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Original Article

RAILWAY TRANSPORT SYSTEM MODELLING APPROACH FOR ROBUSTNESS ANALYSIS

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Highlights:

- developed a simulation model to assess railway timetable robustness against disturbances;
- analyzed key dependencies between infrastructure and operational parameters impacting delays;
- identified and implemented reconfiguration measures to reduce average train delays;
- demonstrated significant improvements in punctuality and network capacity after reconfiguration;
- provided insights into effective strategies for enhancing railway resilience under disturbance conditions.

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Abstract. The article presents an approach to train traffic modelling that allows for the analysis of how railway networks respond to various disturbances, including increased traffic and disturbance events. It discusses different methods of reconfiguration actions in key points of the railway network, which helps reduce delay propagation in the transport system. The 1st part covers building simulation models, which include defining infrastructure, setting train routes, configuring rolling stock, and disturbance scenarios, enabling the analysis of various disruptive events. The simulations allow for testing disturbance scenarios with minimal downtime risk without interfering with the real-world environment. The study results identified key system parameters generating the largest delays, such as platform availability, signaling, and the number of block sections. Probability density distributions for event intervals and durations were analyzed. The Kolmogorov–Smirnov test was used to confirm the fit of empirical distributions with theoretical ones, which were then implemented in the model of railway line No 271, running from Wrocław to Żmigród (Poland). As part of the reconfiguration of this railway line, new platforms were added, the time required for route setting was reduced, and the number of block sections was increased. These actions significantly reduced average delays, improved line capacity, and enhanced the robustness of the railway transport system against disturbances. The reconfiguration effectively reduced delays in areas causing significant time exceedances above 359 s, which was recognized in the Polish railway network as critical.

Keywords: timetable, robustness, simulation, rail transport, railway line.

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1. Introduction

Simulation modelling of train traffic plays a crucial role in designing railway infrastructure, optimizing timetables, managing traffic on congested lines, and improving robustness against disturbances. Simulations enable the detailed analysis of the impact of various operational changes, such as signal adjustments or infrastructure expansion, without the need to implement these changes directly in the real environment. Computer simulations allow testing scenarios related to traffic disturbances, sudden increases in traffic, and extreme weather conditions, which help prepare for emergency situations and minimize downtime risks.

Technological advancements have made simulation models more sophisticated, integrating factors related to the impact of disturbance events and vehicle interactions. Tools like *OpenTrack*, *RailSys*, and *AnyLogic* enable the creation of comprehensive models that assess how the railway network responds to different types of disturbances. Thus, simulations support infrastructure managers, railway operators, transport planners, and researchers in making informed decisions both on a strategic and operational level, contributing to increased flexibility and robustness of railway networks against disturbances.

2. Literature review

Early research on simulation modelling focused on the fundamental aspects of traffic management at the level of individual lines and stations.

Discrete event models, used in the work by Xu *et al.* (2014), allow for the analysis of train traffic considering energy consumption parameters and managing train distances to minimize delays. They are particularly useful for optimizing traffic on single-track railway lines, where interactions between trains can lead to congestion and delays.

As simulations evolved, new tools like *OpenTrack* and *RailSys* gained popularity due to their capabilities in modelling more complex scenarios involving the influence of infrastructure on capacity and schedule stability (Middelkoop *et al.* 2012).

An example is the comparison of *RailSys* and *OpenTrack*, where detailed aspects of railway infrastructure, including signaling and track layouts, can be modelled, which is critical for operational efficiency (D'Ariano 2010).

2.1. Train traffic simulation

The 1st group of studies focuses on the simulation of individual train traffic, considering technical aspects such as traction, rolling resistance, and rail potential.

Research by Mongkoldee *et al.* (2016) demonstrates power flow and potential losses associated with DC voltage in traction systems, which is crucial for optimizing energy consumption.

The simulation described by Aredah *et al.* (2024) focuses on modelling freight train traffic, considering external forces and energy consumption. It enables the analysis of energy efficiency of various propulsion technologies. This is useful for studies on optimizing energy costs and reducing carbon emissions.

Longo *et al.* (2020) presented an approach that considers energy consumption in a mesoscale model. By integrating *OpenTrack* and *modeFRONTIER* tools, simulations allow for analysing energy consumption and generating timetables optimized for energy efficiency.

Li & Gao (2007) introduced a train motion equation model with an additional component accounting for safe spacing between trains. This model, used in moving block systems, accurately reflects dynamic train behavior under high traffic density.

Cole *et al.* (2017) analyze longitudinal train dynamics and models related to interactions between wagons. Such models are key for optimizing freight train traffic with higher energy demands.

2.2. Infrastructure and capacity simulation

The 2nd important area of research is the simulation of railway infrastructure and capacity analysis.

Chen & Han (2014) used *OpenTrack* to analyze capacity on the Beijing–Shanghai line (China), considering different scenarios with train spacing. The analysis revealed that reducing the spacing between trains could increase capacity by up to 72.7%, which is particularly important for high-speed rail in China. These simulations help identify ways to increase capacity without expanding infrastructure.

Schöbel *et al.* (2022) demonstrated that *OpenTrack* can be used to analyze timetable stability across the railway network and assess how different infrastructure configurations affect train traffic. This is crucial for long-term planning.

The article by Szűcs (2001) presents the application of the *Cassandra* system to railway operations simulation, which aids in planning and optimizing railway infrastructure. The system allows for analysing dynamic operations and timetable management while simultaneously modeling infrastructure and logistical constraints.

Bigdeli *et al.* (2009) discussed various graph metrics used to analyze railway networks' criticality and robustness against disturbances. These methods are used in simulations to assess key points in networks and potential bottlenecks, which is crucial for designing networks resilient to failures.

In the work by Kierzkowski & Kisiel (2015a), operational modeling for traffic flow management was demonstrated through examples of simulation models applied to transport logistics management.

The article by Pouryousef & Lautala (2015) proposed a hybrid approach to simulation, combining discrete event simulation with continuous modeling. The goal is to increase the capacity of the railway network and optimize timetables.

Harrod *et al.* (2019) used the *OpenTrack* model to assess timetable robustness against delays on suburban railway lines in Copenhagen (Denmark). The impact of different delay scenarios on punctuality and network capacity was examined. Simulation models offer insight into how increasing the number of trains or speeding up operations affects the overall robustness of the timetable.

Majumder *et al.* (2024) described the use of rough set theory and machine learning methods to evaluate the service quality provided by Indian railways. This allows for the analysis of train performance based on key attributes, such as punctuality, ticket availability, cleanliness, and safety.

Jeremić *et al.* (2021) focused on analyzing robustness against disturbances in the Belgrade (Serbia) railway system, evaluating different timetable variants and assessing the effectiveness of the network in areas with a high risk of delays.

2.3. Simulation of multi-layer transport networks

Another group of studies deals with the modeling of multi-layer transport networks.

Dudakova *et al.* (2023) presented a multi-layer model that allows for analyzing the robustness of the entire transport network against disturbances. This approach enables the evaluation of the impact of failures on different layers of the transport system, which is crucial for increasing infrastructure robustness against operational disturbances.

Du *et al.* (2016) introduced a multi-layer transport network model combining railway and aviation networks. The efficiency of passenger transfers between the 2 networks was analyzed, considering varying transfer costs and passenger flow dynamics.

Alessandretti *et al.* (2023) focused on multimodal urban mobility, integrating different modes of transport such as buses, metros, and railways within a multi-layer network. Adjacency matrices were used to analyze urban infrastructure and its interactions.

Karpenko & Prentkovskis (2022) emphasized the importance of developing supporting technologies that can improve the transport system's response to unforeseen disturbances and reduce the impact of delays.

Wang *et al.* (2022) presented a method for identifying key nodes in a multi-layer railway and aviation network. They used a modified version of betweenness and closeness centrality metrics, adapted to multi-layer dynamics, to identify the nodes with the greatest impact on capacity and the system's robustness. This approach helps in analyzing how nodes connecting different layers (e.g., airports and railway stations) influence overall performance.

2.4. Passenger movement simulation

The next group of studies focuses on the simulation of passenger movement within railway stations.

Deng *et al.* (2023) used *AnyLogic* to simulate emergency evacuations at railway stations. This allowed for the identification of bottlenecks and the optimization of station capacity. The study results showed that appropriate reconfiguration of the station layout can significantly reduce evacuation times and increase passenger safety.

