International Journal of GEOMATE, July, 2025 Vol.29, Issue 131, pp.121-127
ISSN: 2186-2982 (P), 2186-2990 (O), Japan, DOI: https://doi.org/10.21660/2025.131.g14219
Geotechnique, Construction Materials and Environment

EVALUATION OF RAILWAY LINK VULNERABILITY DUE TO FLOOD EVENTS

Darunee Thongsuk[1] and *Ratthaphong Meesit[1]

[1]Department of Civil Engineering, Faculty of Engineering, Burapha University, Chon Buri, Thailand

*Corresponding Author, Received: 28 Nov. 2024, Revised: 04 April 2025, Accepted: 07 April 2025

ABSTRACT: Rail transportation is a vital part of both social infrastructure and economic systems, yet it faces growing challenges from natural disasters, especially flooding, which are becoming more frequent and severe due to climate change. This study analyses the vulnerability of railway networks to flood-related disruptions by applying graph theory and Monte Carlo simulations. A passenger flow-based network model is developed to simulate flood-induced link failures and identify the most critical railway segments whose failure would result in substantial disruption to passenger movement. In contrast to traditional methods that consider only single-link failures, this study introduces an approach by simulating the cascading effects of flooding, enabling both a primary link and its adjacent links to fail based on their spatial proximity and associated flood probabilities. This approach more accurately reflects real-world scenarios where flood impacts are not isolated but spread through interconnected infrastructure. The simulation incorporates weighted probabilities and a Poisson distribution to determine how many neighbouring links might fail, enhancing the realism of the model. Results reveal high-risk edges that, if disrupted, would have a major impact on the network's performance, providing valuable insight for infrastructure managers and policymakers. These findings can support targeted investment in flood prevention and adaptation strategies, such as elevating tracks, improving drainage systems, and implementing real-time monitoring technologies. Furthermore, the insights can guide the development of robust emergency response plans aimed at maintaining service continuity. Overall, the study offers a practical framework for improving the resilience and reliability of railway systems under increasing climate-related risks.

Keywords: Railways, Vulnerability, Disruptions, Flooding.

1. INTRODUCTION

Rail transportation is a critical component of national infrastructure, playing a vital role in facilitating economic growth, trade, and societal development [1]. It provides a cost-effective, energy-efficient, and environmentally friendly mode of transport for both passengers and freight, supporting urban mobility and regional connectivity. As countries expand their railway networks to accommodate increasing demand, ensuring the efficiency and reliability of rail services becomes a key priority. This requires continuous investments in infrastructure, rolling stock, and technology, along with robust operational and maintenance strategies.

To maintain smooth operations, railway networks must be resilient to both routine wear and tear and unexpected events, particularly natural disasters such as floods, landslides, earthquakes, and storms [2]. These events can severely impact rail operations, causing service delays, infrastructure damage, and financial losses. While routine maintenance can help prevent mechanical failures and track degradation, natural disasters introduce additional complexities that require proactive risk assessment and disaster preparedness measures. Without proper mitigation strategies, railway networks remain vulnerable to prolonged disruptions that can negatively affect economic activities and public mobility [3].

Flooding represents a significant threat to railway infrastructure, especially in areas prone to such natural disasters. Heavy rainfall, overflowing rivers, and storm surges can submerge tracks, damage signalling systems, and erode embankments, leading to extensive service disruptions. The damage caused by floods can be widespread, affecting not only railway tracks but also stations, bridges, and electrical systems essential for train operations. In severe cases, prolonged flooding may necessitate extensive repairs, delaying the restoration of normal service and causing economic losses due to disrupted transportation and logistics. A notable example is the 2023 flooding in Narathiwat province, where heavy rainfall submerged key railway sections, leading to the cancellation of services and significant delays for passengers and freight transportation. (Fig. 1) [4].

Although emergency measures such as temporary track reinforcements, water pumps, and alternative transportation arrangements can offer short-term relief, they do not address the underlying vulnerability of the infrastructure [5]. Recurrent flooding events highlight the urgent need for proactive strategies to prevent damage and ensure rapid recovery. Without proper mitigation efforts, railway networks in flood-prone regions remain susceptible to repeated disruptions, compromising their reliability and efficiency. Strengthening railway resilience against flooding is, therefore, crucial to minimizing service interruptions, reducing maintenance costs, and ensuring the continuous operation of rail transport systems [6].

