The Role of Predictive Machine Learning Models and Digital Twins in Advancing Railway Maintenance in Industry 4.0

Prognostic machine learning models in Industry 4.0 are categorised into three types: descriptive, predictive, and prescriptive. Descriptive models analyse industrial data to uncover patterns and anomalies from past events, using techniques such as clustering and outlier detection. Predictive models use supervised learning to forecast when faults may occur and their severity, based on historical data. Prescriptive models go further, recommending actions to minimise fault impacts or prevent failures by solving optimisation problems, such as adjusting operations or reallocating resources. Together, these models enhance efficiency and decision-making in industrial systems (Diez-Olivan et al., 2019).

This discussion focuses on predictive learning models because they offer valuable foresight by accurately forecasting failures using historical and real-time data. This capability enables condition-based maintenance, reducing unnecessary repairs, lowering costs, and improving reliability. Predictive models also overcome the inefficiencies of traditional preventive strategies, aligning with the smarter, data-driven asset management goals of Industry 4.0 (Diez-Olivan et al., 2019; (Hector and Panjanathan, 2024).

In the railway sector, predictive learning models have delivered transformative benefits, improving asset reliability, operational efficiency, and passenger safety. Stochastic Bayesian Models, for example, analyse condition monitoring data—such as acceleration, force, and current—to predict wear in braking systems. This allows timely interventions, extending component lifespans and preventing costly disruptions (Diez-Olivan et al., 2019; Binder, Mezhuyev and Tschandl, 2023).

Similarly, rule-based fuzzy semantic inference processes vibration and current signals to detect early faults in Electric Multiple Units (EMU) trains (Diez-Olivan et al., 2019). Early detection is particularly vital for EMUs, where seamless coordination of interconnected units is essential. Unlike traditional trains, where faulty carriages or locomotives can often be replaced, a fault in an EMU unit can disrupt the entire train's operation. As replacing or isolating a faulty unit is complex, proactive maintenance ensures reliable service and prevents delays (Hata, 1998).

Digital Twins technology further enhances these predictive capabilities. By creating virtual replicas of physical railway assets and integrating real-time sensor data with advanced predictive models, Digital Twins provide accurate simulations and monitoring of infrastructure such as overhead lines and signalling systems. These dynamic models offer a comprehensive view of asset health and allow operators to test scenarios, such as increased traffic or adverse weather, to predict their impact and optimise maintenance schedules (Dimitrova and Tomov, 2021).

In summary, predictive learning models and Digital Twins are revolutionising railway maintenance. By enhancing reliability, reducing downtime, and improving operational efficiency, these technologies align seamlessly with Industry 4.0 goals, ensuring safer, smarter, and more sustainable transport systems.

References:

Binder, M., Mezhuyev, V., & Tschandl, M. (2023). *Predictive Maintenance for Railway Domain: A Systematic Literature Review*. ResearchGate. Available at: https://www.researchgate.net/publication/369572389_Predictive_Maintenance_for_Railway_Domain_a_Systematic_Literature_Review (Accessed 22 Jan. 2025)

Diez-Olivan, A., Del Ser, J., Galar, D. and Sierra, B. (2019) *Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0*. Information Fusion, 50, pp.92-111. Available at: https://www-sciencedirect-com.uniessexlib.idm.oclc.org/science/article/pii/S1566253518304706?via%3Dihub (Accessed 22 Jan. 2025).

Dimitrova, E. and Tomov, S. (2021) *Digital Twins: An Advanced Technology for Railways Maintenance Transformation*. Proceedings of the International Conference on Innovations in Electrical and Electronics Engineering (BulEF*)*. doi: 10.1109/BulEF53491.2021.9690822. Available at: https://ieeexplore.ieee.org/document/9690822/ (Accessed 22 Jan. 2025).

Hata, H. (1998) *What Drives Electric Multiple Units*. *Japan Railway & Transport Review*, 17, pp. 40–44. Available at: https://www.ejrcf.or.jp/jrtr/jrtr17/pdf/f40_technology.pdf (Accessed 26 Jan. 2025).

Hector, I. and Panjanathan, R. (2024) *Predictive maintenance in Industry 4.0: a survey of planning models and machine learning techniques*. *PeerJ Computer Science*, 10, e2016. doi: 10.7717/peerj-cs.2016. Available at: https://pmc.ncbi.nlm.nih.gov/articles/PMC11157603/ (Accessed 22 Jan. 2025).