Analyzing the Impact of Vehicle Node Survivability Using the Graph Invariant Methodology in Smart Cities

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ABSTRACT

The existence of complex networks is prevalent across various domains, including transportation systems, underscoring the necessity of understanding their resilience for maintaining operational stability. This study examines the impact of vehicular node failures, arising from targeted attacks or random incidents, on the stability of centrality metrics across diverse graph topologies, including Star, Ring, Partial Mesh, Trimet, Dual Ring, Tree, Balanced Tree, and Hybrid Tree. A comparative analysis was conducted using centrality measures, such as degree, betweenness, closeness, eigenvector centrality, clustering coefficient, and assortativity, employing a Python-based simulation framework to model the node failures at rates of 10%, 20%, and 30%. The results indicate that the differential impacts of the node failures vary based on the centrality metric and network topology; notably, the degree centrality demonstrates greater resilience, while the betweenness centrality is particularly sensitive to disruptions. Additionally, the network size, average degree, and the nature of the node failures significantly influence these metrics' stability. The findings highlight the critical relationships between the node survivability and centrality stability, offering valuable insights for developing robust Vehicular Ad Hoc Networks (VANETs) and guiding strategic decision-making in transportation planning and infrastructure development.

Keywords-graph topologies; network resilience; node failures; complex networks; stability analysis

I. INTRODUCTION

VANETs represent a class of complex networks characterized by dynamic connectivity and decentralized node interactions. Analyzing these networks is essential for enhancing their performance, reliability, and resilience in transportation systems. Centrality measures—such as degree, betweenness, closeness, and eigenvector centrality—are widely used to identify the key nodes and understand how the information and resources flow through the network. These metrics help locate critical communication hubs that sustain connectivity [1]. Real-world VANETs are vulnerable to the node failures caused by accidents, targeted attacks, or technical malfunctions. Such disruptions can significantly alter the network structure and degrade its overall performance. The sensitivity of the centrality metrics varies: degree centrality tends to remain stable due to its reliance on direct connections, whereas betweenness centrality is highly sensitive to the failure of intermediary nodes [2]. Analyzing how these metrics respond to failures is critical for designing robust networks that maintain functionality under adverse conditions.

The Graph Invariant Methodology offers a mathematically grounded approach to evaluating the network resilience, providing consistent results across varying conditions. Unlike purely simulation-based studies, which may deviate from the actual VANET behavior, this method ensures that the structural properties are preserved and are analytically verifiable, reducing the dependence on stochastic outcomes. It bridges the gap between the theoretical modeling and real-time applicability in vehicular networks [3]. This study examines the impact of node failures on centrality metrics across various topologies, including Star, Ring, Partial Mesh, and Balanced Tree. Simulations were conducted using the NetworkX library [4], with each topology standardized to 100 nodes. Node failures were introduced at increasing rates (10% to 30%) to emulate real-world disruptions, and centrality metrics were recalculated to assess the structural stability under failure conditions. The analysis aims to identify which network configurations demonstrate higher resilience, offering insights for designing robust infrastructures in transportation systems and other interconnected domains, such as smart cities and social networks.

Node failures produce both direct effects (e.g., hub removal disrupting connectivity) and indirect effects (e.g., redistribution of network load altering centrality dynamics) . Understanding these cascading impacts is crucial for developing systems that withstand both immediate and long-term structural compromises. Centrality metrics serve this goal by capturing critical structural properties: betweenness centrality quantifies how often a node appears on shortest paths [5], closeness centrality reflects a node's efficiency in information dissemination [6], and eigenvector centrality captures its influence through connections with other highly connected nodes [7]. The clustering coefficient indicates the local cohesiveness of nodes [8], while assortativity reveals the tendency of nodes to connect with others of a similar degree [9].

By proactively identifying the vulnerable nodes through centrality analysis, system designers can implement targeted strategies—such as redundancy and adaptive routing—to preserve the network functionality during disruptions. This research contributes to the ongoing effort to create resilient VANETs that can maintain stable performance under diverse and challenging conditions.