Fig. 1 Flooding in Narathiwat Province in 2023 [4]

This research focuses on analysing the impact of flooding on railway networks using graph theory and Monte Carlo simulations. By constructing a passenger flow-based model of the network and simulating flood-induced disruptions, we identify the critical links whose failure would have the most significant impact on passenger flows.

A key novelty of this study is the simulation of multiple railway link failures due to flood events, considering the likelihood that neighbouring links will also be affected. Unlike traditional single-link failure analysis, this approach accounts for the interdependencies between rail segments, capturing the cascading effects of flooding on the network. Through this method, we provide deeper insights into the vulnerabilities of railway systems and propose strategies to improve their resilience.

Our findings emphasize the need for robust infrastructure reinforcements and adaptive operational strategies to mitigate the impact of flood events, ensuring the continued reliability and efficiency of rail transport systems.

This paper is organized into five sections. The first section introduces the research problem and outlines the significance of addressing flood-related disruptions in railway networks. The second section provides a comprehensive review of previous studies relevant to railway resilience and vulnerability analysis.

The third section details the methodology employed in this study. The fourth section presents the findings, highlighting the impact of flooding on passenger flow and network connectivity. Finally, the fifth section concludes the study by summarizing key insights and discussing potential strategies for enhancing railway resilience against flood events.

2. RESEARCH SIGNIFICANCE

This study presents a novel approach to assessing railway vulnerability by integrating graph theory with Monte Carlo simulations to model cascading flood-induced disruptions. Unlike conventional models that examine only isolated link failures, this research introduces a spatially dynamic simulation where primary and adjacent links fail simultaneously based on flood probabilities and proximity, using a Poisson distribution. This method captures the interconnected nature of real-world flood impacts on infrastructure. The incorporation of passenger flow data into the network model further enhances its realism and utility. This original framework offers new insights for strategic investment and operational planning to improve rail system resilience.

3. LITERATURE REVIEW

3.1 Disruptions and their impact on a rail system

A disruption refers to a sudden change in circumstances that can occur at any time, and when it does, it can cause delays in rail transport services or, in severe cases, lead to a complete service halt. For example, flooding of railway tracks can cause trains to be delayed beyond the planned schedule [7]. The impact on the system's efficiency following a disruption can be explained as follows (Fig. 2): Starting from when the system operates normally with 100% efficiency, a disruption occurs that reduces the system's efficiency or, in the worst-case scenario, renders the system inoperable (at T2). In such cases, immediate measures are needed to repair or maintain the system to a level that alleviates the situation (acceptable performance). These measures may require preparation time and generally cannot be initiated immediately after the disruption (T3 to T4). Afterward, the system's efficiency may remain at this level until the disruption is fully resolved and the system returns to normal or even improved operation (T5) [8].

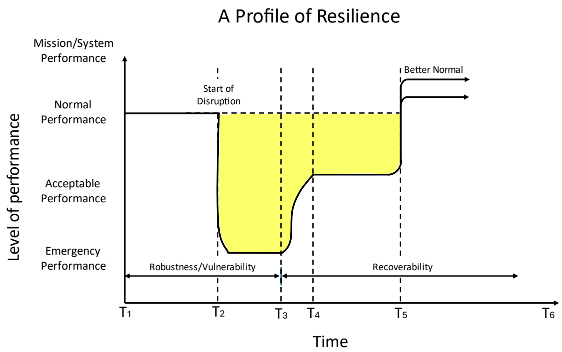

Fig. 2 Relationship between System Performance and Time During a Disruption [9]

3.2 Related research

Hong proposed a quantitative method to assess the vulnerability of the Chinese railway system to natural disasters such as flooding, using historical data and GIS technology [10]. This method includes constructing a railway network, simulating flood scenarios, evaluating the vulnerability of railway links, and calculating quantitative vulnerability values [10]. The vulnerability of the system is measured by the number of disrupted train services and the duration of the disruptions, and a maintenance strategy is proposed to reduce vulnerability, considering both link vulnerability and the number of train services [10]. The experimental results indicate that the highest vulnerability occurs in July, and the proposed vulnerability reduction strategy is more effective than other strategies [10].

