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Original Research Article

Advancing predictive maintenance: a comprehensive case study through industry 4.0

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ABSTRACT

The paper is focused on predictive maintenance in the automotive industry with a specialization in technologies related to Industry 4.0. The emergence of predictive maintenance with Industry 4.0 technologies is also called Maintenance 4.0. The article describes specific Industry 4.0 technologies, such as supervisory control and data acquisition (SCADA) and Predictive Maintenance (PdM), that are being implemented in manufacturing companies. The sample for the case study consisted of a paint shop from the automotive sector that operates in Turkey. In the data collection step, SCADA collected data from pressure sensors to create a historical database for PdM. The purpose of this article is to illustrate, through a case study, the importance of PdM using SCADA using Industry 4.0 instruments such as the Internet of Things and big data. 18 filters, which were replaced every 6 months during preventive maintenance, are now replaced at different intervals through PDM after this study. Based on SCADA data, a total of 2 filters experience blockage in both the primer and topcoat paint processes every 6 months. Over a 12-month period, an extra 9 filters are blocked across all processes. Furthermore, within a 24-month timeframe, a total of 7 more filters become blocked in the entirety of the operational processes. The results showed that the PdM combination increased the effectiveness of care by 45.83%.

Keywords: Automotive Sector, Industry 4.0, Maintenance 4.0, PdM (Predictive Maintenance), SCADA Smart Systems.

1. Introduction

In recent years, Industry 4.0 has been extended to new trends suggesting a new revolution based on the real interaction among manufacturing robots and humans or machines themselves. Industry 4.0 includes the following: smart factories, cyber-physical systems, self-organization, new systems in distribution and procurement, new systems in the development of products and services, adaptation to human needs, and corporate social responsibility. Also, Industry 4.0 consists of several modules such as procurement, logistics, maintenance, finance, and controlling (1, 2, 3, 4). Maintenance activities, which are the main subject of this article, are one of the fundamental components of the production system. It can be claimed that optimization of maintenance and the integration between maintenance and production make the factory smart. In this respect, predictive maintenance (PdM) plays an important role in Industry 4.0. The emergence of PdM with Industry 4.0 technologies is also called Maintenance 4.0. Maintenance 4.0 can be defined as the next application in the strategy for the maintenance of production equipment. PdM for Maintenance 4.0 is a method of preventing asset failure by applying advanced analytic techniques to big data, including technical conditions, usage, environment, maintenance history, and similar equipment. In addition to this approach, it can provide significant advantages such as quality, safety, availability, and cost reduction for industrial processes (1, 2, 5-8).

There are a lot of reports focused on the application of predictive maintenance, which is based on the knowledge from manufacturers of machines and equipment, the experience of engineers, and feedback learned from past maintenance events (7, 9-17). Due to the global automotive industry having become highly competitive, there has been keen interest in PdM theoretical studies for manuscripts (18, 19). Although PdM is an important issue in the automotive industry, previous research has not addressed it adequately as a case study. This field lacks sufficient case studies, making this study original. Through a case study, this paper will exemplify the significance of predictive maintenance concepts with root-cause failure analysis with technological advancements like SCADA systems, the Internet of Things (IoT), and big data.

2. Theoretical Background and Related Work

Maintenance has long been recognized as a crucial aspect of ensuring the reliability and longevity of physical assets. The historical evolution of maintenance approaches reflects the changing needs of industries and the continuous quest for enhanced efficiency and cost-effectiveness.

Maintenance has evolved over the years to meet the demands of changing business trends. In today's technological era, it has become even more crucial for businesses to embrace digital transformation in maintenance (20, 21). Accordingly, Figure 1 illustrates the historical development of maintenance over time (13).

The earliest known maintenance practices, including **reactive and primitive** preservation techniques, date back to ancient civilizations.