Liu & Chen (2020) examined emergency evacuation strategies. The models used indicators such as traffic density, evacuation time, and the distance covered by passengers to assess the effectiveness of different evacuation routes and adjust operational strategies.

Zhu (2023) focused on modeling passenger flow in various station sections using *AnyLogic*, including entrances, ticket vending machines, and exits. The model allows for identifying bottlenecks.

Kierzkowski & Kisiel (2015b) focused on optimizing operational processes using simulations, where passenger flow is modeled to minimize delays and improve station capacity.

Liang & Yuan (2014) studied passenger behavior at a station in terms of exit route selection using *AnyLogic*. The study focused on various options such as stairs, elevators, and escalators, analyzing which were preferred depending on traffic volume. The results provided insights into station capacity evaluation.

2.5. Timetable simulation for robustness analysis

The next group of studies focuses on analyzing timetable robustness against disturbances using railway transport system modeling.

Andersson (2014) defines robustness as the ability of a timetable to maintain smooth operations despite primary and secondary disturbances, such as delays caused by signal failures or unforeseen interruptions in passenger service. Introducing time buffers and adding reserves between train operations helps minimize the propagation of delays and increases schedule flexibility, which is key to improving robustness.

Dewilde *et al.* (2011) emphasize that identifying critical points – locations in the network highly sensitive to delays – allows for the strategic placement of time buffers and reserves. This minimizes the effects of delays in the most congested parts of the timetable.

Khoshniyat & Peterson (2017) assess how the introduction of additional time buffers impacts schedule stability. They use the *RailSys* simulation tool to test timetable robustness.

Meng *et al.* (2019) propose a method for relocating time buffers in the timetable at the most delay-prone locations, improving timetable management and minimizing disturbance propagation. These studies highlight the importance of strategically placing time reserves, especially in high-traffic nodes.

Solinen & Palmqvist (2023) describe changes in Sweden's timetable planning policies, which have increased robustness by introducing rules related to time buffers in key infrastructure points.

Jin *et al.* (2019) conducted studies on mixed integer linear programming methods for adding buffer time to timetables. The method was validated and proved effective in reducing delays on the Guangzhou (China) metro network.

Fischetti *et al.* (2009) present techniques based on linear programming and ad hoc methods aimed at building a robust timetable under delay and disturbance conditions. The results show that these techniques offer fast, high-quality solutions comparable to traditional, but more time-consuming, stochastic programming methods.

Goerigk *et al.* (2014) consider both strict robustness, which provides maximum punctuality guarantees, and light robustness, offering a more flexible approach. Studies show that strict robustness may result in significant travel time extensions, while light robustness offers a compromise between the level of guarantees and travel time.

In research by Kierzkowski & Kisiel (2015c), infrastructure capacity modeling and operational management in conditions of arrival time variability and disturbances were discussed.

Yan & Goverde (2017) proposed a model for cyclic timetables that allows flexibility in stop and travel times while allowing train overtaking on selected sections. The model is based on the periodic event scheduling problem and integrates robustness functions, such as maximizing travel time between events.

Sels *et al.* (2016) developed a model that generates timetables minimizing passenger travel time while increasing robustness against disturbances. Their approach is based on minimizing expected travel time while considering the probabilities of primary delays. These studies demonstrate that achieving robust timetables while minimizing passenger travel time is possible.

Akkan & Gülcü (2018) presented the use of genetic algorithms for railway timetables, where timetable stability is critical in the context of dynamic operational changes.

Salido *et al.* (2008) showed that simulations can be used to build robust timetables by enabling emergency scenario testing and assessing how the timetable responds to different levels of disturbance.

The link between timetable robustness and railway traffic simulation lies in using simulations as tools to test, optimize, and assess how timetables handle various disturbance conditions. Simulations allow conducting analyses without interfering with actual infrastructure, enabling realistic replication of the system's response to delays, failures, and increased traffic. Although considering various aspects of traffic management and timetable optimization, current research on railway transport modelling does not fully analyze the impact of dynamic disturbances, such as changes in infrastructure availability or traffic control. There is a lack of detailed analyses of flexibility, i.e., the ability to quickly adapt to emergencies. Simulation models can be extended by including additional parameters related to the dependencies between individual elements of the simulation model. Introducing changes in dependent parameters would allow for examining their impact on railway punctuality in terms of responding to disruptive events. This is crucial for managing traffic on high-density lines.

3. Process of building a simulation model

The process of building a railway line simulation model, taking into account disturbances, can be divided into 5 fundamental stages:

- defining infrastructure;
- defining train paths;
- defining rolling stock;
- defining timetables;
- implementing disturbance scenarios.

The construction of a simulation model begins with defining the infrastructure, which can be divided into 2 main types: linear and point infrastructure. Linear infrastructure includes tracks, which form the basic framework of the model, and the traction network. In the 1st stage, vertex points are defined, representing points of infrastructure. Next, these vertex points are connected by edges, corresponding to track sections linking various points in the railway network. This process also defines switches. The next step defines parameters such as track length, gradient, curve radius, and switch parameters. After defining the linear infrastructure, the next step is to define the point infrastructure. This includes stations (platforms, tracks), passenger stops, sidings, branch signal boxes, signals, traffic control devices (signal boxes, automatic traffic control systems), engineering structures (bridges, viaducts, tunnels, culverts), traction substations, and railway crossings. Next, speed profiles are defined. The maximum speed trains can operate on a given section depends on the track's characteristics, purpose, and local speed restrictions. The final parameters in defining infrastructure constraints are headway times related to station dwell times and the spacing between trains on the route.

The next stage is defining train paths, which refers to the routes trains will follow between points in the railway network. Predefined routes (vertex points and edges describing the track between stations or important points) and paths (linking various routes into more complex segments) are used to accomplish this. This allows for defining the exact train routes, known as itineraries, which combine routes and paths, reflecting the entire journey of a train through the defined network.

After defining the train paths, the next step is configuring the rolling stock. Each train used in the simulation requires a detailed description, including parameters such as traction characteristics, weight, length, brake type, and train type.

The next step is defining timetables. A database of timetables is configured, containing departure times, arrival times, stations, passenger stops, platform stops, and dwell times for each train, along with its unique number. It is also necessary to account for priorities for different types of trains.

After defining timetables, railway traffic disturbances are introduced into the model. Disturbances can be simulated by adding probability density distributions for the occurrence and duration of various events, such as signal failures, infrastructure damage, speed restrictions, weather conditions, and sudden traffic interruptions. These disturbances can be modeled based on historical delay data or introduced as potential event scenarios, such as planned track closures. Individual events can be assigned to specific kilometers of the railway line, considering the direction of travel and the selected segment. Configuring disturbance scenarios allows for analyzing the impact of events on railway traffic and testing timetable robustness against disturbances. The process of building the simulation model is presented graphically in Figure 1. Each stage serves a distinct purpose: defining infrastructure establishes the foundational network elements; defining train paths outlines routes and optimizes traffic flow; configuring rolling stock details train specifications; defining timetables sets departure and arrival schedules; and implementing disturbance scenarios assesses the model's robustness under various operational conditions. The parameters in the shared rectangles can be defined simultaneously. Detailed parameters and descriptions for each stage of building the simulation model are summarized in Table 1.

After configuring all elements of the model, the simulation can be conducted. During the simulation, parameters such as travel time, punctuality, the impact of disturbances on traffic flow, and the effectiveness of disturbance management strategies are monitored. Based on the simulation results, robustness analysis of the timetables can be performed, and model parameters can be adjusted to enhance the system's robustness against disturbances.

In the context of railway traffic simulation, it is essential to understand the dependencies between individual model parameters. To this end, a dependency matrix (Table 2) was constructed to identify key relationships between parameters. This enables the determination of critical parameters for operational efficiency and how delays and other disturbances may propagate throughout the network. A value of 0 indicates no relationship between parameters, while 1 indicates a relationship.

From the matrix, it can be concluded that the length of the track influences the headway, which means that longer track sections allow for a reduction in the distance between consecutive trains on the route. Furthermore, track length also affects arrival times, as the longer the section between stations, the more time is required to travel that distance. Gradient affects both departure and arrival times, as steeper tracks increase rolling resistance, leading to longer travel times, and is also related to the train's weight.

