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A Review of AI-Driven Railway Traffic Management Using Digital Twin Technology

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ABSTRACT- The railway system is among the most extensive and complex parts of the world's transport system. Traffic management is required to achieve punctuality, optimize capacity, and avoid delays from cascading to other trains. Classic approaches to rail operations have involved definition of dispatching via a manual approach and centralized rule-based control, resulting in poor scalability in regions with lots of mixed-traffic density. This technical report examines technologies that improve rail traffic management using modern optimization methods, machine learning, reinforcement learning, and digital twin methods. Conventional operations research techniques (e.g., mixed integer linear program (MILP), branch & bound, model predictive control) to improve efficiency of scheduling/travel time include AI-driven, deep reinforcement learning-based delay prediction; XGBoost-based prediction of delays, predictive maintenance frameworks. The results of the comparison show that optimization-based techniques continue to provide effective support in strategic planning and creating timetables, whereas they provide limited potential for dynamic, real-time control due to the lack of adaptability to changing operating conditions. Reinforcement learning techniques, on the other hand, will provide greater flexibility in dealing with uncertain, rapidly changing dispatching situations. Supervised models will provide good performance for delay prediction/disruption prediction (e.g., XGBoost), when applied to these rail systems. Lastly, this review suggests that the most promising future direction for intelligent railway traffic management systems will come from the development of hybrid Digital Twin architectures, which will integrate predictive analytics with adaptive control algorithms.

KEYWORDS- Artificial Intelligence, Digital Twin, Railway Traffic Management, Reinforcement Learning.

I. INTRODUCTION

A. Background

The Indian Railways (IR) is one of the world's largest railway networks, covering around 69,000 km of track. Each day, IR runs approximately 13,000 passenger trains and 9,000 freight trains, carrying over 8.4 billion passengers and 1.6 billion tons of freight annually [1]. To manage freight traffic on its network, the IR uses a freight operations information system (FOIS) to help track freight in real time and support decision-making; however, independent audits have concluded that the FOIS system has not met its expected goals or provided timely data related to the status of freight movement [3][4].

Train movements on the IR network are controlled by human operators using centralized traffic control (CTC) and absolute block signalling (ABS) methods [6][7][8], which work well when operating at low densities, but are not scalable as operational increase in complexity.

B. Optimization Challenge

Scheduling railway traffic is often considered an extremely difficult large scale combinatorial optimisation problem because the number of constraints and decision variables increases exponentially with an increase in the size of the network [13]. Compounding the complexity of scheduling is the presence of mixed traffic conditions where different types of trains must operate together such as freight and suburban trains as well as express trains and maintenance trains [10][11][12]. This review paper describes the AI-driven and optimisation-based methods proposed in the existing literature to assist with improving railway traffic management and assesses the relative effectiveness of each method.

This review provides the following contributions to railway traffic management research:

- A structured synthesis of the application of optimisation, machine learning, and digital twin techniques to railway traffic control.
- A technical comparative analysis of the relative strengths and weaknesses of the methods reviewed.
- An identification of the most promising AI-based architectures for future intelligent railway traffic management.
- An identification of open research challenges pertinent to large-scale deployment in Indian Railways and other mixed traffic railway networks.

II. REVIEW METHODOLOGY

The literature review was conducted through collection of articles on railway digital twin, train scheduling optimization, reinforcement learning railway traffic, and delay prediction railway AI from IEEE Xplore, Springer, ScienceDirect, and Google Scholar between 2007 and 2026. The articles were screened first by title and abstract for relevance to railway traffic optimization, predictive maintenance, digital twins, and machine learning. Those studies that had limited application to railway traffic optimization or predictive railway operations or intelligent control of railways were excluded. The articles finally selected were grouped into three types for comparative analysis: operations research/decision analysis methods; AI/ML methods; digital twins/decision support system.

III. LITERATURE REVIEW

A. Operations Research Method

Operations research and mathematical optimization methods have historically been used for railroad scheduling and rescheduling. Mixed Integer Linear Programming (MILP) is among the most researched formulation techniques for schedule optimization because it allows for precedence, headway, occupancy of a platform, etc., to be mathematically accurately modeled.

Ramachandran [9] illustrated the application of MILP in Indian locomotive scheduling to reduce locomotive idle time and to improve locomotive operational inefficiencies. Sartor et al. [14] provided a quasi-periodic strategic timetable for trains using MILP to create "what if" scenarios.

