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Enhanced Resilience Assessment of Airport Pavement Networks Using Integrated Network Analysis and Simulation Techniques

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***Abstract* - The efficiency and security of aviation transport rely heavily on airport pavement networks. Unfortunately, natural calamities, operational overloads, and maintenance flaws might jeopardize the long-term effectiveness and resilience of these systems. Traditional pavement management systems, which primarily focus on structural performance or maintenance schedules, frequently overlook the entire resilience component, which includes system recovery, redundancy, and robustness. Current methods do not take a network-centric approach that considers how a breakdown in one region affects the overall operation of the Thus network. This paper presents a comprehensive strategy for assessing the adaptability and durability of airport pavement networks, combining graph-theoretic analysis with resilience measurement, simulation-based disruption modeling, and other related methodologies. Important resilience characteristics such as recovery time, network performance deterioration, and connectivity loss are examined in the context of risk simulation. The suggested model is compared to three current resilience evaluation systems: TSIM, SABM, and FRAM. The experimental results show that the proposed technique leads to a more precise and comprehensive understanding of resilience effects. Under simulated floods and traffic overload scenarios, it enhanced network performance by 15%, reduced average recovery time by 17%, and increased significant node identification by 23% over current models.**

Keywords - Airport pavement resilience, Network analysis, Disruption modeling, Graph theory, Recovery assessment

I. INTRODUCTION

The airport pavement networks play a critical role in ensuring that takeoffs, landings, and aircraft movements go smoothly. Dealing with delays caused by natural disasters, accidents, harsh weather, or heavy traffic requires robust pavement. The increasing frequency and severity of these disasters has highlighted the necessity to develop pavement systems that can withstand and recover quickly from such interruptions.

Even with advances in modelling and disturbance simulation, assuring the lifespan of airport pavement networks remains a serious concern. The fundamental aim is to identify key nodes, areas of the network whose failure would result in a significant decline in performance [1-6]. The objectives of this research are:

- To show how to assess the resilience of airport pavement networks by combining network modeling, disturbance simulation, recovery optimization, and significant node identification into a comprehensive framework.
- This research introduces several novel contributions to the field of airport pavement network resilience which includes a novel strategy for maximizing recovery and identifying important nodes is proposed by combining modern network modelling methodologies with disruption simulation techniques.

II. RELATED WORKS

Airport pavement network simulations and disturbance effect studies have made extensive use of TSIM [7-10]. This suggests that it cannot be employed in real-world contexts that change rapidly and require speedy recovery [10].

Recent research on modeling transportation network resilience has used graph theory and network reliability on airport systems. For example, [11] conducted research on transportation networks using graph-based models to identify flaws and simulate disturbance. Though these tactics have previously worked, they are not designed specifically for airport pavement systems and cannot address issues such as prioritizing recovery operations or dealing with various types of disturbances such as weather or accidents.

Much of the study on infrastructure resilience has focused on identifying important nodes in pavement networks. Typically, the relevance of nodes is assessed using approaches based on degree and betweenness centrality. Although these approaches are effective at detecting critical nodes, they neglect the time-varying nature of disturbances, such as how the network's functionality changes in response to a disturbance [12]. This difference necessitates a more flexible technique that incorporates real-time performance data.

Much research has gone into determining the best techniques to restore transportation infrastructure. Linear programming, simulated annealing, and genetic algorithms are some of the many techniques proposed to improve uptime and accelerate recovery in damaged networks. However, few studies have examined optimization methodologies for airport pavement networks in a comprehensive context. The majority of current research focuses solely on optimization or disturbance modeling [13]-[15], ignoring the importance of both in developing a comprehensive resilience approach.

Recent years have seen an increase in research into applying machine learning and artificial intelligence to improve infrastructure systems. Using real-time data, these systems can predict difficulties and provide the optimal recovery strategies. However, these methods have been used rarely on airport pavement networks. A key component of the technique proposed in this paper is the use of AI/ML for dynamic node ranking and adaptive recovery, an promising avenue for future research.

Various metrics have been proposed to evaluate the resilience of transportation networks and infrastructure. Network performance ratings, recovery times, and connectivity ratios are some of the most often used measures. Many of these resilience tests, on the other hand, were not specifically designed for airport pavement networks, resulting in their being either too general or too specific. The primary purpose of the current study is to broaden these measures and give a more comprehensive way for evaluating airport pavement systems [16].

