Palacký University Olomouc

Transactions on Transport Sciences
Peer-Reviewed Open Access Journal
SI SCSP conference/2025 DOI: 10.5507/tots.2025.010
journal homepage: www.tots.upol.cz

Defining Railway Traffic Conflicts and Optimising Their Resolution: A Machine Learning Perspective

MATOWICKI MICHAŁ[a], MŁYŃCZAK JAKUB[b], GOŁĘBIOWSKI PIOTR[c], PŘIKRYL JAN[a]

a. Czech Technical University in Prague, Faculty of Transportation Sciences, Konviktska 20, 110 00 Prague
b. Silesian University of Technology, Faculty of Transport and Aviation Engineering, Katowice, Poland
c. Warsaw University of Technology, Faculty of Transport, Koszykowa 75, 00-662 Warsaw, Poland

ABSTRACT: This paper reports on the initial phase of research into automated traffic conflict resolution for suburban railway operations. It defines railway traffic conflicts, categorising types such as catch-up, crossing, and proximity, and establishes optimisation criteria focused on punctuality, efficiency, safety, and passenger satisfaction. Promising machine learning approaches are reviewed, including supervised learning for conflict prediction, reinforcement learning for adaptive resolution, and unsupervised methods for identifying conflict-prone scenarios. The study concludes by proposing a simulation framework for empirical evaluation, providing a foundation for AI-driven advancements in railway traffic management.

KEYWORDS: Machine Learning; identification and classification of conflicts; conflict resolution; railway traffic management; global optimisation;

1. INTRODUCTION

The subject of this article covers the phenomenon described in the literature as "rescheduling" (Cacchiani et. al (2014)). It can be defined as the rearrangement of schedules (work schedules, class schedules, etc.) after the occurrence of an undesirable event. This class of problems is used to deal with extraordinary situations in various branches of the economy and everyday life. One such area is railway transport.

The real-time operation of the railway system is frequently exposed to unexpected disruptions that make it impossible to meet the planned timetable. In addition, there may be problems with rolling stock circulation (train to train transition) and train crew scheduling (train to train transition). From the passenger's point of view, this can result in train delays, loss of connections, insufficient seat supply, train cancellations and more. Therefore, there is a need to resolve the disrupted situation as soon as possible in order to restore the normal operation of railway transport (normal organisation of railway traffic).

With regard to railway transport, Cacchiani et al. (2014) defines the problem of rescheduling as the application of so-called recovery models and algorithms dedicated to real-time railway disturbance and disruption management. Disruptions are divided into two groups – disturbances and disruptions. The first group (disturbances) are relatively minor perturbations to the railway transport system that can be resolved by modifying the timetable, but without changes to the composition of rolling stock and train crew assignment to operate individual trains. An example of a disturbance from the first group is an extended stop at a station beyond what is scheduled. On the other hand, the second group – disruptions, are relatively large incidents that require timetable modifications and the re-assignment of rolling stock and train crews to handle them. Within this group, many train paths on the traffic chart are cancelled. As an example of a disruption from the second group, a track washout by a river can be given. The issue of rescheduling is one of the branches of operations research that has been extensively studied in the literature. The most important keywords related to this