Ghaemi studied the impacts of disruptions in railway services, such as train damage, signal failures, and accidents, by accurately estimating the duration of disruptions to mitigate negative effects [11]. Their research uses a framework consisting of disruption length models, turnaround models, and passenger assignment models [11]. The study on the railway network in the Netherlands demonstrated that both short and long disruption estimates significantly affect the number of impacted passengers, travel time, and the number of passengers needing to reroute and transfer [11].

Szymula and Bešinović proposed a model to assess the vulnerability of railway networks under disruptions using heuristics and mixed-integer linear programming to simulate passenger flows and infrastructure constraints [12]. Experimental results on the railway network in the Netherlands showed that the model efficiently handles passenger flows and rerouting of trains [12]. The importance of links depends on passenger demand, and computation times remain short even with an increased number of disrupted links and larger passenger demand, making network vulnerability assessment both quick and effective [12].

Zhang and Ng studied the robustness of urban railway networks (URN) against cascading failures due to changes in passenger flow [13]. They used a linear threshold (LT) model to simulate the spread of failures and also developed a composite index to assess URN robustness [13]. The simulation results indicated that the robustness of URN varies over time, and increasing passenger flow amplifies the size and impact of cascading failures [13].

Zhu analysed the risk and vulnerability of the Chinese railway system to flooding using flood event simulations and spatial analysis [14]. They found that vulnerability varies by region, with the Yangtze River basin experiencing the most significant impact [14]. Major floods affect approximately 40% of national daily railway operations, with an average daily impact of 2.7% on both railways and passengers [14].

Yang addressed tornado risks to the Yangtze River Delta's railway network by using historical data and the C-vine copula model [15]. The study created three disaster scenarios to assess the impacts of tornadoes on train operations and the results revealed that the Angting–Zhengjiang line faced significant risk, leading to an increase in annual travel time by 0.27 days [15]. Both the Angting–Zhengjiang and Yangzhou–Haian lines had the highest overall risk, highlighting the need for targeted mitigation efforts [15].

Wang studied the impact of flood-induced scouring on train safety over high-pier continuous rigid frame railway bridges in mountainous areas [16]. Using ABAQUS and SIMPACK, developed a train–track–bridge simulation model [16]. Results show that greater scour depth and flood velocity increase bridge deformation and derailment risk at high speeds [16]. The model can support efficient bridge design and flood scenario planning [16].

Zhao assessed the flood recovery capacity of London's urban rail system using complex network modelling combined with simulations of severe flood scenarios (e.g., 30-, 100-, and 1,000-year events) [17]. The study found that flooding could result in the loss of millions of passenger trips and millions of pounds in revenue [17]. The analysis also highlighted that prioritizing the restoration of key stations—those critical in terms of network structure and service delivery—can accelerate system recovery and effectively reduce overall impacts [17].

The study of railway vulnerability to disruptions, particularly from natural disasters, has progressed in assessing network disruptions and regional impacts. Flooding has been analysed through network impact assessments and maintenance strategies, but gaps remain in simulating multiple link failures, incorporating stochastic models, and evaluating passenger impacts comprehensively. Existing studies often focus on single-link failures, overlooking the interdependencies between affected rail segments. By utilizing stochastic models like Monte Carlo simulations, we can better capture the cascading effects of floods and assess network-wide vulnerabilities. Additionally, a more detailed analysis of passenger flow disruptions is needed to develop effective mitigation strategies, optimize alternative routes, and enhance emergency response measures. Addressing these gaps will contribute to a more resilient railway system, ensuring reliable operations during flood events.

4. METHODOLOGY

4.1 Data

The data used in the model are illustrated as follows. Figure 3 presents a sample railway network graph applied for flood vulnerability analysis, consisting of 22 nodes representing stations. Each link between stations is labelled with the probability of flood occurrence along that segment. The station coordinates in the model are based on this network layout. Additionally, the average and variability of passenger flow between stations are visualized in the form of heatmaps. Figure 4 displays the average number of daily passengers traveling from each origin to each destination station, while Figure 5 shows the corresponding standard deviation. For instance, if the average number of passengers traveling from station 1 to station 2 is approximately 1,000 with a standard deviation of about 10, this indicates a relatively consistent travel pattern on that route.

