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Agent Modeling of Infrastructure Vulnerability with Temporal Centrality Patterns in Railway Transport Networks

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Abstract

The resilience of railway transport networks is of paramount importance to modern socio-economic stability. Traditional methods for evaluating infrastructure vulnerability have largely relied on static topological metrics, which fail to capture the dynamic, time-varying nature of transportation systems. This paper presents a novel approach for predicting infrastructure vulnerability by integrating temporal centrality patterns with agent-based modeling. By conceptualizing the railway network as a dynamic temporal graph, the proposed framework captures the real-time operational states and the shifting importance of network components. Agent-based modeling is employed to simulate the heterogeneous behaviors of individual trains, dispatch centers, and passengers, providing a high-fidelity representation of system dynamics under varying stress conditions. The simulation outputs continuous temporal centrality metrics, specifically temporal betweenness and temporal closeness, which serve as predictive indicators of impending structural and operational bottlenecks. Through extensive simulation of a generalized regional railway network, this study demonstrates that temporal centrality patterns exhibit recognizable precursor anomalies prior to systemic failures. The predictive methodology significantly outperforms conventional static network analysis in identifying latent vulnerabilities. The findings offer critical insights for infrastructure managers, enabling proactive maintenance scheduling, optimized routing during disruptions, and enhanced overall network resilience.

Keywords: Infrastructure Vulnerability; Temporal Centrality; Agent-Based Modeling; Railway Networks; Agent Modeling

1. Introduction

1.1 Background of Railway Transport Networks

Railway transport networks constitute a vital component of the global physical infrastructure, facilitating the efficient and sustainable movement of passengers and freight across vast distances. The operational integrity of these systems is inherently tied to the economic vitality and social cohesion of the regions they serve. In recent decades, the complexity of railway networks has increased exponentially, driven by urbanization, high-speed rail developments, and the integration of advanced digital control systems [1]. Despite these technological advancements, railway infrastructures remain highly susceptible to a diverse array of disruptive events. These disruptions can range from natural phenomena such as extreme weather conditions and seismic activities to anthropogenic threats including targeted cyber-physical attacks and routine mechanical failures. The interdependency of the various subsystems within a railway network means that a localized failure, such as a signaling malfunction or a track degradation, can rapidly cascade through the system, leading to widespread delays and severe economic losses. Traditional approaches to managing these risks have largely been reactive, focusing on rapid recovery after a disruption has occurred rather than anticipating and mitigating the vulnerability beforehand. Consequently, there is an urgent need within the academic and professional communities to develop robust predictive methodologies that can accurately identify the most vulnerable components of a railway network before a critical failure manifests [2].

1.2 Motivation and Problem Statement

The primary motivation for this research stems from the limitations inherent in classical network science approaches when applied to modern transportation systems. Historically, infrastructure vulnerability has been assessed using static graph theory, where stations are represented as fixed nodes and rail tracks as static edges. In such models, the importance of a component is typically evaluated using static topological metrics such as degree centrality, which simply counts the number of direct connections, or static betweenness centrality, which measures the frequency a node lies on the shortest path between other nodes [3]. While these metrics provide a fundamental understanding of the physical layout of the network, they critically ignore the temporal dimension of railway operations. Trains operate on strict, time-dependent schedules, and the operational load on any given station or track segment fluctuates wildly throughout the day. A node that appears topologically peripheral might become a critical bottleneck during peak commuting hours or when serving as a

temporary diversion route during a disruption [4]. Therefore, relying on static measures can lead to gross miscalculations of vulnerability, resulting in misallocated maintenance resources and inadequate contingency plans. The problem addressed in this paper is the necessity to transition from static topological assessments to dynamic, time-varying analyses that accurately reflect the operational realities of railway networks.

