Proceedings of the 35th European Safety and Reliability & the 33rd Society for Risk Analysis Europe Conference
Edited by Eirik Bjorheim Abrahamsen, Terje Aven, Frederic Bouder, Roger Flage, Marja Ylönen

doi: 10.3850/978-981-94-3281-3_ESREL-SRA-E2025-P8899-cd

Optimizing Maintenance Strategies in Railway Systems: The Role of Human-Machine Collaboration

Mario Di Nardo

Università Telematica Pegaso, Italy. E-mail: mario.dinardo@unipegaso.it

Affinito Ciro

Department of Chemical, Materials and Industrial Production Engineering, University of Naples Federico II, Naples, 80125, E-mail: ci.affinito@studenti.unina.it

Amella Alessandro

Department of Chemical, Materials and Industrial Production Engineering, University of Naples Federico II, Naples, 80125, E-mail: al.amella@studenti.unina.it

Mozzillo Salvatore

Department of Chemical, Materials and Industrial Production Engineering, University of Naples Federico II, Naples, 80125, E-mail: sal.mozzillo@studenti.unina.it

Abstract: The advent of Industry 4.0 has wholly revolutionized railway maintenance processes by integrating artificial intelligence, robotics, and autonomous systems, providing lots of real-time data, predictive analytics, and automated processes. This integration has caused new problems with human-machine interaction, workplace safety, and workers' physical and mental health in work environments where humans and intelligent machines collaborate. The paper focuses on analyzing different methodologies for monitoring psychological stress and introducing a mathematical model that establishes how good maintenance planning can improve worker safety and health. The primary purpose, in addition to the one already mentioned, is to reduce risks and accidents of operators in the workplace.

Keywords: Industry 4.0, Human-Machine Interaction, Safety, Railway Maintenance, Maintenance Planning.

Introduction

Maintenance is defined as the actions and activities required to maintain the good condition and proper functioning of devices or equipment (Afolalu et al., 2024). Industry 4.0 represents the trend toward increasing digitalization and automation of work environments (Oesterreich & Teuteberg, 2016) through artificial intelligence, robotics, and automated systems that improve collaboration between humans and machines.

This interaction has contributed to improving production efficiency, reducing operating costs, optimizing maintenance management, predicting failures, and planning maintenance interventions more precisely. In particular, there are different methodologies to organize and optimize maintenance, such as Preventive Maintenance (PvM), Predictive Maintenance (PdM), or Condition-Based Maintenance (CBM). The increasing use of intelligent machines that work in close contact with operators has led to an intensification of the pace of the production chain, increasing the pressure related to time and adaptation to changes in demand and customer needs. These factors can compromise safety, performance, and efficiency in the workplace. However, in addition to the numerous advantages, human-machine interaction can have adverse psychological effects on the well-being of workers in terms of stress and cognitive load. This phenomenon is a source of high costs that, added to the costs related to maintenance, constitute a significant problem for companies.

This paper describes how implementing a failure probability function, influenced by operators' possible cognitive errors, significantly affects total maintenance costs.

The paper is organized as follows: Section 1 discusses the evolution of maintenance over time and the growing interaction between humans and robots using Industry 4.0 technologies. Section 2 presents and describes the mathematical model, and Section 3 concludes regarding the model and the use of Industry 4.0 technologies.

1. Literature Review: Evolution

Maintenance refers to ensuring the device or equipment's proper functioning and longevity by addressing and preventing potential problems (Afolalu et al., 2024). In a context of increasing technological development and globalization, companies, especially manufacturing companies, are making numerous efforts to explore and implement a business model that is not only more sustainable but also capable of improving the speed and quality of production processes, with the final goal of producing high-quality products with flexible and reduced-cost production (Luthra & Mangla, 2018; Man & Strandhagen, 2017; Nemoto et al., 2015).