Figure 1 Towards to PdM (22)

These techniques were mainly reactive, meaning that they addressed issues only after they had already occurred. The focus was on corrective maintenance, with very little attention paid to preventive measures (23, 24, 25). The advent of the Industrial Revolution marked a paradigm shift in maintenance strategies. With the introduction of automated production, **preventive maintenance** became more popular. The maintenance involved scheduling regular inspections and repairs to prevent breakdowns and reduce disruptions to production processes. The goal was to improve asset reliability and decrease downtime (9). The maintenance practices went through rapid development during World War II due to the challenges it posed. During this period, the concept of **PdM** started to emerge. Maintenance teams utilized advanced technologies like vibration and oil analysis to predict and prevent potential failures. When implemented correctly, PdM can be successful on appropriate components. Over the last few decades, there have been significant advancements in sensor technologies, data analytics, and the IoT and maintenance 4.0 (PdM) emerged. These technological advancements have brought a revolution in maintenance practices. Condition monitoring has become highly sophisticated, allowing real-time tracking of equipment health. This shift towards condition-based maintenance has enabled organizations to optimize their maintenance schedules and reduce unplanned downtime (25). With the widespread use of PdM in businesses, standardization will occur, and **adaptive maintenance** will emerge.

In recent years, the field of PdM has garnered substantial attention from researchers and practitioners alike. The paper by Cachada (14) discusses the concept of "Maintenance 4.0," which is also known as Predictive Maintenance. It highlights the increasing importance of maintenance in manufacturing methods and explains why maintenance strategies are shifting towards a predictive and constructive approach. Fernández del Amo et al (26) conducted a literature review to analyze the use of Augmented Reality in the maintenance field for knowledge transfer. Smith's (13) comprehensive review sheds light on the evolution of maintenance strategies, emphasizing the growing importance of predictive approaches. According to Smith (13), PdM stands out as a transformative concept in the realm of machinery management. New review papers such as (7, 27) analyze the evolution of maintenance through Industry 4.0 technologies, also known as Maintenance 4.0. These papers highlight the progressive evolution, and the current methods used for maintenance during the fourth industrial revolution. Zhang et al (28) have provided important insights into the effect of PdM on the lifespan of machines. Their study offers evidence that a properly executed PdM plan can significantly prolong the overall lifespan of industrial machinery. The research conducted by Jones and Brown (10) focuses on the technological advancements that have made PdM a leading practice in industries. Their work highlights the integration of sensor technologies, data analytics, and artificial intelligence in monitoring real-time machine conditions. Gupta and Kumar (9) recently published a paper that highlights the importance of big data and artificial intelligence in predictive maintenance. The study emphasizes the need for these advanced technologies to analyze large datasets and make accurate predictions, further establishing the effectiveness of PdM strategies.

In conclusion, researchers' works collectively underscore predictive maintenance's transformative power in optimizing industrial processes, minimizing downtime, and ensuring machinery longevity. Previous research has not to adequately addressed PdM as a case study, resulting in a lack of sufficient case studies. This study is uncommon in filling this gap in the field.

3. Research Method and Outline of The Paper

The industrial case study is situated in the paint shop within a heavy automotive manufacturing site. The paint shop has been operating since 1986, with alternating production schedules of two or three shifts depending on the production volume.

Maintenance procedures before 2022 involved dismantling the machines and carrying out preventive maintenance by wiping them clean. This approach was based on knowledge from the equipment manufacturers, the experience of engineers, and feedback from previous maintenance events. As a part of the preventive maintenance strategy, maintenance activities are carried out during summer and winter breaks when the entire manufacturing site is shut down for six-month periods. The pores of the filters in the facility fill up over time, causing a phenomenon called "dust filter blockage". Subsequent to contamination, a decline in the filter's cleaning capacity is observed, prompting the need for replacement. These filters are subject to periodic replacement, occurring every six months, in alignment with established preventive maintenance strategies. Preventive maintenance was being implemented because there were no smart technology features for the filters that could provide real-time pollution status. Because preventive maintenance is based on the experience of maintenance workers, there were also doubts that the made this maintenance was as effective as expected. Additionally, the maintenance process is disrupted when the employee leaves the job. One of the most important problems was that this period, which was 6 months in the annual production of 30,000 products, could not change linearly when the production quantity changed. In other words, the maintenance period, which was 6 months for a production of 30,000 units, was not 9 months for a production of 20,000 units. Unsystematic calculations of this nature incur both temporal and financial expenses. The absence of standardized parameters guiding these initiatives, primarily undertaken by maintenance personnel, may have led to premature and overly frequent maintenance cycles for the machinery. Conversely, delays in maintenance could precipitate machine malfunctions, consequently disrupting shipments as the paint shop process halts. As many problems existed in preventive maintenance, an improvement initiative was started in 2022. The paint shop process was identified as the root cause of the problems. Defective products were produced, especially when the filters in the paint shop were blocked. The assembly line consists of 6 independent paint shops that are highly automated with robots. Paint shop including KTL (cataphoresis coating), KTL sanding, PVC (polyvinly clorür), primer, topcoat paint, and wax.

