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Enhancing Railways with Industry 4.0: AI-Driven Human-Machine Collaboration and Risk Management

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Industry 4.0, based on Human-Machine Interaction (HMI), represents the evolving collaboration between humans and intelligent systems within advanced industrial environments. In the last years new technologies like the Internet of Things (IoT), Artificial Intelligence (AI) and machine learning, thanks to the spread of robotics, have enhanced productivity and have enabled smart-decision making. The effects of these new technologies are improvements in safety and efficiency, but on the other hand, they have brought some questions about security and ergonomics. In this paper, the authors want to examine the Industry 4.0 technologies in the railway world. It is interesting to focus on the application of artificial intelligence that can bring productivity improvements. Nowadays this is primarily accomplished by the application of AI to the technical rail system's operation, traffic control, diagnostics, upkeep, and modification. These productivity gains are only possible if tasks are completed correctly or more effectively in compliance with current laws. AI can therefore alter the conventional evolutionary management of railway laws, which tends to grow gradually in response to occurrences, accidents, and dangers encountered. Furthermore, AI can assist with management. Some layers of AI are used in this paper's integrated enterprise risk management framework and methodology for the future railway, which promotes organizational learning and continual improvement. A survey of the literature found in databases for regulations, standards, and scientific papers serves as the deductive foundation for the applied approach.

Keywords: Railways, safety, AI, detection, maintenance, machine learning.

1. Introduction

The railway sector, essential for a country's social and economic development, requires advanced risk management to ensure safe, efficient, and sustainable operations. Traditionally, risk management in the sector has focused on optimizing productivity through standardized methods and incremental approaches. However, with the advent of Artificial Intelligence (AI), new opportunities have emerged to redefine how risks are identified, analyzed, and managed, surpassing the limitations of conventional practices. AI's integration in the railway sector enables the adoption of real-time solutions for risk analysis. By processing vast volumes of data and uncovering correlations and trends that might escape human observation, AI fosters a proactive approach that significantly enhances decision-making. This allows for timely risk mitigation and the identification of emerging opportunities. Moreover, AI incorporates reliability-based maintenance tools, optimizing resource allocation and minimizing the risk of service interruptions. In addition to improving safety and operational stability, AI technologies support continuous innovation and the management of organizational changes. The application of AI is not limited to technical aspects such as operations and maintenance; it also extends to strategic and organizational management, fostering synergy between technological and decision-making processes. This integrated approach aims to transform the railway sector into a safer, more efficient, and innovative system capable of addressing the challenges of a rapidly evolving world. Despite technological advancements, accidents remain a primary concern due to their severe impacts, including property damage and loss of life. In 2018, the European Union reported 1,666 major railway accidents, including 442 accidents at level crossings involving pedestrians and 939 instances of moving trains colliding with people (excluding suicides). These incidents resulted in 748 serious injuries and 853 fatalities. Although technological advancements and safety improvements have reduced accidents by 25.3% since 2010, current statistics highlight the need for further safety enhancements. The greatest scope for improvement lies in upgrading the infrastructure of existing railway systems (Ristić-Durrant, 2021). AI, defined as a computerized system capable of performing problem-solving and cognitive activities without human guidance (R. Tang et al., 2022), holds great promise for the railway industry. Though still in development, AI offers potential for optimizing intricate systems, diagnosing infrastructure defects, enhancing customer service, and improving urban network safety and security. According to Gibert et al. (2017), AI will soon become integral to the rail industry, transforming capacity management, lifecycle cost optimization, maintenance processes, and passenger flow forecasting while reducing human and machine errors. This article is structured as follows: Section 1 provides an overview of the primary AI systems currently employed in the railway sector; Section 2 outlines key research questions; Section 3 discusses AI and its applications; Section 4 focuses on machine learning algorithms; Section 5 presents case studies; Section 6 highlights challenges and obstacles to implementation; and Section 7 proposes directions for future research.