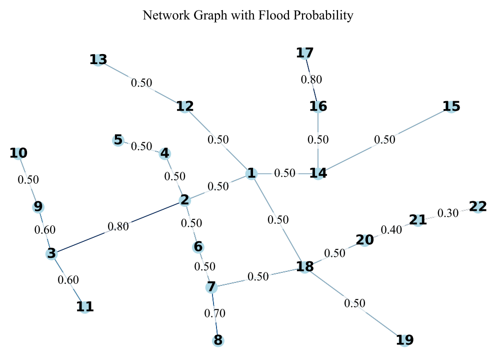

Fig. 3 Network Model and the Probability of Flooding

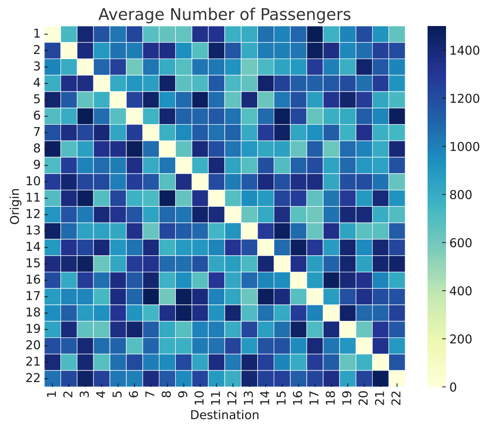

Fig. 4 The Average Number of Daily Passengers for Each Origin (O) and Destination (D) Station

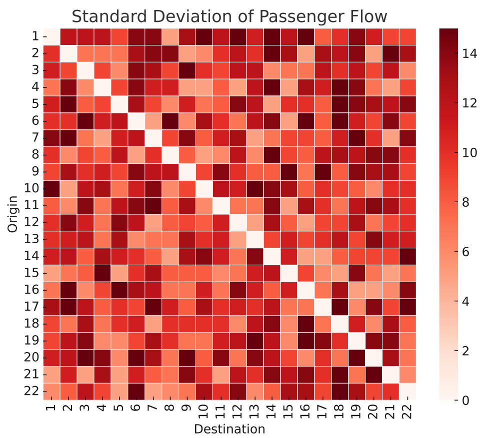

Fig. 5 The Corresponding Standard Deviation for Each O-D

4.2 Algorithm

The provided algorithm (Table 1) implements a Monte Carlo simulation to assess the impact of potential disruptions in a railway network during flooding. The simulation begins by constructing an adjacency matrix that represents the connectivity between various railway stations. This matrix is then used to create a graph where each node symbolises a railway station, and each edge denotes an undirected railway connection between two stations. Simultaneously, an Origin-Destination (O-D) matrix is generated, which models the average and standard deviation of passenger flows between different stations under normal conditions. This O-D matrix provides a baseline for the simulation, allowing for the comparison of passenger flow before and after potential disruptions caused by flooding.

The core algorithm uses the Monte Carlo method to simulate the impact of flooding on the railway network, with a total of 10,000 iterations. In each simulation iteration, random O-D matrices are generated based on a normal distribution, reflecting variability in passenger flow. The algorithm then calculates the total number of passengers that can be transported across the network under normal conditions. Subsequently, the model simulates the impact of flooding on a railway network by randomly selecting a primary link (edge) to fail based on its flood probability. It then identifies neighbouring edges connected to this failed link and randomly selects some of them to also fail, using a Poisson distribution to determine how many are affected. The likelihood of neighbouring edges failing is also weighted by their individual flood probabilities. This approach effectively mimics real-world flood scenarios, where damage often spreads from one location to adjacent areas, and reflects both the uncertainty and cascading nature of infrastructure disruptions. After simulating the disruptions, the algorithm recalculates the number of passengers that can still be transported, with the difference from the original calculation representing the impact of flooding on the railway network's capacity.