In this case study, five essential steps were followed to apply PdM. There are approaches to structure solutions for problems that require machine learning in these steps. The SCADA is used as smart technology in PdM. SCADA systems are essential for modern industrial processes, providing real-time monitoring, control, and data acquisition capabilities. They enable centralized control and monitoring, facilitating seamless operations and data-driven decision-making. SCADA is a system that consists of three main components. Firstly, the Supervisory System, which is the core of SCADA, allows operators to monitor the process in real-time, receive alarms, and control various aspects remotely. Secondly, Remote Terminal Units (RTUs) are placed in the field, and they collect data from sensors and actuators, transmitting it to the supervisory system. Lastly, SCADA relies on robust communication networks to transmit data between the supervisory system and the RTUs (29). Figure 2 illustrates the method and workflow of a PdM of paint shops.

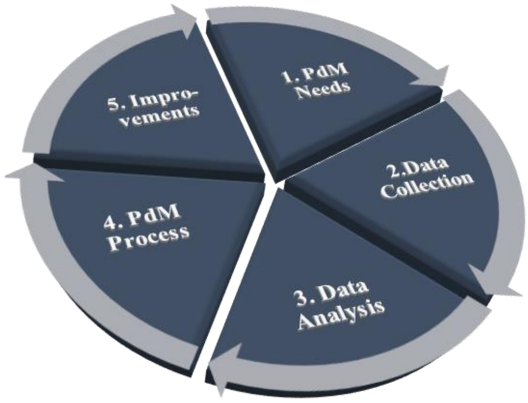


Figure 2 PdM Cycle

The first step consists of understanding the problems of the PdM as well as the need to solve them. SCADA allows operators to monitor critical parameters in real-time and promptly respond to deviations. In this step, it defined a list of potential failure types. **In the data collection step**, data is collected by pressure sensors and transferred to SCADA. The SCADA collected data from sensors to create a historical database for performance analysis and predictive maintenance. **The data analysis phase** includes definitively defining which data to analyze, identifying the data, and correlating it to its meaning. After data analysis, the paint shop data was visualized in the SCADA system. Thus, users could remotely control devices and processes through the SCADA system to optimize operations and ensure safety. **The PdM process** the main step includes selecting relevant data, using the prepared data from the previous analysis step as input, and providing the necessary output. This step is the most important step in the entire PdM cycle. Each step of the PdM cycle described above should be precisely considered. Failure to complete any step will affect subsequent steps and render all efforts futile. The SCADA systems enhance operational efficiency by providing a comprehensive view of the industrial process, minimizing downtime, and optimizing resource utilization. **In the improvements phase,** after initiating a root-cause failure analysis exercise in the paint shop, an improvement initiative was started in 2022 to address clogging problems that persisted in the filter system. The examined SCADA visuals clearly indicated that the surrounding area contained contaminants in the form of dust. The possibility of excessive dust in the paint shop was a constant concern due to its uncontrollable nature. Three improvements were gradually implemented in 2022: (1) changed maintenance strategy (PdM); (2) added SCADA screens; (3) measured PdM efficiency.

4. Results and Discussion

PdM needs

Having a clear understanding of needs lays the foundation for the following stages of the study. Identifying maintenance needs often requires a thorough analysis of historical data, equipment performance, and industry-specific requirements. To find out which process needs PdM the most the root cause, problem-solving techniques such as the Five Whys analysis and Pareto Diagram were utilized and recommended by scientists (30, 31). Figure 3 shows the Pareto diagram for the problem of the dust filter being blockage in all the production, as a result of the Five-Why analysis made on the manufacturing processes. Accordingly, it has been revealed that PdM strategies are needed in paint shops.