2. Research questions

To delve into the technological challenges and opportunities introduced by artificial intelligence (AI), several pertinent topics are outlined in relation to AI applications in railway systems. These questions aim to guide future research towards maximizing the performance, safety, and efficiency of railway networks: AI-Based Object Detection in Railways: Given the limited availability of datasets in the railway sector, what methods can be developed and implemented to standardize datasets? How can these efforts enhance the robustness and accuracy of AI-based object detection systems, particularly in diverse scenarios and varying environmental conditions? Ethics and Explainability in Railway AI Systems: What strategies are most effective for ensuring explainability, ethical responsibility, and human-centered AI governance in railway operations? How can these strategies address safety-critical subdomains where transparency and ethical considerations are paramount? UAVs in Railway Maintenance: How do AI and UAVs (unmanned aerial vehicles) compare to traditional maintenance systems in inspecting and diagnosing railway infrastructure defects? What is the potential for these systems to improve cost- effectiveness and efficiency in railway maintenance? Dynamic Passenger Mobility Prediction: By integrating genetic algorithms with evolutionary computing, how can real-time data be leveraged to enhance the accuracy and effectiveness of passenger and freight demand forecasts in modern, dynamic, and increasingly data-driven railway systems?

3. Artificial intelligence and implementations

Artificial intelligence (AI) has been utilized in railway infrastructure development over the past two decades to enhance reliability, productivity, and safety (Phusakulkajorn et al., 2023). Today, AI operating systems manage many critical components of railway infrastructure, such as tunnels, bridges, energy systems, and switches. AI applications even extend to the use of fiber optic acoustic sensors combined with line-scan cameras and sensors mounted on passenger trains. These technologies enable the detection of rail and wheel issues and the identification of level crossings. Level crossings, although minor components of transportation networks, are vital as they mark intersections between uncontrolled vehicular traffic and managed rail traffic. Consequently, robust safety measures must be implemented due to the significant movement of people across these crossings at medium speeds. Scene identification at level crossings highlights a crucial safety challenge for train drivers, emphasizing the need for improved safety procedures and advanced technologies (Di Nardo, 2023). Additionally, the role of passengers in advocating for safety at road crossings—often overlooked—has been brought to the forefront by Coppola and Silvestri (2020). Train platforms, which are often overcrowded and in close proximity to tracks, pose significant risks of severe injuries and fatalities (Serna et al., 2024). For this reason, safety remains a top priority for railway service providers worldwide. Passive monitoring systems, such as closed- circuit television (CCTV), are commonly used but rely on manual observation, making them prone to errors. By utilizing AI, this approach significantly mitigates risks and improves the overall safety of train platforms through innovative, intelligence-based passive safety mechanisms. AI algorithms also monitor components like brake blocks, pantographs, wheels, and wayside train monitoring systems. Additionally, AI supports rail logistics planning, ensuring more efficient operations and resource management (W. Liu et al., 2020). Advanced AI technologies and sensors enhance the continuous monitoring of infrastructure availability and safety. These early-warning systems allow for timely repairs during regular maintenance periods, significantly reducing disruptions (Ashley & Attoh-Okine, 2021). One example of such advancements is the AI-Powered Railway Regulator Inspection Planning System (Chiu, 2024). Previously, inspection selection relied on human judgment and preset schedules. This system uses natural language processing (NLP) and convolutional neural networks (CNNs) to analyze incident reports and maintenance data, relate semantic meanings, and link events to inspection items. The risk-based inspection method, increasingly adopted in the railway sector, ranks assets based on maintenance severity criteria (Alawad et al., 2020; Alawad & Kaewunruen, 2023). CNNs effectively identify key features in multi-dimensional incident records and efficiently process structured data, thereby improving operational efficiency and safety by reducing human error. Another innovative approach involves using diagnostic data logs for system behavior analysis. This method is particularly common in railway control systems and Industry 4.0 sectors, where extensive diagnostic data is generated (Cinque et al., 2020). The AID4TRAIN Project (Artificial Intelligence- based Diagnostics for TRAins and Industry 4.0) leverages AI and data analytics to streamline root cause analysis. By integrating expert knowledge (depicted as fault trees) with diagnostic logs, the project develops comprehensive fault models. (Cinque et al., 2022). The integration of AI with computer vision (CV) and deep learning (DL) technologies has also proven impactful (Lee, 2015). Advances in cryptography have facilitated the evolution of Cyber-Physical Systems (CPS), which integrate computing devices with physical processes to manage complex intelligent systems (Serna et al., 2024). When applied to intelligent transportation systems, Intelligent Transportation Cyber-Physical Systems (ITCPS) enhance efficiency, reliability, and safety. ITCPS leverages CV to enable machines to perceive, interpret, and act on their surroundings (Poirier et al., 2021). This capability is crucial for real-time, intelligent decision-making in transportation system management. Cloud computing and IoT have also enabled large-scale rail track maintenance and monitoring. By gathering data on environmental conditions, train parts, track conditions, and the entire ecosystem, these technologies help identify defects and implement preventative maintenance, reducing the risk of accidents (Cockburn et al., 2018; Gerhátová et al., 2021). Accurate Remaining Useful Life (RUL) estimates and deterioration pattern modeling are essential to balance maintenance schedules and prevent failures (Luo et al., 2022). However, existing models often struggle to adapt to fresh data. Techniques such as artificial neural networks (ANNs) have shown promise in real-time defect detection and localization. Conditional feed-forward backpropagation neural networks, for instance, can identify defects in rail sections with minimal traffic interference. Predictive modeling of defect locations has demonstrated high accuracy, aligning closely with actual results in both field and lab settings (Pal & Datta, 2024).