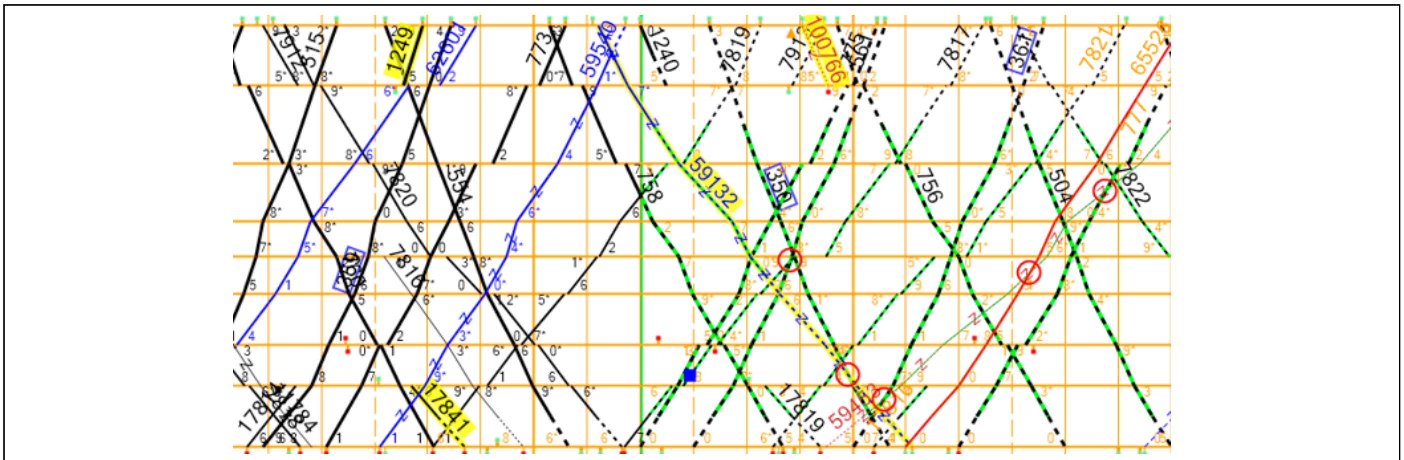

Figure 1: Example of traffic outlook with conflicts identified as red circles (source: AZD Praha GTN solution)

problem are rescheduling, vehicle assignments, and train crew assignments in real time.

Returning to a normal (scheduled) state after an undesirable event (after a perturbation) requires changes to the train timetable, possibly to assign different rolling stock to particular tasks, and the planning of train crews. In the case of minor perturbations, it is sufficient to either reschedule trains (i.e., to determine new moments of entry to block intervals or to seek new train paths), change the train running order, or cancel a service. In the event of significant disruptions, work begins with the re-preparation of the timetable, followed by an analysis of the timetable in terms of rolling stock transitions at terminal stations and train crew transitions, and a new timetable is generated on this basis. In the strategic phase, the infrastructure manager is responsible for timetable construction, while the railway companies are responsible for updating their rolling stock and train crew schedules. These two entities should work together in the operational phase and make the best decisions.

A key difference between the process of timetable construction and resolving traffic conflicts is time available for decision-making. In the latter case, the decision should be made as quickly as possible, usually within a few minutes. Within this short timeframe, multifaceted and complex decisions have to be made, which have to respect many boundary conditions. On top of this, the decisions must be rational, taking into account multiple, often conflicting, objective functions. At present, dispatchers of the infrastructure manager rely on their experience, prior knowledge, and best practices to make these decisions manually, without the aid of decision support tools, particularly intelligent decision support systems. Developing such tools is therefore essential to assist line dispatchers in making informed, efficient decisions for resolving the wide range traffic conflicts in short time.

Besides the manual conflict resolution, many railway networks today still rely on local dispatchers who resolve conflicts only within a single dispatching area rather than across the entire network. As a result, solutions devised at the local level may inadvertently cause additional knock-on effects upstream or downstream, leading to significant delays and inefficiencies overall. Centralized and automated conflict resolution systems have the potential to provide a broader, system-wide view, enabling dispatchers to make better-informed decisions while coordinating with adjacent control areas. By incorporating real-time data, predictive analytics, and machine learning, these solutions can streamline operations, reduce costly disruptions, and improve overall reliability and capacity. Hence, continued research and development of modern automated conflict resolution tools is critical to overcoming the limitations of manual, localized dispatching and creating a more efficient, resilient, and future-proof rail network.

There are many references in the English-language literature to methods and tools for resolving movement conflicts or rescheduling. D'Ariano et al. (2008a) developed the ROMA (Railway traffic Optimisation by Means of Alternative Graphs) model based on alternative graph theory. Using this model, they carried out a series of experiments that involved the railway line between Utrecht and 's-Hertogenbosch and the stations Utrecht Central and Amsterdam Schiphol Airport (D'Ariano et al. (2008b), Schaafsma & Bartholomeus (2007)). Flamini and Pacciarelli (2008) conducted a study on rescheduling for stations at the metro terminal and Gely et al. (2006) between Tours and Bordeaux on the French SNCF railway network. Mannino and Mascis (2009) resolved traffic conflicts on the underground rail network in Milan, Italy (Azienda Trasporti Milanesi (ATM)). Albrecht et al. (2011), in turn, conducted research on the Danish and German networks (as did Lusby et al. (2013)), while Caimi et al. (2012) on the Swiss network for Bern. The literature review presented above only indicated areas where analytical solutions to traffic conflicts have been made using a mathematical formulation of the rescheduling problem. Behind each item cited is a different way of formulating or solving the problem. It should also be noted that only selected implementations have been indicated. There are many more references in the literature on conflict resolution on the railway network with their practical implementation.