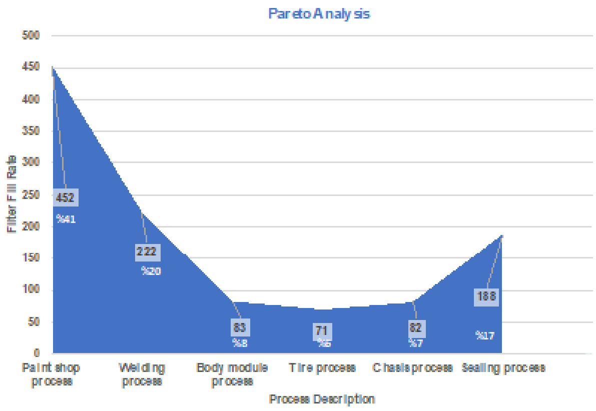


Figure 3 Pareto Analysis of Dust Filter Fill Rate

The figure shows the dust filter fill rate of the production processes. Paint shop filter occupancy is the highest at 41%. Accordingly, the causes of the filter fill have been examined for seven weeks to find the occurrence point of the problem in processes. The occurrence points of the problem are defined as “KTL, KTL sanding, PVC, primer, topcoat paint, and wax.”

Data collection

The SCADA enables the collection and analysis of data, which helps in making informed decisions and supports strategic planning and process optimization. Real-time monitoring and control through SCADA enhance industrial system reliability and safety, preventing and mitigating potential hazards. The SCADA systems facilitate the data collection stage and gather information from various sensors and devices. This stage is crucial for subsequent analyses. SCADA can collect diverse and real-time data, ensuring a rich dataset for predictive maintenance algorithms. The fill rate data of the filters are collected instantly via SCADA as shown in Figure 4.

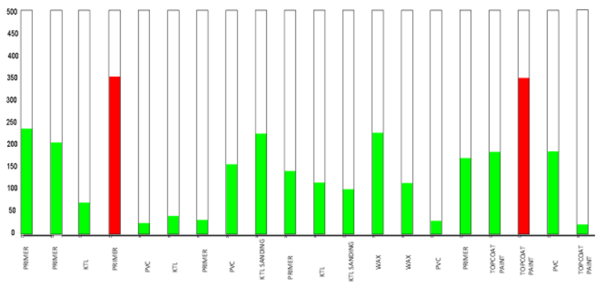


Figure 4 SCADA Data Collection System

The dust filters were collected, and the analysis

of the dust was carried out within the framework of the 'MDHS 14/3 General methods for sampling and gravimetric analysis of respirable and inhalable dust' standard (32). Upper limit pressure differences are established for sensors in line with industry standards. Pressure differentials are continuously monitored through SCADA screens. If the pressure difference, as measured by the sensors, exceeds the pre-defined upper limit, a warning notification will be triggered on the screen, prompting planned maintenance. This approach effectively mitigates the risks associated with estimating maintenance periods, as is often encountered in traditional preventive maintenance methodologies.
As the pressure in the pressure sensors integrated into the filters increases, the sensors send signals to the Programmable Logic Controller (PLC) as shown in Figure 5.

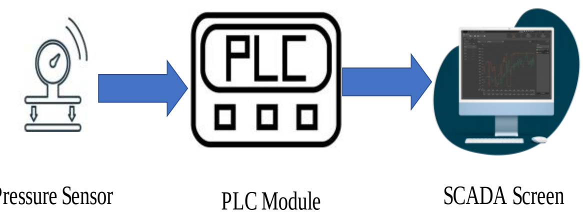


Figure 5 PLC-SCADA Communication Scheme

The pressure sensor transmits the data it captures to the Programmable Logic Controller (PLC). Concurrently, the PLC transfers data to the SCADA system. Leveraging SCADA's intelligent technology, levels of filter blockage are discerned by incorporating parameters associated with filter obstruction, consequently adding alarms and visually representing them through color-coded indicators. Furthermore, through the implementation of Predictive Maintenance (PdM) applications, facilitated by these technologies, the data can be systematically logged, enabling retrospective analysis.

Data analysis

Analyzing the collected data through SCADA systems involved intricate scrutiny of various factors. The study used advanced analytics and machine learning algorithms to examine patterns, anomalies, and predictive indicators. The data analysis stage aimed to unveil potential failure modes, anticipate maintenance needs, and enhance the overall predictive maintenance strategy. The results of this analysis laid the groundwork for developing a refined PdM process.
Dust in the paint shop was measured with a pressure sensor under the routine working conditions of the paint shop as shown in Figure 6.