Finally, the simulation results are analysed to identify the most vulnerable sections of the railway network during flooding. The algorithm computes the average impact and standard deviation of the impact for each railway link, highlighting those that are most critical to the network’s operation. The algorithm includes visualization tools to help interpret the results, such as convergence plots showing how the impact stabilises over multiple simulations, bar charts comparing the average impact of different railway links, and a network graph where the thickness and colour of the edges represent the severity of the impact. These visualisations provide valuable insights into the network's robustness and the potential effects of flooding on passenger transportation, enabling more informed decision-making for flood preparedness and response.

Table 1 Algorithm of Model

Algorithm

Let A be the adjacency matrix of the graph G, where $A_{ij}=1$ if there is an edge between nodes i and j, and $A_{ij}=0$ otherwise.

Let OD_{mean} the mean OD matrix, where $OD_{\text{mean}\,(i,j)}$ represents the mean number of passengers traveling from node i to node j.

Let OD_{std} be the standard deviation OD matrix, where $OD_{\text{std}\,(i,j)}$ represents the standard deviation of the number of passengers traveling from node i to node j.

Let $p(e)$ be the failure probability of edge $e \in E$.

Let G = (V, E) be a graph where V represents nodes and E represents edges.

\# Random OD Matrix Generation
for each (i,j)
$OD_{\text{random}(i,j)} = \max(0, N(OD_{\text{mean}(i,j)}, OD_{\text{std}(i,j)}))$

\# Reachable Passengers Calculation

$$R_{(i,j)} = \begin{cases} OD_{random(i,j)} & \text{if there exists a path from } i \text{ to } j \\ 0 & \text{in } G, \text{otherwise.} \end{cases}$$

Let R_{total} be the sum of all reachable passengers:

$$R_{total} = \sum_{i,j} R_{(i,j)}$$

\# Impact Calculation with Link Failure
failed_edge: random choice weighted by edge probabilities
neighbors: edges connected to either node of failed_edge
failed_neighbors: random choices from neighbors weighted by their flood probabilities
failed_edges: {failed_edge} ∪ {failed_neighbors}

\# Remove **failed_edges** and calculate
The new total reachable passengers $\mathbf{R}_{impact}$
$\mathbf{Impact} = \mathbf{R}_{total} - \mathbf{R}_{impact}$

\# Monte Carlo Simulation
for n =1 to 10000 (total simulations):
Generate OD_{random} calculate R_{total}
for each iteration, compute Impact from failed_edges
Store the impacts for statistical analysis.

\# Convergence Calculation
for e in convergence:

$$Convergence(e) = \frac{1}{n}\sum_{k=1}^{n} Impact(e)$$

\# Statistical Analysis
Calculate the mean and standard deviation of $Impact(e)$ for each edge $e \in E$ and visualisation.

5. RESULTS

The Monte Carlo simulation of 10,000 iterations conducted in this study offers an in-depth assessment of the potential impacts of flooding on the railway network by modelling repeated random edge (link) failures. The analysis focuses on identifying critical links whose disruption would significantly affect passenger movement. For example, the failure of edges (1, 14), (2, 3), and (1, 2)—which correspond to critical segments in the network—resulted in substantial average passenger impacts of approximately 182693, 175717, and 166469, respectively (Fig. 6). The convergence plots illustrate how the estimated average impact stabilizes as the number of simulations increases. This convergence toward the overall mean (indicated by the dashed blue line), along with the narrowing band of standard deviation (shaded area), confirms the reliability of the simulation results when a sufficient number of iterations is performed. These findings enable the identification and prioritization of the most vulnerable links within the network.