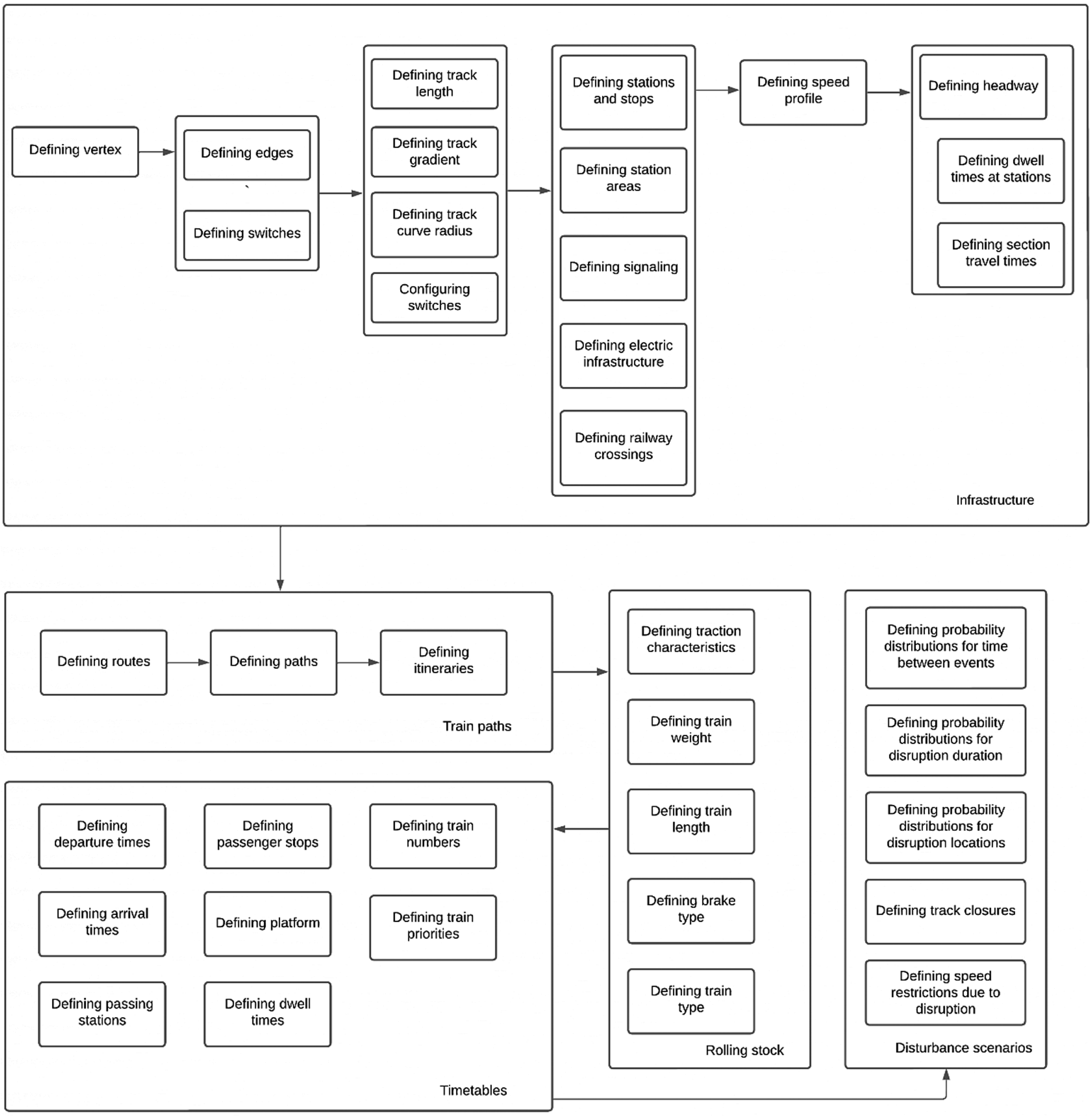

Figure 1. Stages of building a railway line simulation model (source: created by the author)

Table 1. Parameters and descriptions for each stage of the simulation model building process (source: created by the author)

Parameter	Description
Infrastructure parameters	
Vertex	represents infrastructure points such as stations, switches, stops, sidings, and traffic control points; these are locations where edges connect, and trains can change direction or stop
Edges	edges in the railway line simulation model refer to track sections connecting different points in the railway network
Switches	number, types, and configurations of switches, including the speed at which switch positions can be changed
Track length	each track section's length affects travel time and distances between stations
Gradient	expressed in per mille, it influences rolling resistance and energy consumption
Curve radius	affects the speed limits for trains on curves
Stations and stops	locations of stations, platforms, the number of available tracks at stations, platform length, and the availability of transfer points
Station areas	includes edges, vertex points, and signals associated with the station. stop points are also defined, allowing train stop simulation at specific platform locations
Signaling	default position and types of signals (e.g., semaphore signals, shunting signals), and train stop points before signals
Electric infrastructure	voltage in the traction network, location of traction substations, and power limitations
Railroad crossings	the location of railway crossings and pedestrian crossings may impact safety and travel time (speed limits)
Speed profile	maximum speed in different sections of the track, taking into account restrictions related to curves, signaling, and switches
Headway	minimum safe distance between consecutive trains on the same route, ensuring safe traffic management
Train path parameters	
Routes	routes are sets of vertex points and edges that describe the track's path between stations or important points. routes form the basis for defining specific train journeys
Paths	paths connect different routes into more complex segments, such as transitions through stations. this allows for defining exact train itineraries
Itineraries	a combination of routes and paths that reflect the entire train journey through the defined network
Rolling stock parameters	
Traction characteristics of locomotive	engine power, maximum tractive force, energy efficiency, and maximum speed
Train weight	total weight of the train, including the locomotive and cars, affecting energy consumption, braking force, and the ability to overcome gradients
Train length	the total length of the train, important in the context of station track availability
Brake type	the braking capability on various track sections
Train type	refers to the operational characteristics of trains: passenger, freight
Timetable parameters	
Departure times	the times at which trains depart from specific stations or stops
Arrival times	the times at which trains arrive at specific stations or stops
Stations	stations allow for train starts and ends, overtaking, crossing, changing direction, and composition changes. they also enable passenger boarding and alighting
Passenger stops	points on the route where trains stop briefly to allow passengers to board and alight
Platforms	platform availability at a specific time depends on the timetable, train priorities, as well as potential delays and disturbances that may occur en route
Dwell times	trains can start and end their journey, overtake and cross other trains, change direction or composition, and allow passenger exchange
Train number	a unique identifier assigned to each train in the timetable
Train priority	train priority defines how important a train is on a given route compared to other trains. basic priority categories include: express, fast, regional, and freight trains, with freight having the lowest priority
Disturbance scenario parameters	
Probability distributions for time between disturbances	the probability of time between consecutive disturbances. describes how frequently disturbances occur in the railway network
Probability distributions for disturbance duration	the probability of disturbance duration. describes how long disturbances last in the railway network
Disturbance location	the probability of disturbances occurring on a specific track section or kilometer
Track closures	periodic or permanent interruptions in the availability of track sections, during which no railway operations can occur
Speed restriction due to disturbance	temporary restriction of maximum speed on a specific track section due to the presence of a disturbance

Table 2. Dependency matrix between the parameters of the simulation model (source: created by the author)

Parameter	Track length	Gradient	Curve radius	Speed profile	Platforms	Train priority	Signaling	Headway	Departure times	Arrival times
Track length		0	0	0	0	0	0	1	0	1
Gradient	0		0	0	0	0	0	0	1	0
Curve radius	0	0		1	0	0	0	0	0	0
Speed profile	0	0	1		0	0	0	0	1	1
Platforms	0	0	0	0		1	1	1	1	1
Train priority	0	0	0	0	1		0	0	1	1
Signaling	0	0	0	0	1	0		0	0	1
Headway	1	0	0	0	1	0	0		1	1
Departure times	0	1	0	1	1	1	0	1		1
Arrival times	1	0	0	1	1	1	1	1	1	

Curve radius significantly influences the speed profile, as trains must reduce speed on curves with a smaller radius. The speed profile directly impacts both departure and arrival times, as different sections of the route may require different maximum speeds, directly translating into travel times. Platform availability depends on train priority, signaling, headway, and departure and arrival times. In the event of disturbances, platforms are assigned according to train priority, which improves traffic flow during congestion. Train priority affects platform availability and departure and arrival times, as higher-priority trains can be handled more quickly in emergencies situations. Signaling is closely linked to arrival times and platform availability, as signals control traffic on routes and at stations. It also influences headway, as signal settings determine the intervals between trains. Headway affects both departure and arrival times and platform availability, as it includes station times associated with the minimum intervals between train arrivals and departures at stations. Departure and arrival times depend on track length, gradient, speed profile, train priority, and signaling.

