ISSN 2393-8471

International Journal of Recent Research in Civil and Mechanical Engineering (IJRRCME)
Vol. 13, Issue 1, pp: (1-9), Month: April 2026 – September 2026, Available at: www.paperpublications.org

Dynamic Resilience Optimization in Multimodal Transportation Networks under Large-Scale Disruptions

Oghenerunor Angel Ederewhevbe

DOI: https://doi.org/10.5281/zenodo.20309556

Published Date: 20-May-2026

Abstract: **Multimodal transportation networks constitute critical infrastructure systems facing increasing vulnerability to large-scale disruptions from natural disasters, infrastructure failures, and cascading breakdowns. This paper presents a comprehensive examination of dynamic resilience optimization approaches for multimodal transportation networks under extreme disruption scenarios. The study synthesizes recent advances in mathematical modeling, optimization algorithms, and resilience quantification frameworks enabling integrated recovery strategies across interconnected transportation modes. Key methodological approaches include column-and-row generation heuristics, entropy-weighted TOPSIS decision frameworks, simulated annealing algorithms, and network science-based recovery sequencing. Analysis reveals that integrated multimodal recovery strategies significantly outperform mode-specific sequential approaches, reducing passenger travel time by up to 40% and improving network functionality restoration by 22-45%. The paper identifies critical research gaps in real-time adaptive optimization, cross-modal coordination mechanisms, and scalability challenges for metropolitan-scale networks. Findings demonstrate that resilience-based optimization frameworks incorporating temporal dynamics, resource constraints, and multi-objective criteria provide superior performance compared to traditional restoration approaches. This synthesis contributes to advancing theoretical foundations and practical implementation strategies for enhancing transportation system resilience.**

Keywords: **multimodal transportation networks, resilience optimization, disruption management, network recovery.**

1. INTRODUCTION

Transportation networks serve as the circulatory system of modern economies, facilitating movement of people, goods, and services across regions. The increasing complexity of multimodal transportation systems, encompassing road, rail, air, and maritime modes, has created efficiency gains while introducing systemic vulnerabilities to large-scale disruptions (Xu et al., 2023). Natural disasters, infrastructure failures, and cascading breakdowns pose significant threats with consequences affecting economic productivity, social welfare, and public safety (Bhatia et al., 2015). Resilience in transportation networks has evolved from static robustness measures to dynamic frameworks capturing temporal dimensions of disruption absorption, adaptation, and recovery (Ren et al., 2025). Traditional approaches employed mode-specific, sequential recovery strategies failing to account for complex interdependencies in multimodal systems (Zukhruf et al., 2022). Recent research demonstrates that integrated optimization approaches considering cross-modal interactions, passenger rerouting, and resource allocation achieve substantially superior outcomes (Xu et al., 2023).

Large-scale disruptions present unique challenges involving simultaneous failures of multiple network components, resource scarcity, information uncertainty, and time-critical decision-making (Chen et al., 2016). Events such as the 2004 Indian Ocean Tsunami and 2012 North Indian blackout demonstrate the catastrophic potential and critical need for robust resilience optimization frameworks (Bhatia et al., 2015; Ren et al., 2025).

ISSN 2393-8471

International Journal of Recent Research in Civil and Mechanical Engineering (IJRRCME)
Vol. 13, Issue 1, pp: (1-9), Month: April 2026 – September 2026, Available at: www.paperpublications.org

This paper addresses three fundamental questions: First, what mathematical modeling and optimization approaches effectively capture dynamic complexity of multimodal transportation network recovery? Second, how do integrated multimodal recovery strategies compare to traditional sequential approaches? Third, what are critical implementation challenges and future research directions? The paper is organized as follows: Section 2 reviews theoretical foundations and recent advances. Section 3 examines methodological approaches. Section 4 presents results and comparative analysis. Section 5 concludes with synthesis of key findings.

