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A Resilience-Based Hybrid Simulation-Optimization Framework for Decision Support in Railway Disruption Management

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Railway networks in the UK are highly susceptible to disruptions, with delays and cancellations spreading rapidly across interdependent services due to high network congestion. The growing demand for rail travel has pushed capacity to its limit, reducing operational flexibility and overall resilience. At present, Network Rail (NR) manages disruptions through predefined contingency plans that include alternative timetables for particular scenarios and locations. However, selecting and applying these plans remains a manual process that relies heavily on operator judgment, often resulting in slow responses and operational inefficiencies. To overcome these limitations, this study introduces a hybrid simulation-optimization framework for near-real-time disruption management. The framework integrates a validated delay-propagation simulation model with a genetic algorithm (GA) to identify near-optimal service alteration strategies under disruption. A composite performance indicator is introduced to capture the time-dependent evolution of network functionality during disruption, enabling resilience-based evaluation of vulnerability, survivability, and recovery. The framework is applied to a real-world major disruption on the West Coast South Route in the UK and benchmarked against historical operational data. Results show that the optimized strategy achieves a substantial reduction in service cancellations (79.01%) and in the number of compensation-eligible affected services (250%), while maintaining comparable total delay minutes. Analysis of the resilience curve indicates reduced vulnerability, enhanced survivability, and faster recovery than in the historical case. These findings indicate that the proposed approach can support timely, targeted operational interventions and improve network-level resilience during disruptions. The framework offers a practical decision-support tool for railway operators managing disruptions in highly congested railway networks.

Keywords: Railway Disruption Management, Hybrid Simulation-Optimisation Framework, Genetic Algorithm, Reactionary Delay, Discrete-Event Simulation, Railway Performance Optimisation, Delay Propagation, Resilience

1. Introduction

Railway systems play a fundamental role in supporting economic activity, social inclusion, and environmental sustainability. In highly utilized rail networks, even short-duration disruptions can trigger disproportionate performance degradation due to tightly scheduled timetables with minimal operational flexibility. Delays and cancellations propagate rapidly across interconnected services, leading to significant passenger inconvenience and financial penalties for operators. In the UK, rising demand and capacity saturation have heightened the vulnerability of regional rail networks to operational disruptions, while recent performance statistics highlight persistent challenges in punctuality and service reliability (Office of Rail and Road (UK), 2025).

From a risk and resilience perspective, the key challenge is not only preventing disruptions but managing their consequences effectively. Traditional disruption management relies heavily on manually selected contingency plans and operator experience, often resulting in delayed or suboptimal interventions. While optimization-based rescheduling models have been widely studied, many struggle to achieve realism, scalability, and computational tractability, which limits their applicability in real-time operational contexts. (Cacchiani et al., 2014; Shakibayifar et al., 2020). In particular, microscopic optimization models offer high-fidelity representations but are often computationally infeasible for large-scale networks, whereas macroscopic approaches may oversimplify operational dynamics (Veelenturf et al., 2016; Zhu & Goverde, 2019).

Simulation techniques have been widely recognized as cost-effective and time-efficient tools for analyzing the dynamics of complex systems (Garson 2009). By embedding detailed representations of system structure and operational processes, simulation models can reproduce the behavior of large-scale systems that reflect real-world dynamics (Xu et al. 2016). When combined with metaheuristic optimization techniques, such as genetic algorithms (GAs), these models can support near real-time decision-making in complex, large-scale systems (Khanmohammadi et al. 2021; Nitisiri et al. 2019).

This paper proposes a hybrid simulation-optimization framework for railway disruption management, with an explicit focus on resilience evaluation. A validated delay propagation simulation model (Tan et al., 2025a) is integrated with a GA to identify near-optimal service alteration strategies under disruption. Through this integration, the research contributes by developing a resilience-oriented decision-support framework that evaluates the evolution of network functionality during railway disruptions. The framework is scalable to large networks, supports near real-time applications, and adopts a multi-objective optimization formulation to balance operator objectives and impact on passengers.

This paper is organized as follows. Section 2 introduces the resilience evaluation framework and performance measures. Section 3 details the proposed hybrid simulation-optimization methodology. Section 4 presents the results and discussion, and Section 5 concludes the paper and outlines directions for future research.

