Evaluating the Impact of Extreme Temperature Events on the US Rail Network

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ABSTRACT

The United States railway is a critical part of the national infrastructure and economy. Heatwaves are a major weather event that can cause major disruptions and affect the stable operation of the railway. Failure in part of the rail network may have a ripple effect on the rest of the network. As such, there is a need to study the effect of weather on rail networks that require re-routing. The goal of this paper is to investigate the vulnerability of the contiguous United States rail infrastructure against disruptions to operations caused by extreme heat events. This goal is achieved by developing a computational model that utilizes a graph theory approach combined with risk analysis to study the vulnerability of rails based on the difference between their Rail Neutral Temperature (RNT) and the temperature using extreme heat events. In addition, the model can quantify the impact of failure considering the extra travel distances of alternative routes. Ultimately, the model can identify rail segments with high severity which can support decisions to improve rail segments, build new alternative routes, and accordingly increase the overall resilience of the rail infrastructure.

INTRODUCTION

The most common type of accident across the United States is derailments (Meng et al. 2022). All forms of accidents have cost upwards of $170 million in repairs (FRA 2025a). Railway failures lead to delays, costing valuable time and resources to passengers and railway owners alike. In 2021, there was a total of 328,000 train-delay minutes in passenger trains caused by various infrastructure issues (ASCE 2017). Whenever a track fails and a train is forced to make a stop, dispatchers need to immediately reroute incoming trains onto alternate paths or wait until the issue gets resolved to let trains continue forward. Algorithms that do this automatically are typically very costly or expensive to do (Törnquist and Persson 2007). The resulting delays can propagate along the network and schedule, causing a slow down along the entire rail line if not dealt with quickly. Prevention of delays and quick response times are a very high priority for any rail system.

Buckling is one of the most common causes of derailment in the US (Meng et al. 2022), buckling occurs when the steel of the rail expands due to heat and too much force is exerted on the rail, causing it to snap out of place.

Many failures stem from extreme weather conditions. Heat waves contribute to failure by weakening the track and causing thermally induced buckling (Yang and Bradford 2016). The US experienced its worst recorded heat wave in 2012, during this time the FRA had issued a slowdown order across the entire country. In spite of this, there were still 29 derailment accidents that were directly related to heat induced buckling that year (Magill 2014). Much research to the authors best knowledge, do not describe using graph theory to try and calculate the risk a rail in a network might have of buckling, instead, previous research goes over finding the probability of rail failure in a lab environment (Miri et al. 2021), uses a localized approach to find the probability (Zhang and Lee 2008), or predicting buckling using machine learning (Ngamkhanong and Kaewunruen 2022). Methods such as these fail to consider the entire network of rails and instead focus on a component level approach to the study of rail buckling. There is a need to study the vulnerability of the rail network while at a higher-level, considering the aggregated probability and impact of individual rail segments in extreme heat events in a bottom-up approach. This paper seeks to address that knowledge gap and offer a possible solution for decision makers to identify critical rails and rails that may be at risk of failure.

GOAL AND OBJECTIVES

The goal of this paper is to investigate the vulnerability of the contiguous United States rail infrastructure against disruptions to operations caused by extreme heat events. To achieve this, the authors developed and implemented a framework to analyse the rail network by: (1) building a graph network representation of the US rail network; (2) quantifying probability of failure based on difference between RNT and weather temperature; (3) quantifying the impact based on additional travel distance of alternative routes; and (4) calculating the severity of the rails based on probability and impact. The model can perform large-scale analysis to study the effect of disruptions on each segment of the rail network. The outputs of the model can guide decision makers to support rehabilitation and improvement projects for critical rail segments, and construction projects for strategic alternative routes.

METHODOLOGY

An outline of the methodology is shown in Figure 1. First, data for the rail network as related to the graph of the nodes and edges, weather data, and county maps, are collected from public online resources. The data is cleaned and aggregated to create a complete graph of the rail with weather temperature data. Second, the probability of failure of the rails is defined using probability functions. Third, the impact of the rails is qualified by calculating the shortest path between nodes after removing failed rails. Finally, the severity of the rails is calculated. The model is applied as a case study using six major cities during a historical heatwave.