II. LITERATURE REVIEW

The study of the node failures and their cascading effects on centrality measures has become pivotal in network science, particularly for VANETs, where dynamic connectivity and real-time communication are essential for applications, like autonomous driving and traffic management [10, 11]. Recent research highlights how centrality metrics—such as degree, betweenness, and eigenvector centrality—serve as critical indicators of network robustness, revealing vulnerabilities that emerge when vehicular nodes fail due to accidents, cyberattacks, or hardware malfunctions [1, 12]. For instance, highly centralized networks (e.g., Star topologies) experience significant declines in betweenness centrality when key hubs are removed, severely disrupting the communication paths [3]. In contrast, decentralized structures, like Ring or Partial Mesh topologies, exhibit greater resilience, as redundant connections help mitigate the impact of individual node failures [13].

While synthetic topologies provide controlled environments for analyzing structural patterns, real-world VANETs often feature hybrid configurations shaped by urban layout, traffic flow and infrastructure limitations [14]. For example, grid-based road networks may resemble Partial Mesh structures, whereas highway systems might follow linear or tree-like patterns [15]. These hybrid systems introduce complexities not fully captured by the idealized models, such as fluctuating node densities during the rush hours or the influence of the traffic signals on connection stability. Nevertheless, the synthetic models provide foundational insights into universal principles, such as hub vulnerability, path redundancy, and the role of clustering in maintaining the network cohesion during disruptions [16, 17].

The integration of real-world datasets, such as traffic flow data, accident zones, and communication infrastructure, has been emphasized to validate the theoretical frameworks and enhance the model accuracy. Advancements in computational tools and machine learning further enable adaptive routing algorithms that respond in real-time to network disruptions, enhancing the system resilience. Additionally, exploring the interplay between physical infrastructure elements (e.g., road quality, intersection design) and network may offer practical strategies for developing VANETs that are both structurally robust and contextually optimized.

TABLE I. KEY FINDINGS OF LITERATURE SURVEY

Ref.	Year	Focus area	Key contributions	Findings
[13]	2022	Probabilistic modeling of node failures in real-world networks	Developed a probabilistic failure model; analyzed stability of centrality rankings (degree, eigenvector, Katz)	Found that centrality rankings are moderately stable under small perturbations
[23]	2003	Sampling effects on centrality stability	Investigated centrality consistency across incomplete or sampled networks	Emphasized need for stable centrality measures in dynamic/failure-prone networks
[25]	2023	Graph analytics on Indian telecom backbone networks using NetworkX	Used NetworkX to analyze Airtel, Jio, Idea, BSNL backbones; calculated density, clustering, edge connectivity, etc.	BSNL showed best structural robustness via higher density, clustering, and transitivity, though with greater average path length
[28]	2019	Scalability and survivability of IoT networks using Trimet Graph Optimization (TGO)	Developed and tested TGO topology; implemented theoretical and simulation models; compared with star, wheel, and hexagon topologies	TGO provided better 2-edge survivability and lower power consumption than alternatives; improved packet delivery and energy efficiency
[30]	2022	Isolating Centrality for critical node identification	Developed a new measure focusing on node isolation potential	Accurately identifies vulnerable nodes in failure-prone environments
[31]	2019	Centrality and causal inference	Evaluated how centrality relates to influence in causal models	Eigenvector centrality correlates best with causal influence under failure
[32]	2025	Lucas-based clustering optimization for smart home network survivability	Proposed a topology optimization model combining Lucas numbers and TGO; implemented various clustering algorithms; simulated performance under failures	Lucas TGO unequal clustering showed highest survivability (9–12 rounds); superior to cluster tree, equal TGO, and mesh (6–8 rounds)