4. Machine learning and implementations

Recent advancements in Machine Learning, particularly Deep Learning have greatly improved the assessment for critical infrastructures, such as the following: buildings (Pezeshki et al., 2023), marine structures, bridges (Chun et al., 2022; Guo et al., 2023), roads (E. Yang et al., 2023; Zhang et al., 2022) and railways (Guo et al., 2023). As a result, new technologies such as YOLOv8 are being used extensively in the fastener inspection because of its speed in model inference (Y. Tang & Qian, 2024). Furthermore, fastener condition is assessed with a modified R- FCNN. These techniques are exceptionally well adjusted for modern systems that utilize concrete ties and fastening clips because they identify regions of interest in railway systems where damage occurs, such as loose bolts or spiked clips that are broken, misplaced, or missing. Track components can now be automatically identified: this method enhances safety in the automated track maintenance process through this mask RCNN method as each component is correctly placed (Y. Tang et al., 2024). Finally, advancements in sensors and communication networks have enabled the real-time processing of data, removing the limitations imposed by self-storage devices and post monitoring. Predictive maintenance is one of the core advantages of these technologies because they can predict failures, tell how long a component will last, and suggest the most suitable time for repairs or replacements (N. Yang et al., 2024). The application of Machine Learning (ML) techniques will require clear definitions of door failures and precise gathering of failure data. Prioritization of failures is done by utilizing the Failure Mode, Effects and Criticality Analysis which is abbreviated to FMECA. Although the displacement sensors have proven to be beneficial in the monitoring of pneumatic doors, there is still need to better categorize the door failure data so that the classification of operative vehicles is more efficient.

