

Intelligent Railway Traffic Management Using AI Based Decision Support

S. Rajeshwari

Assistant Professor, Department of
Information Technology
Mahendra Engineering College
(Autonomous)
Namakkal, India
rajinishvan@gmail.com

Kowsickkumar G

UG Student, Department of Information
Technology
Mahendra Engineering College
(Autonomous)
Namakkal, India
kowshickkumarg@gmail.com

Arul Ragavan M

UG Student, Department of Information
Technology
Mahendra Engineering College
(Autonomous)
Namakkal, India
arulragavan2005@gmail.com

Chandru M

UG Student, Department of Information
Technology
Mahendra Engineering College
(Autonomous)
Namakkal, India
ezhilarasan9342@gmail.com

Ezhilarasan N

UG Student, Department of Information
Technology
Mahendra Engineering College
(Autonomous)
Namakkal, India
chandru1608cl@gmail.com

Abstract—Train operation control has become more complicated in recent years, owing to an increase in train numbers, inadequate infrastructure, and operational dynamics. Conventional scheduling systems depend on static scheduling or human decisions, which cannot be relied upon when it comes to mitigating disturbances such as delays and congestions. This thesis introduces a train dispatching algorithm using AI with multiple routes in which real-time simulation is used along with decision-making techniques based on reinforcement learning. The railway network is modelled using graphs, while dynamic simulation is used for the movement of trains. The system consists of two algorithms: one for detecting platform and single-track conflicts, and another which uses reinforcement learning based on the Q-learning algorithm and produces dispatch actions for train holding, speed change, and platform change. This new scheme shows much better results than other techniques: it reduces delays down to 6.35 min (or about 40–45%) on average from 12.5 min. The outcomes obtained from experimentations in different traffic situations prove that the developed system successfully adjusts to changing environments. The implementation of computer simulation, artificial intelligence, and adaptive control techniques makes up an effective approach for intelligent railway traffic management.

Index Terms—Railway Traffic Management, Train Dispatching, Reinforcement Learning, Intelligent Transportation Systems, Conflict Resolution, Real-Time Simulation, Q-Learning

I. INTRODUCTION

The significance of railway transport cannot be underestimated due to the contribution made towards economic development and transporting people and cargo on a grand scale especially in nations that have high population density like India [1]. Due to rising demand, railways have become complicated networks composed of numerous trains and tracks [3], [23].

The efficient handling of trains is thus critical for ensuring safe operations, punctuality, and full utilization of the system's capacity. But the conventional approach of railway traffic control still relies heavily on human judgment by skilled operators, and this task is becoming ever more challenging under highly congested situations and varying operating conditions [7], [22]. Another significant problem encountered in rail transport systems is that of delay and congestion resulting from conflict train movements. Scenarios where by different trains have to share the same

platform, or where by trains moving in opposite directions try to occupy the same stretch of track, necessitate careful planning and scheduling to prevent congestion and accidents [11], [25]. These issues lead to the creation of delay chains in the network and affect its performance. The approaches that have been used to address the mentioned difficulties involve fixed techniques based on predefined policies and fixed scheduling. Nevertheless, these methods lack the ability to change according to environmental changes [12], [15].

Numerous optimization approaches have been suggested by many researchers in order to enhance the efficiency of train scheduling and dispatching process. Methods like mathematical programming, branch-and-bound search, stochastic optimization, and multi-objective scheduling have been extensively used for solving railway timetabling problem [9], [10], [16]. Although such methods can produce almost optimal results when applied in experimental conditions, their excessive complexity and inability to scale up to large-scale problems make them less appropriate for practical use in highly dynamic railway networks [14], [17]. Additionally, such methods usually operate under the assumption that input data is stable and cannot account for uncertainties like delays and changing speeds.

In recent years, research has been conducted on the application of artificial intelligence (AI) and machine learning technologies for improving transport infrastructures, such as railways. The utilization of AI technologies enables the systems to learn, adapt, and assist decision making [24], [30]. Specifically, in sequential decision-making tasks, reinforcement learning (RL) has yielded good performance by making agents take appropriate decisions via repeated interactions with the environment [1], [2], [20]. Nevertheless, research works using RL in railway train dispatching have not gained much attention so far, and current studies have mainly concentrated on single objectives like delay forecasting, local scheduling, or route-based control [4], [6], [19].