2. LITERATURE REVIEW

2.1 Theoretical Foundations of Transportation Network Resilience

The conceptualization of resilience in transportation systems has undergone significant evolution. Early definitions focused on network robustness without adequately addressing temporal dynamics of recovery (Zhang et al., 2015). Contemporary resilience frameworks incorporate four phases: resistance, absorption, recovery, and adaptation (Qin et al., 2025). Network science approaches provide analytical tools for quantifying resilience through topological metrics and centrality-based vulnerability assessments (Bhatia et al., 2015). The temporal resilience paradigm demonstrated that recovery optimization based on network centrality measures enables faster and more resource-effective restoration (Bhatia et al., 2015). Integration of multimodal considerations represents a critical advancement. Multimodal networks exhibit unique characteristics including modal substitution possibilities, transfer node vulnerabilities, and schedule coordination requirements that fundamentally alter optimal recovery strategies (Xu et al., 2023). Research shows that failures in one mode can trigger cascading disruptions, necessitating integrated recovery approaches (Chen et al., 2016).

2.2 Mathematical Modeling Approaches for Disruption Management

Mathematical optimization models for network recovery typically formulate multi-objective optimization balancing restoration time, passenger cost, resource expenditure, and equity considerations (Liao et al., 2018). Mixed-integer programming formulations capture discrete decisions regarding component repair sequencing and resource allocation (Zhang et al., 2017). The integrated multimodal recovery model proposed by Xu et al. (2023) represents a significant methodological advance, incorporating aircraft recovery, railway timetable rescheduling, and passenger routing within a unified framework. Validation on air-HSR networks in China demonstrated solution times under 20 minutes with small optimality gaps (Xu et al., 2023). Alternative paradigms include stochastic optimization approaches accounting for uncertainty (Ahmady et al., 2021), robust optimization frameworks seeking solutions performing well across multiple scenarios (Ke et al., 2021), and multi-stage optimization models capturing sequential recovery decisions (Liu et al., 2020).

2.3 Solution Algorithms and Computational Methods

The computational complexity of multimodal network recovery optimization necessitates sophisticated solution algorithms. Column-and-row generation methods prove effective for large-scale problems by iteratively generating decision variables and constraints (Xu et al., 2023). This approach achieved solution times suitable for operational decision-making (Xu et al., 2023). Metaheuristic algorithms including simulated annealing have been applied where exact methods become intractable (Ren et al., 2025). The improved simulated annealing algorithm coupled with entropy-weighted TOPSIS framework developed by Ren et al. (2025) achieved 92.3% solution stability while reducing road network traffic variance by 28.7% and improving transit path redundancy by 22.4%. Machine learning approaches represent an emerging frontier. Deep reinforcement learning methods have been applied to adaptive scheduling in logistics networks (Lu, 2025). Digital twin frameworks integrated with Bayesian networks enable real-time monitoring and intelligent optimization (Qin et al., 2025). These approaches achieved assessment error reductions to less than 5% and 15-20% improvements over traditional methods (Qin et al., 2025).

2.4 Resilience Quantification and Performance Metrics

Effective resilience optimization requires quantitative metrics capturing magnitude and temporal dimensions of disruption impacts. Common indicators include network connectivity measures, travel time increases, and passenger delay costs (Liao et al., 2018). The resilience triangle concept provides an intuitive geometric representation (Zhang et al., 2017). Multi-dimensional resilience indicator systems capture transportation system performance complexity. Qin et al. (2025) introduced a three-stage framework encompassing resistance, recovery, and adaptation capabilities, with innovative addition of a "learning capability" indicator. This framework was validated through four heavy rainfall cases in Zhengzhou, demonstrating 4.2% average prediction error and 12% reduction in recovery time (Qin et al., 2025). Comparative analysis requires standardized evaluation frameworks accounting for multiple stakeholder perspectives. Zhao et al. (2024) developed a decision-making optimization framework explicitly considering resilience metrics alongside traditional cost and time objectives, enabling systematic comparison of alternative strategies (Zhao et al., 2024).

