptime and facility performance is achieved while balancing the cost of investment for relevant resources (Deighton, 2016).
Focusing on the evolution of data-driven maintenance in the context of Industry 4.0 (known as maintenance 4.0), the use of advanced data analytics methods allows to not only predict the moment or probability of failure, but also prescribe recommendations to avoid such a failure and thus optimizing maintenance schedulers and resources (Jasiulewicz et.al., 2020 & World Manufacturing Foundation, 2021). Further, there are a number of artificial intelligence (AI) approaches enhancing maintenance management. These can be categorized under various terms such as knowledge-based or data-based maintenance (Ansari and Glawar, 2018). Diverse semantic technology and machine learning methods like fuzzy logic, case-base reasoning, neural networks and statistical learning as well as text mining beside operation research methods like genetic algorithms are used to automate the detection of data patterns in a data base, and to develop predictive/prescriptive models to support and automate informed decision making (Ansari et. al., 2019).

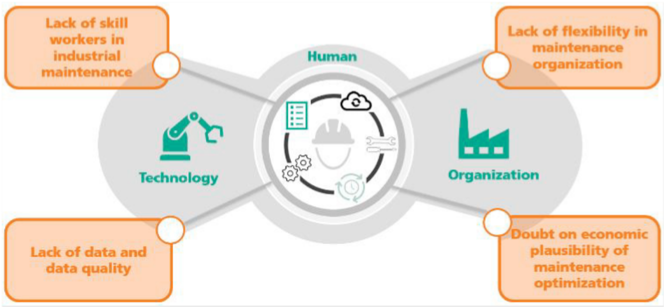

Fig. 1: Scope of research on M2F

2.2 Maintenance Management from a practice perspective

From a practical point of view, a large discrepancy exists regarding the maturity of theoretical maintenance management approaches found in the literature (Henke et al., 2019). While some companies, especially in highly automated and technologically progressive sectors such as the semi-conductor industry, do use many of the existing state of the art approaches, a significant majority of companies, especially small and medium sized enterprises, does not consistently use the available opportunities (IOT-Analytics, 2021). From the authors previous research work and practical experience, this is caused by the following reasons show in Figure 1

i) Doubt on economic plausibility of maintenance optimization: The area of maintenance, and therefore its optimization, is often perceived as not adding value from the current economic perspective (Henke et al., 2019)
ii) Lack of data: The necessary data quality for data-based approaches is often not sufficient (Simard et al.,2019). Especially, the documentation of historical failures is not systematically available in industrial practice or is of inadequate quality or granularity (Jalali et. al., 2019 & Biegel et.al., 2022).
iii) Lack of flexibility in maintenance organization: Even if data-driven and AI-enhanced maintenance

approaches are able to provide a better understanding when a failure might happen, the working environment is oftentimes so inflexible that it is not possible to perform the necessary maintenance activities outside of the production process (Fusko et.al, 2018). Conflict often even arises between the production planning department and the factory maintenance whether and when a time-slot for necessary maintenance activities may be found (Cao et.al, 2021).

iv) Lack of skilled workers in industrial maintenance: Beside technological and organizational issues, the shortage of properly managed competency requirements in digital working systems poses a problem (Kohl et. al., 2021).

To tackle these challenges, different approaches such as Total Productive Management (TPM), Reliability-Centered Maintenance (RCM) and Lean Maintenance have been persuaded to optimize maintenance management (Biedermann and Kinz, 2019). However, a paradigm shift towards a "strategic competitive factor" of maintenance has not taken place yet (Sihn et. al., 2021).

3. FOUR PILLARS OF M2F

In a nutshell, M2F means i) to reduce the proportion of technical and technological malfunctions through the consequent and effective use of (data-driven and AI-enhanced) methods and ii) to make maintenance activities independent from the production process as far as possible, by optimization of flexible shift planning between previous equally considered production and maintenance planning procedures (Sihn et. al., 2021). This requires re-orientation in strategic mind-set of maintenance and production management as well as organizational changes in strategic, tactical and operative levels. Further, empowering blue- and white collars through de-skilling and up-skilling is essential. The Four Pillars of M2F based on Human-Technology-Organization concept are depicted in Figure 2.