2. Rail Network Resilience and Performance Evaluation

2.1. *Rail Network Resilience*

Resilience has emerged as a core concept in the assessment of critical infrastructure systems. In rail transport, resilience is the ability of a rail network to withstand, adapt to, and recover from disruptive events while maintaining acceptable levels of functionality (Bešinović 2020; Poulin & Kane 2021; Woods 2015). Railway resilience is inherently dynamic, as disruptions typically induce an abrupt decline in system performance, followed by a response and recovery phase. This temporal evolution is commonly represented using a resilience curve, which illustrates changes in system functionality over time and after a disruptive event (Bešinović 2020).

Resilience in railway systems can be described through several interrelated performance attributes, including robustness, vulnerability, survivability, response, and recovery. **Robustness** refers to the ability of a system to maintain functionality during disruptions, to withstand uncertainty, and adhere to planned timetables (Miguel A.Salido et al. 2008). **Vulnerability** captures the susceptibility of the network to disruption and the severity of resulting performance degradation, reflecting underlying structural or operational weaknesses (Berdica 2002). **Survivability** denotes the ability of a network to continue operating in a degraded yet functional state following a disruption (Bešinović 2020). The **response** phase encompasses immediate operational actions taken to mitigate impacts and maintain service continuity. Finally, **recovery** describes the restoration of normal operations and is typically assessed by the time required to return to pre-disruption performance levels.

These dimensions collectively provide a structured basis for evaluating the effectiveness of disruption management strategies and comparing alternative operational responses.

2.2. Performance Metrics for Resilience Assessment

Quantifying railway resilience requires performance metrics that capture both operational efficiency and impact on passengers. Reliance on a single metric, such as total delay minutes, risks overlooking critical trade-offs between different dimensions of performance (Ilalokhoin et al. 2023). To address this limitation, this study adopts a multi-metric approach aligned with industry practice and integrates these metrics into a composite performance indicator(Knoester et al. 2024).

Total delay minutes ($\boldsymbol{T_d}$) measure deviations from the planned timetable and are widely used as an indicator of operational reliability. Beyond capturing punctuality, delay minutes reflect the extent of delay propagation across interconnected services, offering insight into the systemic effects of disruption (Tan et al. 2024). From a passenger perspective, delays are among the most immediate and tangible impacts of disruption.

Train cancellations are commonly employed as a containment strategy during severe disruptions to stabilize network operations and prevent further delay propagation, despite their adverse impacts on service availability and passenger satisfaction (*Knock-on Delays - Network Rail* n.d.). Prior studies indicate that targeted cancellations can more effectively absorb disruption impacts while reducing downstream reactionary delays (Tan et al. 2025b). Accordingly, the **number of train cancellations ($\boldsymbol{N_{tc}}$)** is included as a key performance metric in this study and is quantified using an industry-standard cancellation rate, defined as the proportion of journeys not completed, ranging from 0 (no cancellation) to 1 (full cancellation).

Number of affected passengers due to cancellation ($\boldsymbol{N_{cp}}$) provides a more passenger-centric measure of service disruption by accounting for heterogeneous demand across stations and routes. This metric is estimated using origin-destination matrices derived from historical ridership data, ensuring that the passenger impact of cancellations at high-demand locations is appropriately captured.

These metrics are combined into a **composite performance indicator ($\boldsymbol{M_{com}}$)**, which enables continuous monitoring of system functionality over time. Plotting this indicator against time since disruption onset **($\boldsymbol{t}$)** yields trajectories that capture degradation and recovery trajectories throughout the disruption period. Compared with single-metric measures, this integrated approach offers a more comprehensive representation of resilience dynamics and supports more informed operational decision-making. The composite performance indicator is defined in Eq. (1).

$$M_{com,t} = \frac{1}{3}\left[\left(\frac{T_{d,total} - T_{d,t}}{T_{d,total}} + \frac{N_{tc,total} - N_{tc,t}}{N_{tc,total}} + \frac{N_{cp,total} - N_{cp,t}}{N_{cp,total}}\right)\right] \times 100\% \tag{1}$$

$M_{com,t}$ - M_{com} at time t
$T_{d,total}$ - Total T_d
$N_{tc,total}$ - Total N_{tc}
$N_{cp,total}$ - Total N_{cp}
$T_{d,t}$ - T_d at time t
$N_{tc,t}$ - N_{tc} at time t
$N_{cp,t}$ $-$ N_{cp} at time t

3. Methodology

3.1. *Simulation of Delay Propagation*

The simulation component of the proposed framework is based on a mathematical predictive model previously developed and validated using historical disruption data (Tan et al. 2025a). The model is designed to capture the mechanisms by which primary delays from infrastructure disruptions propagate through a multi-track regional railway network, giving rise to reactionary delays.