According to (Parsaei et al., 2025), the primary maintenance strategies that aim to reduce equipment failures and production stops are Corrective Maintenance (CM), Preventive Maintenance (PvM), and Predictive Maintenance (PdM). Corrective Maintenance (CM) is a strategy applied when maintenance action is applied after failure. It includes activities to restore the equipment to its operational state. Preventive Maintenance (PvM), on the other hand, requires that the maintenance action occurs before the failure with a predetermined frequency. Finally, PdM is a strategy where the maintenance action occurs before the failure following careful and precise monitoring of the equipment conditions (Parsaei et al., 2025; Riccio et al., 2024). In particular, PvM is one of the proactive techniques used since the beginning of maintenance system research as an alternative to Corrective Maintenance (CM), as the latter had more extended downtimes and higher long-term costs. The basic principle of a PvM system is that it involves predetermined maintenance activities. For this reason, activities are planned to replace components before they fail and are scheduled during machine shutdowns or shutdowns. The choice of where and when to perform this type of maintenance strategy is very delicate and varies according to the complexity of the sector in which it is implemented (Basri et al., 2017; Riccio et al., 2024)

PdM is an advancement compared to preventive maintenance. Thanks to the increasing diffusion of Industry 4.0 (I4T) technologies, it is now possible to collect and save large amounts of data from production processes. This data can be used not only for PdM, but also to predict future failures and above all to monitor the health status of machinery, anticipating possible failures of equipment and machinery (Riccio et al., 2024)

PvM and PdM are both proactive maintenance approaches, focusing on eliminating the root causes of failures and sharing similar goals. However, PvM still has a limitation: It is performed when the machine is stopped, while PdM is performed while the machine continues to operate, ensuring constant monitoring and continuity of the production process (Basri et al., 2017).

The railway industry is one of the key sectors for economic growth and for public and freight transport (Laiton-Bonadiez et al., 2022). With the advent of Industry 4.0, the railway sector must also adapt to new technological developments, including Artificial Intelligence (AI), the Internet of Things (IoT) and Cloud Computing, technologies that are transforming the way industries address their operational challenges (Cockburn et al., 2018). One of the main problems in the railway sector is maintenance, and its high costs are linked to traditional measurement techniques and inspections carried out by maintainers, which increase the cost curve (Zhang et al., 2018). Real-time monitoring can increase the railway system's reliability, availability, maintainability, and safety (Dordolo et al., 2020).

Integrating the methodologies of the fourth industrial revolution in railway maintenance can bring significant improvements that affect various aspects of the sector. For example, monitoring the status of railway machines and infrastructures can occur in two main phases: the production of the equipment and the installation on the railway network. During production, new technologies aim to minimize defects as much as possible. At the same time, during installation, the constant monitoring of components allows large amounts of information to be provided to AI to prevent possible failures. For example, (Jwo et al., 8243) proposed a model based on deep learning algorithms to automate wheelset inspections, improving reliability and efficiency compared to traditional manual inspections. Also, in train monitoring, the FEDORATA system, which uses wireless sensors, IoT, and a web server for data visualization, has effectively reduced maintenance costs (Brezulianu et al., 639). For railway transport, big data, IoT, and cloud computing allow the collection of valuable information to improve transport management processes. For example, (Jamshidi et al., 2018) proposed a big data-based method to optimize the maintenance process; big data is used to process the huge amount of data generated in the railway context, with significant applications in Condition-Based Maintenance (CBM).

A crucial aspect of Industry 4.0, not only in the railway sector but in the industrial sector in general, concerns human-machine interaction to improve both working conditions and productivity thanks to a combination of the strengths of the individual worker and the speed and precision capabilities of robots. Human-robot interaction (HRI) has established itself as a new approach that allows humans and collaborative robots called "cobots," to combine their capabilities in a shared environment in order to achieve common goals to increase productivity and reduce operating costs (Gervasi et al., 2024). However, the increasing collaboration between humans and cobots has raised several safety concerns. The primary safety hazards in HRI include physical contact and collision, pinch points, and issues related to the speed and force of the robot. Standard techniques to address or mitigate these hazards include using proximity sensors or vision systems to avoid collisions and integrating corrective action systems that prevent collisions without interrupting the robot's operation. Furthermore, some standards, such as ISO 10218-2:2011 and ISO/TS 15066:2016, have been introduced to regulate and improve safety in Human-Robot Interaction (HRI).