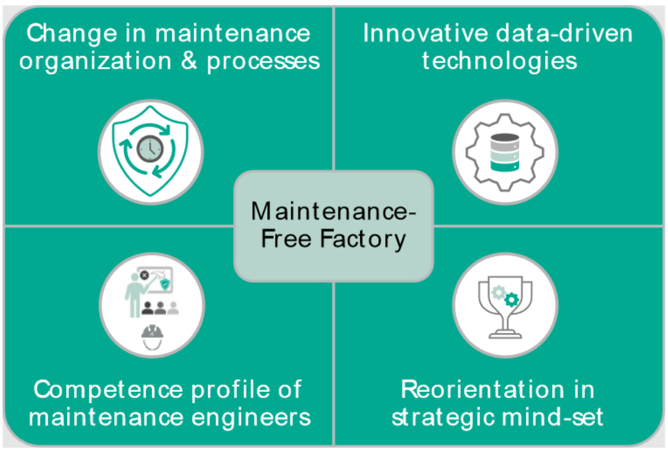

Fig. 2: Four Pillars of M2F based on Human-Technology-Organization concept

It is worth noting that by a M2F it is not intended to consider the concept of self-healing equipment. Rather the vision aims at answering the questions "When is it to be done?" and "What is to be done?" In a cost and resource efficient way to ensure sustainable production management and avoid availability, performance and quality losses. In the body of knowledge in maintenance and operations management, literature review articles focus on future maintenance organization and management e.g. (Illankoon and Tretten, 2021 & Paprocka 2019), lacking holistic view of production and organizational structures or addressing only partial aspects of the future maintenance challenges.

3.1 Profound change in maintenance organization and processes

Considering an overall optimum in terms of productive time, maintenance planning and production scheduling are strongly inter-dependent, affecting both available production time and failure probability (EL Khakfi et.al., 2017). In order to address the challenges regarding M2F, mature planning of rule-based, anticipatory maintenance measures is required, whereby the maintenance activities are to be adapted to the production planning. Maintenance activities need to be detached from production processes by using unproductive times of the production. Maintenance forecasting, planning and strategy should avoid downtimes, failures and waste of any kind as best as possible, to set up a continuous improvement process and to sharpen the view of the entire company process (Henke et.al, 2019).

On an organizational level a profound change in leadership and management processes is necessary on order to highlight how maintenance is an essential driver to achieve a sustainable competitiveness. In front of this maintenance plays an important role in creating resilient production systems. To achieve this goal organizational aspects such as process agility and efficiency, reduction of reaction times or decentralization needs to be considered in a holistic way. Furthermore, related areas and functions, such as human resource management or external service technicians, also need to be addressed (Reichel et al. 2018).

3.2 Implementation of innovative data-driven maintenance technologies

Continuous evaluation of the captured data makes it possible to determine the optimal time for an upcoming maintenance. Automatic reports for maintenance scheduling and proactive repairs reduce maintenance time and decrease overall maintenance costs (Jasiulewicz et.al., 2020). The aim of data-driven approaches is to enhance maintenance strategies by introducing predictive or prescriptive capabilities (Matyas et. al., 2017). This enables a reduction in downtimes and a related increase in uptime. Thus, despite increasing complexity, decisions on implemented measures can be made proactively, thereby increasing plant productivity and reducing costs. Focusing on M2F, the increased planning reliability and availability linked to sustainability factors is of particular importance. This makes it possible to largely avoid a malfunction for a predefined interval or to ensure, through integration with product planning, that no waste is caused by a possible malfunction. This improved decision quality enables maintenance to be combined, performed at waste-free times, or at least the resulting impact on productivity to be minimized (Ansari and Kohl 2022). Although data-driven approaches are able to prevent a significant proportion of occurring unplanned incidents, they won't be prevented entirely. This is caused by common statistical deviations or failures which are derived from human error. In this case, it is necessary to being able to react to the new conditions as quickly as possible, taking into account all relevant decision factors (Karner et.al, 2019). Industrial maintenance, this task is not trivial to accomplish. Maintenance planner must make a decision at short notice that is coordinated with production planning. Complementary optimization parameters, such as resource-efficient production or optimized use of machines and equipment, usually do not play a role at this point due to the resulting planning complexity. By using data-driven approaches such as AI-enhanced maintenance planning it is possible to make an optimal decision in real time, taking into account all decision parameters (Giner et.al., 2021). In summary, data-driven maintenance and the use of AI methods enable not only an increase in availability but also an increase in product quality and a stabilization of production processes, thus making a significant contribution to achieving the vision of M2F. At the same time, AI-enhanced maintenance planning facilitates an optimized response if, despite everything, an unplanned disruption occurs in the production system.