Branch-and-Bound algorithms have also been applied to live train rescheduling. D'Ariano et al. used an alternate graph-based Branch-and-Bound approach to railroad dispatching and reported an average 100-second decrease in secondary delays compared to rule-based dispatching. However, the complexity of computations is a constraint preventing large-scale applications. Furthermore, various researchers have undertaken optimization studies to develop methods for real-time traffic control (i.e., metro and station-level operations) based on mathematical programming formulations for conflict resolution and maximization of throughput [16]. Constraint Logic Programming (CLP), as tested by Trivedi [17], is another option for commuter rail timetables due to its strong feasibility for complex precedence and operational constraints.

Research into other metaheuristic algorithms such as Tabu Search and Ant Colony Optimization (ACO) has also been conducted for the purpose of recovering disruptions and for creating train timetables. Corman et al. [19] suggested an approach to rerouting trains by applying the Tabu Search algorithm for conflict detection and resolving both conflict-free routes during disruptions encountered during rail operations. Huang et al. [20] applied the ACO-based routing algorithm on a mass transport transit system to schedule train routes. The computational tractability provided by both of these approaches allows improved runtimes compared to an exhaustive search solution; however, there may be a compromise in optimality guaranteed.

B. Artificial Intelligence and Machine Learning Methods

With railway telemetry, IoT sensors and the increased availability of live train tracking data, there has been an increased focus on AI-based systems for managing rail networks. The ability of AI techniques to continuously adapt in a dynamic manner, perform predictive analytics capabilities, and provide a scalable dispatching solution are a contrast to the traditional decision tree-like control strategies used by train dispatchers. Many advanced neural networks can perform a complete state estimation on a network-based system and model its expected future movements with a direct output of the current network state at any point in time, as proven by current graph mathematical methods that use spatio-temporal graphs to describe and analyse traffic patterns [2]. Reinforcement learning (RL) is an emerging paradigm which has the potential to revolutionize the methods used to dispatch trains. Work completed by Tian et al. [12] demonstrated that RL techniques such as Deep Q-learning could achieve an average reduction of 25–30% in average delay times for congested suburban rail systems by creating adaptive policies for the scheduling and precedence of routes. Additionally, there has been an increased interest in the use of MARL algorithms for decentralized optimisation of railways. MARL provides the ability to decentralise and optimise individual agent local train decisions while providing for global coordination.

Most of the focus of supervised machine learning methods has been directed toward predictive analytics functions, such as delay forecasting and estimating disruption propagation. For example, Sharma et al. [5] showed that machine learning based delay propagation models can reduce secondary delays by more than 20% in major rail corridors. Also, Pullagura and Katiravan [23] demonstrated that supervised regression and ensemble techniques, such as XGBoost, could provide predictions of train arrival delays with an average error of just 122 seconds. Because of this predictive capability, these models are well-suited for inclusion in proactive dispatch support systems.

C. Predictive Maintenance and Intelligent Infrastructure Monitoring

A similar trend exists for the application of deep learning architecture to related rail traffic optimization areas as well. For example, Deo et al. [29] demonstrated improved throughput of 10 to 12% when they used hybrid CNN-LSTM models to forecast passenger demand and then used that information to make scheduling decisions. Although the models are not directly related to rail traffic management, they highlight the broader applicability of temporal deep learning approaches to the rail industry. Because rail traffic optimization at system level is highly dependent upon maintaining rolling stock and infrastructure, the use of predictive maintenance has also been growing in relevance to optimizing rail operations. Train-control strategies are also being investigated for prediction-control based systems designed to provide proactive adjustments to operations and dynamic regulatory adjustments to traffic within railway systems [22]. Khalilzadeh et al. [21] describe the use of multi-layer perceptron (MLP) based predictive maintenance systems for detection of faults in mechanical subsystems used throughout the rail industry and see that they have substantially reduced the amount of propagated delays due to early intervention. As predictive maintenance outputs are integrated into traffic management systems, there is an opportunity for proactive rerouting and schedule adjustment to reduce the effects of failures on service.