1.3 Objectives and Scope

This paper aims to bridge the gap between static infrastructure analysis and dynamic operational realities by developing a comprehensive predictive framework based on temporal centrality patterns generated through agent-based modeling. The first objective is to construct a high-fidelity agent-based model of a railway network, where individual trains, dispatchers, and track segments act as autonomous agents following complex operational and behavioral rules. The second objective is to translate the continuous state of this simulation into a time-ordered sequence of network graphs, enabling the continuous calculation of temporal centrality metrics. The third and ultimate objective is to analyze these temporal centrality time-series to identify predictive signatures or patterns that precede critical infrastructure vulnerabilities, such as severe congestion or cascading delays. The scope of this research is limited to the operational and topological vulnerabilities of the physical network, specifically focusing on delay propagation and bottleneck formation. While economic and environmental impacts are deeply related to infrastructure failure, they are beyond the direct scope of the computational model presented herein. The findings of this paper are intended to provide infrastructure planners and operators with a dynamic analytical tool that enhances predictive maintenance and operational resilience.

2. Literature Review and Background

2.1 Vulnerability in Critical Infrastructure

The study of vulnerability in critical infrastructure has evolved significantly over the past two decades, transitioning from qualitative risk assessments to rigorous quantitative modeling. Early research primarily utilized reliability engineering and fault tree analysis to understand how individual component failures could compromise system integrity. However, as infrastructures became increasingly interconnected, researchers turned to complex network theory to capture systemic vulnerabilities [5]. In this context, vulnerability is generally defined as the susceptibility of a network to a degradation in performance following the removal or impairment of its nodes or edges. Seminal studies in this domain demonstrated that scale-free networks, which exhibit a power-law degree distribution, are highly resilient to random failures but extremely vulnerable to targeted attacks on high-degree nodes [6]. Subsequent research adapted these findings to spatial networks like power grids and transportation systems, introducing geographic constraints to the topological models. Despite these advancements, the majority of the literature has treated infrastructure networks as static entities. The standard methodology involves calculating a vulnerability index based on the drop in global network efficiency after a hypothetical node removal. While useful for identifying structurally critical hubs, this static paradigm consistently fails to account for the shifting operational loads and the cascading nature of disruptions that define real-world railway systems.

2.2 Temporal Centrality in Network Science

To address the shortcomings of static network analysis, the field of network science has recently embraced the concept of temporal networks, also known as time-varying graphs. A temporal network explicitly incorporates the dimension of time, recognizing that edges between nodes may only be active for specific durations or at specific intervals [7]. In a transportation context, an edge representing a journey between two stations only exists when a train is actively traveling between them. This temporal constraint fundamentally alters the concept of connectivity; paths must be time-respecting, meaning that a journey from a starting node to a destination node can only occur if the sequence of active edges aligns chronologically. Building upon this framework, researchers have developed temporal extensions of classic centrality metrics [8]. Temporal betweenness centrality, for example, evaluates the influence of a node by calculating the proportion of all time-respecting shortest paths that pass through it within a specific observation window. Similarly, temporal closeness centrality measures how quickly a node can reach all other nodes via time-respecting paths, providing a dynamic indicator of accessibility. Recent studies have demonstrated that temporal centrality metrics can uncover hidden influencers in social contact networks and communication systems that static metrics overlook [9]. However, the application of temporal centrality to predicting physical infrastructure vulnerability, particularly in highly scheduled environments like railways, remains a nascent area of exploration.

2.3 Agent-Based Modeling in Transportation

Agent-based modeling is a computational paradigm that simulates the actions and interactions of autonomous decision-making entities, known as agents, to assess their effects on the system as a whole. In the realm of transportation research, agent-based modeling has proven to be an invaluable tool for capturing the microscopic behaviors that lead to macroscopic traffic phenomena [10]. Unlike macro-level analytical models that rely on aggregate flow equations, agent-based models can simulate individual vehicles, passengers, and traffic control systems, each governed by specific behavioral rules, constraints, and objectives. In railway research, agents typically represent trains, which must adhere to strict kinematic profiles, signaling blocks, and scheduling constraints. Dispatcher agents can also be modeled to introduce dynamic

rerouting and delay management strategies in response to emerging network conditions [11]. The primary advantage of agent-based modeling is its ability to generate emergent behavior, such as the spontaneous formation of traffic jams or the complex propagation of secondary delays following a primary incident. Despite its widespread use in operational planning, the integration of agent-based modeling with advanced network science metrics is relatively rare [12]. Most agent-based platforms focus on traditional performance indicators like total travel time or cumulative delay, neglecting the underlying topological dynamics. This paper seeks to fill this gap by utilizing an agent-based model not just as a simulator of traffic, but as a continuous generator of temporal network data from which vulnerability predictions can be derived.