5. AI and Machine Learning Applications

5.1.1. *Accidents*

Accidents pose a real threat for businesses related to production and they can lead to negative outcomes like property damage as well as injuries. Both dangerous and non-dangerous goods are supposed to be transported by trains, as it is one of the safest means of land transportation available. However, over the last few years there has been an increase in train derailments which cast serious issues on the safety of both transit and railway trains. The situation becomes even more concerning in the case of dangerous goods being transported, as the consequences of a derailment can easily escalate (Bridgelall & Tolliver, 2021; Ebrahimi et al., 2021; Shi et al., 2023)

5.1.2. *Obstacle identification*

AI-based techniques and conventional computer vision (CV) techniques are the two types in which obstacle detection techniques are classified based on vision (Ristic-Durrant, 2021). Techniques with AI, mainly deep learning, incorporate neural networks to maximize detection through feature extraction, while conventional computer vision techniques utilize manually designed features (Nanni et al., 2017). Contemporary detectors can be divided into two large categories, single-stage and two-stage (Sikora et al., 2021), based on how they group individual processes. Convolutional Neural Networks (CNNs) provides better resilience than other CV (Barney et al., 2001). However, these techniques do not work well with railway specific activities such as identifying objects on rails from a distance because there are no railway specific datasets available which makes assessment of these techniques challenging. During the SMART project, a new method was developed for vision hardware to be capable of estimating object distances. This approach consists of two components – a neural network that calculates the distance and a deep learning object detection network. The bounding box (BB) of the detected object is extracted by the object detector using any bounding box mask based deep learning algorithm available in the literature (Ristic-Durrant, 2020). SMART software was then field-tested on the Serbian railway infrastructure. These tests used a sensor enclosure installed on the front profile of the locomotive. An onboard long-range obstacle detection (OD) system, even if perfect, will still miss potential items that may prove to be a blockade at the curves. This creates an unprecedented problem for the railways.

5.1.3. *Diagnostics*

The most cost-efficient method for operational maintenance is periodic visual inspections, however this method is ineffective when the precise locations of defects are not known (Popov et al., 2023). Track inspections are now carried out by advanced trains like the New Measurement Train (NMT), which can travel at 200 km/h while measuring various parameters. Displacement transducers, laser sensors, accelerometers, and high-resolution cameras are only a few of the many devices with which these measurements are taken. These sensors can be programmed to inspect the data they collect or transmit it to a central unit for further examination. Specifically, the track-side mounted sensors are used for monitoring the bogies, rail and wheel interactions, impacts of wheel loads, and profiling of the wheel, therefore their use is restricted to specific locations on the track (Li et al., 2017). Due to their small size, low cost, and low power consumption, the most employed sensors in these instruments are inertial sensors. One of the goals in On Track Data Driven AI and Machine Learning (ML) Methods is to make use of the artificial intelligence (AI) models that have become popular in the last decade. Various methods have been studied such as Random Forest models (Falamarzi et al.2018), Support Vector Machines (Hu et al., 2016), and Artificial Neural Networks – ANN (Sadeghi & Askarinejad, 2012). These models assist in automatic detection and categorization of track faults discriminatively from a range of geometric parameters. AI algorithms effectively detected oval shape or circular flaws.

5.1.4 *Signaling*

The all-electronic railway signal computer interlocking fault detection system was designed to provide an important improvement in functioning and maintenance of railway signal systems (Cao & Zhao, 2023). It consists of three major parts: expert system, database management, and information on defects collection and processing. The system ensures that the electronic railway signal equipment works properly by providing necessary problem identification and maintenance support great for tough anomaly detection problems, but in industrial control system networks, traditional methods for detecting anomaly routinely suffer accuracy issues. One interesting approach consists in a multi-level adaptive coupling (Yang et al., 2024). The microcomputer interlocking device for rail transit signals employs a two- machine thermal back up and a two-by-two optional architecture with two main CPUs, one slave CPU, a comparator, and a converter, which allow the system to meet SIL4 safety standards. These components work together through Ethernet and serial communication with the vehicle controller, area controller, and station interlocking system for proper operation. The system's architecture allows for the simultaneous reception of data from several sources, enabling comparison of the signals from different CPUs. This is very useful for spotting inconsistencies or issues with connectivity (Yang et al. 2021). When no discrepancies are found, the CPUs output a common calculation which results in transmission of a legitimate signal. One interesting approach consists in a multi-level adaptive coupling technique based on machine learning (ML) augmented with whitelists. The methods enhanced by AI algorithms are rapidly piquing interest, these algorithms are well known for their strong learning patterns together with key features such as contextual variability and large scale data processing to identify unknown threats. As a result, AI-based algorithms are seen as a possible future direction for many industries. A focused examination of advances and changes in AI from 1961 to 2018 was done by Lu et al. and they focused on key processes, real-world applications, algorithms, and trends and fads that are on the rise (Lu, 2019).