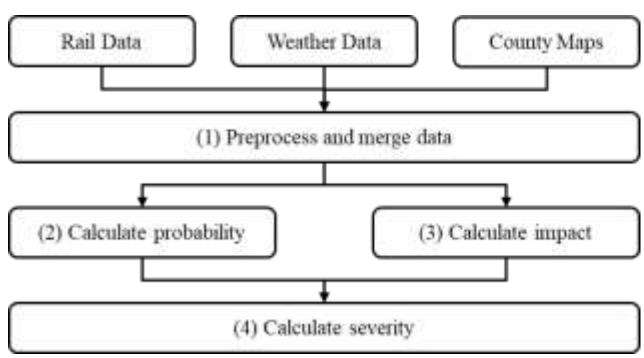

Figure 1. Flowchart of the methodology.

Data Collection and Workflow The model developed in this paper is a graph representation of the US rail network that includes (1) precise nodes and edges of the rail segment to calculate the distances between them; (2) historical temperature data for all counties in the US; and (3) county GIS data to link the county temperatures to allocate the rail temperature based on location and time. Accordingly, three data sources are collected from public online sources: rail GIS data from the FRA (2025b), weather data collected from the NOAA (2025), and county boundary data collected by US census (2025). The weather data contains the monthly lowest, average, and highest recorded temperatures by county, dating from 1922 to modern day. The county GIS data is combined with rail GIS data to link the rails to their respective counties. Accordingly, the rails can be assigned historical temperatures for any historic date. In addition, by having a complete graph of the rail network, the shorted path between any two nodes, and its distance, can be calculated.

Shortest Path The model required calculating the shorted distance between any two nodes. The calculations are repeated to calculate the shortest path after removing failed rail. Therefore, there is a need for an effective shortest path algorithm. Shortest path algorithms have been investigated in a plethora of previous research. In this paper, the authors use the widely used and accepted Dijkstra shortest path algorithm (Dijkstra 1959). The length of the rail segments is used as the weight parameter of the algorithm. As a case study, six nodes representing major cities were chosen as start and end points for shortest path calculations as shown in Figure 2. These points were chosen because of their high node centrality and for being large commercial areas. These points are selected as a case study; however, the model can be easily applied to any other nodes as needed.

Figure 2. Example of the shortest paths between selected major nodes.

Severity The analysis in this model aims the quantify the severity of the effect of extreme heat events on rail segments. The concept of severity combines (1) probability: which, in this paper, relates the difference between the RNT and the weather temperature which increases the probability of creating heat induced buckling; and (2) impact: which relates to how much extra travel distance result from the alternative routes if the rail fails. Accordingly, severity is the level of risk every rail node has, severity is defined as $Severity_r = Probability_r * Impact_r$ where $Probability_r$ is the probability of failure each rail per mile and $Impact_r$ is the difference in length between the original shortest path and the new alternate path. The following sections explain probability and impact in more details.

Probability The probability of failure of a rail segment due to heat-related buckling increases based on the difference between its RNT and the current temperature of the rail. In this paper, the probability of the rail failure is quantified using a cumulative normal distribution function. A normal distribution is selected considering that the deviation in temperature compared to the RNT may be positive or negative and is continuous. The RNT for a rail segment is assumed to be the annual average temperature of the county. The current temperature of the rail is assigned based on the current date of the scenario being analysed. It is also assumed that the real temperature of the rail would be 30 Fahrenheit above ambient temperature due to the direct light of the sun (Zhang and Lee 2008). The probability of failure of each rail node is therefore calculated as shown in Equation (1). $Probability_r$ is defined as a function of the cumulative normal distribution of the hot and cold temperatures, using the temperature of a rail on a given day $(T_{r,d})$ and the rail neutral temperature (RNT_r) added to the change in temperature doubled $2 * \Delta T$. A randomly picked example at Lincoln, New Mexico is shown in Figure 3.

$$P_r\left(RNT_r, T_{r,d}, \Delta T_{cold}, \Delta T_{Hot}\right) = \ Norm_{Hot}(T_{r,d}, (RNT_r + 2 * \Delta T_{Hot}) \quad (1)$$