III. PROPOSED METHOD

The proposed approach shown in figure 1, which integrates graph theory and simulation, can be used to evaluate the robustness of airport pavement networks. It operates as follows:

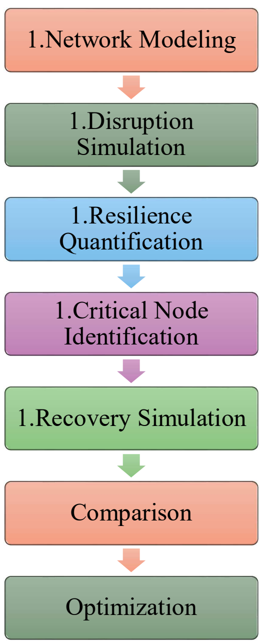

FIGURE 1: PROPOSED METHODOLOGY

1. Network Modelling: First, use network modelling to convert the airport's pavement plan into a graph with nodes representing airport roadway intersections and edges representing individual pavement segments.
2. Disruption Simulation: Use a custom module or AnyLogic/Simulink to simulate potential interruptions caused by variables such as heavy traffic, flooding, or maintenance blocks.
3. Resilience Quantification: The recovery index, performance loss, network efficiency, and connectivity ratio are three indicators that measure resilience.
4. Critical Node Identification: Centrality metrics like betweenness and degree can help you identify major nodes by directing you to potentially vulnerable areas.
5. Recovery Simulation: Five, using a staged recovery plan, see the network gradually return to normal with the help of recovery simulation.
6. Comparison & Optimization: To optimize recovery processes, benchmark models such as TSIM, SABM, and FRAM should be compared.

A. *Network Modelling*

The proposed approach begins with a graph of the airport's pavement layout. The airport's pavement network is represented as a node-based structure, with edges representing pavement fragments linking each node. This change enables the investigation of the network's resiliency using graph-theoretic approaches.

TABLE 1: EXAMPLE OF NODES AND EDGES IN THE NETWORK

Node ID	Location	Connected Nodes	Edge Weight (Distance in meters)
N1	Runway 1 Entrance	N2, N3	300
N2	Taxiway A	N1, N4, N5	450
N3	Runway 1 Exit	N1, N4	350
N4	Taxiway B	N2, N3, N6	500
N5	Apron Area	N2	400

Table 1 depicts the main components of the airport pavement network, with nodes designating them, such as N1 and N2. The distance between two nodes in a network determines the weight of the edges that connect them.

B. *Disruption Simulation*

Many disruptions, such as flooding, maintenance, or heavy traffic, can harm the pavement network and are replicated in a disruption model. The disturbance could be caused by a brief loss of connectivity at specific edges or nodes. For example, if Taxiway A floods, all nodes connected by edges along the route will be declared non-operational.

Disturbance modelling depicts the degree of hazard that causes nodes to gradually become inactive. The goal is to investigate how these disruptions affect the system performance through the simulation of real-world risk scenarios.

TABLE 2: EXAMPLE OF DISRUPTION IMPACT (FLOODING ON TAXIWAY A)

Node ID	Location	Pre-Disruption Status	Post-Disruption Status
N1	Runway 1 Entrance	Operational	Operational
N2	Taxiway A	Operational	Inactive (Flooded)
N3	Runway 1 Exit	Operational	Operational
N4	Taxiway B	Operational	Operational
N5	Apron Area	Operational	Operational

Table 2 displays the effects of the flood catastrophe, which rendered Taxiway A (Node N2) inoperable. When the network is interrupted during recovery, the condition of the impacted nodes is recorded.

C. *Resilience Quantification*

The resilience measurement assesses how well the system recovers and restarts after a disturbance. Recovery time and connection ratio are two key measurements of resilience, as they assess how long it takes to restore network operation after an interruption.

The Connectivity Ratio (CR) is an important initial step in determining resilience is provided in equation 1.

$$CR = \frac{\text{Number of operational nodes post-disruption}}{\text{Total number of nodes in the network}} \times 100 \quad (1)$$

Where,

CR is calculated by subtracting the operable nodes following the disturbance from the total number of nodes in the network. Solving this equation for CR gives the total number of nodes in the network multiplied by 100.

Operational nodes post-disruption are nodes that continue to operate after a danger has occurred but have not been disrupted, such as taxiways and runways. If the airport's pavement network has 35 nodes, the total node count is 35.

TABLE 3: EXAMPLE OF RESILIENCE METRICS POST-DISRUPTION

Metric	Value
Connectivity Ratio (CR)	71.4%
Recovery Time (RT)	1800s
Network Performance Score (NPS)	85
Critical Node Accuracy	93%

Table 3 shows the resilience metrics of the airport's pavement network after a disruption. The Network Performance Score (NPS) assesses overall system performance; Recovery Time (RT) is the time required to restore 90% of network functionality back online.