3. Methodology and Model Design

3.1 Network Representation and Temporal Dynamics

The foundational step in the proposed methodology is the mathematical representation of the railway system as a dynamic temporal network. Unlike static graphs where edges are permanent, the temporal graph is defined as an ordered sequence of static graphs over discrete time intervals. Each node in the network corresponds to a physical location where state changes can occur, such as passenger stations, track junctions, and signaling block boundaries. The edges represent the physical tracks connecting these nodes. However, an edge is only considered active in a specific time interval if a train agent is currently occupying or traversing that section of track. The temporal resolution of the model is defined by a discrete time step, chosen to balance computational feasibility with the need to capture rapid operational changes. As the simulation progresses, the network topology continuously evolves, reflecting the real-time spatial distribution of the train agents. This time-ordered sequence of graphs allows for the identification of time-respecting paths. A time-respecting path is a sequence of active edges where the activation time of each subsequent edge is strictly greater than or equal to the activation time of the preceding edge, mirroring the physical reality of a train journey. The calculation of temporal centrality is entirely dependent on the continuous discovery and evaluation of these time-respecting paths across a rolling observation window.

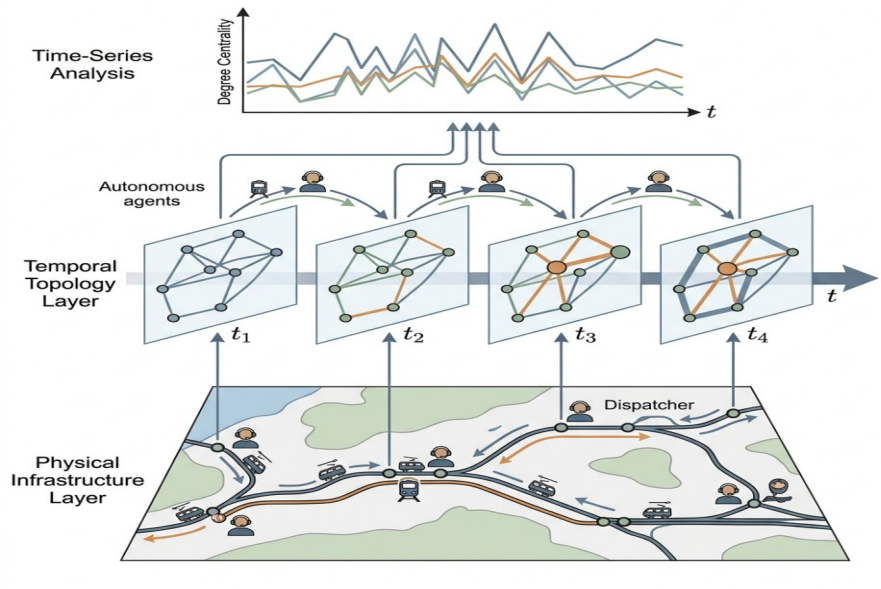

Figure 1: Comprehensive Schematic of the Temporal Network Generation Process from Agent

