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Modeling the neutral state of the "Human-operator" system

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Abstract: Artificial intelligence is increasingly being applied in railway control to support real time dispatching, train trajectory optimization, automatic train operation, and safety supervision. This review examines how AI is used across the main control layers of railway systems, including network traffic management, train level control, safety assurance, predictive support, and virtual coupling. The literature shows that reinforcement learning and other data driven methods can improve adaptability and execution speed, especially under disturbance and uncertainty. However, the review also shows that AI does not replace the classical foundations of railway control. Feasibility still depends on infrastructure constraints, signalling logic, braking laws, operational rules, and explicit safety supervision. The strongest recent approaches are therefore hybrid, combining learning based decision making with optimization, expert knowledge, shielding, formal safety methods, and supervisory control. Virtual coupling further highlights this trend by linking traffic management, train following, and safety into one tightly constrained control problem. Overall, the field is moving toward layered intelligent railway architectures in which prediction, optimization, learning, and safety assurance operate together rather than separately.

Keywords: artificial intelligence, railway traffic control, train dispatching, train rescheduling, automatic train operation, reinforcement learning, safe reinforcement learning, train trajectory optimization, railway safety, virtual coupling

1. Introduction

Artificial intelligence is becoming an important part of modern railway systems. In recent years, railway control has begun to move beyond fixed rule based procedures toward adaptive decision support, online optimization, and increasingly autonomous operation. This change is driven by the growing complexity of rail networks, the need for higher capacity and punctuality, and the demand for stronger safety performance under disturbed operating conditions. As a result, researchers are now studying how AI can support both network level traffic management and train level control.

In railway operations, two closely connected control problems stand out. The first is traffic management, where the objective is to reschedule trains, resolve conflicts, reduce delay propagation, and maintain network stability. The second is train operation, where the objective is to generate safe and efficient speed commands, improve punctuality, reduce energy use, and ensure accurate stopping. AI methods such as reinforcement learning, deep learning, and hybrid expert systems have shown promise in both areas. However, railway control is a safety critical domain, which means that AI cannot be treated as a free standing optimizer. It must operate within strict operational, physical, and signalling constraints.

Another important feature of the literature is that AI in railways did not emerge in isolation. Before the rise of deep learning, railway dispatching and train control were already supported by strong traditions in optimization, decision support, and control engineering. Classical work on rescheduling, conflict detection, rerouting, and delay management established the operational foundation on which recent AI methods are built. For this reason, current research should not be understood as a replacement of classical railway control, but as an extension of it through more adaptive and data driven techniques.

The main challenge is therefore not simply whether AI can improve railway performance. The more important question is how AI can be integrated into railway control architectures in a way that remains explainable, monitorable, and safe. Recent studies increasingly point toward hybrid solutions that combine learning based methods with expert rules, optimization models, shielding mechanisms, and formal safety supervision. This tendency is especially visible in advanced applications such as automatic train operation, safe reinforcement learning, and virtual coupling.

This article reviews the role of artificial intelligence in railway traffic control and safety. It examines the main strands of the literature, including traffic management and rescheduling, automatic train operation, safety assurance, predictive support systems, and virtual coupling. The review also compares major method families and highlights the broader shift toward layered and hybrid intelligent control architectures in railway systems.

2. Research methodology

From optimization based dispatching to learning based control.

The strongest backbone of the literature remains the classical dispatching and rescheduling tradition. D'Ariano and colleagues developed conflict resolution, train speed coordination, and local rerouting strategies for real time timetable perturbations [5, 6]. Their work showed that practical dispatching could be formalized as a sequence and routing problem under strict infrastructure and operational constraints. Corman and coauthors extended this line by reviewing online dynamic traffic management models and by integrating train scheduling with delay management in real time [7, 8]. Cacchiani and colleagues then consolidated the broader recovery literature, showing how rescheduling

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models balance exactness, computational tractability, and operational realism [4].

This earlier body of work matters because recent reinforcement learning methods do not solve a different railway problem. They solve the same control problem with a different search mechanism. Early reinforcement learning studies targeted narrower settings such as single track rescheduling [11] or limited network disturbances [34]. Later work improved scalability by designing state and action spaces that do not grow directly with every timetable instance [12]. More recent studies learn reusable dispatching policies for high speed timetable rescheduling and extend them through graph representations, multi task learning, and multi agent coordination [13, 35, 14, 15].

The practical appeal of reinforcement learning is speed at execution time and adaptability to disturbance patterns. The main weakness is that policy quality and safety become harder to interpret than in classical optimization. This tension is visible across the literature. Review papers repeatedly note that machine learning can exploit rich historical data and capture patterns missed by simplified models, but they also warn that black box decision rules are hard to justify in safety critical control [1 , 2].

Table 1

Comparison of method families

Method family	Best suited tasks	Strengths	Main limits
Exact and heuristic optimization	Conflict resolution, rerouting, delay management	Transparent constraints, strong operational fit, mature validation	Harder to scale for large networks in strict real time [4, 7]
Reinforcement learning	Online dispatching, adaptive rescheduling, train control	Fast online decisions after training, can learn from disturbance rich data, transferable policies in some settings [12, 13]	Weak interpretability, safety not guaranteed without extra structure [1 , 20]
Hybrid expert and learning methods	Automatic train operation, trajectory control	Combines domain rules with flexible adaptation, easier to keep practical constraints in loop [16, 18]	Still depends on careful reward design and scenario coverage
Safe RL and shielding	Speed control, interval control, autonomous operation	Adds explicit protection against unsafe actions and speed violations [19,20]	Usually validated in simulation or bounded corridors rather than full network operations
Predictive deep learning	Delay prediction, passenger flow, risk states, anomaly detection	Strong pattern extraction from large temporal and spatial datasets [18,19]	Prediction quality degrades under rare disruptions and may remain hard to explain [20]

AI for network traffic management

For network level traffic control, the core operational task is still disturbance management. Delays must be contained before they propagate across shared track, stations, junctions, rolling stock rotations, and passenger connections. The literature shows three broad approaches.