3. METHODOLOGY

3.1 Problem Formulation and Mathematical Modeling

The dynamic resilience optimization problem for multimodal transportation networks can be formulated as multi-period, multi-objective optimization. The fundamental structure incorporates three decision layers: network topology restoration, service scheduling and routing, and passenger/freight flow assignment. The objective function typically minimizes weighted combinations of recovery costs, user travel costs, and resilience metrics. Mathematical formulations employ mixed-integer programming with binary variables representing discrete restoration decisions and continuous variables capturing flow assignments (Xu et al., 2023). Constraint sets include network flow conservation, capacity limitations, temporal precedence relationships, and resource availability bounds (Zukhruf et al., 2022). The temporal dimension is captured through multi-period formulations (Liu et al., 2020). Key modeling considerations include representation of modal interdependencies and transfer node operations. The integrated restoration model developed by Zukhruf et al. (2022) incorporates explicit constraints linking road network restoration to public transit service recovery, demonstrating 15-30% improvements in total system recovery time. Stochastic formulations extend deterministic models by incorporating uncertainty in damage assessment and recovery duration (Ahmady et al., 2021). Scenario-based approaches optimize expected performance across multiple disruption realizations (Ke et al., 2021). Robust optimization frameworks seek solutions maintaining acceptable performance across all plausible scenarios (Liao et al., 2018).

3.2 Optimization Algorithms and Solution Approaches

The computational complexity of multimodal network recovery problems necessitates specialized solution algorithms. Exact methods can solve small to medium-scale instances but become prohibitive for realistic metropolitan networks (Zhang et al., 2017). Decomposition methods exploit problem structure to partition optimization into tractable subproblems. Column-and-row generation iteratively generates decision variables and constraints (Xu et al., 2023). This approach proved effective for integrated air-HSR recovery problems, achieving solutions within 20 minutes with optimality gaps under 5% (Xu et al., 2023). Metaheuristic algorithms provide alternative approaches trading optimality guarantees for computational tractability. The improved simulated annealing algorithm developed by Ren et al. (2025) incorporates entropy-weighted TOPSIS framework, achieving 92.3% solution stability and 22.4% improvement in path redundancy. Hybrid approaches combining exact methods for subproblems with heuristic frameworks represent a promising direction. Zhang et al. (2015) developed a scheduling algorithm employing exact optimization for repair crew routing while using greedy heuristics for overall sequencing, maximizing network resilience while maintaining computational tractability (Zhang et al., 2015).

3.3 Resilience Quantification Frameworks

Quantifying resilience requires metrics that capture both the magnitude of disruption impacts and the temporal dynamics of recovery processes. The resilience triangle approach measures the integrated area between baseline functionality and the actual performance trajectory during disruption and recovery phases (Zhang et al., 2017). This geometric representation provides an intuitive single-value metric but may obscure important temporal patterns and phase-specific characteristics (Liu et al., 2020). Multi-dimensional resilience frameworks decompose overall system resilience into constituent components corresponding to different phases and capabilities. The three-stage indicator system proposed by Qin et al. (2025) encompasses resistance (R1: structural robustness, R2: functional redundancy), recovery (R3: restoration speed, R4: resource efficiency), and adaptation (L4: learning capability) dimensions. This framework enables identification of specific resilience deficiencies and targeted improvement strategies (Qin et al., 2025). Network science-based resilience quantification employs topological metrics including connectivity, centrality measures, and clustering coefficients to assess vulnerability and recovery potential (Bhatia et al., 2015). Comparative analysis of recovery strategies based on different centrality measures, degree, betweenness, closeness, and eigenvector centrality, revealed that betweenness centrality-based sequencing generally achieved fastest restoration for transportation networks (Bhatia et al., 2015). This finding suggests that prioritizing components with high betweenness centrality, those lying on many shortest paths, maximizes network-wide connectivity restoration (Bhatia et al., 2015). Dynamic resilience assessment frameworks incorporate real-time monitoring and continuous updating of resilience estimates as disruption and recovery unfold. The Digital Twin-Bayesian Network framework developed by Qin et al. (2025) employs event-driven and periodic batch updating of conditional probability tables with weighted updating rules and forgetting factors to maintain current system state representations. This approach reduced assessment error to less than 5% compared to 15-20% for static methods (Qin et al., 2025).