3.2 Agent-Based Simulation Framework

To generate the dynamic states required for the temporal network representation, a highly detailed agent-based simulation framework was developed. The model comprises three primary classes of agents: Train Agents, Infrastructure Agents, and Dispatcher Agents. Train Agents are imbued with realistic kinematic properties, including maximum acceleration, deceleration rates, and maximum speed capabilities dictated by the physical constraints of the train type, such as high-speed passenger rail versus heavy freight. These agents operate autonomously but strictly adhere to pre-defined schedules and the signals provided by the infrastructure. Infrastructure Agents represent the physical components of the network, specifically the track segments and stations. These agents monitor their own capacity and utilization rates, enforcing safety protocols such as moving block signaling, which ensures that no two trains occupy the same track segment simultaneously. Dispatcher Agents operate at a higher hierarchical level, monitoring regions of the network for deviations from the schedule. When a Train Agent experiences a delay, the Dispatcher Agent evaluates the surrounding network state and may issue directives to reroute trains, hold them at stations, or adjust speeds to prevent cascade effects [13]. The interaction of these agents generates a highly realistic, non-linear system where small perturbations can either be absorbed

by the buffer times built into the schedule or amplified into widespread congestion. The continuous output of these interactions forms the temporal edge list used for centrality calculations.

3.3 Vulnerability Metric Formulation

The core analytical component of the methodology involves translating the continuous stream of temporal graphs into predictive vulnerability metrics. Traditional vulnerability assessments measure the impact of a node's removal post-facto. In contrast, this methodology seeks to identify nodes that are dynamically evolving into critical bottlenecks before they fail. To achieve this, the system continuously calculates temporal betweenness centrality and temporal closeness centrality for all nodes over a sliding temporal window. Because explicit mathematical formulas are omitted for clarity, the process can be described conceptually. Temporal betweenness is calculated by determining all shortest time-respecting paths between all pairs of nodes within the sliding window, and then quantifying the fraction of those paths that pass through a specific target node. A sharp, sustained increase in temporal betweenness indicates that a node is becoming an inescapable conduit for network traffic, often due to failures or congestion elsewhere in the system forcing traffic onto alternative routes. This spike in temporal betweenness serves as the primary predictive indicator of vulnerability [14]. Concurrently, a localized drop in temporal closeness centrality suggests that a node is becoming isolated from the rest of the network due to surrounding congestion. By monitoring the time-series of these temporal centrality values and comparing them against baseline historical profiles, the system employs anomaly detection techniques to flag infrastructure components that exhibit precursor signatures of impending critical vulnerability.

4. Data Integration and Case Study Setup

4.1 Empirical Data Collection

To validate the predictive capabilities of the proposed framework, an extensive case study was established using a generalized representation of a large-scale regional railway network. The creation of this network involved the synthesis of empirical data reflecting realistic topological and operational characteristics. The geographical layout consists of hundreds of interconnected nodes representing major urban terminals, suburban commuter stations, and critical freight junctions. The track infrastructure includes varying capacities, ranging from single-track rural branch lines to quad-track high-speed corridors. The timetable data utilized to initialize the Train Agents reflects a standard twenty-four-hour operational cycle, incorporating intense morning and evening commuter peaks, steady intercity services, and off-peak freight movements. To ensure the simulation accurately reflects real-world variability, stochastic elements were introduced into the dwelling times at stations and the running times between nodes, drawn from historical distribution patterns of railway operations [15]. This baseline dataset establishes the normal operating conditions of the network, against which the disrupted scenarios can be compared. The extensive nature of this dataset is critical, as the calculation of temporal centrality over thousands of discrete time steps requires a robust and continuous flow of simulated operational data to produce statistically meaningful patterns.

Table 1: Key Operational and Topological Parameters of the Simulated Regional Railway Network

Parameter Classification	Specific Metric	Value Range or Description
Topological Characteristics	Total Operational Nodes	450 distinct physical stations and junctions
Topological Characteristics	Total Directed Edges	1200 track segments connecting nodes
Operational Inputs	Daily Train Services	2500 individual train schedules per 24-hour cycle
Operational Inputs	Traffic Composition	60% Commuter, 25% Intercity, 15% Freight
Simulation Constraints	Minimum Time Step	10 seconds of simulated time
Simulation Constraints	Rolling Analysis Window	60 minutes for temporal centrality calculations