2. DEFINING RAILWAY TRAFFIC CONFLICTS

According to the EU Directive 2016/797 on the interoperability of the rail system within the European Union, railway traffic can be defined as the procedures and related equipment enabling the coherent operation of the different structural subsystems (infrastructure, energy, control-command and signalling (trackside and on-board layers), rolling stock), both during normal and degraded operation, including, in particular, train formation and train driving (traffic management layer), traffic planning and traffic management. In addition, the professional qualifications that may be required to operate any railway service are relevant to railway traffic. According to the aforementioned Directive, railway traffic is one of the three functional subsystems of the railway system (alongside maintenance and telematics applications).

Several people are responsible for ensuring that train traffic runs as safely and uninterruptedly as possible. On the part of the railway undertaking, these are the transport offer constructors - the timetable constructors in the traffic planning layer. In the traffic management layer, these are the train crew - the train manager and possibly the conductor(s) - and the traction crew (the engine driver, possibly together with a second engine driver or a trainee engine driver). On the other hand, in the traffic management layer, these are the dispatchers of the undertakings. On the infrastructure manager's side, in the traffic planning layer, they are the timetable constructors, in the traffic operation layer, they are the traffic controllers, signallers and other operating staff, and in the traffic management layer, they are the line dispatchers.

Trains run on the railway network according to a predetermined plan - the timetable. It represents the ideal organisation of railway traffic, where all safety conditions are maintained, and the guarantee of possible uninterrupted (uninterrupted) train running is guaranteed. As train traffic is stochastic, there is a risk that some unforeseen event may disrupt the ideal organisation of train traffic on the network. This event may be related to a problem in any of the structural subsystems (for example, a defect in a component of the railway infrastructure, a problem in the traction energy supply, a failure of the control or supervision equipment or a failure of the rolling stock) or factors outside the control of the railway (for example, severe weather conditions or an accident with a human or a road vehicle). This disruption can have more or less negative consequences. As a consequence of the delay of a specific train due to a specific event (which is called primary delay), secondary delays may occur (both for other trains and the initially delayed train). Their amount depends mainly on how much of the changed train path (changed due to the delay generated by the occurrence of the undesirable event) will have traffic conflicts with the paths of other trains that are running as scheduled or may be delayed by another undesirable event, and how they will be resolved.

3. PROMISING MACHINE LEARNING APPROACHES

The increasing complexity of railway traffic management and the need for real-time conflict resolution necessitate advanced computational approaches. Machine learning (ML) offers a powerful toolkit to address this challenge by enabling automated detection, prediction, and resolution of railway conflicts. This section explores the most promising ML techniques applicable to traffic conflict optimisation, evaluating their suitability for real-time and predictive decision-making in railway operations.

ML approaches applicable to railway conflict resolution can be broadly categorised into supervised learning, reinforcement learning (RL), and unsupervised learning. Each paradigm offers distinct advantages depending on the complexity and dynamism of the problem.

- **Supervised Learning** is useful for predicting train delays and classifying conflict scenarios based on labelled historical data.
- **Reinforcement Learning** enables adaptive decision-making in dynamic railway environments, optimising traffic flow through sequential actions.
- **Unsupervised Learning** can cluster traffic patterns to identify potential conflict-prone areas and infer new conflict resolution strategies.

These ML methods, when integrated with a railway Traffic Management System (TMS), can significantly improve real-time conflict resolution.

3.1 Supervised Learning for Conflict Prediction and Classification

In railway traffic management, anticipating conflicts before they occur is crucial for ensuring smooth operations and minimising disruptions. In this context, supervised learning methods offer a powerful means of predicting train delays and classifying potential conflict scenarios. By training models on past railway operations, supervised learning can enhance decision-making processes by providing early warnings of possible conflicts, allowing for timely intervention (Selin and Ismail (2013)).