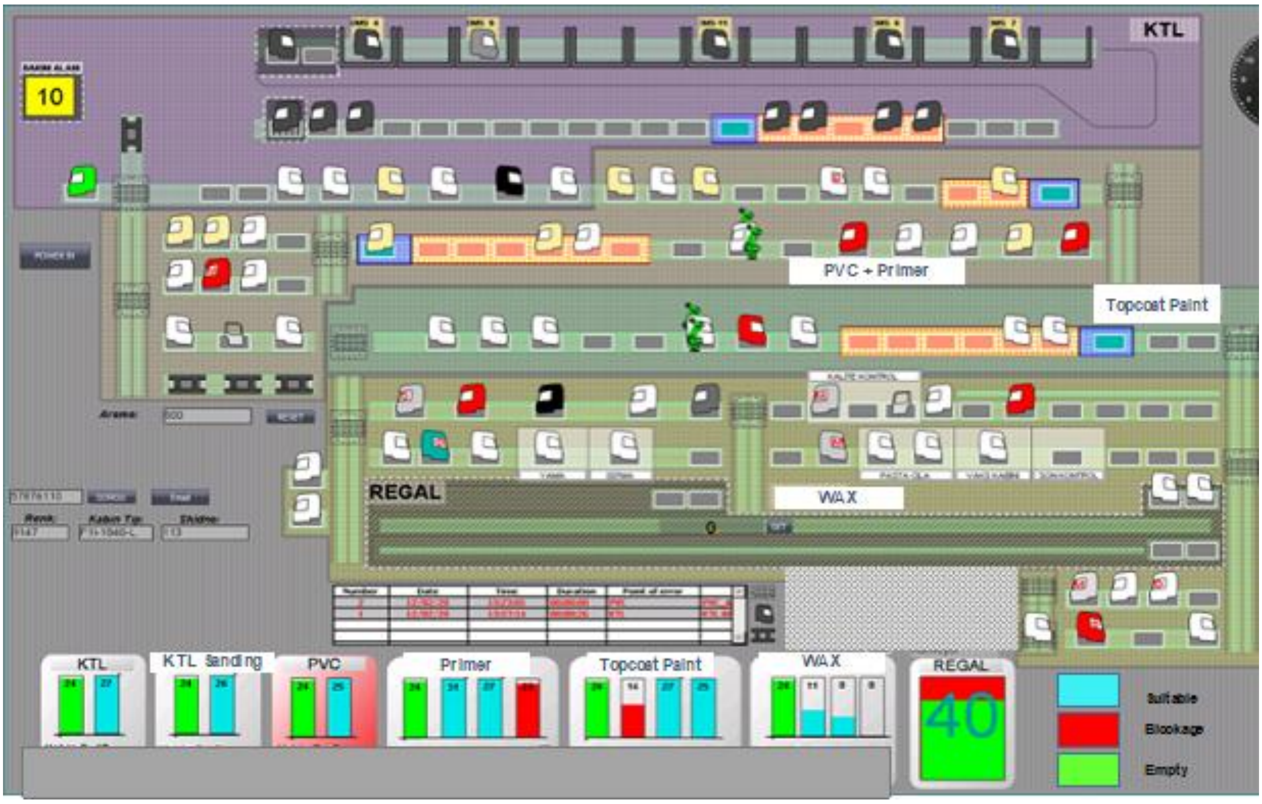


Figure 6 SCADA Screen

Figure 6 shows the 6 monthly paint shop dust filter blockage rates for 2022. If preventive maintenance was still applied to the paint shop, then 18 filters would have needed to be replaced within 6 months. However, with the application of PdM, according to the SCADA screen, the pressure sensors indicated that only 2 dust filters have become blockaged within the same 6-month period.