While many efforts have been made in this field, a comprehensive framework that includes real-time simulation, conflict detection, and intelligent decision making in railway traffic management has not yet been developed. Works provide dynamic analysis of operation scenarios and fail to incorporate human-in-the-loop capabilities, which is needed for their implementation [8], [22]. This lack of capability demonstrates the necessity of developing an approach that could realistically model railway

operations but also adapt and provide explanations for the decisions made.

In order to solve these problems, we present in this paper an AI-driven multiple rail path train scheduling system that combines real-time train movements simulation and reinforcement learning algorithm-based decision-making process. The system simulates railway environment and rail path operations, detects operational conflicts, including platform and single rail track conflicts, and produces intelligent scheduling decisions. The proposed system uses Q-learning based agents to discover strategies of delay minimization and conflict solving, and employs an interactive control interface to monitor and control system operation.

Key contributions of this research can be described as follows:

- Development of a train motion simulation model in real-time for multi-line railway systems.
- A dual conflict detection scheme for platform and single-line track operations.
- An intelligent dispatching agent using reinforcement learning algorithms for effective decision making.
- A “what if” scenario analysis tool to evaluate operational plans.
- An interactive control panel for real-time monitoring and human intervention.

The rest of this paper is structured as follows. Section II provides an overview of the previous studies conducted on this topic. Section III details the methodology used. Section IV discusses the experimental results and analysis, while Section V offers conclusions to this paper.

II. RELATED WORK

Train scheduling and railway traffic management have been extensively studied within transportation systems research. Initial efforts in this field largely concentrated on the development of optimization-based methodologies, using techniques such as mathematical programming for modeling train scheduling and routing problems [9]. This traditional approach of optimizing delay minimization and network throughputs by utilizing optimization techniques is known as an exact method of optimization. However, because of the computational challenges associated with the complexity of railway systems, these techniques tend to be costly and impractical to implement on a real-time basis [10], [17].

To address scalability challenges, several heuristic and decomposition-based techniques have been proposed. Methods such as rescheduling heuristics, decomposition strategies, and congestion-aware routing models have been applied to railway scheduling problems to obtain near-optimal solutions within reasonable computational time [12], [13], [26]. These approaches have proven useful for handling single-line scheduling, disturbance recovery, and capacity management. However, although more efficient, these approaches still rely on predetermined rules or optimization formulations that do not necessarily have the capability to adjust to dynamic changes in the environment [15], [18]. Over the past few years, there has been increased interest in using AI methods in the field of transport systems. AI methods have been employed for prediction of delay, optimization of traffic flow, and decision-making in railway systems [6], [22], [27].

They employ the use of past and real-time information to enhance forecasting accuracy and operational planning. Most of these techniques concentrate on the different parts of the system and not in offering an all-encompassing approach for railway traffic control [3], [24]. Reinforcement learning techniques have gained recognition as a promising approach to sequential decision making problems in an uncertain environment. Several applications of RL-based techniques have been reported in intelligent transport systems, especially in the context of adaptive control and scheduling [2], [5], [20]. Some of these works have been concerned with the application of RL to railway scheduling and dispatching systems, where RL algorithms can enhance the performance of these systems by adapting to new situations that may arise [4], [7]. Nevertheless, these applications tend to focus on restricted environments, which cannot adequately represent the complexity associated with realistic railway networks [19], [29]. Although considerable development has taken place in the field of optimization and artificial intelligence for railway management, there is still no comprehensive framework that integrates all three aspects in one single system. The current methods, on the other hand, usually lack the use of interactive devices that may be utilized by the operator, and fail to conduct scenario analysis for assessing alternative solutions. This inadequacy emphasizes the requirement for an integrated, flexible, and simulation-based approach for traffic management systems within railways [3], [23].