3.3 Significant change in the competence profile of maintenance blue and white collars

Due to the significant increase in digitization and automation, as well as the complexity of production equipment, competence requirements for maintenance personnel have been changing, in both front-end (i.e., blue-collars at shopfloor) and back-end (i.e., white-collars responsible for planning, monitoring, controlling and management). Maintenance managers in the era of Industry 4.0 face great challenges in terms of reducing undesired outputs (e.g., CO2 emissions), reducing equipment downtime, lowering costs, complying with desired production lead times and doing it all with less risk to safety, cybersecurity while avoiding damages to the environment. The competence profile of blue-collars is also under a massive change due to integration of intelligent assistance systems like conversational AI and physical assistance systems in the maintenance work systems. On the one side, they gain benefits from technologies to improve work efficiency and quality e.g., in documentation (Ansari et.al., 2021). On the other, they need to become more flexible in terms of knowledge sharing and work-integrated learning (Nixdorf et.al, 2021). Considering Industry 4.0' technologies especially ICT and Operational Technologies (OT), the capability of data collection, analysis and visualization is significantly increasing. Hence, maintenance blue- and white collars, and consequently business managers, may benefit from the value of data in troubleshooting, planning, monitoring and controlling activities, respectively. Effective analysis of data in circular value chain enables OEMs and machines users to deepen their understanding of equipment, processes, services, employees, suppliers, and regulators requirements (Jasiulewicz et.al., 2020).
Besides, the M2F addresses a contradiction that needs to be explained. In production and manufacturing lines, people are still needed to maintain, monitor and guarantee safety of equipment and production machines. In this sense, maintenance and repair tasks in the M2F will not become redundant but change its nature. In the future, emerging competences and skills will be required while part of today competence and skill sets will be denied. However, maintenance tasks will increasingly tend towards cognitive tasks and will be strongly characterized by the knowledge-transfer from experienced employees in production systems (Ansari, 2019). Accordingly, the understanding of the role of maintenance is also changing, i.e., the entire value-added chain and the maintenance circular ecosystem will have to be taken into account.

3.4 A reorientation in strategic mind-set companies

Maintenance involves sensitive decision-making that affect the entire production systems. One may distinguish between (i) the long term strategic and maintenance concept, (ii) medium term planning, (iii) short term scheduling, and finally (iv) control and performance indicators. Major strategic decisions concerning maintenance are made in the design process of systems. What type of maintenance is appropriate and when should it be done? This is laid down in the so-called maintenance concept during product design, aka maintainability and maintenance-by-design. Many optimization models address this problem and the relation with production is implicit in few of them (Budai et.al., 2008). In M2F, the goal of maintenance is to help shape a sustainable and resilient production system (Henke et.al., 2019). To achieve this, new concepts like resilience should be further integrated into the context of maintenance.
To this end, it will be necessary to invest more time and effort in the planning and design of the production system in the future. By means of methods such as weak point analysis, condition assessments, load measurement or failure mode and effects analysis (FMEA), the risk of unproductive unplanned disruptions can be reduced, and any failure consequences can be mitigated (Öhlinger et.al., 2021).
Another opportunity for minimizing malfunctions is the targeted cooperation between the plant manufacturer and machine users. This opens up a wide range of opportunities for manufacturers in the area of digital business models and innovative service concepts. Likewise new stakeholders e.g., "insurance companies" should be involved in the maintenance ecosystems, as the concept of failure-based maintenance has been recently presented in Ansari et.al., 2020.
In this context, approaches and solutions are necessary to show how much maintenance can influence the long-term competitiveness of a company and business success of OEMs. The challenge here is to make the value contribution of maintenance measurable and thus achieving a corresponding appreciation at management level and a rethinking towards a strategic competitive factor. Instead of the question "What costs does maintenance cause?", the question "What costs does maintenance prevent?" is being investigated (Matyas 2017 & Biedermann and Kinz, 2019).