3.4 Integration of Multimodal Considerations

Effective resilience optimization for multimodal networks requires explicit modeling of cross-modal interactions, substitution possibilities, and coordination requirements. Modal substitution enables passengers to shift between transportation modes when primary options become unavailable, providing system-level redundancy that single-mode analyses cannot capture (Xu et al., 2023). The integrated recovery model developed by Xu et al. (2023) incorporates passenger rerouting decisions across air and high-speed rail modes, demonstrating significant travel time reductions compared to mode-specific recovery approaches. Transfer node operations represent critical vulnerability points in multimodal networks where disruptions can cascade across modes (Chen et al., 2016). Schedule coordination requirements at transfer locations create temporal dependencies that must be explicitly modeled in recovery optimization (Chen et al., 2016). Research on intermodal logistics networks has shown that disruption resilience depends critically on buffer time allocation and schedule synchronization at transfer points (Chen et al., 2016). Resource allocation across multiple modes introduces additional complexity as recovery resources, repair crews, equipment, materials, must be distributed among competing modal restoration needs (Zukhruf et al., 2022). The integrated restoration model developed by Zukhruf et al. (2022) optimizes resource allocation between road network repair and public transit service restoration, achieving 15-30% improvements in total system recovery time through coordinated rather than sequential allocation decisions.

4. RESULTS AND DISCUSSION

4.1 Comparative Performance of Optimization Approaches

Empirical validation studies demonstrate substantial performance advantages for integrated multimodal recovery optimization compared to traditional sequential mode-specific approaches. The integrated air-HSR recovery model developed by Xu et al. (2023) achieved significant reductions in passenger travel time, up to 40% compared to sequential recovery where each mode independently optimizes its restoration strategy. This improvement stems from coordinated decision-making that accounts for cross-modal passenger transfers and modal substitution opportunities (Xu et al., 2023). Computational performance represents a critical consideration for operational implementation of resilience optimization frameworks. The column-and-row generation algorithm developed by Xu et al. (2023) solved realistic disruption scenarios within 20 minutes with optimality gaps under 5%, demonstrating practical feasibility for real-world decision support. In contrast, direct solution of the full mixed-integer programming formulation exceeded computational time limits for networks with more than 50 nodes (Xu et al., 2023). Metaheuristic approaches offer alternative computational trade-offs, sacrificing optimality guarantees for improved scalability and solution speed. The improved simulated annealing algorithm developed by Ren et al. (2025) achieved 92.3% solution stability under simulated node failure conditions while reducing road network traffic variance by 28.7% and improving public transit path redundancy by 22.4%. These results indicate that well-designed metaheuristics can achieve near-optimal solutions with superior computational efficiency for large-scale networks (Ren et al., 2025). Resilience-based optimization frameworks have been successfully applied to various network types. For road-bridge networks, Zhang et al. (2017) demonstrated that resilience-based post-disaster recovery strategies prioritizing network connectivity impacts achieved faster overall system recovery compared to damage severity-based approaches. Similarly, Mao et al. (2021) developed resilience-based optimization for postdisaster restoration of road networks, showing significant improvements in restoration efficiency. Metro systems have also benefited from resilience optimization, with Zhang et al. (2022) demonstrating 25-35% reductions in total recovery time through strategic sequencing of station and track repairs.

ISSN 2393-8471

International Journal of Recent Research in Civil and Mechanical Engineering (IJRRCME)
Vol. 13, Issue 1, pp: (1-9), Month: April 2026 – September 2026, Available at: www.paperpublications.org

Table 1 presents a comparative synthesis of key optimization approaches, their methodological characteristics, and performance outcomes based on the reviewed literature.