PdM process

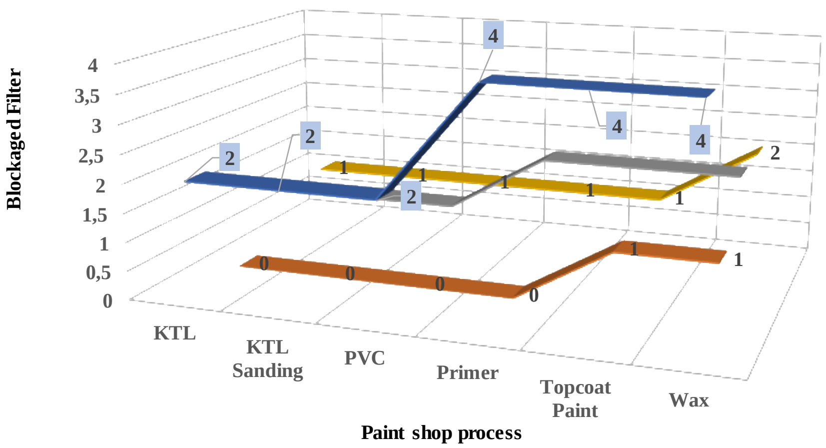
The PdM process was implemented systematically using data analysis insights and SCADA data to create predictive models and algorithms. These models were instrumental in forecasting potential equipment failures, determining optimal maintenance intervals, and prioritizing critical maintenance tasks. The PdM process, enriched by SCADA technologies, demonstrated efficacy in minimizing unplanned downtime and maximizing equipment reliability. The study has considered 18 filters in 6 different paint shop processes from one of maintenance as a case study. Pressure sensor data of the machine are considered as input features. As shown in Figure 4, in the six-month period, in 6 processes, 2 filters were blockaged in the primer and topcoat paint processes. Based on SCADA data, a total of 2 filters experience blockage in both the primer and topcoat paint processes every 6 months. Over a 12-month period, extra the 9 filters blockaged across all processes. Furthermore, within a 24-month timeframe, a total of 7 more filters become blocked in the entirety of the operational processes. This situation and 3 maintenance schedules in several periods for maintenance are illustrated in (Figure 7).

18 filters, which were replaced every 6 months during preventive maintenance before 2022, are now replaced at different intervals through PDM after this study.

Improvement

Continuous improvement was a crucial aspect of the study, intending to enhance the effectiveness of the implemented PdM strategy. The insights gained from SCADA data, together with feedback from the PdM process, were used to iteratively refine the system. The identification of areas for improvement resulted in adjustments in predictive models, maintenance schedules, and the overall PdM framework.

When analyzing costs in the prevent maintenance at the paint shop from before the improvements, every six months, a total number of 18 filters had been changed on the paint shop of which each was reported as blockaged. After PdM, SCADA data reveals blockage in 2 filters every 6 months in the primer and topcoat processes, totaling 9 filters in 12 months. Over 24 months, an additional 7 filters become blocked across all processes. The total cost of one filter is 200€. Also, different costs and savings for both preventive maintenance and PdM are illustrated in (Table 1).



	KTL	KTL Sanding	PVC	Primer	Topcoat Paint	Wax
Amount of filter	2	2	2	4	4	4
6 months	0	0	0	0	1	1
12 months	1	1	1	2	2	2
24 months	1	1	1	1	1	2

Figure 7 PdM Schedules for Paint Shop Filter

Table 1 Preventive and Predictive Maintenance Costs – Savings

Paint shop process	Preventive Maintenance Amount of Filter	Preventive Maintenance Costs (€) 24 monthly	PdM Amount of Filter		PdM Costs (€) 24 monthly	PdM Costs (€) 24 monthly
			PdM Amount of Filter 6 monthly	PdM Amount of Filter 12 monthly	PdM Amount of Filter 24 monthly	
KTL	2	1,600		1	1	600
KTL Sanding	2	1,600		1	1	600
PVC	2	1,600		1	1	600
Primer	4	3,200	1	2	1	1,800
Topcoat Paint	4	3,200	1	2	1	1,800
Wax	4	3,200		2	2	1,200
Total	**18**	**14,400 €**	**2**	**9**	**7**	**6,600€**

Since 7 filters were changed in 24 months, 2 years of savings were calculated. The filter cost, which was 14,400€ when performing preventive maintenance, was reduced to 6,600€ by implementing PdM. Thus, a savings of 45.83% was achieved.

5. Conclusions

This study highlights the significant impact of PdM integrated with Industry 4.0 technologies, specifically SCADA, in the automotive industry, also known as Maintenance 4.0. Through a detailed case study focused on a Turkish automotive paint shop, the utilization of SCADA for data collection from pressure sensors has proven instrumental in creating a comprehensive database for PdM. SCADA technology is crucial in modern industries to monitor, control, and optimize processes efficiently. Although there is not much application in the literature at the moment, SCADA's importance is expected to grow as similar studies evolve.