In Human-Robot Interaction, there is an increasing interest in studying workers' mental conditions, such as stress and mental load, as these factors influence the interaction with robots. To optimize the quality of the interaction and the results, some researchers, including Ahmed et al., suggest the importance of controlling both human characteristics (stress and mental load) and process characteristics (work mode and robot speed) (Gualtieri et al., 2022). Methods to evaluate these interactions include performance metrics and subjective feedback, such as questionnaires (SUS, SAM, NASA-TLX, SWAT, and ISA) that measure usability, emotional states, and perceived workload.

However, questionnaires are particularly effective for short and qualitative tasks; for complex and prolonged tasks, interrupting the activity to answer can be disruptive, and in these cases, monitoring physiological data (e.g., heart rate or brain activity) is helpful to collect information without interrupting operations (Gervasi et al., 2024).

The lack of cognitive ergonomics can cause an increase in errors, resulting from confusion, cognitive overload, or difficulty in interpreting information, directly impacting operating costs. This is reflected in dissatisfaction, stress, demotivation, and absenteeism, resulting in costs for hiring, selecting, and training new staff. A non-optimized system requires longer usage times and increases the cognitive load, with decreased productivity and efficiency directly affecting profits. Finally, the health costs for the company and society should not be underestimated, as a job that requires high concentration or causes stress and mental fatigue can lead to health problems (such as burnout or chronic stress, technostress). Fig.1 shows the effects of Industry 4.0 on health and safety at work, organizing the impacts into different categories: psychological, cognitive, physical, and organizational (Bispo & Amaral, 2024).

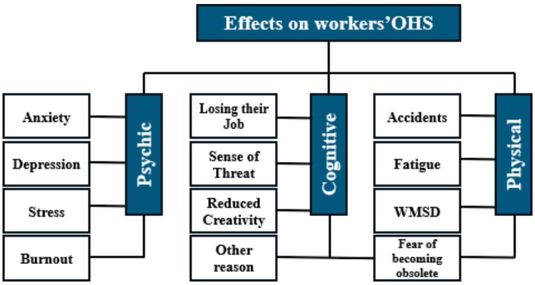

Fig.1 Categories of effects generated by Industry 4.0 on operators OHS (derived by Bispo & Amaral, 2024)

2. Methodology

Based on the work carried out by (Çelik & König, 2022), the function that could better explain the effect of an operator's cognitive stress within the maintenance planning process, particularly railway maintenance, is a sigmoid function Fig.2. In literature, this type of function is widely used in numerous fields, especially in neuroscience (Williams et al., 2009), therefore very similar to the problem relating to the cognitive stress of maintenance workers.

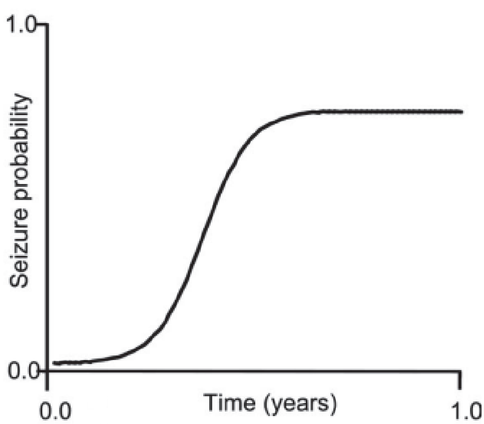

Fig.2 Sigmoid Curve (adapted by (Williams et al., 2009)