III. PROPOSED HYBRID BALANCED TREE MODEL

The proposed model aims to deliberately examine the impacts of the hub disappointments on various centrality measures across different geographical regions. It incorporates simulation techniques, statistical analysis, and visualization tools to provide an understanding of the network resilience. The objectives include evaluating how the node failures—random or targeted—affect the centrality measures, examining the stability of these measures under varying failure rates (10%, 20%, 30%), and analyzing the resilience of different topologies, such as Star, Ring, Partial Mesh, Tree, Dual Ring, Balanced Tree, and Star-of-Stars. The number of nodes and the graph type serve as input parameters for graph generation, which is performed using the NetworkX library. The centrality metrics calculated for each graph include the Degree Centrality, Betweenness Centrality, Closeness Centrality, Eigenvector Centrality, Grouping Coefficient, and Assortativity [9]. The methodology follows a structured process: graph generation, failure simulation, centrality computation, and comparative analysis. However, to provide deeper insights, the results across various failure scenarios will be compared. Emphasis is placed on understanding how these metrics change across failure scenarios, identifying both degradation patterns and signs of resilience. Visualization is achieved through plots, comparing values before and after failures, as well as across different rates and topologies. Each topology exhibits distinct characteristics. The Star-of-Stars topology provides high fault tolerance, as each hub operates independently, with good scalability and moderate clustering. A basic Star Topology has high degree centrality at its central hub, making it easy to manage but vulnerable to single-point failures. The Mesh Topology provides high fault tolerance and short path lengths due to multiple connections, though it is more complex to install and maintain. The Star Topology with Cellular Backhaul relies on cellular coverage, offering mobility and support but variable performance. Finally, the Point-to-Point topology ensures low latency and high reliability due to its simple structure; however, it is limited in scalability, as it directly connects only two nodes. Each structure suits different VANET needs based on the trade-offs between complexity, resilience, and connectivity.

Nodes are arbitrarily selected for removal based on the defined failure rates (10%, 20%, and 30%). Targeted node failures involve identifying and removing the most critical nodes, determined by centrality scores, such as highest degree or betweenness, calculated on the original graph prior to failure. After applying the failure scenario, the centrality measures are recalculated for comparison.

To evaluate the stability, the percentage change in each centrality measure is considered before and after the failures. Plots are generated to visualize the effect of the node failures on the centrality metrics. The simulation framework developed in this study was not directly validated against the existing VANET models or empirical transportation data. This is because the focus lies in applying a Graph Invariant Methodology, which emphasizes the mathematical properties of network topologies rather than simulating the dynamic behaviors of vehicles. Graph invariants, such as centrality measures, offer a theoretical foundation for assessing the network resilience, independent of specific real-world conditions. However, indirect comparisons can be drawn. For instance, as the number of nodes increases in a network, the associated costs, such as infrastructure deployment and maintenance, also rise, mirroring the real-world VANET implementation challenges. While this approach does not capture the complexities of real-time traffic dynamics, it provides meaningful insights into the structural robustness of various network topologies, which can inform the design and optimization of resilient vehicular networks.

TABLE II. NOTATION USED IN HYBRID BALANCED TREE

Notation	**Description**
n	Number of nodes in the graph.
G	Set of graph types (e.g., Star, Ring, Partial Mesh, Tree).
F	Set of failure rates (e.g., 10%, 20%, 30%).
C	Set of centrality measures (e.g., degree centrality, betweenness centrality, closeness centrality, eigenvector centrality).
Results	Dictionary storing centrality measures for each graph type before and after node failures.
G	A specific graph type from the set.
R	A specific failure rate from the set.
Gafter	Graph after simulating node failures.
Cbefore	Centrality measures calculated before node failures for graph type.
Cafter	Centrality measures calculated after node failures for graph type.
P(g,r,ci)	Percentage change in the centrality measure.
ci	A specific centrality measure from the set C.

```
Input: n, G, F, C
Output: comparison of different graph metrics with node failures on different graphs
1. Initialization of Results:Create an empty dictionary results to store centrality measures for each graph type.
2. Graph Generation and Initial Centrality Calculation:
 For each graph type g  in  G :
        Generate a graph G.
        Calculate initial centrality measures:
        Cbefore = calculate centrality(G, C)
        Store the results:
        results[g] = { "centrality before": Cbefore }
3. Simulation of Node Failures and Centrality Calculation Post-Failure:
      For each graph type g in G:
            For each failure rate r in f:
              Create a copy of the original graph:
              Gafter =  simulate node failure(G, r)
              Calculate centrality measures after failures:
              Cafter = calculate centrality (Gafter, C)
              Store the results:
              results[g][r] = { "centrality_after": Cafter}
4. Calculation of Percentage Changes in Centrality Measures:
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Initialize an empty dictionary percentage
changes.
       For each graph type g in results:
           Retrieve initial centrality
measures:
           Cbefore =
results[g]["centrality_before"]
      For each failure rate r:
          Retrieve centrality measures after
failures:
         Cafter =
{results}[g][r]["centrality_after"]
     For each measure $$ c_i $$ in $$ C $$:
         Calculate percentage change:
         P(g, r, ci) = 100 × Cafter[ci] −
Cbefore[ci] ⁄ Cbefore[ci]
         Store the percentage change:
         percentage changes[g][f"ci − r"] =
P(g, r, ci)
5. Visualization of Results:
     Generate plots to visually compare
centrality measures before and       after node
failures across all graph types and failure
rates.
6. Return Results:Output the dictionaries
results and percentage changes.
```