Disruptions are generalized as partial or full track blockages, reflecting the operational consequences of a wide range of incident types. Primary delays occur when trains encounter a disrupted section or must wait to access reduced-capacity infrastructure. Reactionary delays arise when delayed or held trains obstruct subsequent services or prevent scheduled departures elsewhere in the network.

The railway network is represented as a topological structure, with nodes and links derived from the working timetable. Train movement is modelled at the trip level, defined as travel between two consecutive stations, while a journey consists of a sequence of trips from origin to termination. This level of granularity enables flexible modelling of partial cancellations and localized operational interventions. A discrete event simulation (DES) framework advances the simulation clock and updates train states based on scheduled and realized arrival and departure times. Train movements are governed by operational constraints, including track occupancy conflicts, minimum headway requirements, and station dwell times, causing delays to propagate when a delayed train restricts subsequent services.

A baseline simulation without intervention is first executed to characterize natural delay propagation under disruption. The resulting delay profiles serve as a reference against which the effectiveness of alternative service strategies can be evaluated and as the basis for the subsequent optimization module framework.

3.2. *Modelling the Cascading Effects of Interventions*

Directly re-running the full simulation for every candidate intervention strategy would be computationally infeasible within an optimization framework. To address this limitation, an analytical procedure is introduced to estimate the cascading effect of train cancellations on downstream delay propagation, building on the logic of the baseline simulation (Tan et al. 2025a).

For each cancelled trip, the procedure evaluates whether removing that service mitigates downstream conflicts and absorbs accumulated delays. Cancellations are categorized according to whether the affected train has already departed or has not yet entered service. If the train has already departed, the cancellation is classified as a primary delay; otherwise, it is grouped as a reactionary delay. A baseline simulation captures the delay contribution of each train service and its downstream impacts under disrupted conditions. By cancelling a service, its contribution to downstream delay propagation is effectively removed, thereby allowing the system-wide delay impact of the intervention to be estimated analytically without rerunning the full simulation.

Operational constraints are imposed to ensure realism. In particular, estimated delay reductions are constrained to avoid exceeding the delays introduced by the disruption, and delays incurred by earlier trips within the same journey are treated as irreversible.

3.3. Optimization of Service Alterations Using Genetic Algorithms (GA)

A GA is employed to identify near-optimal service alteration strategies under disruption. GAs are well-suited to this application due to the large, discrete, and non-linear nature of the decision space, as well as their ability to handle multiple conflicting objectives within a reasonable computational time. In this study, optimization focuses on determining which train trips to cancel to mitigate the network-wide impacts of the disruption.

Each trip affected by the disruption is represented by a binary decision indicating whether the trip remains active or is cancelled. These variables are concatenated to form a chromosome representing a complete service alteration strategy across the disrupted network. Accordingly, the number of genes in a chromosome is determined by the number of trips affected by the disruption, ensuring that the optimization problem scales dynamically with disruption severity. Operational consistency across trips within the same journey is enforced by the constraints described in Section 3.4.

For each chromosome, the resulting operational impacts are evaluated using the propagating-effect estimation procedure described in Section 3.2. This enables efficient assessment of the fitness of candidate solutions without repeated full-scale simulation, supporting near-real-time optimization.

The objective function minimizes a weighted sum of four normalized performance metrics: T_d, N_{tc}, N_{cp}, and **additional compensation cost to affected passengers (C_a)**. C_a captures the financial implications of service disruption under the Delay Compensation Scheme (*Delay Repay Claim*, 2025). In the UK, compensation is triggered when delays exceed specified thresholds, leading to substantial cumulative passenger compensation costs for operators (Department for Transport, 2024). Although compensation costs depend on delay duration, they represent an aggregated economic impact rather than a continuous indicator of system functionality over time. Consequently, this metric is not included in the M_{com} used to evaluate the temporal network performance. Instead, $C_a$is incorporated into the optimization objective to account for financial risk when identifying optimal service alteration strategies. The objective function is presented in Eq. (2).

$$\min f(x) = \omega_1 \alpha T_d(x) + \omega_2 \beta C_a(x) + \omega_3 \gamma N_{tc}(x) + \omega_4 \delta N_{cp}(x) \tag{2}$$

$$x_i = \begin{cases} 1, & \text{if trip } i \text{ is active} \\ 0, & \text{if trip } i \text{ is cancelled} \end{cases} \quad \forall i \in J$$

J − Total number of affected trips

Scaling coefficients $(\alpha, \beta, \gamma, \delta)$ are used to achieve a comparable influence across the performance metrics. Their values are obtained through a regression-based decomposition that quantifies the contribution of each input variable to the overall model output. Weight coefficients $(\omega_1, \omega_2, \omega_3, \omega_4)$ are incorporated into the objective function to allow operational priorities and policy preferences of the operators to be reflected in the optimization process. This formulation supports flexible decision-making aligned with operational objectives.