A defect of this function is related to the fact that it can progress abruptly, quickly reaching the saturation condition. By introducing a sensitivity coefficient of the logistic function β, which indicates how quickly the cognitive error approaches the critical threshold (Critical), it was possible to limit this defect. A solution that was impossible to obtain using an exponential function characterized by an even more sudden evolution. So, a function is defined relating to the probability of the cognitive error Eq.(1) with the parameters reported in Table 1.

$$P_{\text{cognitive error}}(S_c) = \frac{1}{1 + e^{-\beta \cdot (S_c - S_{\text{critic}})}} \quad (1)$$

Table 1. List of parameters

Notation	Definition
$P_{\text{cognitive error}}$	Probability of cognitive error
β	Parameter for the slope of the logistics function
Sc	Cognitive stress level of the operator
S_{critic}	Maximum stress threshold

Once this function has been defined, in general, the total probability of failure Eq.(2) is evaluated, considering the cognitive stress, which is given by the probability of failure of the single railway component as a function of the mileage and the probability of cognitive error of the operator, multiplied by an amplification coefficient ɣ, which represents the influence of the cognitive stress of the personnel on the risk of failure. This function is adopted, since adding only the two probabilities would have given greater emphasis to the cognitive error, moving away from a realistic condition. The parameters are reported in Table 2.

$$P_{\text{failure}}(S_c) = P_{bf} \cdot (1 + \gamma \cdot P_{ce}(S_c)) \quad (2)$$

Table 2. List of parameters

Notation	Definition
$P_{failure}(S_c)$	Total failure probability
$P_{base\ failure}$	Failure probability based on mileage
γ	Amplification coefficient
$P_{cognitive\ error}(S_c)$	Cognitive failure probability of the operator

In conclusion, to obtain an overview of railway maintenance planning in relation to the operator's cognitive stress, a cost function Eq.(3) is employed. This function considers the number of preventive maintenance interventions based on Condition-Based Maintenance (CBM) and the associated costs, combined with the corrective costs resulting from the probability of failure as a function of the operator's cognitive stress. The parameters are reported in Table 3.

$$C_{tot} = n \cdot C_{rated} + P_{failure}(S_c) \cdot C_{corrective} \quad (3)$$

Table 3. List of parameters

Notation	Definition
C_{tot}	The total cost of maintenance
n	Number of preventive interventions
C_{rated}	Cost for each preventive maintenance intervention
$P_{Failure}(S_c)$	Total failure probability
$C_{corrective}$	Cost of each corrective maintenance intervention

2.1 Experimental Case

To analyse the effectiveness of the proposed mathematical model, an experimental study focusing on railway maintenance planning is designed. The goal is to quantify the total failure probability and the associated maintenance costs, considering the influence of operator cognitive stress. The values used may vary according to the type of vehicle and infrastructure.

Context and Parameters: The case assumes a railway company planning the maintenance of its vehicles, considering the following parameters in Table 4:

Table 4. List of parameters

Notation	Value
$P_{base\ failure}$	0.02
γ	3.0
β	0.5
S_{critic}	6
S_c	8
n	10
C_{rated}	500€
$C_{corrective}$	5000€

The function, $P_{cognitive\ error}(S_c)$, is modelled as a sigmoid function.

Results and Calculation:

By considering a S_{critic} equal to 6 and substituting this value in Eq.(1), we obtain:

$$P_{cognitive\ error}(6) = \frac{1}{1 + e^{-0.5 \cdot (6-8)}} = 0.270$$

For Eq.(2), the value is calculated as:

$$P_{failure}(S_c) = 0.02 \cdot (1 + 3.0 \cdot 0.270) = 0.036$$

Finally, for Eq.(3), we obtain a value equal to:

$$C_{tot} = 10 \cdot 500 + 0.036 \cdot 5000 = 5180€$$

The case study highlights the model's applicability in assessing failure probabilities and maintenance costs under realist conditions. The total failure probability was found to be 3.6 %

significantly influenced by operator cognitive stress. The total maintenance cost, which included preventive and corrective interventions, was calculated at 5180€. This example shows the importance of considering human factors in maintenance planning to optimize safety and cost efficiency.