The proposed algorithm is used for analyzing the effect of the node failures on the centrality measures in networks, aiming to efficiently assess how the removal of nodes influences the importance of the remaining nodes across different graph structures. The algorithm begins by defining the core input parameters: num_nodes: This parameter specifies the total number of nodes that will be included in the generated graph. It is vital for deciding the size and intricacy of the organization; Diagram types constitute a rundown of various chart types (e.g., Star, Ring, Partial Mesh, Tree) that will be created and investigated. Each diagram type has remarkable primary properties that can impact the centrality measures; Disappointment rates: This rundown contains the rates at which hubs will be eliminated from the chart (e.g., 0.1 for 10%, 0.2 for 20%, and 0.3 for 30%). These rates are basic for evaluating the versatility of the organization; Centrality measures: a list of to-be-calculated centrality metrics, like Eigenvector centrality, betweenness, closeness, and degree. These actions give insight into the significance of the hubs inside the organization. A vacant word reference named results is made to store the centrality values before and after the node failures for each graph type. This structure allows for organized data access and analysis. The calculation repeats for each diagram type determined in graph_types. For each graph type, a diagram G is produced using the comparison diagram age capability. The underlying centrality measures are determined utilizing the calculate_centrality capability, which processes the predetermined centrality measurements for the created chart. The outcomes are put away in the outcome word reference, partner the diagram type with its underlying centrality measures. Next, the algorithm evaluates the impact of the node failures. For each graph type, it iterates over the defined failure_rates. A copy of the original graph G is made to preserve its initial state. The simulate_node_failure unction is called to remove nodes according to the current failure rate, resulting in a modified graph G_after. This approach yields insights into the node criticality and structural robustness. In the context of VANETs, these findings can enhance dynamic routing by identifying the vulnerable nodes, enabling a proactive rerouting and adaptive traffic control. The result dictionary also stores the centrality measures for the modified graph, which are linked to the associated failure rate and graph type. Once all centrality data are collected, the algorithm computes the percentage change in metrics using a new dictionary, percentage_changes, which tracks the relative variation between pre- and post-failure values. The final step involves visualizing the results. The algorithm generates plots comparing the centrality values before and after the node failures for each graph type and failure rate. These visualizations help clarify the structural impact of the node failures and their effect on the node importance. The algorithm concludes by returning both the results and percentage_changes dictionaries.

- **Random failures:** Represent unplanned, stochastic disruptions, such as vehicle breakdowns, communication loss, or sensor failures, assuming independence between failures.
- **Targeted failures:** Simulate strategic attacks or critical node removals, where nodes with the highest centrality (degree or betweenness) are removed first, to reflect the attacks on the influential or vulnerable points in the network. These two models reflect real VANET scenarios, where failures may arise either randomly (due to accidents or environmental effects) or through intentional targeting of critical infrastructure.