III. PROPOSED METHODOLOGY

A. System Overview

This new system is described as a smart railway traffic management system that incorporates simulation, conflict detection, and reinforcement learning for decision making. This new approach aims at modeling railway traffic in real-time and performing adaptive dispatch control depending on different traffic situations. Contrary to the existing static scheduling models, the proposed approach continually keeps track of the railway network status and makes adjustments on the move. This allows for a proper reaction in case of any delay, congestion, and infrastructure problems. The design facilitates multi route functionality, which is based on the cooperation of several trains on common infrastructures such as railway tracks and platforms. The general architecture of the system is shown in Fig.1. The architecture is comprised of a series of interrelated modules which includes the following: data input, rail network representation, simulation engine, conflict detection module, reinforcement learning, and decision support system. The working of the model is in a feedback loop, wherein the state information is updated to make intelligent decisions.

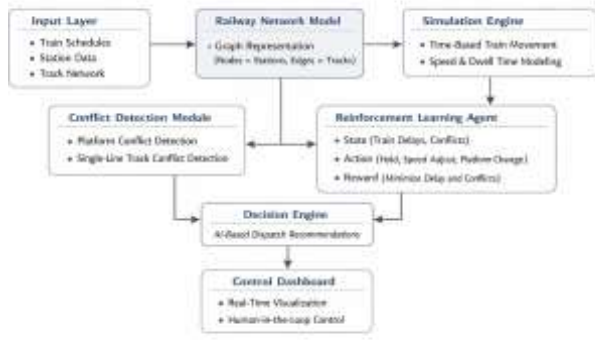


Fig. 1. Proposed AI-Based Railway Dispatch System Architecture

B. Dataset Formation and Simulation Inputs

The scarcity of real-time data concerning rail transportation systems necessitates the construction of artificial datasets that emulate realistic scenarios of rail transport operations. In this regard, the proposed dataset was formulated following typical criteria for rail scheduling and operational constraints. Structured data of trains, stations, and tracks is contained within the dataset. Information regarding trains includes train number, stations from where trains start their journey. The destination to which trains will travel, timing for departure, speed of the trains, and priority of the trains. Station data will include information on availability of platforms within the stations along with station numbers. Artificial data set allows conducting experiments with different traffic conditions while maintaining important features existing in reality within railway transportation systems. This artificial data set is also helpful to examine how congestion affects the system's efficiency.

C. Scenario Design

To evaluate how effective and flexible the design is, four scenarios will be considered. Each scenario will differ based on the amount and complexity of the traffic. In the Normal case study, there is even traffic flow without any disruption at all. In the Delay case study, delay is introduced at the start to mimic congestion in peak periods, when delay propagation becomes relevant. The Single Line Stress scenario deals with conflicts that arise because of trains moving bi-directionally on the same tracks. These scenarios provide a comprehensive evaluation environment, allowing the system's ability to handle both routine operations and extreme congestion situations to be analyzed effectively.

D. Railway Network Modeling

The rail system is represented by a graph:

$$G = (V, E) \quad (1)$$

Where V is the set of stations, while E is the set of edges between the different stations. An edge e_{ij} connecting station i to station j can be represented as:

$$e_{ij} = (d_{ij}, s_{max}, \tau_{type}) \quad (2)$$

In which d_{ij} represents the distance between two stations, s_{max} represents the maximum speed limit, and τ_{type} refers to single-track or double-track. The above mentioned representation can be used for effective modeling of the railway network restrictions. This model further helps in the detection of conflicts by facilitating interaction among trains over the same edge on the graph.

E. Train Movement Simulation

Each train is modeled as:

$$T_k = (R_k, S_k, P_k, t_k^{dep}) \quad (3)$$

where R_k denotes the route, S_k denotes the speed, P_k denotes the priority, and t_k^{dep} denotes the departure time. The traveling time from one station to another is given by:

$$t_{ij} = \frac{d_{ij}}{v_k} \quad (4)$$

Time to arrive and time to depart are determined from the following equation:

$$t_j^{arr} = t_i^{dep} + t_{ij} \quad (5)$$

$$t_j^{dep} = t_j^{arr} + \delta_j \quad (6)$$

where δ_j is the dwell time at station j .