The previously fixed schedule for filter replacements, occurring every 6 months during preventive maintenance, has now been dynamically adjusted based on real-time data insights. This adaptive approach, driven by SCADA data, has led to a significant enhancement in the efficiency of maintenance procedures. Specifically, the study reveals a remarkable reduction in filter blockages across various operational processes. Filters, originally replaced uniformly every 6 months, are now replaced at different intervals determined by PdM. The PdM approach identified critical patterns, with 2 filters experiencing blockage every 6 months in both primer and topcoat paint processes. Additionally, an extra 9 filters were identified as blocked over 12 months, and 7 more within a 24-month timeframe across all processes.

The cost of 7 filters changed in 24 months was reduced from 14,400€ to 6,600€ by implementing PdM, resulting in 2 years of savings. Quantitatively, the results indicate a substantial improvement in the overall effectiveness of maintenance, with an impressive increase of 45.83%. This demonstrates the tangible benefits of embracing PdM in conjunction with Industry 4.0 technologies, showcasing a more responsive and proactive maintenance strategy. The findings of this case study underscore the potential for significant cost savings, operational efficiency gains, and extended equipment lifespan within the automotive industry, thereby validating the strategic integration of Maintenance 4.0 principles. As industries continue to evolve towards smart and connected systems, this research contributes valuable insights into the practical implementation and success of predictive maintenance strategies within the automotive manufacturing landscape. In future studies, there is significant potential for exploring advanced scheduling and dynamic maintenance scheduling methods within the context of PdM in the automotive industry.

Declaration of ethical standards

The author of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Authors' contributions

The author managed the research endeavor, overseeing the entire study's progression. She conceived the fundamental conceptual notions and formulated the overarching theoretical framework. Data collection from the case study was executed by her. The analysis, article composition, results documentation, and paper review and editing were undertaken by author.

Conflict of interest

There is no conflict of interest in this study.

6. References

1. Ceruti A, Marzocca P, Liverani A, Bil C, Maintenance in aeronautics in an industry 4.0 context: The role of augmented reality and additive manufacturing. J Comput Des Eng, 6(4), 516-526, 2019.
2. Lee M, Yun J, Pyka A, Won D, Kodama F, Schiuma G, Yan MR, how to respond to the Fourth Industrial Revolution, or the Second Information Technology Revolution? Dynamic new combinations between technology, market, and society through open innovation. Journal of Open Innovation: Technology, Market, and Complexity, 4(3), 1-21, 2018.
3. Tjahjono B, Esplugues C, Ares E, Pelaez G, what does Industry 4.0 mean to supply chain? Procedia Manuf, 13, 1175-1182, 2017.
4. Bartodziej CJ The concept Industry 4.0. In The Concept Industry 4.0. Springer Gabler: Wiesbaden, 2017.
5. Chiu YC, Cheng FT, Huang HC, developing a factory-wide intelligent predictive maintenance system based on Industry 4.0. Journal of the Chinese Institute of Engineers, 40(7), 562-571, 2017.
6. Chung M, Kim J, the internet information and technology research directions based on the fourth industrial revolution. KSII Transactions on Internet, Information Systems, 10(3), 1311-1320, 2016.
7. Kaczmarek M, Gola A, Maintenance 4.0 technologies for sustainable manufacturing an overview. IFAC-PapersOnLine, 52(10), 91-96, 2019.
8. Carnero, M. C., Selection of diagnostic techniques and instrumentation in a predictive maintenance program: A case study. Decision support systems, 38(4), 539-555, 2005.
9. Gupta R, Kumar A., Integration of big data and artificial intelligence in predictive maintenance: A review. Int J Adv Manuf Technol, 40(1), 56-78, 2022.
10. Jones A, Brown M., Advances in predictive maintenance technologies. International Journal of Reliability Engineering and Asset Management, 15(2), 321-345, 2020.
11. Sahal R, Breslin JG, Ali MI, Big data and stream processing platforms for Industry 4.0 requirements mapping for a predictive maintenance use case. J Manuf Syst, 54, 138-151, 2020.
12. Ruiz-Sarmiento JR, Monroy J, Moreno FA, Galindo C, Bonelo JM, Gonzalez-Jimenez J., A predictive model for the maintenance of industrial machinery in the context of Industry 4.0. Eng Appl Artif Intell, 87, 103289, 2020.
13. Smith J., A history of maintenance: From ancient civilizations to the industrial revolution. Journal of Maintenance History, 25(2), 123-145, 2000.
14. Cachada A, Barbosa J, Leitño P, Gcraldcs CA, Deusdado L, Costa J, Romero L., Maintenance 4.0: Intelligent and predictive maintenance system architecture. In 2018 IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA), Vol. 1, 139-146, 2018.
15. Kiangala KS, Wang Z., Initiating predictive maintenance for a conveyor motor in a bottling plant using Industry 4.0 concepts. Int J Adv Manuf Technol, 97(9-12), 3251-3271, 2018.
16. Sakib N, Wuest T., Challenges and opportunities of condition-based predictive maintenance: A review. Procedia CIRP, 78, 267-272, 2018.
17. Ferreiro S, Konde E, Fernández S, Prado A., Industry 4.0: predictive intelligent maintenance for production equipment. In European Conference of the Prognostics and Health Management Society, 1-8, 2016.
18. Einabadi B, Baboli A, Ebrahimi M., Dynamic predictive maintenance in Industry 4.0 based on real time information: Case study