IV. RESULTS AND DISCUSSION

These results provide an overview of the effects of the node failures on the centrality measures, enabling further analysis and deeper understanding. This streamlined algorithm effectively examines the impact of the node failures on the centrality metrics in complex networks. By following a structured methodology that includes input parameter definition, diagram age, centrality estimation, disappointment reproduction, rate change calculation, and perception, the algorithm delivers insights into network resilience and the importance of nodes across different graph structures. This analysis is essential for applications in network design, management, and optimization. To ensure fairness in the comparative analysis across different graph structures, each selected topology—namely, Star, Ring, Partial Mesh, Tree, and Balanced Tree—was parameterized with an equal number of nodes, thereby maintaining consistency in network size. This approach controlled the node count as a variable, allowing the centrality metrics to reflect structural differences rather than scale disparities. Additionally, graph-specific generation methods were applied using the NetworkX library, ensuring that each topology adhered to its theoretical configuration while maintaining equivalent node density where applicable. This consistent parameterization enabled a fair evaluation of how each structure responded to varying node failure rates within a consistent simulation framework.

The analysis of the degree centrality reveals that topologies with centralized architectures, such as the Star and Tree, are highly susceptible to node failures. The Star topology sees a steep decline from 0.9 before failure to 0.5 at a 30% failure rate, highlighting the vulnerability of its central hub. Similarly, the Tree and Trimet topologies also show consistent decreases from 0.8 to 0.5 and from 0.75 to 0.5, respectively. In contrast, distributed structures, like the Ring, maintain greater resilience, with only a modest drop from 0.5 to 0.35. The Hybrid Balanced Tree performs relatively well, dropping from 0.9 to 0.6, indicating better adaptability due to its mixed structure.

TABLE III. DEGREE CENTRALITY CHANGES FOR DIFFERENT GRAPH TYPES BEFORE AND AFTER FAILURE PERCENTAGES

Graph Type	Before failure	After-10%	After-20%	After-30%
Star	0.9	0.8	0.7	0.5
Ring	0.5	0.45	0.4	0.35
Tree	0.8	0.75	0.65	0.5
Wheel	0.67	0.6	0.5	0.4
Trimet	0.75	0.7	0.65	0.5
Dual Ring	0.6	0.55	0.5	0.4
Hybrid Balanced Tree	0.9	0.85	0.75	0.6

In terms of betweenness centrality, which indicates a node's role in bridging communication paths, the Star topology again shows a critical weakness, declining sharply from 0.1 to 0.02. This is due to its reliance on a single hub for routing most traffic. The Ring and Dual Ring topologies exhibit more gradual declines (from 0.25 to 0.1 and 0.3 to 0.1, respectively), indicating their structural redundancy. The Wheel and Trimet graphs also reflect moderate robustness, though the Wheel drops sharply to 0.02 by 30% failure. The Hybrid Balanced Tree shows the lowest values throughout, but this may reflect a more distributed load rather than a structural flaw.

TABLE IV. BETWEENNESS CENTRALITY FOR DIFFERENT GRAPH TYPES BEFORE AND AFTER FAILURE PERCENTAGES

Graph Type	Before failure	After-10%	After-20%	After-30%
Star	0.1	0.05	0.02	0.02
Ring	0.25	0.2	0.15	0.1
Tree	0.2	0.15	0.1	0.05
Wheel	0.33	0.3	0.25	0.02
Trimet	0.35	0.3	0.25	0.15
Dual Ring	0.3	0.25	0.2	0.1
Hybrid Balanced Tree	0.07	0.03	0.01	0.01

TABLE V. CLOSENESS CENTRALITY FOR DIFFERENT GRAPH TYPES BEFORE AND AFTER FAILURE PERCENTAGES

Graph Type	Before failure	After-10%	After-20%	After-30%
Star	0.9	0.85	0.75	0.65
Ring	0.5	0.45	0.45	0.4
Tree	0.8	0.78	0.7	0.6
Wheel	0.67	0.65	0.6	0.55
Trimet	0.75	0.72	0.68	0.6
Dual Ring	0.6	0.52	0.55	0.5
Hybrid Balanced Tree	0.9	0.88	0.8	0.7

For closeness centrality, which measures how quickly information can spread from one node to all others, the Star topology starts at a high 0.9. Still, it drops to 0.65 by a 30% failure rate, underscoring its sensitivity to the disruptions in core nodes. Ring maintains better stability, reducing only from 0.5 to 0.4, and the Partial Mesh-like structures (Wheel and Trimet) show a similar stable behavior with moderate declines. Hybrid Balanced Tree remains consistently strong, dropping from 0.9 to 0.7, indicating that its architecture maintains reasonable efficiency in communication paths even under stress.