4. Case study

4.1. Simulation model

To investigate the robustness of the timetable against disturbances, a model of railway line No 271, running from Wrocław to Żmigród (Poland), was built. This line is part of the national transport network and is essential for passenger traffic, characterized by intensive use. The railway line starts at Wrocław Główny station, which serves as a major transportation hub for the region. The line is equipped with a modern, computerized traffic control system that utilizes automatic block systems. This system allows real-time monitoring of train traffic and efficient management of operational situations. The analyzed section is 47.15 km long and includes 16 control points, comprising 6 stations, 6 passenger stops, and 4 branch signal boxes that facilitate railway traffic. Each point on the route, such as stations, stops, or branch signal boxes, was accurately modeled in the simulation, including the railway control systems. On this section, trains are operated by national passenger carriers, with 36 pairs of trains running daily. The types of trains on this route are varied and include 21 regional trains, 2 intercity trains, and 13 express trains. Each of these trains has an assigned priority, which is crucial for managing traffic during disturbances. Express trains, with the highest priority, are granted precedence on the route and have minimal platform stop times, while regional and intercity trains adapt to their current traffic situation to minimize delays on key sections. The simulation model included all key elements of the infrastructure, including the track layout, platforms, signaling, timetable, and all control points along the route. Detailed parameters of the simulation model are summarized in Table 3.

In the model, speed restrictions were carefully taken into account for various infrastructure elements, such as switches, stations, and individual track sections, allowing for a realistic representation of the railway line. On switches, speed is limited based on the type and angle of the switch. The modeled railway line, with speed restrictions on the switches near Wrocław Główny station, is shown in Figure 2. In the model, trains reduce their speed when entering and exiting switches, reflecting actual operational practices. Speed restrictions at stations were also modeled, taking into account conditions for stopping, passenger service, and platform capacity. These speeds reflect both entry into and exit from stations. The model considers the maximum allowable speeds on the sections between stations and other control points, which may vary depending on terrain profile, curves, and gradients. Speed on these sections is restricted according to the maximum speed guidelines for passenger trains on railway line No 271 (PKP 2017). The simulation model was also designed to adapt to varying traffic levels, including low or fluctuating periods. During such conditions, the model adjusts parameters such as train headways and platform assignment, optimizing for lower traffic density. This adaptability allows the model to provide realistic assessments across diverse operational scenarios, enhancing its generalizability. Additionally, the model can accommodate varying train priorities on mixed-use tracks, where both passenger and freight trains operate. The model assigns different priority levels, with freight trains given the lowest priority, allowing for realistic simulation of scenarios that prioritize passenger traffic while still incorporating freight operations. This feature enhances the model's adaptability to diverse operational needs and expands its applicability across various railway networks and strategies.

Table 3. Simulation model parameters (source: created by the author)

Parameter	Value	Parameter	Value
Vertex	4215 vertex points	itineraries	41
Edges	4425 edges	departure times	549
Switches	189 switches	arrival times	520
Track length	47.15 km	dwell times	487
Stations and stops	6 stations; 6 passenger stops; branch signal boxes	platforms	29
Signaling	119 semaphores	train numbers	36 train pairs
Electric infrastructure	3 kV	train priority	21 regional; 2 intercity; 13 express trains
Railroad crossings	18 railroad crossings	probability distributions for time between disturbances	described in Section 4.2
Routes	315	probability distributions for disturbance duration	
Paths	53	disturbance locations	

Figure 2. Simulated railway line with speed restrictions on switches near Wrocław Główny station (source: elaborated by the author using the *OpenRailwayMap* – *https://www.openrailwaymap.org*)

3 dependent parameters were identified, generating the largest delays. These parameters were used to perform timetable reconfiguration, which is described in the later part of the article. The 1st indicator T_p is the average delay resulting from platform availability – Equation (1). It illustrates how the limited number of available platforms at stations affects the average waiting time for trains to access a free platform. It considers the priority $P_{i,p}$ of the pth train using platform i, the platform availability indicator $A_{i,p}$ for the pth train (1 – available, 0 – unavailable), and the waiting time $D_{i,p}$ for the pth train to access platform i. The value of T_p was calculated based on all iterations of the simulation for each train and platform, allowing for the assessment of how platform availability contributes to delays in the entire railway system:

$$\bar{T}_p = \frac{1}{R}\cdot\sum_{r=1}^{R}\left(\frac{1}{N}\cdot\sum_{i=1}^{N}\left(\frac{1}{P_p}\cdot\sum_{P_p=1}^{P_p}\left(P_{i,p}\cdot A_{i,p}\cdot D_{i,p}\right)^{[r]}\right)\right), \quad (1)$$

where: R – number of simulation iterations; N – number of platforms; $[r]$ – index of a specific simulation iteration; P_p – number of trains using the platforms.

The 2nd indicator T_s represents the average delay caused by the time spent waiting for a signal at the semaphore – Equation (2). This indicator measures how long trains have to wait for a signal allowing passage. It is related to track route setting and directly affects train departure times from stations. It takes into account the signal status $S_{j,p}$ for the pth train at the jth semaphore (1 – available signal, 0 – no signal) and the waiting time $W_{j,p}$ for the pth train at the jth semaphore. The value of T_s was calculated for all simulation iterations for each train and semaphore:

$$\bar{T}_s = \frac{1}{R}\cdot\sum_{r=1}^{R}\left(\frac{1}{M}\cdot\sum_{j=1}^{M}\left(\frac{1}{P_s}\cdot\sum_{P_s=1}^{P_s}\left(S_{j,p}\cdot W_{j,p}\right)^{[r]}\right)\right), \quad (2)$$

where: R – number of simulation iterations; M – number of signals; $[r]$ – index of a specific simulation iteration; P_s – number of trains waiting for a signal to be cleared.

The 3rd indicator T_h represents the average delay caused by the time spent waiting for the release of a block section – Equation (3). This indicator measures how long trains must wait until the previous train vacates the block section. It takes into account the availability of the block section $W_{k,p}$ (1 – block available, 0 – block occupied) and the waiting time $T_{k,p}$ for the pth train to release the block section on section k. The value of T_h was calculated based on all simulation iterations for each train and track section, which allows for the assessment of how block management affects traffic flow and delays:

$$\overline{T}_h = \frac{1}{R}\cdot\sum_{r=1}^{R}\left(\frac{1}{L}\cdot\sum_{k=1}^{L}\left(\frac{1}{P_h}\cdot\sum_{P_h=1}^{P_h}\left(W_{k,p}\cdot T_{k,p}\right)^{[r]}\right)\right), \qquad (3)$$

where: R – number of simulation iterations; L – number of track sections with block sections; $[r]$ – index of a specific simulation iteration; P_h – number of trains on a given track section.

The above indicators provide information about the factors generating delays in the simulated system and allow for further reconfiguration of timetables and infrastructure.

4.2. Disturbances scenarios

Real disturbance data was implemented for the simulation model, developed based on actual data collected from railway line No 271. 100000 records were gathered, including detailed information such as the event date, duration, train number, cause, and primary and secondary delays. Events were categorized into infrastructure, environmental, and rolling stock categories. In the infrastructure category, the most frequent events were: switch failures (2451 records), failures of railway crossing devices (1975 records), and failures of traffic control devices (1426 records). In the environmental category, the most common were: animal collisions (3084 records), delayed issuance of departure signals (2928 records), and improper application of right-of-way rules (2748 records). In the rolling stock category, the most frequent events were: rolling stock failures (1952 records), police interventions on trains (1654 records), and secondary delays caused by the driver (1379 records).