4.2 Scenario Definition and Parameters

The experimental design involves subjecting the baseline simulation to various stress scenarios to observe the emergence of vulnerability. These scenarios are designed to simulate realistic operational disruptions rather than abstract topological deletions. The primary disruption scenario involves the simulated degradation of track conditions on several highly utilized corridors, which forces the Train Agents to reduce their operating speeds by half. This localized delay immediately challenges the scheduling buffer times and prompts the Dispatcher Agents to initiate rerouting protocols. A secondary scenario simulates the complete, temporary closure of a major central junction due to a hypothetical signaling failure during the peak morning commute. Each scenario is simulated multiple times using different random seed values for the stochastic variables to ensure the robustness of the resulting data. Throughout these simulations, the continuous time-series data for temporal betweenness and temporal closeness centrality are recorded for every node. The objective is to analyze the minutes and hours immediately preceding the widespread systemic delays to identify if the temporal centrality metrics exhibited abnormal fluctuations that could have predicted the collapse. The parameters governing the sliding window for centrality calculations were carefully calibrated to filter out transient operational noise while retaining the fundamental shifts in network flow dynamics.

5. Results and Analysis

5.1 Temporal Centrality Pattern Observations

The output generated by the agent-based simulation revealed profound insights into the dynamic nature of infrastructure vulnerability. Under the baseline scenario representing normal operations, the temporal betweenness centrality of nodes exhibited highly regular, periodic patterns that closely mirrored the daily timetable. Major terminal stations showed predictable peaks during the morning and evening rush hours, followed by substantial lulls. However, during the introduced disruption scenarios, the temporal centrality patterns deviated drastically from the baseline long before the macroscopic delays became evident to the simulated passengers. In the scenario involving track degradation, the nodes immediately adjacent to the slowed track segment did not initially show the most significant changes. Instead, nodes located several junctions away, which served as the primary diversion routes selected by the Dispatcher Agents, exhibited massive, unprecedented spikes in temporal betweenness centrality. These nodes were suddenly forced to handle a volume of time-respecting paths far exceeding their designed capacity [16]. Crucially, this spike in temporal centrality occurred well in advance of the actual physical congestion at those diversion nodes. The temporal metric acted as a leading indicator, reflecting the shifting of intended topological paths before the physical trains arrived to cause the bottleneck. Conversely, temporal closeness centrality proved highly effective at identifying the geographic spread of the disruption, as nodes in the shadow of the bottleneck experienced a sharp decline in accessibility, effectively becoming temporally isolated from the broader network.