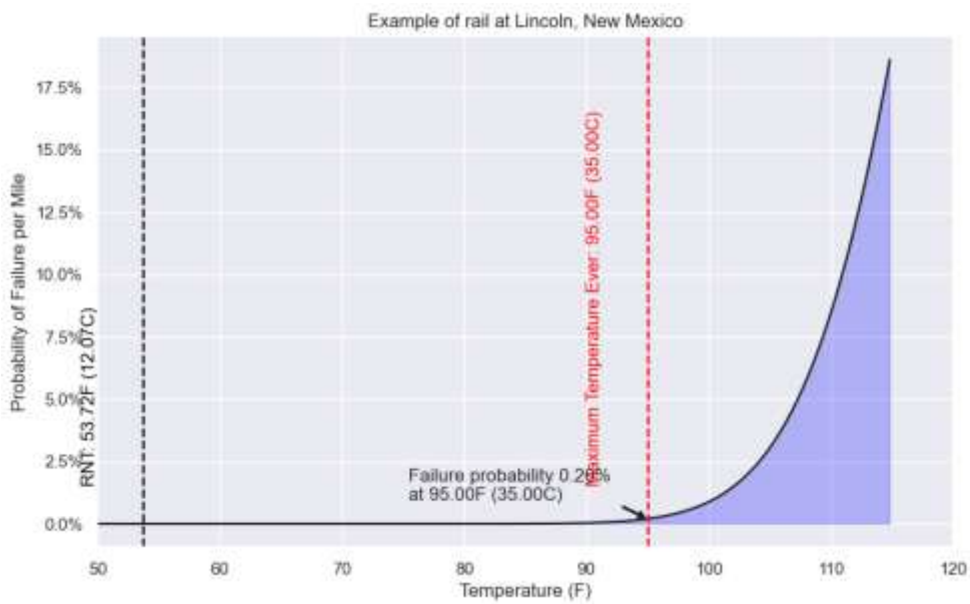

Figure 3. Example distributions of failure.

Impact The impact of the rails on a shortest path between two points is calculated in a loop that removes each rail segment at a time and re-calculates the new distance of the shortest alternative route. A flowchart of the loop is shown in Figure 4. If, after removing a rail segment, a path exists, then the difference in lengths is calculated and stored as its impact. However, if no path is found, the segment is marked as critical. It should be noted that the approach of this algorithm is exhaustive and checks every segment in a path, not just those that are likely to fail due to extreme temperature.