For each event category, probability density distributions were developed for the time between disturbances and their duration based on real data. Figure 3 shows the probability density distributions for the time between disturbances and the duration of events for the infrastructure category. These were then implemented into the simulation model, allowing for a realistic representation of disturbances. As a result, various disturbance scenarios were generated, simulating their impact on railway traffic capacity and punctuality under near-real conditions.

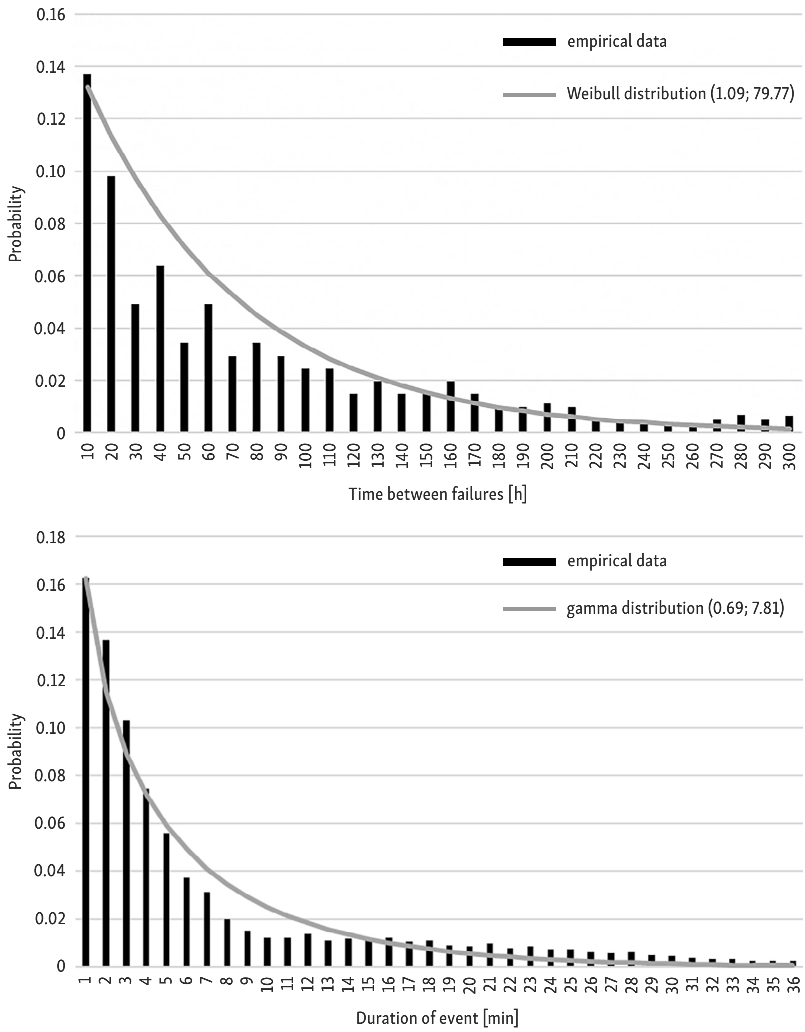

Figure 3. Probability density distribution for time between disturbances and event duration for the infrastructure category (source: created by the author)

Based on the fitted theoretical distributions, probability density distributions for time between disturbances and their duration were generated. The Kolmogorov–Smirnov test confirmed the quality of the fit at a significance level of 0.05. The critical value of the parameter is $\lambda_{kr} = 1.36$. The null hypothesis H_0, which states that the empirical distribution matches the theoretical distribution, was accepted.

The input data used to validate the railway line simulation model over 100 iterations includes probability density distributions for the occurrence of events and the intervals between failures. The output data consists of train delays. Figure 4 shows a comparison between the empirical distribution of train delays and the delay distribution generated by the simulation model for station Skokowa.

In order to obtain reliable results, 100 iterations of the simulation were conducted, which aimed to replicate realistic operational conditions on the analyzed railway line. In each repetition, disturbance events were randomly selected based on the implemented probability density distributions. This approach allowed for the generation of diverse disturbance scenarios.

Based on the results from all 100 iterations, the average delay values for the entire railway line were calculated, which are presented in the dependency matrix discussed in Chapter 2. This analysis helped to identify which dependencies between the model parameters generate the most significant delays when disturbances occur (over 60 s). It provides information about the impact of various events on the fluidity and punctuality of railway traffic. The results for the dependencies generating the largest delays are summarized in Table 4.

In the Polish railway network, a train is considered delayed if it records a delay of more than 359 s (UTK 2024). The focus was on dependencies where delays exceeded this value:

- ***platforms – train priority (453 s)***: the availability of platforms and the train's priority affect how quickly trains can enter and exit stations. Higher-priority trains are given precedence in accessing platforms, which can cause lower-priority trains to be delayed. Events such as switch failures or track closures near stations can lead to longer delays, as limited platform availability extends waiting times for a free track;
- ***signaling – departure times (392 s)***: problems with the signaling system can cause trains to wait for clearance to depart. Events related to signal failures or the improper issuance of departure signals can lead to delays in departure times.
- ***track length – headway (376 s)***: track length directly affects the time required for travel and the minimum time intervals between consecutive trains on the route. Longer track sections with short headways between trains cause delays.

Table 4. Average train delays for dependencies between simulation model parameters (source: created by the author)

Parameter	Dependent parameter	Average delay [s]
Platforms	train priority	453
Signaling	departure times	392
Track length	headway	376
Train priority	arrival times	224
Signaling	track length	123
Headway	arrival times	71
Headway	departure times	69
Platforms	departure times	64
Platforms	signaling	62

4.3. Reconfiguration

In the simulation model, changes were introduced to reduce the average delays resulting from dependencies between key parameters. These changes included the addition of a new platform, modification of signal times, and an increase in the number of block sections, allowing for a reduction in the impact of disturbances. The reconfiguration was carried out in 3 stages:

- ***the 1st stage*** involved analyzing platform availability at stations. The algorithm shown in Figure 5 begins with identifying trains waiting for platform availability at a given station. Then, it checks if the platform is available.

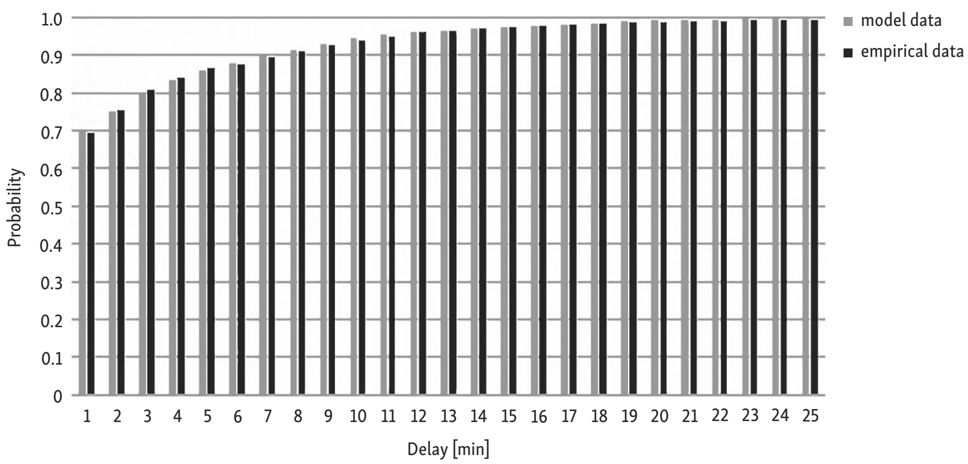

Figure 4. Comparison of empirical and simulated train delay distributions for Skokowa station (source: created by the author)