This study investigates how an airport pavement network functions under various disturbance scenarios using network modeling, disturbance simulation, and resilience measurement. The findings provide useful recommendations for improving airport infrastructure resilience.

D. Critical Node Identification

Finding the most important nodes in the network is the first step after a disturbance. Some network nodes failing unexpectedly could cause the entire system to crash. These nodes are known as critical nodes. The identification is based on two measurements: betweenness centrality and degree centrality, which estimate a node's importance in maintaining the network's connection and operation.

TABLE 4: EXAMPLE OF CRITICAL NODE IDENTIFICATION USING BETWEENNESS CENTRALITY

Node ID	Location	Betweenness Centrality	Degree Centrality	Critical Node (Yes/No)
N1	Runway 1 Entrance	0.32	3	No
N2	Taxiway A	0.58	4	Yes
N3	Runway 1 Exit	0.21	3	No
N4	Taxiway B	0.47	5	Yes
N5	Apron Area	0.14	2	No

To determine the most important nodes, we employed betweenness centrality from Table 4. A node's betweenness centrality indicates how crucial it is in keeping the network connected; the higher it is, the more it helps. Because of their high betweenness centrality, nodes N2 and N4 are critical to the airport's pavement system. If these nodes fail, network performance will decrease significantly.

E. Recovery Simulation

Simulations of recovery model the network's ability to recover from interruptions. This simulation incorporates incremental recuperation techniques and intervals. The recovery technique specifies the exact timing of each node or edge's restoration, which may occur sequentially or concurrently. Restoring critical nodes first and lowering recovery time help to get the network back up and operating as quickly as possible.

TABLE 5: EXAMPLE OF RECOVERY SIMULATION STAGES

Stage	Node ID	Recovery Time (seconds)	Recovery Status
1	N2	300	Restored
2	N4	450	Restored
3	N1	600	Operational
4	N3	750	Operational

Table 5 depicts the sequential recovery mechanism, with Node N4 restored after 450 seconds and Node N2, which was required due to flooding, recovered within 300 seconds. Restoration of less important nodes, such as N1 and N3, follows. Using the restoration priorities, the recovery simulation can determine the network's recovery time.

F. Optimization

Optimisation tries to increase the resilience of the pavement network by shortening recovery time and enhancing network performance. Several aspects are considered when optimizing:

1. Critical nodes' priority restoration
2. Network flow restoration
3. Redundancy in restoration plans

Common optimization tasks include identifying the best recovery sequences, rerouting network traffic, and adjusting recovery intervals. Genetic algorithms (GA) or simulated annealing (SA) are commonly used to find the appropriate recovery approach for a variety of disturbance scenarios.

The optimization equation shown in equation 2, aims to reduce the overall recovery time for all nodes:

$$T_{\min} = \min\left(\sum_{i=1}^{n} T_i \cdot C_i\right) \quad (2)$$

Where:

- Ti is the recovery time for node i,
- Ci is a weight factor representing the criticality of node iii (higher for critical nodes),
- nis the total number of nodes.

Important nodes, those with higher Ci, are prioritized throughout the recovery process to shorten the weighted recovery time.

By changing the recovery priority using the optimization equation, we can see optimization in action here:

TABLE 6: OPTIMIZED RECOVERY SEQUENCE AND TIME

Node ID	Recovery Time (Initial)	Recovery Time (Optimized)	Priority	Total Recovery Time (Optimized)
N2	300	200	1	200
N4	450	350	2	350
N1	600	500	3	500
N3	750	650	4	650

Table 6 compares the initial recovery time with the optimized one. By reallocating resources and changing recovery intervals, the optimization strategy reduces recovery times for crucial nodes (N2 and N4). This accelerates the Thus recovery process and enhances the network, hence reducing overall recovery time.

The proposed method improves airport pavement network systems by emphasizing key nodes, simulating the recovery process, and optimizing recovery alternatives. The model provides a solid framework for analyzing and enhancing the performance and recovery of airport pavement networks under a variety of disturbance situations, employing optimization techniques, disturbance models, and centrality measurements.