in automotive industries. IFAC-PapersOnLine, 52(13), 1069-1074, 2019.
19. Pophaley M, Vyas RK., Choice criteria for maintenance strategy in automotive industries. International Journal of Management Science and Engineering Management, 5(6), 446-452, 2010.
20. Gallab M, Bouloiz H, Garbolino E, Tkiouat M, ElKilani MA, Bureau N., Risk analysis of maintenance activities in a LPG supply chain with a Multi-Agent approach. J Loss Prev Process Ind, 47, 41-56, 2017.
21. Sharma A, Yadava G, Deshmukh S., A literature review and future perspectives on maintenance optimisation. J Qual Maint Eng, 17(1), 5-25, 2011.
22. Achouch M, Dimitrova M, Ziane K, Sattarpanah Karganroudi S, Dhouib R, Ibrahim H, Adda M., On predictive maintenance in Industry 4.0: Overview, models, and challenges. Appl Sci, 12(16), 8081, 1-22, 2022.
23. Creehan KD., Establishing optimal maintenance practices in a traditional manufacturing environment. Journal of the Chinese Institute of Industrial Engineers, 22(1), (2005) 11-18, 2005.
24. Lee J, Ardakani HD, Yang S, Bagheri B., Industrial big data analytics and cyber-physical systems for future maintenance, service innovation. Procedia CIRP, 38, 3-7, 2015.
25. Patwardhan A, Verma AK, Kumar U., A survey on predictive maintenance through big data. Current Trends in Reliability, Availability, Maintainability and Safety, 437-445, 2016.
26. Fernández del Amo I, Erkoyuncu J, Roy R, Palmarini R, Onoufriou D., A systematic review of augmented reality content-related techniques for knowledge transfer in maintenance applications. Comput Ind, 103, 47-71, 2018.
27. Silvestri L, Forcina A, Introna V, Santolamazza A, Cesarotti V., Maintenance transformation through Industry 4.0 technologies: A systematic literature review. Comput Ind, 123, 103335, 2020.
28. Zhang W, Yang D, Wang H., Data-driven methods for predictive maintenance of industrial equipment: A survey. IEEE Syst J, 13(3), 2213-2227, 2019.
29. Kiangala KS, Wang Z., An Industry 4.0 approach to develop auto parameter configuration of a bottling process in a small to medium scale industry using PLC and SCADA. Procedia Manuf, 35, 725-730, 2019.
30. Banica CF, Belu N., Application of 8D methodology-an effective problem solving tool in automotive industry. Scientific Bulletin Automotive Series, XXV (29), 1-7, 2019.
31. Barosani S, Bhalwankar N, Deshmukh V, Kokane S, Kulkarni PR., A review on 8D problem solving process, Int J Res Appl Sci Eng Technol, 4 (4), 529-535, 2017.
32. MDHS 14/3 General methods for sampling and gravimetric analysis of respirable and inhalable dust https://online.br.sgs.com/Extranet/Environ/web/pdf/particulados.pdf access, 20.07.2023.