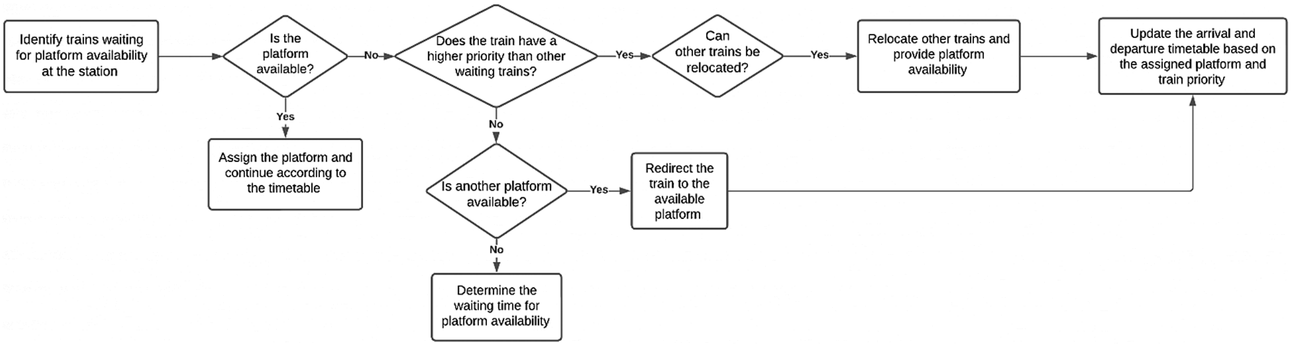

Figure 5. Platform availability analysis algorithm at a station (source: created by the author)

If the platform is available, the train is assigned to that platform and continues according to the schedule. If the platform is not available, the priority of the waiting train is compared to that of other trains using the platform. If the waiting train has higher priority, the possibility of relocating other trains to different platforms is analyzed to free up the platform. Other trains will be relocated, and the platform will be made available to the higher-priority train if possible. If the platform is unavailable and other trains cannot be relocated, the availability of alternative platforms is checked. The train is directed to the alternate platform if another platform is available. The waiting time for the platform to become available is determined if no platform is available. At the end of the algorithm, the arrival and departure schedule is updated based on assigned platforms and train priorities.

To reduce delays related to platform availability and train priority, an additional platform was added at the busiest station – Wrocław Główny (marked with a red rectangle in Figure 6). The additional platform allows more trains to be served simultaneously, reducing the waiting time for lower-priority trains. The prioritization system was also updated to give precedence to higher-priority trains, especially during peak hours;

- ***the 2nd stage*** involved identifying and shortening extended paths, resulting in faster signal clearance. The algorithm shown in Figure 7 begins by identifying trains waiting for path assignment. Next, the number of switches that must be reset on the selected path is checked. If the number of switches to be reset is minimal, the algorithm analyses the paths of other trains on the line. If the number of switches exceeds the minimum, an alternative path with fewer switch resets is selected. After analyzing the paths of other trains, the algorithm checks whether the selected train's path conflicts with other trains' paths. If a conflict occurs, the algorithm resolves it by determining the path order based on train priorities. The path that minimizes the train's distance and the time required to reset the switches is selected for all available paths. Finally, the algorithm updates the arrival and departure schedules based on the shorter signal clearance times.

  The reduction of delays caused by the dependency between path setting and departure times was achieved by shortening the path setting time (Figure 8), resulting in faster signal clearance at the semaphore. Faster signal clearance increases the station's capacity. The signaling system considers the train's priority, allowing for readiness signals to be issued to trains that should be dispatched with precedence;
- ***the 3rd stage*** involved identifying train waiting times due to headway. The algorithm shown in Figure 9 begins by identifying track sections where trains are waiting due to the required headway, which represents the minimum time interval between consecutive trains. Next, the algorithm checks if increasing the number of block sections is possible. If so, the algorithm increases the number of block sections on the given track section, which can reduce train waiting times. The following step analyzes whether the current headway can be shortened. If possible, the algorithm shortens the headway to the minimum level that complies with safety standards. If this is not possible, the headway remains unchanged. At the end of the algorithm, the arrival and departure timetable is updated, considering the increased number of block sections and headway changes, which optimizes line capacity and reduces delays.

The simulation model was expanded to double the number of block sections to reduce delays resulting from the relationship between track length and headway (Figure 10). This increased the line's capacity and reduced delays caused by the need to maintain large gaps between trains.

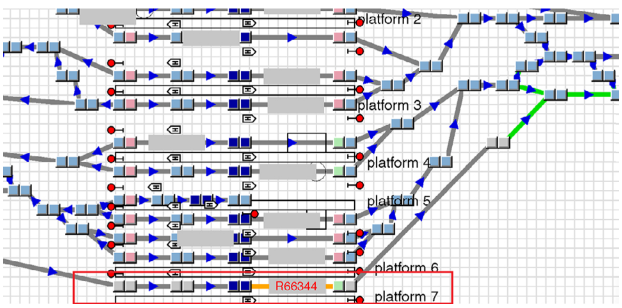

Figure 6. Additional platform at the busiest station (source: elaborated by the author using the *OpenTrack*)

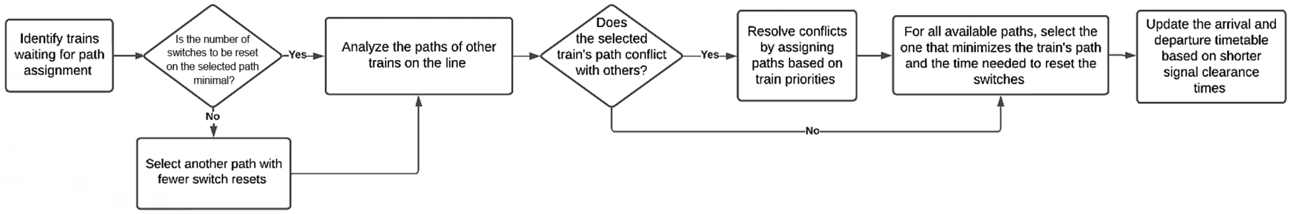

Figure 7. Train path analysis algorithm (source: created by the author)

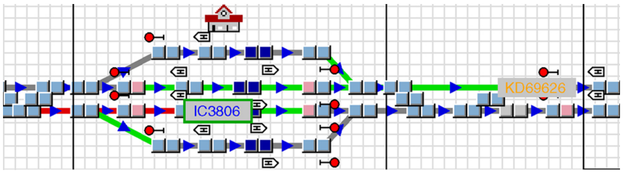

Figure 8. Shortened train paths
(source: elaborated by the author using the *OpenTrack*)

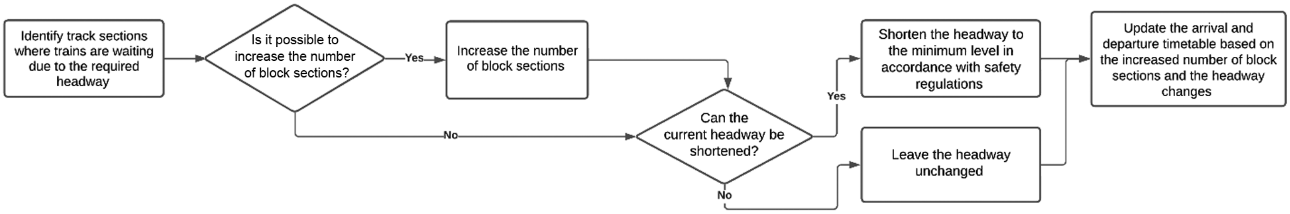

Figure 9. Headway waiting time analysis algorithm (source: created by the author)

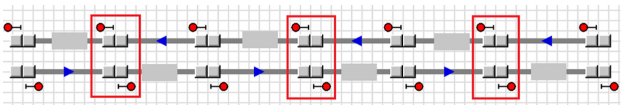

Figure 10. Expansion of block sections (source: elaborated by the author using the *OpenTrack*)

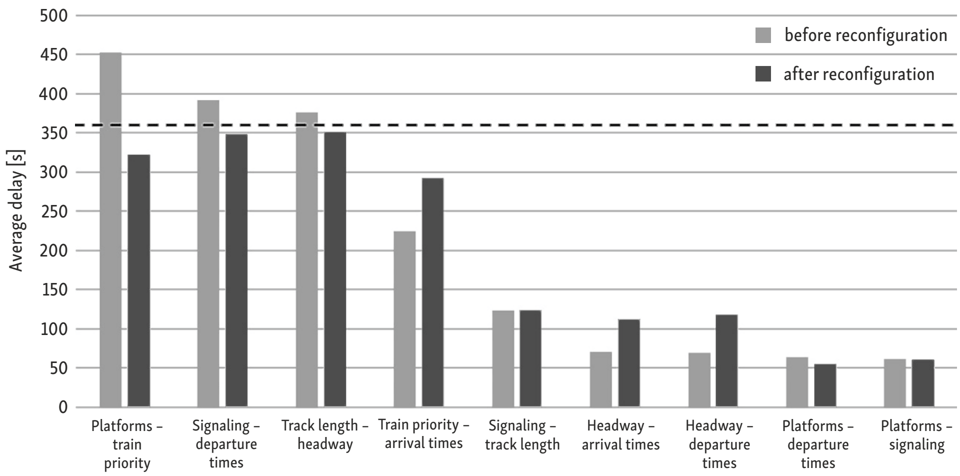

Figure 11. Average delay values for dependent parameters before and after reconfiguration (source: created by the author)

When comparing the addition of platforms to the expansion of block sections, the model showed that platform additions are most effective in high-traffic areas with frequent passenger services. On the other hand, increasing block sections proved particularly valuable in sections with mixed passenger and freight traffic, where headway reductions are critical for maintaining punctuality.