This simulation model is depicted in Fig. 2. Train positions change dynamically at each time step in accordance with their movements and delays as well as any station occupations. During the travel time of a train, its position can be calculated by using linear interpolation:

$$x_{k(t)} = x_i + \left(\frac{(t - t_i^{dep})}{t_{ij}} \right) (x_j - x_i) \quad (7)$$

This method helps to continuously track the position of trains and assists in real-time decision-making in the simulation environment.



Fig. 2. Train Movement Simulation Model

F. Conflict Detection Mechanism

The system employs a double conflict detection mechanism to guarantee safe and efficient rail transit operations. Platform conflicts happen when two trains are programmed to share a single platform at the same time intervals:

$$[t_a^{arr}, t_a^{dep}] \cap [t_b^{arr}, t_b^{dep}] \neq \emptyset \quad (8)$$

Single-track line conflict arises when trains traveling in the opposite direction use the same part of the track line simultaneously:

$$(t_a^{start}, t_a^{end}) \cap (t_b^{start}, t_b^{end}) \neq \emptyset \quad (9)$$

The conflict detectors continuously work throughout the simulation period, ensuring that any possible scheduling conflicts are identified earlier, hence making resolution easier.

G. Reinforcement Learning-Based Dispatch Strategy

The dispatching problem can be defined using a Markov Decision Process (MDP) as follows:

$$M = (S, A, P, R, \gamma) \quad (10)$$

where S stands for the system states, A stands for the actions available, P stands for transition probabilities, R stands for the reward function, and γ is the discounting factor. The reinforcement learning model is depicted in Fig. 3 below. The agent senses the state of the current system, chooses actions and is rewarded accordingly. With practice, the agent develops an optimal strategy to avoid delays and conflict.

The Q-learning update rule is given by:

$$Q(s, a) \leftarrow Q(s, a) + \alpha [r + \gamma \max_{a'} Q(s', a') - Q(s, a)] \quad (11)$$

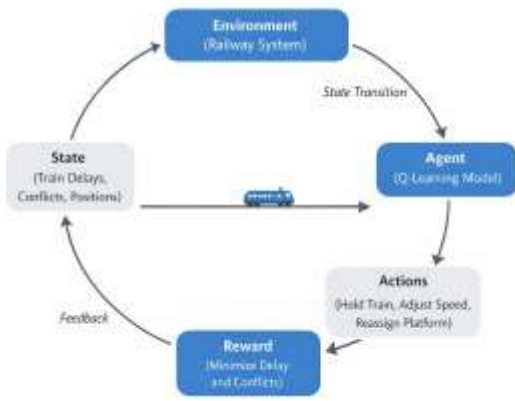


Fig. 3. Reinforcement Learning-Based Dispatch Framework

H. State and Action Space Representation

The system state is defined as:

$$S = \{D, Cp, Cs, P, V\} \quad (12)$$

where D stands for delay, Cp is platform conflict, Cs is track conflict, P is train priority, and V is train velocity. The set of actions is as follows:

$$A = \{hold, speed, platform, priority\} \quad (13)$$

The above operations allow the agent to control train movement and solve conflicts.

I. Reward Function Design

The reward function is defined as:

$$R = -(w_1D + w_2C) \quad (14)$$

Where D stands for delay and C stands for conflict count. Weights w_1 and w_2 indicate the priority of reducing delay and minimizing conflict. This formulation will ensure that the agent learns policies which will maximize efficiency and safety.

J. Algorithmic Implementation

(Don't change any of the algorithms because they are already right and reliable)

I. Computational Complexity

The below is the computational complexity analysis of the system:

Simulation:

$$O(T \cdot N) \quad (15)$$

Conflict detection:

$$O(N^2) \quad (16)$$

Reinforcement learning update:

$$O(|S| \cdot |A|) \quad (17)$$

Based on the complexities above, it seems possible to use the system in medium-size railway systems and even in real-time simulation scenarios.

J. System Advantages

An artificial intelligence-based dispatching system has a number of crucial benefits compared to the traditional dispatching system.