4. FUTURE RESEARCH AGENDA ON M2F: FLEXIBLE SHIFT PLANNING

To realize M2F in practice, flexible scheduling is a promising area of investigation, which may reveal yet hidden improvement potentials for manufacturing enterprises. The function of predictive scheduling is to obtain stable and robust schedules for a production facility (Paprocka, 2019), in which maintenance is adjusted to production. In particular, flexible maintenance delas with rebuilding the concept of shift models. Currently, the concept of shift models considers maintenance outside of productive production hours and is based on a working shift that is intrinsically detached from production. In M2F, the working hours and the shift schedule should be closely coordinated with the production schedule, so that the factory maintenance is always on standby during the production processes but can also carry out maintenance activities outside production hours or during break times, depending on the shift. This is however not a trivial change as it confronts several regulatory and management barriers. To explore the possibilities, three potential use-cases are sketched below and summarized in Table 1.

. Table1: Overview of Use-Cases

Use Cases	Characteristics of the working time model	Expected benefits
Single shift production	-Offset of shift models -Possible Overlap of the shift models -On-call service for maintenance outside of maintenance shift model	-Planned maintenance activities are carried outside the production time
Three Shift Production	-Offset of break times -Proactive use of (production) shift changes for maintenance	-Unproductive times, such as shift changes or breaks are used for maintenance
Communication between maintenance and production planning	-Rule-based communication	-Reduction of manual efforts for planning -Holistic optimization

4.1 Use Case: Intelligent working models for single shift production

To give an example, in single-shift production in many cases in classical batch production maintenance and production are still using the same working model. In M2F, the maintenance work should be carried out before or after the production processes. This is made possible due to an independent maintenance shift that operates at different working hours than the regular production shift. During production operation an On-call service unit of maintenance engineer is responsible for carrying out unplanned reactive maintenance activities.
Effort, resulting for the implementation of an additional shift model, will be outweighed by the added efficiency from working outside if the production time. To still ensure the important direct communication between production and maintenance staff in the regard of knowledge exchange and sustainable problem solving, it is essential keeping a certain overlapping between the two shift models.

4.2 Use Case: Intelligent working models for three Shift Production

In the case of a three-shift production e.g., in automotive production, planning maintenance activities is significantly more complex and requires more effort than in the case of a single shift production. Maintenance activities especially inspections and non-time intensive service activities should be scheduled during the shift changes or breaks of the production employees. To justify investment for data-driven maintenance technologies, unproductive downtimes and associated costs should be minimized in the future, i.e., return on investments. For this purpose, the scheduling horizon should first be divided into several periods to ensure that a machine is still maintained after a longer period of use. Then the scheduling of maintenance activities is regularly planned within the planning period, even if one machine may fail due to its degradation and usage. The consequent repair and replacement will make machines unavailable, which disorders production scheduling. Hence, how to schedule maintenance planning to keep machines in good operation condition and high reliability, and further make production scheduling based on machine maintenance has become a vital issue for the achievement of intelligent manufacturing.
The M2F would require that the shifts of the production staff and the maintenance staff are planned flexibly, instead of running simultaneously. This means that unproductive times, such as shift changes or breaks in production should be scheduled for maintenance activities.

4.3 Use Case: Rule-based communication between maintenance and production planning

In many cases, it is not possible to come up with an intelligent working model which allows to shift maintenance activities outside of production times. In this case it is still possible to optimize the way of communication between maintenance planning and production planning.
Using a rule-based communication the often-inefficient friction between planners can be mitigated. To give an example: Based on either experience knowledge or data-driven results, the maintenance planner does request a time-slot for a maintenance activity at least three months in advance. Based on an integrated planning approach, the production planning department offers a week slot (+ / - 14 days) for the planned activity. Latest 7 days before the planned maintenance activity, a concrete day slot is set, and maintenance is informed. At least 2 days before the service, a concrete time slot is set and maintenance is informed. Finally, maintenance is informed whenever the last production-lot prior to the planned maintenance is processed and therefore, the final preparation for the maintenance activities may be started.

The above discussion briefly provides perspectives of the authors on M2F to rebuild maintenance for sustainable and resilient production management. Due to the ongoing nature of research, the four pillars of M2F still requires deeper investigations, especially to provide a solid definition and related frameworks. This shapes the main direction of future research focusing on flexible shift planning as a plausible application area.