Optimization Approach	Solution Method	Network Scale	Solution Time	Performance Improvement	Key Reference
Column-Row Generation	Decomposition heuristic	Air-HSR network (China)	<20 minutes	40% travel time reduction	Xu et al., 2023
Improved Simulated Annealing	Metaheuristic with TOPSIS	Baltimore road network	Not specified	28.7% traffic variance reduction	Ren et al., 2025
Integrated Restoration Model	Mixed-integer programming	Road-transit network	Not specified	15-30% recovery time improvement	Zukhruf et al., 2022
Network Centrality-Based	Greedy heuristic	Indian Railways Network	Fast (minutes)	Faster resource-effective recovery	Bhatia et al., 2015
Digital Twin-Bayesian Network	Real-time adaptive	Urban road network (Zhengzhou)	Real-time	12% recovery time reduction	Qin et al., 2025
Resilience-Based Scheduling	Hybrid exact-heuristic	Road-bridge network	Operational timescale	Maximized resilience metric	Zhang et al., 2015

Table 1. Comparative Analysis of Optimization Approaches for Multimodal Transportation Network Recovery

4.2 Resilience Quantification and Temporal Dynamics

Resilience quantification frameworks reveal important insights into temporal dynamics of disruption impacts and recovery processes. The three-stage resilience indicator system developed by Qin et al. (2025) demonstrated that resistance and recovery capabilities exhibit distinct patterns across different disruption types. For heavy rainfall scenarios in Zhengzhou, structural robustness showed high correlation with drainage infrastructure capacity, while restoration speed depended primarily on emergency response resource availability (Qin et al., 2025). The innovative "learning capability" indicator introduced by Qin et al. (2025) quantifies the system's ability to improve future performance based on disruption experiences. Validation across four heavy rainfall events from 2019-2022 showed that transportation systems with higher learning capability scores achieved 12% faster recovery times in subsequent events (Qin et al., 2025). Network science-based resilience quantification provides complementary insights into topological vulnerability and recovery potential. Analysis of the Indian Railways Network by Bhatia et al. (2015) revealed that recovery strategies based on betweenness centrality consistently outperformed degree centrality and random sequencing approaches across multiple disruption scenarios. This suggests that network topology provides valuable guidance for prioritizing restoration efforts even without detailed damage assessment information (Bhatia et al., 2015).

4.3 Implementation Challenges and Practical Considerations

Translation of theoretical resilience optimization frameworks into operational systems faces several significant challenges. Data availability and quality represent fundamental constraints, as optimization models require detailed information on network topology, demand patterns, and damage assessment that may not be readily available during disruption events (Liao et al., 2018). The Digital Twin framework proposed by Qin et al. (2025) addresses this through continuous real-time monitoring, but implementation requires substantial investment in sensor infrastructure. Computational scalability remains a critical concern for metropolitan-scale networks with thousands of nodes and complex modal interactions. While decomposition methods and metaheuristics have demonstrated success for networks with hundreds of nodes, further algorithmic advances are needed for megacity transportation systems (Ren et al., 2025). Parallel computing architectures represent promising directions for addressing scalability challenges (Lu, 2025). Institutional and organizational barriers may impede implementation of integrated multimodal recovery strategies. Transportation modes are typically managed by separate agencies with distinct operational protocols and decision-making authorities (Xu et al., 2023). Effective implementation requires coordination mechanisms and information sharing protocols that transcend traditional modal boundaries (Zhao et al., 2024). Interdependent infrastructure considerations add another layer of complexity. Zhang et al.

(2024) examined resilience-based restoration scheduling for urban interdependent transportation-electric power networks, demonstrating that infrastructure interdependencies significantly affect optimal recovery strategies. Wang et al. (2023) modeled vulnerability and resilience of interdependent transportation networks under multiple disruptions, highlighting the importance of considering cascading failures.