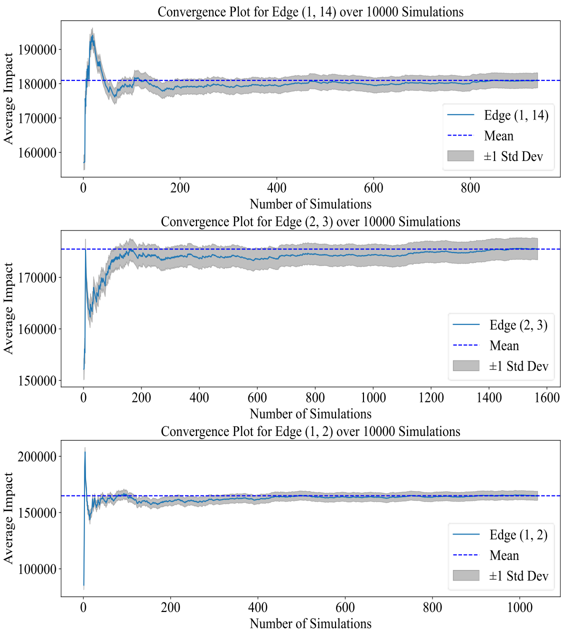

Fig. 6 Convergence graph of Top 3 Highest Average Impacts

Figure 7 illustrates the average passenger impact across the railway network, with both the colour intensity and thickness of the links representing the magnitude of the impact. Links with darker colours and greater width correspond to higher average impacts, while lighter and thinner links indicate lower impacts.

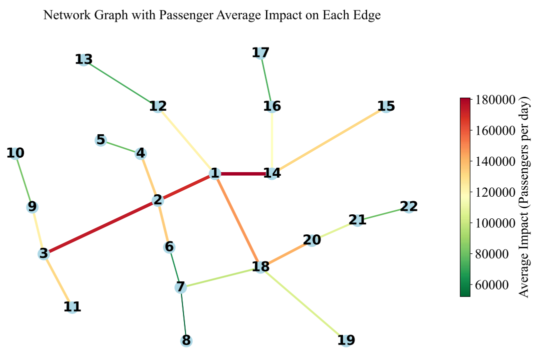

Fig. 7 Network Graph with Average Impact

From the figure, it is evident that the link between nodes 1 and 14 stands out with the darkest shade, indicating it has the highest average impact on passenger flow in the event of disruption. This highlights the critical importance of this segment in maintaining overall network connectivity and capacity.

Figure 8 presents the top 10 edges in the railway network ranked by average passenger impact, along with their respective standard deviations. The variability shown in the error bars highlights the complex and dynamic nature of flood-induced disruptions. Notably, edges such as (1, 14), (2, 3), and (1, 2) exhibit both high average impacts and relatively large standard deviations, indicating that the consequences of their failure can fluctuate significantly depending on the specific flood scenario and temporal passenger distribution. This reinforces the idea that flooding affects the network unevenly, with certain links experiencing more severe disruptions. In contrast, edges like (3, 11), (14, 5), and (3, 9) which show lower average impacts and smaller variability, are likely to be less critical, possibly due to lower traffic volumes or the presence of viable alternative routes that can absorb the displaced demand during interruptions.

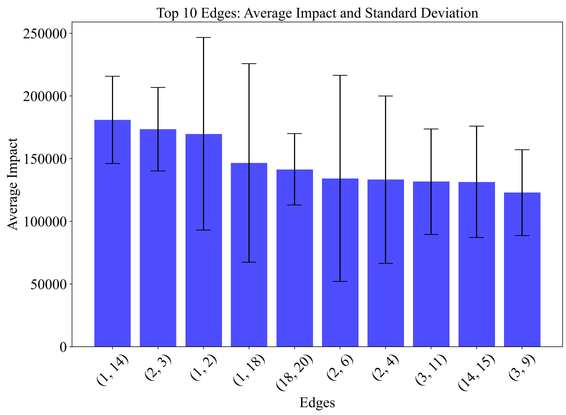

Fig. 8 Average Impact and Standard Deviation for Each Edge

6. CONCLUSIONS

From the analysis of the vulnerability of the railway network using the Monte Carlo model, it has been determined which links in the network are highly vulnerable. The small-scale network model created is a prototype used as an example for analysis. The results from this flood simulation have significant real-world implications, as climate change increases the frequency and severity of extreme weather events, including flooding. Therefore, railway networks need to adapt to these changing conditions. The findings from this study can guide targeted infrastructure investments by focusing on strengthening the most vulnerable and high-impact links against flood risks. This may include constructing flood defences, elevating railway tracks, improving drainage systems, and implementing real-time monitoring and response strategies. Additionally, the insights gained can be used to develop more robust emergency management plans that prioritize maintaining connectivity in the most critical parts of the network. By applying these findings to real-world scenarios, railway networks can enhance their resilience, ensuring they remain operational and reliable even in the face of increasingly severe flooding events.