6. Challenges

The adoption of AI in the railway sector presents several complex challenges that must be critically assessed. According to Chen et al. (2021), although AI systems are designed to be more accurate and efficient than traditional technologies, they can encounter malfunctions in demanding operational environments and unanticipated scenarios, posing significant risks to operational safety. A major concern lies in opaque AI systems understanding the reasoning behind AI decisions is extremely difficult. This opacity fosters skepticism and raises critical ethical and legal questions, particularly when AI decisions directly affect people. As Lu et al. (2018) point out, the adoption of AI may create legal grey areas, as existing legal and regulatory frameworks often take considerable time to adapt to new technologies. To address these challenges, the AI High-Level Expert Group stresses the importance of explainability and transparency in AI systems, especially in sensitive domains like railways. The group also highlights concerns over potential job losses due to AI implementation, advocating for a human-centric approach to mitigate such impacts. Additionally, Chen et al. (2021) emphasize that collaboration across countries may be hindered by the substantial structural differences in railway systems worldwide, which complicates the integration of AI on a global scale. Data accuracy remains a critical yet persistent obstacle. As noted by Lu et al. (2018), incomplete or erroneous data can lead to false positives or misdiagnoses, thereby undermining the effectiveness of AI systems. Cost is another significant barrier. Implementing AI solutions requires substantial investment in advanced technologies, software, training, and ongoing model management. Smaller railway companies may find these costs prohibitive. Moreover, as argued by Network Rail, the initial and recurring expenses of implementing such complex systems can be overwhelming. Furthermore, as noted by Loram Innovations Inc., the railway sector often exhibits skepticism toward adopting new technologies. This cultural resistance within organizations could lead to significant in-house opposition to the use of AI systems.

7. Research propositions

Looking ahead, researchers should prioritize two key areas: enhancing autonomous maintenance systems and developing advanced algorithms for forecasting passenger mobility. Key research propositions for future work include: enhancing real-world bbject detection in railway-systems: a critical limitation in AI-based railway object detection is the lack of comprehensive, openly available datasets. Future research should focus on creating datasets that cover diverse object classes, railway scenarios and environmental conditions. Ethical frameworks for AI in Railway Operations: Building on the EU High-Level Expert Group's guidelines, researchers should explore the implementation of transparent and explainable AI systems in railway subdomains such as passenger operations, maintenance, and traffic management. Integrating UAVs for Proactive Railway Maintenance: The use of drones for detecting infrastructure issues is an emerging area of interest. Future studies should evaluate the efficiency, accuracy, and cost-effectiveness of drone-based inspections compared to traditional maintenance methods. Evolutionary Algorithms for Dynamic Passenger Mobility Prediction: Research in this area should focus on leveraging evolutionary computing to improve decision-making for scheduling and resource allocation.

8. Conclusions

The integration of AI into railway systems offers significant opportunities to enhance safety, efficiency, and sustainability. Techniques such as obstacle detection and predictive maintenance powered by deep learning hold considerable promise. However, their success depends on the availability of standardized datasets and the completion of extensive experiments under real-world conditions. To foster trust and ensure safety, ethical guidelines—such as explainable AI, regulatory compliance, and human-centric design principles—must be prioritized. Moreover, traditional approaches in railway operations can undergo substantial transformation through innovations like evolutionary computing for mobility prediction and drone-based infrastructure monitoring. Addressing these challenges will require collaboration among researchers, industry stakeholders, and policymakers. Such efforts will set future standards, drive innovation, and align railway advancements with societal and market needs.

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