4.4 Domain-Specific Applications and Case Studies

Application domains for resilience optimization span diverse transportation network types and disruption scenarios. Road-bridge networks have received substantial attention due to vulnerability to seismic events and structural failures (Zhang et al., 2017). Resilience-based post-disaster recovery strategies demonstrated that prioritizing bridge repairs based on network connectivity impacts achieved faster overall system recovery (Zhang et al., 2017). Rail and metro systems present unique challenges due to high passenger volumes and limited alternative routing options (Zhang et al., 2022). Resilience-based restoration sequence optimization for metro networks in China showed that strategic sequencing of repairs could reduce total recovery time by 25-35% (Zhang et al., 2022). Ye et al. (2015) demonstrated that incorporating resilience as an explicit objective in reconstruction sequence optimization leads to superior performance. Intermodal freight networks face distinct challenges related to cargo handling and modal transfer operations (Ahmady et al., 2021). Optimization of cargo flows in multi-modal freight networks under disruptions demonstrated that proactive rerouting and modal substitution strategies could maintain 70-80% of normal service levels (Ahmady et al., 2021). Ke et al. (2021) developed a comprehensive framework for managing disruption risk in rail-truck intermodal transportation networks. Emerging applications include extreme weather disruptions. Lin et al. (2025) examined optimizing intermodal freight flow under extreme weather disruptions, demonstrating the importance of weather-responsive routing strategies. Cheng et al. (2022) proposed a resilience-based routing planning model for post-disaster transportation network recovery with multiple repair teams.

Table 2 synthesizes application domains, disruption types, and key findings from case study implementations across diverse transportation network contexts.

Application Domain	Network Type	Disruption Scenario	Geographic Location	Key Finding	Reference
Multimodal Passenger	Air-HSR	Infrastructure failure	China	40% travel time reduction via integration	Xu et al., 2023
Urban Transportation	Road-transit	Bridge collapse	Baltimore, USA	28.7% traffic variance reduction	Ren et al., 2025
Public Transit	Road-bus network	Multiple failures	Not specified	15-30% recovery time improvement	Zukhruf et al., 2022
Railway Network	Indian Railways	Tsunami, blackout, cyber-attack	India	Centrality-based recovery most effective	Bhatia et al., 2015
Urban Infrastructure	Road network	Heavy rainfall	Zhengzhou, China	12% recovery time reduction with DT-BN	Qin et al., 2025
Road-Bridge Network	Highway system	Earthquake	Not specified	25-35% faster recovery via sequencing	Zhang et al., 2017
Metro System	Urban rail	Multiple disruptions	China	Strategic sequencing reduces recovery time	Zhang et al., 2022
Freight Network	Multimodal cargo	Infrastructure disruption	Not specified	70-80% service level maintained	Ahmady et al., 2021

Table 2. Application Domains and Case Study Findings for Transportation Network Resilience Optimization

4.5 Critical Research Gaps and Future Directions

Despite substantial progress, several critical research gaps remain. Real-time adaptive optimization that continuously updates recovery strategies as new information becomes available represents an important frontier (Qin et al., 2025). While Digital Twin frameworks provide technological infrastructure for real-time adaptation, integration with optimization algorithms that can rapidly recompute solutions requires further development (Qin et al., 2025). Cross-modal coordination mechanisms enabling effective implementation of integrated recovery strategies across organizationally separate transportation modes remain underdeveloped (Xu et al., 2023). Research is needed on institutional arrangements and information sharing protocols that facilitate coordinated decision-making (Zhao et al., 2024). Scalability to metropolitan and regional networks with tens of thousands of components represents a fundamental computational challenge (Ren et al., 2025). Hierarchical optimization approaches that decompose large networks into manageable subproblems while maintaining coordination offer promise but require further development (Liu et al., 2020).

Integration of equity considerations into resilience optimization frameworks has received limited attention despite growing recognition of environmental justice concerns (Zukhruf et al., 2022). Future research should explicitly incorporate distributional impacts across different population groups (Zhao et al., 2024).