One of the most practical applications of supervised learning in railway operations is delay prediction, which relies on models trained on extensive historical datasets, including train schedules, dwell times, weather conditions, and infrastructure availability. Decision trees, Random Forests, and Gradient Boosting Machines (GBM) have demonstrated strong performance in this domain by identifying patterns that lead to train delays (Tiong, Ma & Palmqvist (2003), Sarhani and Voß (2024), and Karimi-Mamaghan et. al (2021)). By continuously updating these models with new data, railway operators can generate accurate delay forecasts, allowing dispatchers to take preventive measures before conflicts arise.

Beyond delay prediction, supervised learning can also be used for conflict classification, enabling the system to categorise different types of railway traffic conflicts, such as catch-up, crossing, and proximity conflicts (as outlined in Section 2). Support Vector Machines (SVMs) and Neural Networks have proven effective in distinguishing between these conflict types by analysing real-time data on train positions, movement speeds, and schedule adherence. By automating this classification process, Karimi-Mamaghan et. al (2021) argues that traffic controllers can receive real-time alerts about emerging conflicts, enabling faster and more informed decision-making.

Supervised learning models have been effectively employed both to predict train delays and classify conflict scenarios. For instance, the Swedish MATRIX project developed and evaluated a ML model to assist train dispatchers in resolving potential timetable conflicts during disturbances (Sai Prashanth (2024))**Error! Reference source not found.**.

Despite their advantages, supervised learning models require large, high-quality datasets to achieve reliable performance. The success of these models depends on the availability of comprehensive historical records, which may not always be structured or complete. Additionally, while supervised models excel at predicting and classifying conflicts, they do not inherently suggest optimal resolutions, making their integration with other decision-support mechanisms, such as reinforcement learning, an essential step toward achieving a fully automated traffic conflict management system.

3.2 Reinforcement Learning for Dynamic Conflict Resolution

While supervised learning focuses on forecasting conflicts, reinforcement learning (RL) provides a machine learning framework that learns how to actively resolve them in real-time. Unlike traditional optimisation techniques, which rely on static rules and heuristics, RL-based approaches learn optimal strategies through trial and error, making them particularly effective in highly dynamic environments such as railway operations. By continuously interacting with the railway network, RL agents refine their decision-making policies to minimise disruptions and improve scheduling efficiency.

According to Lingbin et al. (2019) one of the most promising applications of RL in railway traffic management is adaptive train dispatching, where RL models optimise train departure sequences and track allocations based on real-time network conditions. Conventional dispatching systems rely on predefined priority rules, which may not always be optimal under unexpected disruptions. RL-based systems, on the other hand, dynamically adjust train schedules to minimise delays while ensuring safe separation between trains. Deep Q-Networks (DQN) and policy gradient methods have been successfully used in similar domains to optimise sequential decision-making, demonstrating their potential for improving railway traffic flow says Nguyen et al. (2019).

Another key advantage of RL is its ability to reschedule train operations dynamically in response to unforeseen disturbances, such as track blockages or equipment failures. Multi-Agent Reinforcement Learning (MARL) extends RL capabilities by enabling collaborative approach in resolving conflicts (Zhuang et al. (2022)). Instead of optimising decisions in isolation, MARL facilitates coordinated conflict resolution across multiple network segments, resulting in more efficient traffic flow and reduced cascading delays.

Despite its strong potential, RL in railway applications poses several challenges. Training RL models requires extensive simulations in environments that accurately represent real-world railway dynamics, including variations in infrastructure, train speeds, and passenger demand. Additionally, ensuring safe exploration is critical; while RL agents typically learn by trial and error, railway operations cannot afford risky decision-making during live deployment. Techniques such as constrained RL and risk-aware learning can help mitigate this issue by ensuring that learned policies adhere to operational safety constraints.

The integration of RL into real-world TMS also requires a careful balance between automation and human oversight. While RL-based decision-support systems can propose optimal conflict resolution strategies, railway operators may still need the final authority to validate and implement these recommendations. A hybrid approach, combining RL with expert-driven rule systems, may offer the most practical path toward integrating AI-driven traffic management into existing railway control workflows.