The first is decision support rooted in mathematical models. These systems predict conflicts and compute feasible retiming, reordering, or rerouting actions under detailed operating rules [6]. They remain strong where transparency and operational accountability are critical.

The second is data driven dispatching. Wen and colleagues divide this literature into delay distribution, delay propagation, and timetable rescheduling, and argue that machine learning is especially promising when rich operational data are available [1]. Delay prediction reviews reinforce this point. Spanninger and colleagues show that data driven methods often outperform event driven methods in raw prediction accuracy, while event driven models remain more interpretable and more robust under severe disruptions [11]. This suggests that prediction alone is not enough. A traffic management system still needs a control layer able to act on those predictions.

The third approach is reinforcement learning for direct dispatching policy generation. In this line, the controller learns which train should move first, how conflicts should be resolved, or how local timetable adjustments should be made [11, 12, 13, 14]. The main contribution of this work is not merely better objective values. It is the replacement of handcrafted dispatching rules with learned policies that can respond quickly when the network state changes.

AI for automatic train operation

At train level, the literature is shaped by automatic train operation rather than network rescheduling. Yin and colleagues surveyed ATO as a system problem involving punctuality, stopping accuracy, comfort, energy use, and safe speed supervision [7]. Earlier work combined expert systems with reinforcement learning to mimic experienced

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driving behavior while still optimizing train performance [6].

Later studies deepen this approach with continuous control algorithms. Zhou and colleagues integrate expert knowledge with deep reinforcement learning, using rule extraction and safe velocity supervision to keep the controller within punctuality, comfort, and speed limit constraints [18]. Chen and colleagues report that deep Q learning can improve energy consumption, punctuality, and parking accuracy under urban rail operating constraints [19]. Related trajectory optimization studies show that deep deterministic policy methods can generate feasible train speed profiles quickly enough for online use under different running times and line conditions [20]. Supervised reinforcement learning variants further improve adaptation to disturbances in intelligent ATO settings.

A consistent pattern emerges from this work. Pure learning is rarely trusted on its own. Most successful ATO studies embed train physics, signal limits, braking logic, or expert driving knowledge into the learning loop. In railway control, AI performs best as a constrained optimizer rather than an unconstrained decision maker.

Safety assurance and risk aware autonomy

Safety is the decisive filter for every claim of railway intelligence. Several recent papers respond directly to the weakness of standard reinforcement learning in safety critical settings. Shield based methods are designed to prevent unsafe actions during both learning and execution. Zhao and colleagues show that safe reinforcement learning with an explicit protective shield can keep optimized speed profiles within speed limits more reliably than soft penalty methods [20]. Their later work extends this logic into a broader framework for autonomous urban rail operation, combining shielding, search, and additional learning to satisfy speed and schedule constraints [3]. Interval control and anti collision studies push the same agenda by adding safe RL layers or predictive tasks to train separation control [4, 5].

Another branch of the literature treats safety as a state estimation and decision problem. Hazard and risk prediction models for train control systems use recurrent networks or hybrid deep learning and formal methods to identify unsafe states in CBTC and related control architectures [31, 10]. Chelouati and colleagues frame anti collision decisions for autonomous trains as a POMDP problem, emphasizing continuous risk assessment under uncertainty rather than simple rule triggering [6]. Tonk and colleagues add a systems view by arguing for explicit safety assurance methodologies for autonomous trains rather than assuming that performance improvements imply acceptability [9].

Virtual coupling as the next frontier

Virtual coupling brings together traffic efficiency and safety in one problem. The idea is to run trains at much shorter separations through cooperative control and train to train communication, increasing line capacity beyond conventional moving block systems. Reviews of this field show why it is attractive and why it is difficult.

The control literature includes consensus based methods, model predictive control, sliding mode control, machine learning based control, and constraint following control [33]. Machine learning is attractive because it can avoid detailed model identification and can run faster than heavy optimization once trained. Yet virtual coupling also exposes the sharpest safety concerns in the whole AI rail literature. Communication failure, uncertain braking and adhesion, cybersecurity risk, interlocking logic at junctions, degraded modes, and string stability all remain open problems [2, 3]. In this domain, AI expands the feasible control space, but safety engineering still sets the boundary of deployment.

Overall assessment

The literature supports four broad conclusions.

- AI is now a serious method family for railway control, not a peripheral add on. This is clearest in real time rescheduling, ATO, and predictive traffic management [3, 2].
- Reinforcement learning has become the dominant AI paradigm for operational control, especially where fast online response matters [11, 13, 14].
- Safety remains the main barrier to deployment. The strongest recent work therefore adds shields, formal constraints, risk prediction, or supervisory logic instead of relying on reward design alone [2, 3, 9, 10].
- The next wave is likely to be hybrid. Prediction, optimization, formal safety methods, and learning based control are converging rather than competing [1, 2, 3].

3. Conclusion

The research landscape suggests that the future automatic train traffic control system will not be fully rule based and will not be fully learned. It will be layered. Predictive models will estimate delays, passenger demand, and risk states. Dispatching agents will propose rescheduling actions across the network. Train level controllers will optimize speed and energy use in real time. Around all of them, safety assurance logic will remain non negotiable. The central academic question is therefore no longer whether AI can improve railway traffic control. The better question is how AI can be integrated into railway control architectures so that efficiency gains remain explainable, monitorable, and bounded by safety at every decision point [8, 18, 20,].

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