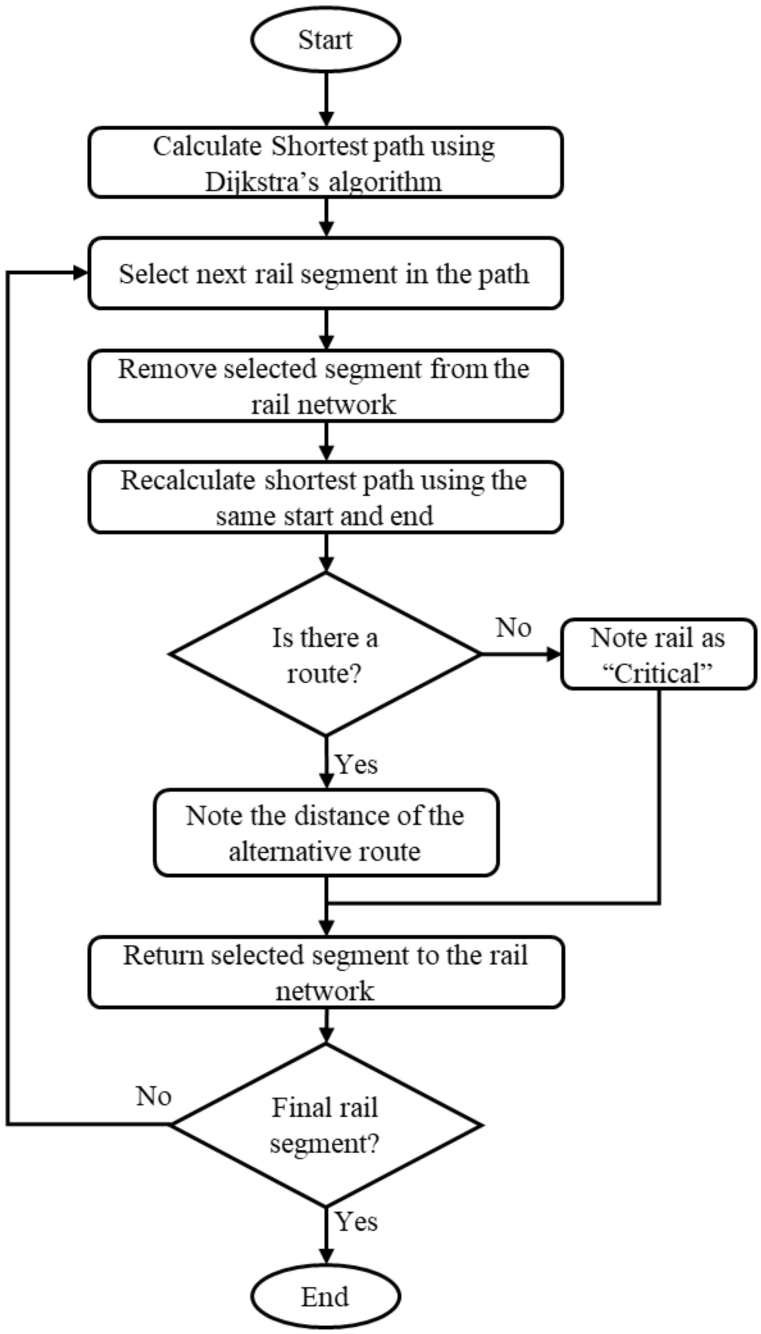

Figure 4. Flowchart for calculating the impact.

Case Study The model is applied on an example of a heatwave. Analysis of the weather data as shown in Figure 5, indicates that the US had a historical heatwave in July 2024 based on the average temperature of all counties, which reached 112.20 Fahrenheit. All the rail temperatures are assigned temperatures based on the county temperatures on that day. The model is also tested with a focus on the paths between 6 major cities as previously shown in Figure 2. Although the model is tested on that case, it is important to note it can be similarly applied to any other date, temperature data, and nodes.

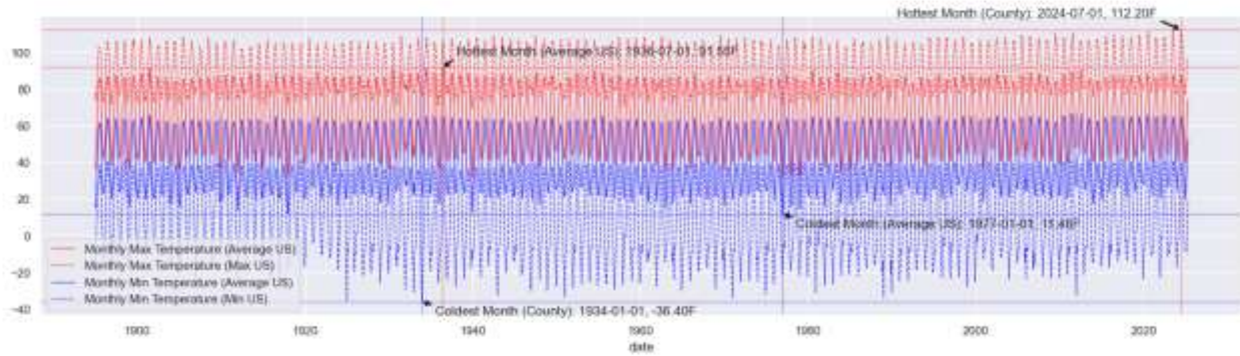

Figure 5. Historical county temperature data.

RESULTS AND ANALYSIS

Graph Model The graph model was successfully created using combined rail GIS, county GIS, and county weather data. The graph has 81,247 nodes and 81,172 edges including their lengths, and weather data including min, mean, and max temperature from 1922 to 2024. Maps visualizing the rails and temperatures are shown in Figure 6. The maps show the large difference in temperature between the different areas of the US. In addition, some areas, including the Midwest, have a large variation between hot temperatures in the summer and freezing winters, which adds stress on the rail network. The probability of failure of the rails is calculated based on the temperatures assigned to the graph.

Shortest Path and Alternative Routes As related to the impact, the Dijkstra algorithm was successfully applied to the model to calculate the shorted paths. Furthermore, testing of the impact loop method was successful in finding alternative routes when edges fail. An example of some alternative routes between the six nodes in shown in Figure 7.