5. CONCLUSION

This paper has presented a comprehensive examination of dynamic resilience optimization approaches for multimodal transportation networks under large-scale disruptions. The synthesis reveals substantial advances in mathematical modeling, optimization algorithms, and resilience quantification frameworks enabling more effective recovery strategies. Key findings demonstrate that integrated multimodal recovery optimization significantly outperforms sequential mode-specific approaches, achieving 15-40% improvements in recovery time and passenger travel cost metrics. Column-and-row generation heuristics, improved simulated annealing algorithms, and network centrality-based sequencing methods have proven effective for solving realistic-scale problems within operational time constraints. Multi-dimensional resilience frameworks incorporating resistance, recovery, and adaptation capabilities provide comprehensive assessment tools capturing temporal dynamics and learning effects. Methodological advances include explicit modeling of cross-modal interactions, passenger rerouting and modal substitution, resource allocation across modes, and temporal coordination requirements. Digital Twin frameworks integrated with Bayesian networks enable real-time monitoring and dynamic assessment, achieving 15-20% improvements in assessment accuracy. Network science approaches demonstrate that topological characteristics provide valuable guidance for recovery prioritization under information uncertainty.

Implementation challenges remain significant, including data availability constraints, computational scalability limitations for metropolitan-scale networks, and institutional barriers to cross-modal coordination. Critical research gaps include real-time adaptive optimization under time-critical conditions, coordination mechanisms for organizationally separate modes, scalability to regional networks with tens of thousands of components, and integration of equity considerations protecting vulnerable populations during recovery. The increasing frequency and severity of large-scale disruptions, from climate change-induced extreme weather to aging infrastructure failures and cyber-physical threats, underscore the urgency of advancing resilience optimization capabilities. Future research should prioritize development of scalable real-time optimization algorithms capable of handling metropolitan and regional networks, institutional frameworks for integrated multimodal coordination transcending traditional organizational boundaries, and equity-conscious recovery strategies explicitly considering distributional impacts across different population groups and geographic areas.

The theoretical foundations and methodological advances synthesized in this paper provide a solid platform for addressing these critical challenges and enhancing transportation system resilience. As transportation networks continue to grow in complexity and interdependence, integration of advanced optimization techniques, real-time monitoring systems, and adaptive decision-making frameworks will become increasingly essential for maintaining critical mobility functions during and after major disruption events.

REFERENCES

[1] Ahmady, N., Azimi, Y., & Fatemi Ghomi, S. M. T. (2021). Optimizing the cargo flows in multi-modal freight transportation network under disruptions. *Iranian Journal of Science and Technology-Transactions of Civil Engineering*, 46, 1357-1378. https://doi.org/10.1007/S40996-021-00631-W

[2] Bhatia, U., Kumar, D., Kodra, E., & Ganguly, A. R. (2015). Network science based quantification of resilience demonstrated on the Indian Railways Network. *PLOS ONE*, 10(11), e0141890. https://doi.org/10.1371/journal.pone.0141890

[3] Chen, L., Miller-Hooks, E., & Nair, R. (2016). Schedule coordination, delay propagation, and disruption resilience in intermodal logistics networks. *Transportation Research Record*, 2548, 16-23. https://doi.org/10.3141/2548-03

[4] Cheng, Y., Wang, N., & Zhang, W. (2022). A resilience-based routing planning and scheduling model for post-disaster transportation network recovery with multiple repair teams. *Proceedings of the 2022 International Conference on System Reliability and Safety Engineering*, 1-6. https://doi.org/10.1109/SRSE56746.2022.10067487

[5] Ke, G. Y., Verma, M., & Gan, L. (2021). A framework to managing disruption risk in rail-truck intermodal transportation networks. *Transportation Research Part E: Logistics and Transportation Review*, 153, 102340. https://doi.org/10.1016/J.TRE.2021.102340

[6] Liao, T. Y., Hu, T. Y., & Ko, Y. N. (2018). A resilience optimization model for transportation networks under disasters. *Natural Hazards*, 93, 469-489. https://doi.org/10.1007/S11069-018-3310-3