3.3 Unsupervised Learning for Conflict Detection and Pattern Recognition

Beyond resolving conflicts in real time, an essential aspect of railway traffic management is identifying conflict-prone areas and understanding underlying traffic patterns. Unsupervised learning techniques provide valuable insights by discovering structures in data without requiring predefined labels, making them particularly useful for clustering and anomaly detection.

One practical application of unsupervised learning in railway traffic management is detecting high-risk conflict zones based on historical congestion patterns. Md Siddiqur, Laurent and Josaine (2022) note that by clustering railway segments with frequent traffic bottlenecks, algorithms such as k-Means and DBSCAN can identify regions where conflicts are most likely to occur, helping infrastructure managers implement proactive measures such as track expansion, scheduling modifications, or automated conflict resolution strategies.

Another significant use of unsupervised learning is anomaly detection in train operations, which can serve as an early warning system for potential conflicts. Unsupervised models, such as autoencoders and Isolation Forests, can analyse deviations from normal traffic behaviour, identifying train movements that do not align with expected operational patterns. These anomalies may indicate scheduling conflicts, unexpected delays, or even potential safety hazards.

The significant potential of deep unsupervised learning algorithms for road traffic conflict identification and validation was identified by Lu (2022). By identifying the most influential variables in train scheduling and movement, PCA facilitates the development of more efficient traffic management models. These insights can then be used to refine existing rule-based systems or improve ML-based decision-making frameworks.

3.4 Integration of Machine Learning into Traffic Management Systems

For ML-based conflict resolution to be effective in practice, it must be seamlessly integrated into existing TMS. This integration involves both offline and online solutions, each serving distinct but complementary roles. Offline ML models analyse historical data to uncover patterns and inform long-term planning, while online ML models operate in real time, continuously updating predictions and recommendations based on live data inputs.

One of the key challenges in deploying ML within TMS is ensuring interpretability and reliability. While complex deep learning models can achieve high predictive accuracy, railway operators require transparent decision-making processes to trust and act upon AI-driven recommendations. A hybrid approach, combining traditional rule-based scheduling with ML-driven optimisation, offers a practical pathway to adoption. This ensures that AI augments, rather than replaces, human expertise in railway dispatching and traffic control. This approach is apprised by projects supported with EU funds such as Europe's Rail or RAIL projects as noted by Ferreira (2023).

Lessons from other transportation sectors, such as air traffic control and urban road traffic management, provide valuable insights into ML integration strategies as well. For instance, reinforcement learning has been successfully applied in air traffic flow management (Crespo, Li and Gomes de Barros (2012)), while unsupervised clustering methods are widely used in urban congestion analysis as pointed by Nguyen et al. (2019). These applications suggest that similar methodologies can be adapted for railway systems to enhance scheduling robustness and minimise disruptions.

Moving forward, a simulation-based framework (see Figure 2) will be essential for evaluating the effectiveness of different ML models before real-world deployment. A well-designed simulation environment will allow railway planners to test ML-driven conflict resolution under diverse operational scenarios, comparing different algorithms in terms of resolution time, efficiency, and scalability. Such an empirical evaluation will provide a foundation for refining ML approaches and ensuring their practical applicability in large-scale railway networks.

By leveraging machine learning for both proactive conflict detection and real-time resolution, railway operators can move toward a more intelligent, adaptive, and resilient traffic management system. The continued advancement of ML-driven optimisation strategies holds the potential to significantly improve railway reliability, reduce delays, and enhance overall passenger and freight transport efficiency.

4. DRAFT OF FUTURE SIMULATION FRAMEWORK

Next phase of the project will focus on the evaluation and numerical simulation of the effectiveness of investigated algorithms. The evaluation framework should consist of three principal components: (1) a simulation environment that accurately models railway infrastructure, train dynamics, and conflict scenarios; (2) an ML module trained on historical and synthetic data to predict and resolve potential conflicts; and (3) an integration interface that allows real-time data exchange between the simulation and the ML system. By systematically varying traffic density, incident frequency, and operational conditions, the framework facilitates comprehensive sensitivity and robust analyses. Statistical techniques, such as hypothesis testing and confidence interval estimation, are employed to validate performance gains over conventional conflict resolution strategies.