REFERENCES

Ansari, F., Glawar, R., 2018. Knowledge-based maintenance, in: Matyas, K. (Ed.), *Instandhaltungslogistik. Qualität und Produktivität steigern*, 7th Edition, 7., erweiterte Auflage ed. Hanser, München, pp. 318–342.

Ansari, F., (2019). Knowledge Management 4.0: Theoretical and Practical Considerations in Cyber Physical Production Systems. *IFAC-PapersOnLine* 52 (13)

Ansari, F.; Glawar, R.; Nemeth, T. (2019): Prima: A prescriptive maintenance model for cyber-physical production systems. *International Journal of Computer Integrated Manufacturing*, Vol. 32, 4-5, pp. 482–503

Ansari, F.; Nixdorf, S., Sihn, W. (2020). Insurability of Cyber Physical Production Systems. *IFAC-PapersOnLine* Volume 53, Issue 3, 2020, pp. 295-300.

Ansari, F.; Kohl, L.; Giner, J.; Meier, H. (2021) Text mining for AI enhanced failure detection and avail-ability optimization in production systems, *CIRP Annals - Manufacturing Technology*, Vol. 70, Issue 1, 2021, pp. 373-376.

Ansari, F.; Kohl, L. (2022) AI-enhanced Maintenance for Building Resilience and Viability in Supply Chains, Supply Network Dynamics and Control, A. Dolgui, D. Ivanov & B. Sokolov (Eds.), *Springer, (In Press)*

Biedermann, H. and Kinz, A. (2019). Lean smart maintenance—value adding, flexible, and intelligent asset management. *BHM Berg-und Hüttenmännische Monatshefte*, 164(1):13–18.

Biegel, T.; Jourdan, N.; Madreiter, T.; Kohl, L.; Fahle, S.; Ansari, F.; Metternich, J. (2022). Combining process monitoring with text mining for anomaly detection in discrete manufacturing. *Proceedings of Conference on Learning Factories* , April 11-13

Bousdekis, A.; Magoutas, B.; Apostolou, D.; Mentzas, G. (2015). A proactive decision making framework for condition-based maintenance. *Industrial Management* 115(7), 1225–1250.

Budai, G., Dekker, R., & Nicolai, R. P. (2008). Maintenance and Production: A Review of Planning Models. *Complex system maintenance handbook (*pp. 321–344). London: Springer.

Cao, X.; Li, P.; Duan, Y. (2021). Joint Decision-Making Model for Production Planning and Maintenance of Fully Mechanized Mining Equipment. *IEEE Access*, 9, 46960-46974.

Deighton, M.G., (2016). Maintenance Management, in:, Facility Integrity Management. *Elsevier*, pp. 87–139.

El Khalfi, A.; Aarab, S.; El Barkany, A., (2017). The integration of maintenance plans and production scheduling taking account of outsourcing: a literature review. *IJPQM* 21 (1)

Fusko, M.; Rakyta, M.; Krajcovic, M.; Dulina, L.; Gaso, M.; Grznar, P. (2018). Basics of designing maintenance processes in industry 4.0. *MM Science Journal*, 2018(3), 2252-2259.

Glawar, R.,; Ansari, F.; Matyas, K. (2021). Evaluation of Economic Plausibility of Integrating Maintenance Strategies in Autonomous Production Control: A Case Study in Automotive Industry. *IFAC-PapersOnLine,* 54(1), 43-48.

Glawar, R.; Ansari, F.; Kardos, C.; Matyas, K.; Sihn, W. (2019). Conceptual Design of an Integrated Autonomous Production Control Model in association with a Prescriptive Maintenance Model (PriMa). *Procedia CIRP*, 80, 482–487.

Giner, J.; Lamprecht, R.; Gallina, V.; Laflamme, C.; Sielaff, L.; Sihn, W. (2021). Demonstrating Reinforcement Learning for Maintenance Scheduling in a Production Environment. *26th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)* (pp. 1-8). IEEE.

Golpîra, H.; Tirkolaee, E. B. (2019). Stable maintenance tasks scheduling: A bi-objective robust optimization model. *Computers & Industrial Engineering*, 137

Gyulai, D.; Pfeiffer, A.M Gallina, V. (2018). New perspectives in production control: situation-aware decision making with machine learning approaches. *CIRP STC-O*

Henke, M., Heller, T., & Stich, V. (2019). Smart Maintenance - Der Weg vom Status quo zur Zielvision. *Acatech Studie*

Illankoon, P.; Tretten, P.; (2021). Collaborating AI and human experts in the maintenance domain. *AI & Soc* 36 (3), 817–828.