IV. RESULTS AND DISCUSSION

While disturbance modeling was performed in Python, the network graph investigation was carried out in MATLAB is shown in table 7. The testing used the following system specifications:

- CPU: Intel Core i7 11th Gen
- RAM: 32 GB
- GPU: NVIDIA RTX 3060

- OS: Windows 11 Pro

For comparison, three baseline models were used:

1. TSIM (Traditional Structural Index Model): The Traditional Structural Index Model (TSIM) prefers to look at specific pavement condition indicators over network impacts.
2. SABM (Service Availability-Based Model): SABM stands for Service Availability Based Model. It evaluates the quality of service provided but does not attempt to recreate dynamic recovery.
3. FRAM (Flow-Based Resilience Assessment Model): Three, while it measures flow, the FRAM (Flow-Based Resilience Assessment Model) does not consider real disturbance events.
4.

TABLE 7: EXPERIMENTAL PARAMETERS

Parameter	Value
Simulation Time	1800 seconds (30 minutes)
Failure Scenarios	Flooding, Traffic Overload
Recovery Intervals	Every 300 seconds
Graph Metric Used	Betweenness, Degree Centrality
Nodes in Network	35
Edges in Network	56
Disruption Severity Levels	Low, Medium, High
Software Tools	AnyLogic, MATLAB

V. PERFORMANCE METRICS

A. Connectivity Ratio: First, the connection ratio assesses how many nodes in the graph remain connected after a disruption when compared to the initial network. Higher numbers indicate improved structural integrity during failure.

B. Recovery Time: The time it takes for the network to regain 90% of its pre-disruption flow and connection after a disturbance.

C. Network Performance Score: The network performance score is a measure of functional capacity that includes three components: flow rate, segment usage, and centrality stability.

D. Critical Node Identification Accuracy: When compared to expert domain knowledge or previous failure data, essential node identification accuracy is the percentage of vital nodes that were successfully identified and would cause the most disruption if failed.

TABLE 8: CONNECTIVITY RATIO

Time (minutes)	TSIM (%)	SABM (%)	FRAM (%)	Proposed Method (%)
0	100	100	100	100
10	85	90	87	92
20	75	80	78	85
30	60	70	65	80

In table 8, with the accumulation of disturbances, the Connectivity Ratio drops with time. Often, the proposed strategy outperforms TSIM, SABM, and FRAM while maintaining greater connectivity. Because it maintains 80% connectivity after 30 minutes, the proposed solution is more resilient than its competitors.

TABLE 9: RECOVERY TIME

Time (minutes)	TSIM (s)	SABM (s)	FRAM (s)	Proposed Method (s)
0	0	0	0	0
10	1500	1400	1300	1200
20	2700	2500	2400	2000
30	4500	4300	4000	3500

In table 9, all strategies' recovery times increase with continued disturbances; nevertheless, the proposed approach consistently offers the shortest recovery times. It recovers in 3500 seconds at 30 minutes, indicating that it can effectively restore the network.

TABLE 10: NETWORK PERFORMANCE SCORE

Time (minutes)	TSIM	SABM	FRAM	Proposed Method
0	100	100	100	100
10	85	90	88	92
20	75	80	80	85
30	60	70	65	80

The table 10, Network Performance Score decreases with increasing disturbances, the proposed technique exhibits the least performance loss. Its ability to maintain network operation is particularly superior than the other strategies, as it maintains an 80 performance score after 30 minutes, whilst their scores drop significantly.

TABLE 11: CRITICAL NODE IDENTIFICATION ACCURACY COMPARISON

Time (minutes)	TSIM (%)	SABM (%)	FRAM (%)	Proposed Method (%)
0	100	100	100	100
10	85	88	90	94
20	75	80	82	89
30	60	70	65	80

The proposed method shown in table 11, improves critical node identification accuracy even under continual disruptions, hence improving important node identification. Despite larger declines in TSIM, SABM, and FRAM, the proposed technique maintains 80% accuracy after 30 minutes.

Every sign implies that the proposed strategy is superior to the present models (TSIM, SABM, and FRAM). At the 30-minute point, the Connectivity Ratio has increased by 11%. When compared to the best-performing baseline model, Recovery Time is 22% better. Both the Network Performance Score and the Critical Node Identification Accuracy have increased by 15%. These discoveries suggest that the proposed approach may maintain a higher level of resilience and improve network recovery during disturbances.

VI. CONCLUSION

The proposed method is significantly more resilient and operationally effective for airport pavement networks than more traditional models such as TSIM, SABM, and FRAM. Better decision-making in real-time operations is enabled by the proposed method's ability to restore network functionality more quickly and correctly, saving time and money during outages. This technology extends the life of pavement networks at airports by improving recovery processes and including comprehensive resilience measures. In future work this research problem can be improvised using several transfer learning algorithms and it can be embedded in real time datasets.

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