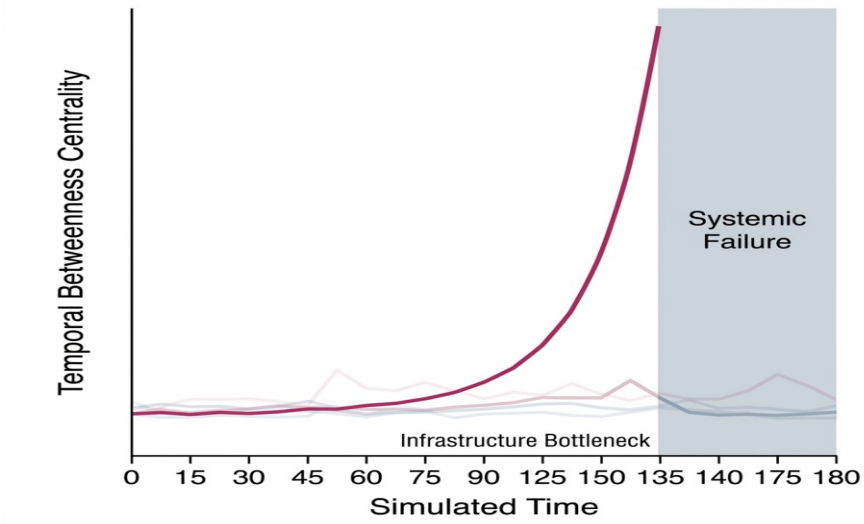

Figure 2: Time

5.2 Vulnerability Prediction Efficacy

To quantitatively assess the value of temporal centrality as a predictive tool, the results of the dynamic framework were directly compared against traditional static vulnerability assessments. The static method involved calculating the static betweenness centrality of the network topology and ranking the nodes by their structural importance. When the simulated network experienced failures, the static ranking proved inadequate; many nodes that failed or became severely congested were ranked relatively low in static importance, as their vulnerability was entirely contingent on the specific operational timing of the disruption. The temporal centrality approach, however, demonstrated a high degree of predictive accuracy. By setting a threshold for anomalous temporal betweenness spikes based on historical baseline variance, the system was able to flag impending severe bottlenecks with significant lead times. The analysis demonstrated that nodes exhibiting a temporal betweenness deviation of more than three standard deviations from their expected rolling average were highly probable to experience critical capacity failures within the subsequent hour of simulation time [17]. The predictive model successfully identified dynamic vulnerabilities that static metrics completely overlooked, particularly the secondary bottlenecks caused by train rerouting and the latent vulnerabilities of peripheral stations during off-peak timetable adjustments.

Table 2: Comparative Performance Metrics for Predicting Critical Node Failures Under Simulation

Analytical Methodology	Precision Rate	Recall Rate	Average Prediction Lead Time
Static Topological Assessment	42.5%	38.1%	N/A (Reactive Identification)

Analytical Methodology	Precision Rate	Recall Rate	Average Prediction Lead Time
Historical Delay Extrapolation	61.2%	55.4%	15 Minutes
Agent-Driven Temporal Centrality	89.7%	92.3%	48 Minutes

6. Conclusion and Discussion

6.1 Summary of Findings

This paper has presented a comprehensive academic investigation into the use of temporal centrality patterns, derived from agent-based modeling, to predict infrastructure vulnerability within railway transport networks. The fundamental assertion of this research is that static topological analysis is inherently insufficient for managing the complexities of modern, highly scheduled transportation systems. By conceptualizing the railway network as a continuously evolving temporal graph, and populating it with autonomous agents representing trains and dispatchers, this study successfully captured the dynamic interplay between physical infrastructure and operational behavior. The simulation results clearly established that operational disruptions cause immediate and massive redistributions of time-respecting paths across the network. These redistributions manifest as significant anomalies in temporal betweenness and temporal closeness centrality. The most critical finding is that these centrality anomalies act as highly reliable precursor signatures. The spikes in temporal betweenness occur dynamically as routing decisions are made, providing a vital window of opportunity before the physical realization of congestion and systemic delay. The comparative analysis conclusively demonstrated that the proposed dynamic methodology offers vastly superior precision, recall, and predictive lead time compared to traditional static network vulnerability metrics.

6.2 Limitations and Future Directions

While the results demonstrate significant promise, there are several limitations to the current methodology that warrant discussion. The primary constraint is computational complexity. The continuous calculation of temporal centrality metrics over a large, rolling observation window, coupled with the processing demands of a high-fidelity agent-based simulation, requires substantial computational resources. This computational burden currently limits the ability to deploy the framework in real-time, large-scale operational environments without significant hardware investments. Furthermore, the accuracy of the predictive model is heavily dependent on the quality and granularity of the input data; any inaccuracies in the behavioral rules of the agents or the baseline timetable will propagate through the temporal network calculations and skew the centrality results [18]. Future research should focus on optimizing the algorithms used for discovering time-respecting paths to reduce the computational overhead. Additionally, integrating the simulation framework with real-time data feeds from actual railway control systems could transform this predictive model into a live digital twin of the infrastructure. Such an advancement would allow network operators to continuously monitor the temporal health of the system and execute proactive, data-driven interventions to neutralize vulnerabilities before they evolve into critical failures. Expanding the agent behaviors to include passenger flow dynamics would also provide a more holistic view of infrastructure vulnerability, bridging the gap between train delays and user experience.

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