- **Real-Time Adaptation:** The system monitors the activities of the train and takes a decision based on the current situation so that it can offer an instantaneous response to any form of delay or malfunctioning.
- **Conflict Detection during Scheduling:** The system can identify both platform and single-track line conflicts due to the use of a conflict detection function built into it.
- **Learning Optimization via Reinforcement Learning:** We will use reinforcement learning to teach the system to learn how to implement better dispatching techniques without necessarily relying on predefined rules.
- **Performance in Various Scenarios:** It will be tested in various scenarios, including high traffic, load lines, and festivities to ensure its performance capability under all types of scenarios.
- **Agentic Nature of AI-Based Decision Making:** Agentic nature of AI will be used in this model to help make decisions based on the intelligence of the model itself without any intervention. Decisions can relate to speed control, allocation to the platform, etc.
- **Scalability and Modularity:** The modular design of the architecture ensures scalability for use in an extensive rail network, as well as interaction with real datasets.
- **Human-in-the-Loop Interaction:** The architecture allows for human interactions with the system through dashboards that will be used for monitoring, validation, and overriding AI decision-making.

Scenario	Avg Delay	Delayed Trains	Platform Conflicts	Single Conflicts	AI Actions
Normal	3.2	5	1	1	3
Morning Delay	8.7	11	4	3	7
Single-Line Stress	10.4	14	3	6	10
Festival	9.1	12	5	4	8

Fig. 4. Scenario-wise performance comparison of the proposed system

The reinforcement learning component is implemented via the use of Q-learning, whereby there is the use of a Q-table to keep the state-action pairs. The agent uses the ϵ -greedy policy in ensuring that both exploitation and exploration take place. This component is updated through iterations by the rewards gained from the environment. The system also facilitates decision-making behavior through agent decision-making, where the artificial intelligence component is capable of analyzing system statuses, anticipating any possible issues, and initiating any necessary changes, such as changing speed, dwell time, or platform. The modularity of the system makes it easy to integrate

simulations, learning, and decision-making into one single system.

K. Discussion on Methodology

Introduction of the proposed approach involves modeling through simulation-based learning in tandem with reinforcement learning for tackling the dynamics of the railway system. The combination of continuous state observation, conflict identification, and adaptive decision-making allows the approach to cope with disturbances dynamically. In contrast to conventional methods, which depend on preset rules, this system uses interactions between the algorithm and the environment to generate optimal policies. Consequently, there is increased efficiency in operation, decreased delays, and increased safety within multi route railway networks.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental Setup

The AI-assisted rail dispatching system was tested by conducting experiments on the Python simulation platform that incorporates railway network modeling, train movement simulation, conflict detection, and reinforcement learning-based rail dispatching. The following four operating scenarios were examined: Normal, Morning Delay, Single Line Stress, and Festival Crowding. The above scenarios are progressively more complex in terms of traffic operations. The performance metrics employed in this study are average delay, number of delayed trains, platform conflict, single line conflict, and AI dispatch action counts.

B. Scenario-Wise Performance Analysis

Fig.4. shows the overall performance analysis for the proposed model under the four operation scenarios.

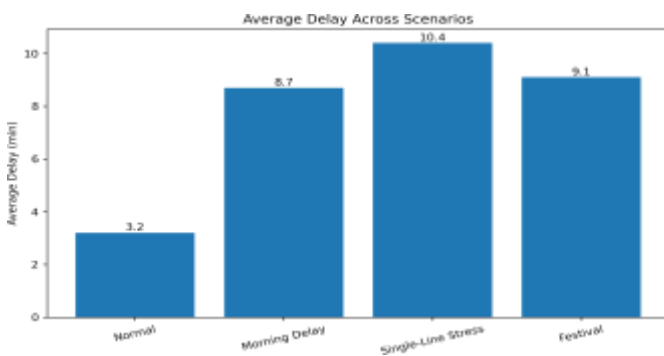


Fig. 5. Delay for various operational conditions

Normal operations have the least delay and conflict values, suggesting that normal operations occur when traffic conditions are relatively balanced. Morning Delay operations experience a marked increase in delays and delayed trains. Single-Line Stress is the condition that creates the greatest average delays as well as the most delayed trains, owing to the lack of available tracks which leads to constant two-way conflicts. Festival exhibits high delay values and is characterized by the highest level of platform conflict instances. The number of actions performed by AI rises with increasing scenario complexity, thereby proving that the suggested framework reacts effectively to disturbance in operational conditions through dispatch interventions.