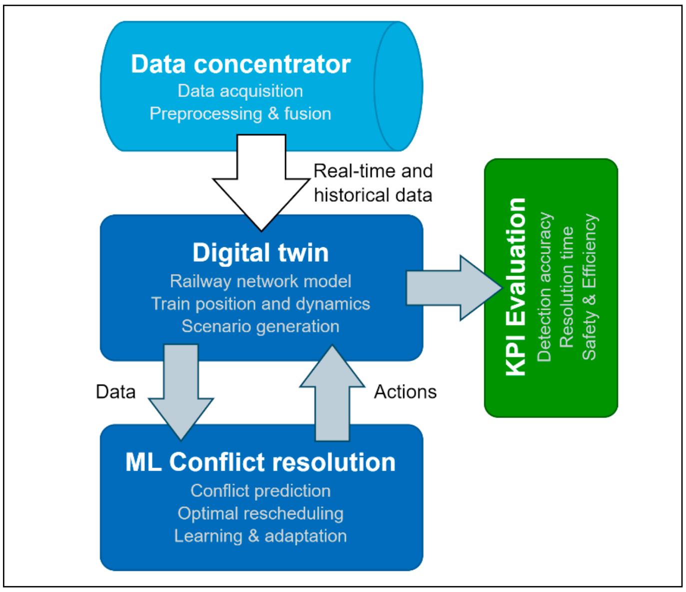

Figure 1: Building blocks of conflict resolution testing framework

5. CONCLUSION AND FUTURE WORK

This paper presented an overview of railway traffic conflicts and mechanisms related to their resolution, emphasizing the need to deploy automated rescheduling systems for efficient railway disruption management. We categorized conflict types, identified key optimization criteria, and reviewed promising ML techniques for optimal conflict resolution, including supervised learning for conflict prediction, reinforcement learning for dynamic resolution, and unsupervised learning for conflict patterns recognition. The findings highlight the limitations of current manual conflict resolution methods, which often lead to suboptimal, locally-focused decisions. Automated approaches leveraging ML have the potential to provide more efficient, system-wide solutions, reducing delays and improving overall network resilience.

The next phase of research will focus on developing a simulation framework for evaluating ML-based conflict resolution strategies. This framework will integrate real-world railway traffic data, allowing for empirical testing of ML algorithms under varying operational conditions. Key areas of investigation will include real-time implementation feasibility, decision interpretability for dispatchers, and safety constraints in automated scheduling adjustments. Additionally, further research will explore the integration of ML-based decision-support tools into existing Traffic Management Systems (TMS) to ensure seamless adoption by railway operators.

By advancing AI-driven traffic conflict resolution, this research contributes to the broader goal of enhancing railway efficiency, reliability, and sustainability. The long-term vision is a fully adaptive and intelligent railway traffic management system, where machine learning supports dispatchers in making optimal, system-wide decisions in real-time. Future work will also explore the application of hybrid AI-human decision-making frameworks, ensuring that automation complements, rather than replaces, human expertise in railway operations importance.

REFERENCES

Albrecht, T., Binder, A., & Gassel, C. (2011). An overview on real-time speed control in rail-bound public transportation systems. Proceedings of the 2nd International Conference on Models and Technologies for Intelligent Transportation Systems, Leuven, Belgium.

Amundsen, F. H., & Hydén, C. (1977). Proceedings from the First Workshop on Traffic Conflicts. Oslo.

Cacchiani, V., Huisman, D., Kidd, M., Kroon, L., Toth, P., Veelenturf, L., & Wagenaar, J. (2014). An overview of recovery models and algorithms for real-time railway rescheduling. Transportation Research Part B: Methodological, 63, 15–37.

Caimi, G., Fuchsberger, M., Laumanns, M., & Lüthi, M. (2012). A model predictive control approach for discrete-time rescheduling in complex central railway station areas. Computers & Operations Research, 39, 2578–2593.

Crespo, A. M. F., Weigang, L., & de Barros, A. G. (2012). Reinforcement learning agents to tactical air traffic flow management. International Journal of Aviation Management, 1(3), 145–161.

D'Ariano, A., Corman, F., Pacciarelli, D., & Pranzo, M. (2008). Reordering and local rerouting strategies to manage train traffic in real time. Transportation Science, 42(4), 405–419.

D'Ariano, A., Pacciarelli, D., & Pranzo, M. (2008). Assessment of flexible timetables in real-time traffic management of a railway bottleneck. Transportation Research Part C: Emerging Technologies, 16(2), 232–245.