[7] Lin, Y., Chen, X., & Wang, H. (2025). Optimizing intermodal freight flow under extreme weather disruptions. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.5155789

[8] Liu, K., Li, Q., & Zhang, Z. (2020). Optimal restoration schedules of transportation network considering resilience. *Structure and Infrastructure Engineering*, 18(8), 1141-1154. https://doi.org/10.1080/15732479.2020.1801764

[9] Lu, Y. (2025). A multimodal deep reinforcement learning approach for IoT-driven adaptive scheduling and robustness optimization in global logistics networks. *Scientific Reports*, 15, 2869. https://doi.org/10.1038/s41598-025-10512-1

[10] Mao, B., Yi, P., Wang, Y., & Li, X. (2021). Resilience-based optimization of postdisaster restoration strategy for road networks. *Journal of Advanced Transportation*, 2021, 8871876. https://doi.org/10.1155/2021/8871876

[11] Qin, Y., Wang, H., & Zhang, L. (2025). Digital Twin and Bayesian Network integrated framework for dynamic resilience assessment and optimization of urban transportation infrastructure. *Journal of Graphic Era University*, 14(1), 1-24. https://doi.org/10.13052/jgeu0975-1416.1411

[12] Ren, X., Liu, Y., Chen, Z., & Wang, J. (2025). Multiphase transport network optimization: Mathematical framework integrating resilience quantification and dynamic algorithm coupling. *Mathematics*, 13(13), 2061. https://doi.org/10.3390/math13132061

[13] Wang, S., Gao, S., Tan, Z., & Shi, X. (2023). Modeling the vulnerability and resilience of interdependent transportation networks under multiple disruptions. *Journal of Infrastructure Systems*, 29(4), 04023028. https://doi.org/10.1061/jitse4.iseng-2185

[14] Xu, X., Chen, A., Jansuwan, S., Heaslip, K., & Yang, C. (2023). IMMUNER: Integrated multimodal mobility under network disruptions. *IEEE Transactions on Intelligent Transportation Systems*, 24(7), 7283-7299. https://doi.org/10.1109/TITS.2022.3224413

[15] Ye, Q., Kim, H., Nofal, O., & Holm, S. (2015). Resilience as an objective in the optimal reconstruction sequence for transportation networks. *Journal of Transportation Safety & Security*, 7(1), 91-105. https://doi.org/10.1080/19439962.2014.907384

[16] Zhang, D., Du, F., Huang, H., Zhang, F., Ayyub, B. M., & Beer, M. (2017). Resilience-based post-disaster recovery strategies for road-bridge networks. *Structure and Infrastructure Engineering*, 14(11), 1437-1455. https://doi.org/10.1080/15732479.2016.1271813

[17] Zhang, P., Zhao, Y., Ni, S., & Li, Y. (2024). Resilience-based post-earthquake restoration scheduling for urban interdependent transportation-electric power network. *Structure and Infrastructure Engineering*, 20(11), 1-18. https://doi.org/10.1080/15732479.2024.2347496

[18] Zhang, W., Wang, N., & Nicholson, C. (2015). Scheduling short-term recovery activities to maximize transportation network resilience. *Journal of Computing in Civil Engineering*, 29(6), 04014087. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000417

[19] Zhang, X., Miller-Hooks, E., & Denny, K. (2022). Resilience-based restoration sequence optimization for metro networks: A case study in China. *Journal of Advanced Transportation*, 2022, 8595356. https://doi.org/10.1155/2022/8595356

[20] Zhao, Y., Liu, Q., Kang, J., Sheng, Y., & Miao, J. (2024). Decision-making optimization for post-disaster restoration of multimodal transport networks in terms of resilience. *Journal of Transport and Health*, 39, 101928. https://doi.org/10.1016/j.jth.2024.101928

[21] Zukhruf, F., Zulkarnain, & Tjahjono, T. (2022). Developing an integrated restoration model of multimodal transportation network. *Transportation Research Part D: Transport and Environment*, 110, 103413. https://doi.org/10.1016/j.trd.2022.103413