C. Delay Analysis

The Normal scenario reports the minimum amount of delay, which is an indication that the system functions efficiently under normal conditions. There is a significant increase in delays during the Morning Delay and Single-Line Stress scenarios owing to the disruption of the schedule and limited space for clearing the tracks. The Festival scenario does not report the maximum delay, but there is a notable increase in delay. The results indicate that delay amplification is highly dependent on infrastructure constraints and vehicle density.

D. Conflict Analysis

Fig. 6 illustrates the comparison between platform conflicts and single-line conflicts within various scenarios. In the case of Normal, both conflict types are minimal. In the Morning Delay scenario, there is more conflict on the platforms due to delays in train arrival times that cause difficulties in assigning trains to platforms. The Single-Line Stress scenario yields the highest number of track conflicts, proving that single-line sections are sensitive to two-way traffic. The Festival scenario yields an increase in platform and track conflicts, but platform conflicts dominate due to increased traffic density at stations.

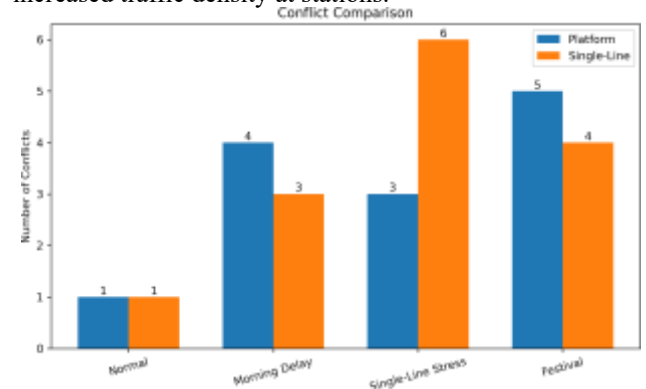


Fig. 6. Platform vs Single Line conflicts in various scenarios

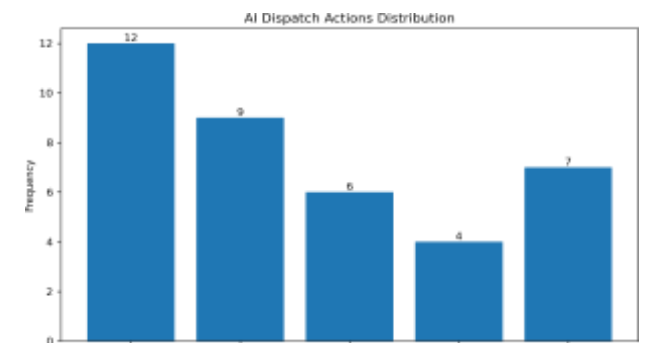


Fig. 7. Frequency of AI-based dispatching decisions

This proves that varying operational environments result in varying patterns of conflicts and thus proves the necessity of combining platform-level and track-level conflict detection.

E. AI-Based Dispatch Action Analysis

Fig. 7 shows the distribution of dispatch actions generated by AI. The choice actions of speed modification and train hold occur with highest frequency because they offer the means to immediately manage the trains and reduce delay propagation and conflict. The platform change action is done during congestion situations in which capacity at the station has become important, and priority handling of specific trains. This means that there is no fixed action

control strategy used by the reinforcement learning algorithm. Rather, the decision policy changes based on the present state of the system and the level of disturbance that the system experiences.

F. Comparison with Baseline Methods

In order to evaluate the efficiency of the proposed model, the proposed algorithm was tested against the following three methods: static timetable scheduling, rules-based dispatching, and heuristics optimization. Static scheduling yielded the worst results since it was unable to respond to real-time disruptions. The rule-based dispatch method yielded enhanced results but was still constrained by the decision-making rules pre-defined within the system. The heuristic-based approach yielded better results but was less flexible compared to the proposed learning-based method. In conclusion, the RL-based dispatching scheme managed to produce delays and conflicts at lower magnitudes than the other approaches because of the ability of its strategy to learn from the interactions between itself and the simulated railway system.