IoT Analytics GmbH (2021). *Predictive Maintenance Market Report 2021-2026*. Retrieved from https://iot-analytics.com/product/predictive-maintenance-market-report-2021-2026/

Jalali, A.; Heistracher, C.; Schindler, A.; Haslhofer, B.; Nemeth, T., Glawar, R.; De Boer, P. (2019). Predicting time-to-failure of plasma etching equipment using machine learning. *IEEE International Conference on Prognostics and Health Management* (ICPHM) (pp. 1-8).

Jasiulewicz-Kaczmarek, M., Legutko, S., & Kluk, P. (2020). *Management and Production Engineering Review. Production Engineering Committee of the Polish Academy of Science*s, Polish Association for Production Management.

Karner, M.; Glawar, R.; Sihn, W.; Matyas, K. (2019). An industry-oriented approach for machine condition-based production scheduling. *Procedia CIRP*, 81, 938-943.

Kohl, L.; Fuchs, B.; Berndt, R.; Valtiner, D.; Ansari, F.; Schlund, S. (2021). Künstliche Intelligenz im Kompetenzmanagement, *ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb*, Carl Hanser Verlag, 116 (7-8), pp. 534-537.

Liu, Q.; Dong, M.; Chen, F. F. (2018). Single-machine-based joint optimization of predictive maintenance planning and production scheduling. *Robotics and Computer-Integrated Manufacturing*, 51, 238–247.

Matyas, K., Nemeth, T., Kovacs, K., Glawar, R., 2017. A procedural approach for realizing prescriptive maintenance planning in manufacturing industries. *CIRP Annals* 66 (1), 461–464.

Monostori, L.; Kádár, B.; Bauernhansl, T.; Kondoh, S.; Kumara, S.; Reinhart, G.; Sauer, O.; Schuh, G.; Sihn, W.; Ueda, K. (2016). *Cyber-physical systems in manufacturing. CIRP Annals* 65 (2), 621–641.

Neri, A., Cagno, E., Di Sebastiano, G., & Trianni, A. (2018). Industrial sustainability: Modelling drivers and mechanisms with barriers. *Journal of Cleaner Production*, 194, 452–472

Nixdorf, S.; Madreiter, T.; Hofer, S.; Ansari, F. (2022). A Work-based Learning Approach for Developing Robotics Skills of Maintenance Professionals. *Proceedings of Conference on Learning Factories (CLF 2022)*, April 11-13, 2022

Öhlinger, F., Friedmann, A., Adolf, T., Ryll, F., Toth, D., Glawar, R., 2021. Vorgehensmodell für risikobasierte Resilienzstrategien. *Zeitschrift für wirtschaftlichen Fabrikbetrieb* 116 (4), 198–202

Paprocka, I., 2019. The model of maintenance planning and production scheduling for maximising robustness. *International Journal of Production Research* 57 (14), 4480–4501.

Reichel, J., Müller, G., Haeffs, J., 2018. Betriebliche Instandhaltung. *Springer Berlin Heidelberg*, 430 pp.

Schreiber, M., Schutte, C., Braunreuther, S., Reinhart, G., 2020. A performance measurement system for integrated production and maintenance planning. *Procedia CIRP* 93,

Sihn W.; Glawar R.; Reichsthaler L.; Wakolbinger G. (2021): Die Vision der „instandhaltungsfreien Fabrik"; Von der Vision zu einem neuen Verständnis der Instandhaltung, *34. internationale Forum für industrielle Instandhaltung*, ÖVIA

Simard V.; Rönnqvist M.; Lebel L.; Lehoux, N. (2019). A general framework for data uncertainty and quality classification. *IFAC-PapersOnLine*, 52(13), 277-282.

World Manufacturing Foundation (2021). AI as an enabler for long-term resilience in manufacturing. *Emerging Topics for long-term resilience in manufacturing.* Retrieved from: *https://worldmanufacturing.org/back-to-the-future-emerging-topics-for-long-term-resilience-in-manufacturing/*