2.2 Discussion

The experimental case demonstrates how to work the proposed model by integrating operator cognitive stress for failure probability calculations to improve railway maintenance planning. However, the model has limitations such as the simplification of cognitive stress into a single variable, parameters being treated as static and not dynamic, environmental and equipment conditions, or the cost of Corrective and Preventive Maintenance being considered fixed. Despite this limitation, this model provides a good solution to improve maintenance planning.
Future improvement could consider a dynamic context by including operator fatigue, environmental and equipment conditions or team dynamics. The paper presents a proposed mathematical model that quantifies the influence of cognitive errors on overall maintenance costs, highlighting the critical relationships between these variables. Furthermore, the implications of these findings are significant for organizations adopting Industry 4.0 technologies in the context of railway maintenance, as they can improve operational efficiency and inform strategic decision-making.
The proposed sigmoid-based probability model offers unique advantages over traditional exponential or linear models by accounting for gradual changes in cognitive stress. This approach provides help for railway maintenance planning.

3. Conclusion

Using Industry 4.0 technologies in the railway sector improves operational efficiency, sustainability, and safety. Tools like IoT, Big Data, and AI enable predictive maintenance, reduce downtime, and optimize resource use. In addition, advanced solutions help reduce energy consumption and environmental impact, making rail transport greener and more innovative.

Through its objective function, the proposed model's main objective is to optimize railway maintenance activities by considering and minimizing operating costs and workers' well-being. In an environment increasingly characterized by advanced technologies, such as collaborative robots, this approach is essential to ensuring the right balance between efficiency and operators' well-being.

Future model developments focus on greater customization, adaptability, and integration with advanced technologies and real-time monitoring systems. These improvements will increase the efficiency of railway maintenance operations and help create a more sustainable, safe, and productive work environment, promoting harmony between man and machine.

References

Afolalu, S. A., Monye, S. I., Ogundipe, A. T., Azeez, T. M., & Ikumapayi, O. M. (2024). Maintenance strategies and procedures: An overview. *International Conference on Science, Engineering and Business for Driving Sustainable Development Goals, SEB4SDG 2024.* DOI: 10.1109/SEB4SDG60871.2024.10630278

Basri, E. I., Razak, I. H. A., Ab-Samat, H., & Kamaruddin, S. (2017). Preventive maintenance (PM) planning: A review. *Journal of Quality in Maintenance Engineering, 23*(2), 114–143. DOI: 10.1108/JQME-04-2016-0014

Bispo, L. G. M., & Amaral, F. G. (2024). The impact of Industry 4.0 on occupational health and safety: A systematic literature review. *Journal of Safety Research, 90,* 254–271. DOI: 10.1016/j.jsr.2024.04.009

Brezulianu, A., Aghion, C., Hagan, M., Geman, O., Chiuchisan, I., Balan, A. L., Balan, D. G., & Balas, V. E. (n.d.). Active control parameters monitoring for freight trains, using wireless sensor network platform and Internet of Things. *Processes, 8*(6). DOI: 10.3390/PR8060639

Çelik, F., & König, M. (2022). A sigmoid-optimized encoder–decoder network for crack segmentation with copy-edit-paste transfer learning. *Computer-Aided Civil and Infrastructure Engineering, 37*(14), 1875–1890. DOI: 10.1111/MICE.12844

Cockburn, I., Henderson, R., & Stern, S. (2018). The impact of artificial intelligence on innovation. Retrieved from DOI: 10.7208/9780226613475-006/pdf?licenseType=restricted

Dordolo, L., Germino, S., Ramoscelli, G., Permingeat, A., Mancon, C., Francucci, L., Laiuppa, A., Balina, D., & Lutenberg, A. (2020). Modular system for the monitoring of railway signaling equipment. *IEEE Latin America Transactions, 18*(2), 280–287. DOI: 10.1109/TLA.2020.9085281