Ferreira, M. (2023). Deliverable 2.3: Use Cases for planned technical development of the project. FP1MOTIONAL project. Retrieved from https://rail-research.europa.eu/wp-content/uploads/2025/02/MOTIONAL-Deliverable-2-3.pdf

Flamini, M., & Pacciarelli, D. (2008). Real time management of a metro rail terminus. European Journal of Operational Research, 189(3), 746–761.

Gély, L., Dessagne, G., & Lerin, C. (2006). Modelling train rescheduling with optimisation and operational research techniques: Results and applications at SNCF. In Proceedings of WCRR, Montréal.

Jiamin Zhang, Zhang, J., et al. (2023). Artificial intelligence applied on traffic planning and management for rail transport: A review and perspective. Discrete Dynamics in Nature and Society. https://doi.org/...

Josyula, S. P. (2024). Machine learning based decision-support for train traffic disturbance management: An experimental study. MATRIX Project Report.

Karimi-Mamaghan, M., Mohammadi, M., Meyer, P., Karimi-Mamaghan, A. M., & Talbi, E.-G. (2022). Machine learning at the service of meta-heuristics for solving combinatorial optimisation problems: A state-of-the-art. European Journal of Operational Research, 296(2), 393–422. https://doi.org/10.1016/j.ejor.2021.04.032

Kwaśnikowski, J., & Gramza, G. (2007). Analiza wybranych zakłóceń w ruchu kolejowym. Problemy Eksploatacji, 89–96.

Lingbin, N., Li, Y., Zhou, M., Song, H., & Dong, H. (2019). A deep reinforcement learning approach to high-speed train timetable rescheduling under disturbances. In 2019 IEEE Intelligent Transportation Systems Conference (ITSC) (pp. 3469–3474). https://doi.org/10.1109/ITSC.2019.8917180

Lu, J. (2022). Traffic conflict identification and validation using deep unsupervised learning (Doctoral dissertation). University of California, Berkeley.

Lusby, R. M., Larsen, J., Ehrgott, M., & Ryan, D. M. (2013). A set-packing inspired method for real-time junction train routing. Computers & Operations Research, 40, 713–724.

Mannino, C., & Mascis, A. (2009). Optimal real-time traffic control in metro stations. Operations Research, 57(4), 1026–1039.

Md Rahman, S., Lapasset, L., & Mothe, J. (2022). Multi-label classification of aircraft heading changes using neural networks to resolve conflicts. In ICAART (3) (pp. 403–411).

Mitsuaki, O., Kashiyama, T., & Sekimoto, Y. (2018). Deep reinforcement learning approach for train rescheduling utilising graph theory. In 2018 IEEE International Conference on Big Data (Big Data) (pp. 4525–4533). https://doi.org/10.1109/BigData.2018.8622214

Nguyen, T. T., et al. (2019). Feature extraction and clustering analysis of highway congestion. Transportation Research Part C: Emerging Technologies, 100, 238–258.

RAILS Project. (n.d.). Roadmaps for AI integration in the rail sector. Retrieved from https://rails-project.eu/

Schaafsma, A., & Bartholomeus, M. (2007). Dynamic traffic management in the Schiphol bottleneck. In Hansen, I. A., Radtke, A., Pachl, J., & Wendler, E. (Eds.), Proceedings of the Second International Seminar on Railway Operations Modelling and Analysis, Hannover, Germany.

Selim, D., & Sahin, I. (2013). Train rescheduling with genetic algorithms and artificial neural networks for single-track railways. Transportation Research Part C: Emerging Technologies, 27, 1–15. https://doi.org/10.1016/j.trc.2012.11.001

Sarhani, M., & Voß, S. (2024). Prediction of rail transit delays with machine learning: How to exploit open data sources. Multimodal Transportation, 3(2), 100120.

Tiong, K. Y., Ma, Z., & Palmqvist, C. W. (2023). A review of data-driven approaches to predict train delays. Transportation Research Part C: Emerging Technologies, 148, 104027.

Wang, Z., Pan, W., Li, H., Wang, X., & Zuo, Q. (2022). Review of deep reinforcement learning approaches for conflict resolution in air traffic control. Aerospace, 9(6), 294.