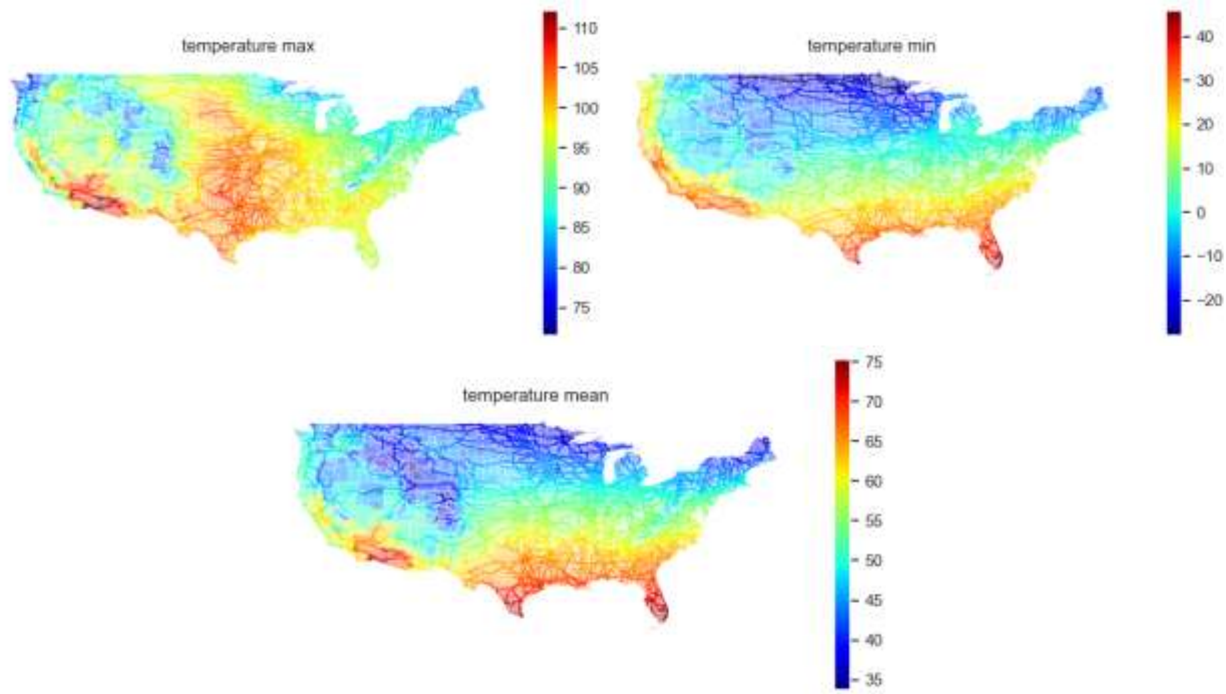

Figure 6. Maps of the max, min, and mean US temperatures.

Figure 7. Alternate shortest paths.

Impact The impact of a rail segment is the difference between the length of the original path and the alternate path when that segment is removed from service. The impact of all the rails connecting the major cities chosen was calculated. The results are shown in Figure 8. The map shows a high impact on disruptions on rails near the southern border of the US, this area does not have many alternatives nearby and rerouting is costly to time. Many other segments such as in the states of Washington, Florida, Alabama, Mississippi, and Louisiana. The analysis also shows that rail segments in deep South Texas between the cities of Brownsville and San Antonio are critical, they do not have an alternate path and would have trains be stopped until repairs were made.

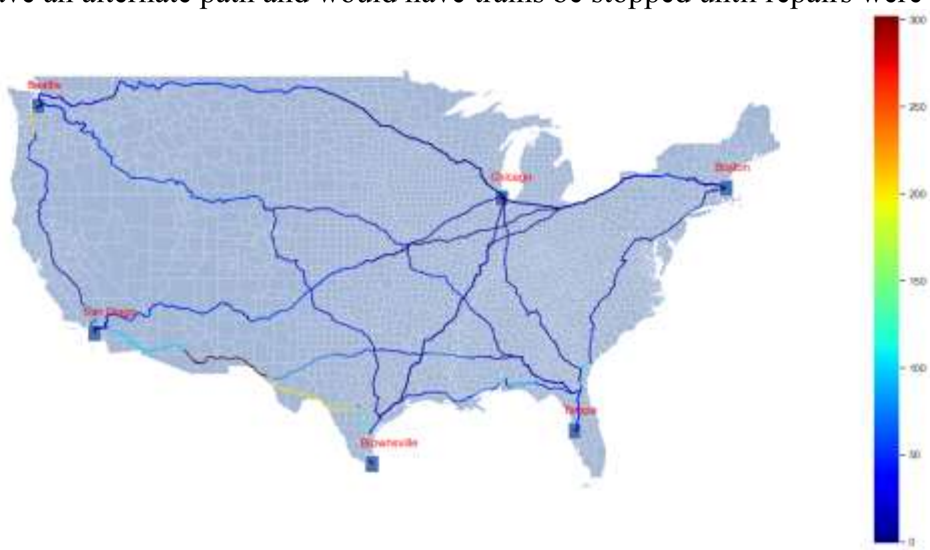

Figure 8. Impact of rails.