The GA evolves candidate solutions using tournament selection, two-point crossover, and mutation operators. Elitism is incorporated to preserve high-quality solutions. A population size (N_{pop}) of 50 individuals is adopted to ensure sufficient genetic diversity and effective exploration of the solution space. The evolutionary process is limited to 100 generations, allowing the algorithm to converge while mitigating premature convergence and avoiding unnecessary computation as fitness improvements plateau. The parameter settings are summarized in Table 1.

Table 1 Parameters of GA.

Parameter	Value
Number of Generation, N_{gen}	100
Population Size, N_{pop}	50
Elitism Rate	1
Crossover Probability	0.7
Mutation Probability	0.2
Scaling Coefficients $(\alpha, \beta, \gamma, \delta)$	1, 7, 2, 1
Weight Coefficients $(\omega_1, \omega_2, \omega_3, \omega_4)$	1, 1, 1, 1

3.4. Operational Constraints and Assumptions

Several operational constraints are embedded within the optimization framework to ensure feasibility:

- Partial cancellations enforce termination of all subsequent trips within the same journey, reflecting real-world operational practice.
- Trains may only be terminated at stations with suitable siding or depot capacity.
- Rolling stock and crew reallocation are assumed to be feasible at a network-wide level for tractability.
- Freight services are excluded during disruption periods to prioritize passenger train services.

4. Results and Discussion

The proposed framework is applied to the West Coast South Route (Network Rail, n.d.), a highly utilized regional rail network in the UK. A major disruption involving a partial blockage near Watford Junction (Incident 428433) is adopted as the case study in this paper. This incident involved the closure of two of four tracks and affected 37 passenger train services over a 35-minute period. This real-world disruption provides a robust benchmark for evaluating the performance of the proposed optimization framework against real-life operational practice.

The optimization model is applied with equal weight coefficients to identify an alternative set of service alterations, and the resulting performance is compared directly with historical empirical data. As shown in Figure 1, the optimized strategy achieves a substantial 79.01% reduction in total service cancellations relative to historical operational practice. In contrast, the reduction in total delay minutes is more modest, at 13.94%, highlighting an inherent trade-off between service continuity and delay reduction. By cancelling fewer services, the optimized strategy maintains a higher level of network utilization, which limits the extent to which congestion-induced delays can be eliminated. As a result, delays are redistributed rather than fully suppressed, leading to longer traversal times for some services through the disrupted area.

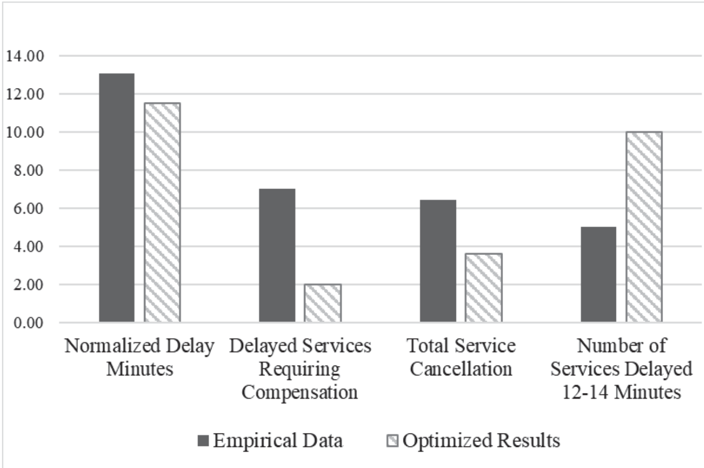

Figure 1 Comparison of empirical data and model-generated optimized results.