D. Digital Twins and Decision Support Systems

The Digital Twin technology represents an innovative way of engineering railway systems for the future by providing a synchronized virtual model of the real-life railway infrastructure and operations. Digital Twins allow for real-time monitoring, simulation, predictive maintenance, and 'what-if' scenarios before any operational decision is made [27][28]. One area of research and development identified in foundational Digital Twin literature is the future role of Digital Twins to aid in railway maintenance, enhance resilience, and intelligently manage railways as enabling technology for future railway cyber-physical systems [27][28]. Digital Twin platforms can support digital twin rail traffic management by serving as a simulation environment for reinforcement learning agents, predictive analytics pipelines, and optimization solvers. Additionally, simulation-optimization methods were examined to provide robust solutions for railway timetable creation under uncertain operational conditions, thus supporting the role of simulation as a decision support tool for managing railway traffic supply and demand within [25]. This architecture supports closed-loop operations by having the digital twin receive continuous live telemetry updates, predictive analytics estimates of disruptions, and an optimization/AI module recommending the best dispatching decision. For example, Nielsen et al. [26] provide evidence that rolling horizon disruption management concepts align with digital twin scheduling paradigms. Kersbergen et al. [24] demonstrated that the use of Model Predictive Control (MPC)-based railway traffic management could reduce delays by 63% to 96% based on the parameters for the case studies examined.

As such, the intersection of Digital Twin simulation, predictive machine learning, and reinforcement learning dispatch is increasingly recognized as the preferred framework for next-generation intelligent railway traffic management systems.

IV. COMPARATIVE ANALYSIS

Table 1: Comparative Analysis of Railway Traffic Management Techniques

Authors	Technique / Model	Strengths	Weaknesses	Best Use Case
Ramachandran [9]	MILP	Produces mathematically optimal schedules; strong constraint modeling	Poor scalability; computationally expensive for real-time large networks	Strategic timetable planning
Sartor et al. [14]	Quasi-Periodic MILP	Effective for what-if timetable analysis	Static planning only; not adaptive to disturbances	Long-term timetable design
D'Ariano et al. [15]	Branch-and-Bound	Near-optimal real-time dispatching; reduced delays	Exponential complexity with network size	Corridor rescheduling
Trivedi [17]	Constraint Logic Programming	Excellent constraint handling flexibility	Slower convergence for large search spaces	Commuter timetable feasibility
Corman et al. [18]	Tabu Search	Fast rerouting; practical disruption handling	Heuristic only; may miss global optimum	Real-time rerouting
Huang [19]	Ant Colony Optimization	Efficient metaheuristic for periodic timetabling	Parameter sensitive; convergence instability	Metro/MRT timetabling
Tian et al. [12]	Cooperative DRL	Strong adaptive dispatching; scalable in dynamic settings	Complex training; high compute requirements	Heavy-haul / dynamic scheduling
Sharma et al. [5]	Supervised ML Delay Prediction	Predicts delay propagation accurately	No direct optimization capability	Delay forecasting
Pullagura & Katiravan [23]	XGBoost/Regression	High prediction accuracy; low inference latency	Limited to predictive analytics only	Arrival delay estimation
Kersbergen et al. [24]	Model Predictive Control	Strong optimization guarantees; robust under constraints	High computational burden	Medium-scale network control
Kaewunruen et al. [27]	Railway Digital Twin	Enables real-time simulation and predictive maintenance	Requires extensive data/sensor infrastructure	Enterprise traffic management

V. DISCUSSION

In this analysis of previous research, it has become clear that there is a significant gap in the available evidence for operationally deployed Artificial Intelligence (AI) based Railway Traffic Management Systems. Existing studies on Reinforcement Learning (RL) and Optimization are typically validated only in simulation environments and there is very little evidence of real-world (live) deployment of these systems within railway operations. Additionally, Explainability and Trust in AI are significant barriers preventing the adoption of AI within safety-critical Dispatching Systems, whereby human operators need to have a clear (interpretable) rationale for the Automated Recommendations being made. In terms of increasing transparency and accountability through AI Assisted Decision Making Systems, the Explainable AI (XAI) Frameworks identified through this review provide a promising set of methodologies. Certification and Regulatory Compliance are additional challenges that need to be taken into consideration when looking for successfully deployed railway signaling and dispatching systems as there are strict regulations concerning the Safety and Reliability of these systems. Finally, while Indian Railways is large and complex in terms of operational scale, there are very few studies which focus on Indian mixed-traffic railway operations and therefore, there is a clear requirement for more region-specific applied research to be conducted.