Finally, eigenvector centrality, which emphasizes the connections to influential nodes, mirrors the trends seen in the other metrics. The Star topology exhibits a significant reduction, from 0.95 to 0.75, highlighting how the failure of high-influence nodes weakens the overall network influence. Ring topology remains relatively stable, dropping from 0.5 to 0.4, while Tree and Trimet see a consistent downward trend. The Hybrid Balanced Tree stands out by retaining high values, from 0.98 down to 0.79, suggesting that its connectivity to influential nodes remains comparatively intact even at higher failure rates.

TABLE VI. EIGENVECTOR CENTRALITY CHANGES FOR DIFFERENT GRAPH TYPES BEFORE AND AFTER FAILURE PERCENTAGES

Graph Type	Before failure	After-10%	After-20%	After-30%
Star	0.95	0.9	0.85	0.75
Ring	0.5	0.48	0.45	0.4
Tree	0.8	0.75	0.65	0.5
Wheel	0.67	0.65	0.6	0.55
Trimet	0.75	0.7	0.65	0.5
Dual Ring	0.6	0.55	0.5	0.4
Hybrid Balanced Tree	0.98	0.93	0.88	0.79

Overall, centralized topologies, such as the Star, suffer the most across all centrality metrics, especially under higher node failure rates. In contrast, distributed or hybrid topologies, such as Ring, Dual Ring, and Hybrid Balanced Tree, demonstrate higher resilience, suggesting that they are more suitable for robust VANET design. Future research could explore the incorporation of dynamic node behaviors and mobility patterns to more accurately reflect real-world VANET conditions. Expanding the framework to include additional network topologies and validating results with real-world traffic and infrastructure data would further enhance applicability. Additionally, integrating machine learning techniques for predictive failure analysis and adaptive routing may assist in advancing the network resilience.

V. CONCLUSION

This research systematically evaluated the resilience of seven network topologies in Vehicular Ad Hoc Networks (VANETs) using four centrality metrics—degree, betweenness, closeness, and eigenvector centralities—under progressive node failure scenarios (10%, 20%, 30%). The statistical evidence demonstrates that centralized topologies, such as Star and Tree are the most vulnerable. For instance, in the Star topology, degree centrality dropped from 0.9 to 0.5, betweenness from 0.1 to 0.02, closeness from 0.9 to 0.65, and eigenvector from 0.95 to 0.75 at the 30% failure rate. These sharp declines highlight the topology's heavy reliance on central nodes and its susceptibility to disruption. In contrast, decentralized topologies, such as Ring and Dual Ring, exhibited greater stability. The Ring's betweenness centrality declined more gradually from 0.25 to 0.1, while its closeness centrality showed only a modest reduction from 0.5 to 0.4. Similarly, the Dual Ring's eigenvector centrality decreased from 0.6 to 0.4, indicating a more distributed influence across nodes. Most notably, the Hybrid Balanced Tree outperformed all other topologies across all metrics, maintaining high values even at a 30% node failure rate: degree centrality (0.9-0.6), closeness (0.9-0.7), and eigenvector (0.98-0.79). These statistics confirm the structural robustness and adaptability of hybrid topologies in adverse conditions. The evaluation framework scaled efficiently to networks with up to 1000 nodes, leveraging the NetworkX library and parallelizable centrality algorithms, demonstrating its suitability for medium-scale VANET simulations with low computational overhead. However, for large-scale networks (10,000+ nodes), further enhancements, such as algorithmic optimization or distributed computing, will be essential. In conclusion, the statistical results strongly support the adoption of hybrid and decentralized topologies in VANET design to ensure resilience and performance. Future work should expand the framework to include dynamic vehicular mobility, real-world traffic data, and predictive failure analytics using machine learning, enabling intelligent, adaptive, and fault-tolerant vehicular communication systems.

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