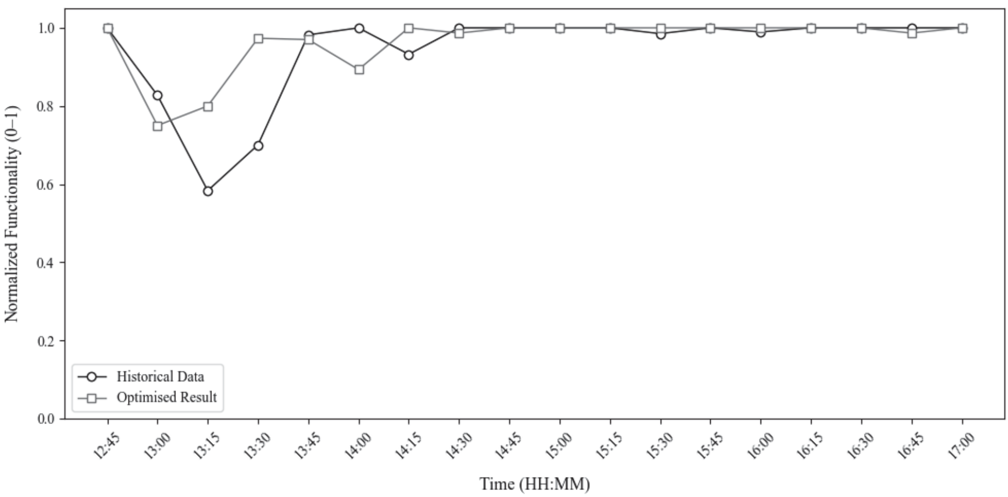

Figure 2 Evolution of network functionality over time during disruption

Furthermore, the optimized strategy results in a 250% reduction in the number of compensation-eligible delayed services compared with historical operations. This improvement arises from a deliberate redistribution of delays across train services. In the optimized results, the number of services experiencing delays in the 12-14 minutes range is approximately double that observed in the historical data. Rather than allowing a larger number of services to exceed the 15-minute compensation threshold, the algorithm distributes smaller delays more evenly across the network. As a result, fewer trains become eligible for compensation, leading to lower overall financial liabilities for operators.

To evaluate the temporal evolution of system performance, $\boldsymbol{M_{com}}$ is used to construct resilience curves, as shown in Figure 2. Both the historical and optimized cases exhibit similar qualitative trends, characterized by a decline in performance at the onset of disruption, followed by a recovery phase.

At the onset of disruption, both curves exhibit a sharp decline in network functionality, indicating the limited robustness of the highly congested network. Nevertheless, the optimized strategy stabilizes earlier and at a higher performance level, with a minimum functionality of approximately 0.72, compared with 0.58 in the historical case. This indicates reduced vulnerability, as the optimization model limits the magnitude of initial performance through earlier, more targeted interventions. During the disruption period, the optimized performance curve remains consistently above the historical curve, indicating that the network sustains a higher level of functionality under degraded operating conditions.

The recovery phase also differs between the two cases. In the optimized scenario, the network exhibits a faster response, with recovery beginning earlier and progressing more smoothly, resulting in a shorter duration of reduced performance. Both cases return to near-normal functionality by approximately 14:45, with only minor fluctuations thereafter due to residual reactionary delays. A comparison of network functionality over time demonstrates that the proposed framework enhances network resilience primarily by reducing response time and prioritizing service alterations that yield greater network-wide benefit.

All simulation and optimization computations were performed on an Intel Core i9-13900K processor and completed in approximately five minutes. The resilience-curve analysis shows that optimization reduces vulnerability and enhances survivability relative to empirical operational practice. It also accelerates recovery, thereby improving the ability of the network to manage and recover from disruptions.

5. Conclusions and Future Research

This paper presents a resilience-oriented hybrid simulation-optimisation framework to support near-real-time decision-making in railway disruption management. By integrating a validated delay propagation simulation model with a GA, the framework enables systematic evaluation of service alteration strategies while explicitly accounting for network-wide operational and passenger impacts. The approach is designed to balance realism, scalability, and computational efficiency, addressing key limitations of existing disruption management models.

The framework is evaluated using a real-world disruption on the West Coast South Route, providing a realistic benchmark for comparison with historical operations. When benchmarked against historical data, the optimised strategy improves operational outcomes by reducing total delay minutes, service cancellations, and compensation-eligible delays. The framework also allows operators to adjust the relative importance of performance measures to reflect differing operational priorities, providing flexibility in tailoring intervention strategies to specific disruption contexts.

Beyond static performance metrics, the use of a composite performance indicator enabled a time-dependent assessment of network functionality through resilience curves. The results showed that the proposed framework reduces vulnerability, enhances survivability, and accelerates recovery compared to the historical operational responses. These improvements are primarily attributed to faster response times and the prioritisation of service alterations that deliver greater network-wide benefit during disruptions.

Overall, the findings demonstrate that the proposed framework provides a practical and resilience-informed decision-support tool for railway disruption management in highly congested regional networks. Future work will focus on extending the framework to incorporate additional operational constraints, a broader range of disruption types, and adaptive weighting schemes to support dynamic prioritisation across varying risk and policy contexts. Broader validation across multiple disruption scenarios will also be investigated in future work.

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