Gervasi, R., Capponi, M., Mastrogiacomo, L., & Franceschini, F. (2024). Analyzing psychophysical state and cognitive performance in human-robot collaboration for repetitive assembly processes. *Production Engineering, 18*(1), 19–33. DOI: 10.1007/s11740-023-01230-6

Gualtieri, L., Fraboni, F., De Marchi, M., & Rauch, E. (2022). Development and evaluation of design guidelines for cognitive ergonomics in human-robot collaborative assembly systems. *Applied Ergonomics, 104,* 103807. DOI: 10.1016/j.apergo.2022.103807

Jamshidi, A., Hajizadeh, S., Su, Z., Naeimi, M., Núñez, A., Dollevoet, R., De Schutter, B., & Li, Z. (2018). A decision support approach for condition-based maintenance of rails based on big data analysis. *Transportation Research Part C: Emerging Technologies, 95,* 185–206. DOI: 10.1016/j.trc.2018.07.007

Jwo, J. S., Lin, C. S., Lee, C. H., Zhang, L., & Huang, S. M. (n.d.). Intelligent system for railway wheelset press-fit inspection using deep learning. *Applied Sciences, 11*(17). DOI: 10.3390/app11178243

Laiton-Bonadiez, C., Branch-Bedoya, J. W., Zapata-Cortes, J., Paipa-Sanabria, E., & Arango-Serna, M. (2022). Industry 4.0 technologies applied to the rail transportation industry: A systematic review. *Sensors, 22*(7). DOI: 10.3390/S22072491

Luthra, S., & Mangla, S. K. (2018). Evaluating challenges to Industry 4.0 initiatives for supply chain sustainability in emerging economies. *Process Safety and Environmental Protection, 117,* 168–179. DOI: 10.1016/J.PSEP.2018.04.018

Man, J. C. De, & Strandhagen, J. O. (2017). An Industry 4.0 research agenda for sustainable business models. *Procedia CIRP, 63,* 721–726. DOI: 10.1016/J.PROCIR.2017.03.315

Nemoto, Y., Akasaka, F., & Shimomura, Y. (2015). A framework for managing and utilizing product-service system design knowledge. *Production Planning & Control, 26*(14–15), 1278–1289. DOI: 10.1080/09537287.2015.1033493

Oesterreich, T. D., & Teuteberg, F. (2016). Understanding the implications of digitisation and automation in the context of Industry 4.0: A triangulation approach and elements of a research agenda for the construction industry. *Computers in Industry, 83,* 121–139. DOI: 10.1016/J.COMPIND.2016.09.006

Parsaei, S., Pirouzmand, A., Nematollahi, M. R., Ahmadi, A., & Zerehpoosh, M. R. (2024). Risk-effective optimal maintenance regime for a periodically tested safety component subjected to imperfect repair. *Annals of Nuclear Energy, 211,* 110902. DOI: 10.1016/j.anucene.2024.110902

Riccio, C., Menanno, M., Zennaro, I., & Savino, M. M. (2024). A new methodological framework for optimizing predictive maintenance using machine learning combined with product quality parameters. *Machines, 12*(7). DOI: 10.3390/MACHINES12070443

Williams, P. A., White, A. M., Clark, S., Ferraro, D. J., Swiercz, W., Staley, K. J., & Dudek, F. E. (2009). Development of spontaneous recurrent seizures after kainate-induced status epilepticus. *Journal of Neuroscience, 29*(7), 2103–2112. DOI: 10.1523/JNEUROSCI.0980-08.2009

Zhang, H., Jin, X., Wu, Q. M. J., Wang, Y., He, Z., & Yang, Y. (2018). Automatic visual detection system of railway surface defects with curvature filter and improved Gaussian mixture model. *IEEE Transactions on Instrumentation* *and Measurement, 67*(7), 1593–1608. DOI: 10.1109/TIM.2018.2803830