Based on this review of selected literature, the railway traffic management methodologies can generally be categorized into Optimization based, Predictive and Adaptive Learning approaches. Each of the three categories, as outlined within this review, has its own advantages and limitations within regard to the scale, uncertainty and dynamic nature of the Railway Environment. Using optimization techniques such as (Mixed Integer Linear Programming) MILP, Branch-and-Bound and Model Predictive Control will yield schedules that are grounded mathematically and generate provide optimal or nearly optimal schedule solutions. These methods also have a fit for the strategic generation of timetables and the medium-sized dispatch processes since the state of the system is sufficiently deterministic, and there is adequate computation time available for execution/solve. The scalable attributes of optimization techniques break down considerably with increases in the number of trains, junctions, and operational constraints and thus limit the practical application of optimization techniques for large-scale, real-time national railways networks.

Machine learning-based predictive modeling techniques provide superior performance in forecasting rail disruption events, estimating how delays will propagate through network operations, and predicting rolling stock failures. XGBoost and ensemble regression methods show a high degree of performance on structured tabular forms of railway data, primarily due to their resistance to feature non-linearity and to missing variables; moreover, they also have very low inference latency, which provide excellent deployment capabilities within operational railroad environments. However, predictive modeling techniques will not provide scheduled or dispatched recommendations directly.

Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) have shown the most promise for adapting to uncertainty (i.e., stochastic) traffic control. Optimization-based techniques require explicit mathematical formulations for creating dispatching solutions; RL agents utilize an interactive/simulate connection with real-world railway environments to formulate their dispatching policies and, in turn, their RL systems adapt to variable (stochastic) disturbances, density of variable traffic flows, and cascading delay events. This technology will enable distributed decision-making using multiple agents across segments of a network and/or train agents at various locations. There are still a number of challenges to overcome for a robust solution (e.g., lack of explainability, lack of training stability, and lack of safety assurances prior to operational deployment) for multi-agent RL systems. The current body of research suggests that there is not a single, superior approach for achieving all railway transportation management objectives, but there continues to be a growing trend toward the integration of different technologies into hybrid systems based on their relative strengths. More specifically, the literature has shown that there is an established body of work on this subject that supports the use of predictive ML models, digital twin platforms, and RL/optimization modules to generate integrated AI-powered digital twin environments that are expected to represent the most promising framework for the next generation of intelligent railway control centers.

VI. FUTURE RESEARCH DIRECTIONS

A. The KAVACH (TCAS) System Integration with the Future Digital Twin Framework:

As future digital twins are developed, they must be integrated with KAVACH TCAS systems and modern train protection systems, allowing for a complete safety-aware closed-loop framework that allows for traffic optimization and dispatch verification.

B. Using Explainable AI (XAI) to Instill Trust in Dispatchers:

Reinforcement learning (RL) and predictive AI systems should be designed to include an explainable layer of operation, thereby increasing the level of transparency and confidence of the dispatcher with AI-assisted decision-making.

C. Expanding Digital Twins Across the Network:

Current digital twin projects are developed to the corridor level only; future work should focus on exploring distributed architecture approaches for developing digital twins capable of being deployed at the division and national scale.

D. Real-Time IoT/5G-R Data Integration:

It is vital for ensuring digital twins remain synchronised as well as to provide capacity for fast responsive adaptation based on real-time collected sensor data.

E. Multi-Agent Reinforcement Learning:

Multi-Agent RL can be used to enable decentralised traffic control of distributed rail corridors due to the limitations of computationally intensive centralised optimisation.

VII. CONCLUSION

This literature review signifies innovation in the combination of Digital Twin technology, Artificial Intelligence (AI) algorithms, and Optimisation methodologies for efficient and effective railway traffic management, specifically, within large and complex operational environments such as Indian Railways as they relate to large-scale and/or complex railway operations. Reinforcement learning demonstrates the best capability for providing the adaptive means of performing real-time scheduling and dispatching. Conversely, supervised learning methodologies such as XGBoost perform the best form of predicting delay. The Digital Twin platform technology provides a practical approach for developing a decision support system that integrates both predictive and optimisation models to support railway operations and should be continued through the following areas: large-scale real-world deployment; explainable AI and interoperability with progressive rail signalling technologies.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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