Future research could focus on enhancing the Monte Carlo model by incorporating additional climate-related factors, such as diverse extreme weather scenarios and long-term climate projections. Expanding the model's application to larger and more complex railway networks will be crucial for evaluating vulnerabilities across broader regions. This approach could lead to more precise strategies for reinforcing railway infrastructure, ensuring it remains resilient.

7. REFERENCES

[1] Hong L., Ye B., Yan H., Zhang H., Ouyang M. and (Sean) He, X. Spatiotemporal vulnerability analysis of railway systems with heterogeneous train flows. Transportation Research Part A: Policy and Practice, Vol. 130, 2019, pp.725–744.

[2] Palin E. J., Stipanovic Oslakovic I., Gavin K., and Quinn A. Implications of climate change for railway infrastructure. Wiley Interdisciplinary Reviews: Climate Change, vol. 12, Issue 5, 2021, pp.1–41.

[3] Chen J., Liang C., Liu J., Du B., Yin Y., and Peng Q. Resilience assessment of a highway–railway complementary network under rainstorms. Transportation Research Part D: Transport and Environment, vol. 121, 2023.

[4] MGRonline. Narathiwat in Crisis! Floods Submerge Railway Tracks Between Maruebo and Tanyongmas Stations; State Railway of Thailand Announces Changes to Origin and Destination Stations for 12 Southern Routes and Suspends 2 Trains. 2023.

[5] Liu J., Lin Z., and Liu R. A reinforcement learning approach to solving very-short term train rescheduling problem for a single-track rail corridor. Journal of Rail Transport Planning & Management, vol. 32, 2024, pp.100483.

[6] Kaewunruen S. and Tang T. Dynamic behaviour of railway ballast exposed to flooding conditions. International Journal of GEOMATE, vol. 16, Issue 57, 2019, pp.101–108.

[7] Barker K., Ramirez-Marquez E., and Rocco, M. Resilience-based network component importance measures. Reliability Engineering & System

Safety, vol. 117, 2013, pp.89–97.
[8] KANG C., Yau E., Wah K., and Khiang C. Framework for managing system-of-systems ilities. Advances in Intelligent Systems and Computing, vol. 426, 2016, pp.31–43.
[9] Thongsuk D., Kaemkhuntod P., Siriyakorn W., and Meesit R. Analysing the vulnerability of railway network in Thailand. The 28th National Convention on Civil Engineering, 2023, pp. 1–7.
[10] Hong L., Ouyang M., Peeta S., He X., and Yan, Y. Vulnerability assessment and mitigation for the Chinese railway system under floods. Reliability Engineering and System Safety, Vol. 137, 2015, pp. 58–68.
[11] Ghaemi N., Zilko A., Yan F., Cats O., Kurowicka D., and Goverde R. M. P. Impact of railway disruption predictions and rescheduling on passenger delays. Journal of Rail Transport Planning and Management, Vol. 8, Issue 2, 2018, pp. 103–122.
[12] Szymula C., and Bešinović N. Passenger-centered vulnerability assessment of railway networks. Transportation Research Part B: Methodological, Vol. 136, 2020, pp. 30–61.
[13] Zhang Y., and Ng S. T. Robustness of urban railway networks against the cascading failures induced by the fluctuation of passenger flow. Reliability Engineering and System Safety, Vol. 219, 2021, pp. 108227.
[14] Zhu W., Liu K., Wang M., Ward P. J., and Koks E. E. System vulnerability to flood events and risk assessment of railway systems based on national and river basin scales in China. Natural Hazards and Earth System Sciences, Vol. 22, Issue 5, 2022, pp. 1519–1540.
[15] Yang C., Yin W., Liu X., Huang Y., Lu D., and Zhang J. Tornado-induced risk analysis of railway system considering the correlation of parameters. Reliability Engineering and System Safety, Vol. 249, Issue 111, 2024, pp. 110239.
[16] Wang J., Zhao T., Zhu J., and Gou H. Simulation test of continuous rigid frame railway bridge under flood scouring. Structures, Vol. 66, 2024, pp. 106893.
[17] Zhao Z., Huo A., Liu Q., Yang L., Luo C., Ahmed A., and Elbeltagi A. Assessment of urban inundation and prediction of combined flood disaster in the middle reaches of Yellow river basin under extreme precipitation. Journal of Hydrology, Vol. 640, 2024.