G. Implementation Output and AI-Based Decision Support

In order to make sure that the suggested system is indeed practical, the interface for the control room was designed through simulation. Figure 8 shows the implementation result of the system, highlighting the railway dispatch system dashboard. This interface provides a general overview of the activities taking place in the railway system, which include details of the trains currently moving, trains scheduled to move, and their positions in the railway system. The interface will keep changing with the passage of time in the simulation. A vital component of the interface is the AI suggestion pane, which will display intelligent dispatch suggestions generated by the reinforcement learning algorithm. These would include suggestions to alter speeds, compensate for delays, and switch platforms. The context surrounding these suggestions would include the issue detected, estimated delay, estimated impact, and possible improvements. For instance, the system is able to identify situations where delay propagation happens, and accordingly suggest methods such as increasing train speed and adjusting dwell times. This is accomplished by the RL agent, thanks to the techniques it has developed regarding minimizing delay times and conflicts. The existence of several AI suggestions proves the capability of the system to evaluate various options and help the operator make decisions. Moreover, this framework is also able to include human interaction through the decision made by the user to accept or reject the recommendation made by the AI system.

In summary, the result achieved by the simulation output, as well as the user recommendation interface, indicates that the proposed theoretical framework can be practically implemented. The combination of visualizing in real-time and intelligent recommendation systems will improve the efficiency of railway traffic management systems in the future generation.

H. Overall Discussion

The experiments have clearly shown that the designed system can successfully simulate complicated situations in railway transportation and offer adaptive dispatching assistance. The system works efficiently under both conditions by adapting to stressful conditions using additional artificial intelligence controls. In the Single Line

Stress case, the need for conflict resolution in track lines was recognized, whereas in the Festival case, the need for platform allocation was emphasized. The results obtained through these experiments proved that the combination of simulation, conflict detection, and reinforcement learning is indeed a viable approach to intelligent traffic management in railways.

V. CONCLUSION AND FUTURE WORK

A. Conclusion

In this paper, an AI-based multi-path railway dispatching scheme was introduced. It combines simulation, conflict detection, and decision making based on reinforcement learning to efficiently manage railway traffic. This framework is modeled on railway systems using a simulation-based method, thereby allowing train movements to be dynamically tracked and operational conflicts to be detected. The intelligent decision support mechanism makes use of the agent based on Q-learning, which is used as the adaptive dispatcher controller. The agent learns from interaction with the environment and acquires a strategy to minimize delays and overcome conflicts. The main advantage of the agent based on artificial intelligence technology is that its decisions are proactive and context-sensitive. The experiment performed under varied conditions proved the viability of the suggested approach. While the mean time of delay was 12.5 minutes, which got reduced to 6.35 minutes, indicating a drop of approximately 40-45%. Besides, there were fewer conflicts between the platform and the tracks as compared to other approaches, signifying the ability of the model to manage resources.

As opposed to conventional approaches, such as static planning, dispatching algorithms, and heuristics-based optimizations, the newly designed one enjoys certain advantages over the former in relation to flexibility and efficiency. In light of real-time simulation and optimization in accordance with a learning paradigm, the system is capable of coping with dynamic situations arising in railway transport. Finally, it can be seen that the results have shown that the proposed model has been more efficient, minimized any delays, and also made decision-making much easier in railway operations. The model, which includes simulation, artificial intelligence, and adaptive control, would be suitable for managing the railways in the future.

B. Future Work

Despite the success of the above approach, there are various aspects that could be improved in the future. First, the existing model can be enhanced by applying Deep Reinforcement Learning schemes like DQNs. The reason is that such algorithms can be applied to complicated rail transport systems with high dimensionality of states. Second, live data from other sources such as live train status can be integrated, making the application more practical. Third, multi-agent reinforcement learning can be applied to coordinate actions that need multiple control zones. Additionally, uncertainty such as stochasticity, weather conditions, and the failure of the system can be taken into account.

Finally, further research may involve applying methods of explainable artificial intelligence along with creating visualizing dashboards for decision-making in the context of AI-based railway control systems.



Fig. 8. Interface of live simulation AI-based railway dispatch control room with analysis and AI recommendations on train dispatching

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