4.4. Results

In the analysis of the results, an examination was conducted on the impact of reconfiguration actions, specifically focusing on platform availability, train path setting, and headway, on overall delay reduction. Figure 11 shows the average delay values depending on the analyzed de-

Table 5. Reduction in average delays after specific reconfiguration measures (source: created by the author)

Parameter	Average delay before reconfiguration [s]	Average delay after reconfiguration [s]	Reconfiguration action
Platforms – train priority	453	322	added an extra platform at Wrocław Główny station
Signaling – departure times	392	348	reduced path setting time from 120 to 80 s
Track length – headway	376	351	doubled the number of block sections along key track sections

pendent parameters. The dotted line marks the threshold delay – 359 s, above which trains are considered delayed. The figure presents the results before reconfiguration, where delays exceeded the threshold for 3 parameters, and after reconfiguration. The addition of an extra platform at Wrocław Główny station significantly decreased average delays from 453 s to 322 s, achieving a reduction of approximately 29% by enhancing station capacity. For signaling, reducing the path-setting time from 120 to 80 s lowered delays from 392 s to 348 s, resulting in a reduction of around 11%, demonstrating the effectiveness of faster signal clearance in improving traffic flow. Doubling the number of block sections along key track segments decreased delays from 376 to 351 s, yielding a reduction of about 7%, indicating that optimized headway reduces wait times between trains and enhances traffic management. Table 5 illustrates the effectiveness of each reconfiguration action in achieving overall delay reduction within the simulated railway model.

5. Conclusions

The conducted simulation study highlights the significant impact of key dependencies between model parameters on train delays. A detailed analysis of dependencies between infrastructure and operational parameters, such as: platform availability, signaling, and track length revealed how these relationships affect delays and the overall efficiency of the railway system. These findings underscore the importance of optimizing these parameters to enhance punctuality and smooth train operations.

The primary contribution of this study is the development of a simulation model designed to assess railway timetable resilience against disturbances. The model allows for analyzing critical parameters that impact delays and provides a structured approach to identify and implement reconfiguration measures aimed at reducing average train delays. The novelty of this study lies in the practical reconfiguration measures applied to a real-world railway network model (railway line no. 271). The reconfiguration measures applied: the addition of a new platform, shortening signal path-setting times, and increasing block sections, demonstrated significant improvements in both punctuality and network capacity. The implemented changes reduced average delays by approximately 29% for platform availability, 11% for signaling, and 7% for headway optimization, confirming the model's utility in enhancing railway resilience under varying conditions. The practical applications of this model extend to various types of rail networks, including both urban commuter and intercity systems. By adjusting model parameters, such as train priority and path allocation, the model can analyze different network configurations and operational strategies, offering railway operators a flexible tool for testing reconfiguration scenarios and improving robustness in diverse operational contexts.

In future research, it is planned to develop an advanced method of railway system reconfiguration, which will be based on precise determination of boundary parameters for key infrastructure and operational elements. The goal will be to define optimal operating conditions under which delays can be minimized while maintaining high capacity. This process will include a detailed analysis of the impact of individual variables on the overall system performance, allowing for dynamic changes and adaptation of operational parameters depending on current traffic conditions. This will enable the development of a flexible traffic management model capable of responding to disturbances while minimizing their impact on the functioning of the entire system. In addition, future studies will explore other parameters that contribute to delays but do not require significant infrastructure investments. Although platform availability significantly impacts train punctuality, adding new platforms can be costly and spatially constrained. Therefore, upcoming research will prioritize adjustments to parameters such as signal timing, train priority management, and optimized scheduling practices, which can enhance network performance without major physical expansion of the system.

References

Akkan, C.; Gülcü, A. 2018. A bi-criteria hybrid genetic algorithm with robustness objective for the course timetabling problem, *Computers & Operations Research* 90: 22–32. https://doi.org/10.1016/j.cor.2017.09.007

Alessandretti, L.; Natera Orozco, L. G.; Saberi, M.; Szell, M.; Battiston, F. 2023. Multimodal urban mobility and multilayer transport networks, *Environment and Planning B*: *Urban Analytics and City Science* 50(8): 2038–2070. https://doi.org/10.1177/23998083221108190

Andersson, E. V. 2014. *Assessment of Robustness in Railway Traffic Timetables*. Linköping Studies in Science and Technology. Licentiate Thesis No 1636. Linköping University, Norrköping, Sweden. 107 p. https://doi.org/10.3384/lic.diva-103676

Aredah, A. S.; Fadhloun, K.; Rakha, H. A. 2024. *NeTrainSim*: a network-level simulator for modeling freight train longitudinal motion and energy consumption, *Railway Engineering Science* 32(4): 480–498. https://doi.org/10.1007/s40534-024-00331-x

Bigdeli, A.; Tizghadam, A.; Leon-Garcia, A. 2009. Comparison of network criticality, algebraic connectivity, and other graph metrics, in *SIMPLEX'09*: *Proceedings of the 1st Annual Workshop on Simplifying Complex Network for Practitioners*, 1 July 2009, Venice, Italy, 1–6. https://doi.org/10.1145/1610304.1610308

Chen, Z.; Han, B. M. 2014. Simulation study based on *OpenTrack* on carrying capacity in district of Beijing–Shanghai high-speed railway, *Applied Mechanics and Materials* 505–506: 567–570. https://doi.org/10.4028/www.scientific.net/AMM.505-506.567

Cole, C.; Spiryagin, M.; Wu, Q.; Sun, Y. Q. 2017. Modelling, simulation and applications of longitudinal train dynamics, *Vehicle System Dynamics*: *International Journal of Vehicle Mechanics and Mobility* 55(10): 1498–1571. https://doi.org/10.1080/00423114.2017.1330484

D'Ariano, A. 2010. Improving real-time train dispatching performance: optimization models and algorithms for re-timing, re-ordering and local re-routing, *4OR* 8(4): 429–432. https://doi.org/10.1007/s10288-010-0131-y

Deng, J.; Meng, Y.; Fu, Y.; Du, Y.; Guo, H. 2023. Research on the simulation of emergency evacuation of rail transit stations based on *Anylogic*, in *2023 IEEE 7th Information Technology and Mechatronics Engineering Conference* (*ITOEC*), 15–17 September 2023, Chongqing, China, 1163–1167. https://doi.org/10.1109/ITOEC57671.2023.10291978

Dewilde, T.; Sels, P.; Cattrysse, D.; Vansteenwegen, P. 2011. Defining robustness of a railway timetable, in *Proceedings of 4th International Seminar on Railway Operations Modelling and Analysis* (*IAROR*): *RailRome2011*, 16–18 February 2011, Rome, Italy, 1–20.