Severity The severity of the network was calculated by multiplying the probability and impact values at every rail. A map of the results is shown in Figure 9. The results reveal a perspective into the risks of extreme heat on the rails that is more holistic that looking at the probability or impact separately. The results reveal that some rails, particularly in the states of North Dakota, Montana, and Idaho, have a high severity. Other routes may have low severity despite having a high probability or high impact, because they have many alternative short alternative routes, or low probability of failure, respectively.

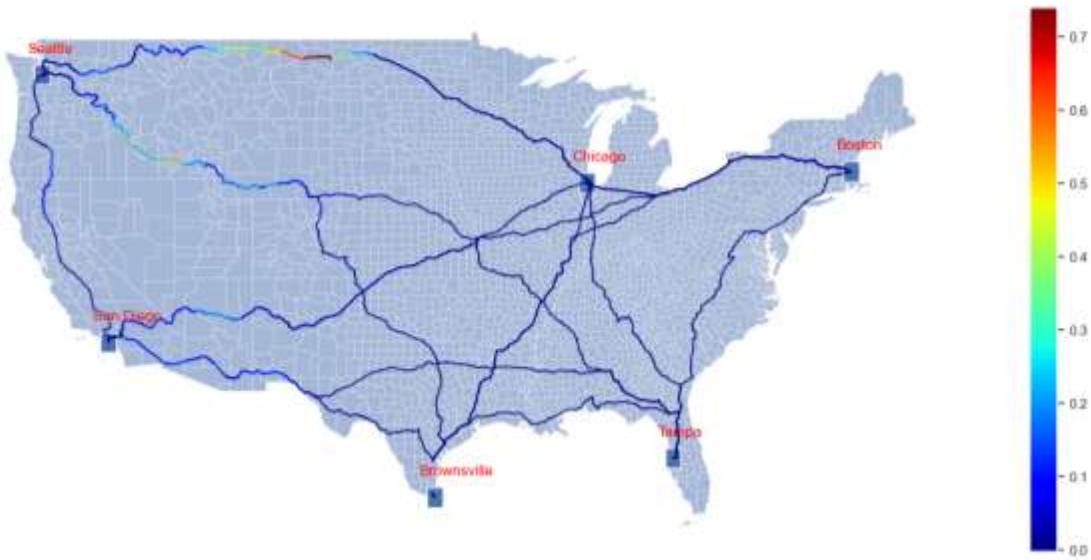

Figure 9. Severity of the rail network in July 2024.

CONCLUSION

The goal of this paper was to investigate the vulnerability of the contiguous United States rail infrastructure against disruptions to operations caused by extreme heat events. This was achieved by developing a customizable graph-based model that combines GIS data for the entire US rail network, historical monthly weather data over the past century, and GIS data for the counties to link the rails to temperature data. Where previous research focuses on using low level approaches, this work linking the weather data with graph data has not been previously attempted, to the authors best knowledge. The vulnerability of the rails was calculated the severity based on the probability and impact of disruptions. The probability is calculated based on the RNT and weather temperature. The impact was calculated based on the additional distance requires by alternative routes. The findings show that severity provides a unique perspective that combines both the probability and impact. Although some rails may have a high probability of failure, they may have many short alternatives; while some other rails may low probability of failure but very long alternatives, if any. The model has some limitations that may be addressed in future work; (1) the model does not consider the differences in the types, materials, and construction methods of rails, which have an effect of the adaptability of the rail to temperature variations; (2) the model does not consider the different loads and capacities of trains on rail segments which may increase the impact of disruptions due congestion and also increase the stress on rail elements (3) the temperature of the rails are based the county temperature. Future work may investigate more precise locational temperature data. Additionally, an interactive application that uses the model will be developed. Ultimately, the developed model aims to promote a new perspective of looking at the vulnerability of the rails based on the combined probability of heat induced buckling and impact due to having longer alternative routes. The severity results can guide decision makers to fund construction projects to improve old rails and strategically build new alternative routes where necessary. The model and findings can be used to assist funding new projects to improve the resilience of existing rails, and the model can be used to plan new railways to lower the negative effects of railways going down for maintenance. All of these contribute to promoting the safety of the railway and manage weather related risks.

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