Du, W.-B.; Zhou, X.-L.; Jusup, M.; Wang, Z. 2016. Physics of transportation: towards optimal capacity using the multilayer network framework, *Scientific Reports* 6: 19059. https://doi.org/10.1038/srep19059

Dudakova, A. V.; Goncharova, N. Y.; Kazakov, A. L.; Bolshakov, R. S. 2023. The modeling of technological processes of a railway marshalling yard using any logic, *AIP Conference Proceedings* 2624(1): 040049. https://doi.org/10.1063/5.0132718

Fischetti, M.; Salvagnin, D.; Zanette, A. 2009. Fast approaches to improve the robustness of a railway timetable, *Transportation Science* 43(3): 321–335. https://doi.org/10.1287/trsc.1090.0264

Goerigk, M.; Schmidt, M.; Schöbel, A.; Knoth, M.; Müller-Hannemann, M. 2014. The price of strict and light robustness in timetable information, *Transportation Science* 48(2): 225–242. https://doi.org/10.1287/trsc.2013.0470

Harrod, S.; Cerreto, F.; Nielsen, O. A. 2019. A closed form railway line delay propagation model, *Transportation Research Part C*: *Emerging Technologies* 102: 189–209. https://doi.org/10.1016/j.trc.2019.02.022

Jeremić, D.; Milosavljević, M.; Vujović, D. 2021. Simulation model of Belgrade suburban passenger trains service using *OpenTrack*, in *Proceedings – Third International Conference "Transport for Today's Society"*, 14–16 October 2021, Bitola, Republic of North Macedonia, 108–111. https://doi.org/10.20544/TTS2021.1.1.21.p26

Jin, B.; Feng, X.; Wang, Q.; Wang, X.; Liu, C. 2019. Improving timetable robustness through optimal distribution of runtime supplement, in *2019 IEEE Intelligent Transportation Systems Conference* (*ITSC*), 27–30 October 2019, 2803–2808. https://doi.org/10.1109/ITSC.2019.8917477

Karpenko, M.; Prentkovskis, O. 2022. Review of researches tendency in the future of the road transport, in *Transport Means 2022. Sustainability*: *Research and Solutions*: *Proceedings of the 26th International Scientific Conference*, 5–7 October 2022, Kaunas, Lithuania, 2: 724–728.

Khoshniyat, F.; Peterson, A. 2017. Improving train service reliability by applying an effective timetable robustness strategy, *Journal of Intelligent Transportation Systems*: *Technology*, *Planning*, *and Operations* 21(6): 525–543. https://doi.org/10.1080/15472450.2017.1326114

Kierzkowski, A.; Kisiel, T. 2015a. Functional readiness of the check-in desk system at an airport, *Advances in Intelligent Systems and Computing* 365: 223–233. https://doi.org/10.1007/978-3-319-19216-1_21

Kierzkowski, A.; Kisiel, T. 2015b. Modelling the passenger flow at an airport terminal to increase the safety level, in *International Conference on Military Technologies* (*ICMT*) *2015*, 19–21 May 2015, Brno, Czechia, 1–7. https://doi.org/10.1109/MILTECHS.2015.7153693

Kierzkowski, A.; Kisiel, T. 2015c. Simulation model of logistic support for functioning of ground handling agent, taking into account a random time of aircrafts arrival, in *International Conference on Military Technologies* (*ICMT*) 2015, 19–21 May 2015, Brno, Czechia, 1–6. https://doi.org/10.1109/MILTECHS.2015.7153694

Li, K.; Gao, Z. 2007. An improved equation model for the train movement, *Simulation Modelling Practice and Theory* 15(9): 1156–1162. https://doi.org/10.1016/j.simpat.2007.07.006

Liang, Y. J.; Yuan, Z. Z. 2014. Assignment performance at Beijing south railway station based on *Anylogic* simulation, *Advanced Materials Research* 989–994: 2283–2287. https://doi.org/10.4028/www.scientific.net/AMR.989-994.2283

Liu, L.; Chen, H. 2020. Pedestrian emergency evacuation strategy in subway station based on *AnyLogic*, in *CICTP 2020*: *Transportation Evolution Impacting Future Mobility*, 14–16 August 2020, Xi'an, China, 3524–3533. https://doi.org/10.1061/9780784482933.304

Longo, G.; Montrone, T.; Poloni, C. 2020. A new multi-objective solution approach using *modeFRONTIER* and *OpenTrack* for energy-efficient train timetabling problem, *Computational Methods in Applied Sciences* 54: 103–119. https://doi.org/10.1007/978-3-030-37752-6_7

Majumder, S.; Singh, Aa.; Singh, An.; Karpenko, M.; Sharma, H. K.; Mukhopadhyay, S. 2024. On the analytical study of the service quality of Indian railways under soft-computing paradigm, *Transport* 39(1): 54–63. https://doi.org/10.3846/transport.2024.21385

Meng, L.; Muneeb Abid, M.; Jiang, X.; Khattak, A.; Babar Khan, M. 2019. Increasing robustness by reallocating the margins in the timetable, *Journal of Advanced Transportation* 2019: 1382394. https://doi.org/10.1155/2019/1382394

Middelkoop, D.; Steneker, J.; Meijer, S.; Sehic, E.; Mazzarello, M. 2012. Simulation backbone for gaming simulation in railways: a case study, in *Proceedings of the 2012 Winter Simulation Conference* (*WSC*), 9–12 December 2012, Berlin, Germany, 1–13. https://doi.org/10.1109/WSC.2012.6465195

Mongkoldee, K.; Leeton, U.; Kulworawanichpong, T. 2016. Single train movement modelling and simulation with rail potential consideration, in *2016 IEEE/SICE International Symposium on System Integration* (*SII*), 13–15 December 2016, Sapporo, Japan, 7–12. https://doi.org/10.1109/SII.2016.7843967

PKP. 2017. *Wykaz maksymalnych prędkości – pociągi pasażerskie*. PKP Polskie Linie Kolejowe S. A., Warszawa, Polska. 74 s. Available from Internet: https://www.plk-sa.pl/files/public/user_upload/pdf/Reg_przydzielania_tras/Regulamin_2016_2017/07.04.2016/N_ZAL_2.1P_20160407092753.pdf (in Polish).

Pouryousef, H.; Lautala, P. 2015. Hybrid simulation approach for improving railway capacity and train schedules, *Journal of Rail Transport Planning & Management* 5(4): 211–224. https://doi.org/10.1016/j.jrtpm.2015.10.001

Salido, M. A.; Barber, F.; Ingolotti, L. 2008. Robustness in railway transportation scheduling, in *2008 7th World Congress on Intelligent Control and Automation*, 25–27 June 2008, Chongqing, China, 2880–2885.
https://doi.org/10.1109/WCICA.2008.4594481

Schöbel, A.; Schreiner, H.; Baltram, S. 2022. Design of railway infrastructure with *OpenTrack* in Austria, in *CETRA 2022*: *7th International Conference on Road and Rail Infrastructure*, 11–13 May 2022, Pula, Croatia, 787–792.
https://doi.org/10.5592/CO/CETRA.2022.1347

Sels, P.; Dewilde, T.; Cattrysse, D.; Vansteenwegen, P. 2016. Reducing the passenger travel time in practice by the automated construction of a robust railway timetable, *Transportation Research Part B*: *Methodological* 84: 124–156.
https://doi.org/10.1016/j.trb.2015.12.007

Solinen, E.; Palmqvist, C.-W. 2023. Development of new railway timetabling rules for increased robustness, *Transport Policy* 133: 198–208. https://doi.org/10.1016/j.tranpol.2023.02.003

Szűcs, G. 2001. Railway simulation with the CASSANDRA simulation system, *Journal of Computing and Information Technology* 9(2): 133–142. https://doi.org/10.2498/cit.2001.02.04

UTK. 2024. *Punktualność pociągów pasażerskich w 2023 r*. Urzędu Transportu Kolejowego (UTK), Warszawa, Polska. 40 s. Available from Internet: https://dane.utk.gov.pl/sts/analizy-i-opracowania/21214,Punktualnosc-pociagow-pasazerskich-w-2023-r.html (in Polish).

Wang, C.; Xia, Y.; Zhu, L. 2022. A method for identifying the important node in multi-layer logistic networks, *Frontiers in Physics* 10: 968645. https://doi.org/10.3389/fphy.2022.968645

Xu, X.-M.; Li, K.-P.; Yang, L.-X. 2014. Discrete event model-based simulation for train movement on a single-line railway, *Chinese Physics B* 23(8): 080205.
https://doi.org/10.1088/1674-1056/23/8/080205

Yan, F.; Goverde, R. M. P. 2017. Railway timetable optimization considering robustness and overtakings, in *2017 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems* (*MT-ITS*), 26–28 June 2017, Naples, Italy, 291–296. https://doi.org/10.1109/MTITS.2017.8005683

Zhu, Q. 2023. Passenger flow simulation of Xiamafang metro station based on *AnyLogic*, *Highlights in Science*, *Engineering and Technology* 37: 142–156.
https://doi.org/10.54097/hset.v37i.6069