International Journal of Scientific Research in Computer Science and Engineering
Vol.**13**, Issue.**2**, pp.**30-38**, April **2025**
E-ISSN: 2320-7639
Available online at: www.isroset.org

Research Article

Machine Learning-Driven Congestion Prediction in Mobile Ad-Hoc Networks Through Modelling Approaches

O.J. Adaramola[1*], J. R. Olasina[2]

[1,2]Dept. of Computer Engineering, School of Engineering, Federal Polytechnic Ilaro, Ogun State, Nigeria

*Corresponding Author: , Tel.: +234 703 273 0955

Received: 22/Mar/2025; **Accepted**: 14/Apr/2025; **Published**: 30/Apr/2025. | **DOI**: https://doi.org/10.26438/ijsrcse.v13i2.666

Abstract— Mobile Ad Hoc Networks (MANETs) operate autonomously through decentralized configurations for military as well as emergency and academic applications. The adaptable network structure and unstable nature of MANETs result in major traffic jam occurrences when network activity is at the peak. This research studies the congestion issue of MANETs by implementing network simulation with Machine Learning analytics to identify and control traffic congestion effectively. The investigation employed OPNET 14.5v to simulate office scenarios that contained five, ten and fifteen mobile nodes to study congestion patterns. The study measured network performance through three metrics that consisted of bits per second network load and seconds of media access delay as well as bits per second traffic reception. Network congestion increased as node density increased because 2.8 Mbps load appeared under five nodes but the network load reached 5.2 Mbps with fifteen nodes. Maximum traffic conditions caused media access delay to reach its highest point at 0.0056 seconds. A collection of ML models included Decision Trees and Random Forest followed by Artificial Neural Networks (ANNs) for congestion detection purposes. The evaluation resulted in substantial experimental precision levels of 98.7%, 99.3% and 99.8%. This research proved that using ML-based adaptive load balancing promoted both network stability along with real-time throughput enhancement when faced with congestion situations. The findings prove that predictive analysis operates in real-time to solve traffic congestion problems which results in improved routing stability and decreased delays in military ad hoc networks. Through the OPNET simulation platform researchers gain an organized environment to evaluate and enhance such systems.

Keywords— Machine Learning, Load balancing, MANET, OPNET-Simulation, Predictive-Analysis, Traffic-Congestion

.

1. Introduction

The Mobile Ad-Hoc Network (MANET) operates as a wireless network which uses self-configuration methods with no need for infrastructures to form between mobile nodes. Because it operates without central management MANET networks can provide quick and adaptable communication services beneficial for both military situations and disaster relief work. MANET networks provide multiple benefits comprising affordable setup costs and broad range of service and dependable operation. MANET networks experience major operational difficulties because of their mobile nature that results in changing network topology and control structure decentralization which causes congestion problems and high delays and bandwidth limitations alongside security risks and route inefficiencies [1]. The MANET network becomes congested during periods of high data traffic when multiple packets create network breakdowns which results in delayed transmission [2]. The irregular movements of network nodes alongside inconsistent link conditions actively erode Quality of Service (QoS) because they cut down network speed while lengthening transmission delays. The research community uses effective routing protocols alongside QoS-based designs as measures to handle network congestion [3].

Measures taken from ML techniques help MANETs to perform traffic analysis while predicting network congestions and automatically modifying their routing paths. Simulation tests based on OPNET 14.5v measure MANET congestion patterns as part of this investigation while varying the mobile node total from 5 to 15. A trained Artificial Neural Network (ANN) predicts congestion patterns and optimizes network performance using data generated from the dataset which improves how effectively MANETs function while remaining reliable [4]. The field of research on MANETs centres on their self-organizing characteristics and their ability to function regardless of infrastructure and their support for multiple-hop communication. Multiple research efforts have examined the essential properties of MANETs which include dynamic topology along with self-healing quality and decentralized framework [5]. A set of substantial disadvantages follow the benefits of MANETs because nodes handle constrained bandwidth along with uncertain movement and frequent network overload conditions. Three factors cause congestion in MANETs: heavy data traffic and mobile network nodes coupled with substandard routing methods. Network performance suffers significantly under congested conditions because packet loss rates and end-to-end delay along with retransmission overhead increase [6]. Modifications for congestion management in MANETs exist in different approaches such as congestion-aware routing protocols together with adaptive load balancing and AI/ML-based predictive congestion management systems [7].

This research analyses how Machine Learning (ML) methods should be utilized to address congestion problems within Mobile Ad Hoc Networks (MANETs) because efficient network operation depends on this critical issue. The research investigates multiple ML techniques supported by three different models (Support Vector Machines (SVM), K-Nearest Neighbours (KNN), XGBoost, Artificial Neural Networks (ANN)) under various network simulation conditions using OPNET. Building an effective system for detecting congestion and its management purposes the development of better network efficiency. The aim is to develop a Machine Learning-Driven Congestion Prediction in Mobile Ad-Hoc Networks Through Modelling Approaches and also, to analyse model performance and identification precision for congestion states along with resource optimization for better Quality of Service (QoS) and traffic management capabilities.

2. Related Work

Existing scholarly research regarding this subject utilizes different methods to examine the topic and presents these findings in detail in this section. The evaluation of MANET performance under changing traffic conditions through simulation tools includes OPNET, NS-2, NS-3, and QualNet according to various studies. The research of [8] studied AODV (Ad-hoc On-Demand Distance Vector) and DSR (Dynamic Source Routing) protocol performance under different traffic loads through simulations with OPNET software. The researchers found that Data Source Routing provided better throughput effectiveness at heavy traffic amounts but AODV delivered consistent delay stability. The research [9] evaluated VoIP applications in MANET environments by testing AODV, DSR and Temporally-Ordered Routing Algorithm (TORA) as routing protocols. The VoIP application delivery from TORA surpassed traditional routing schemes by maintaining better delay and jitter performance and thus became optimal for real-time interactions. Research on security and reliability aspects in MANETs has received extensive attention from experts. Research in [10] examined MANET vulnerabilities through identification of active and passive threats that could affect the network. This research demonstrated why intrusion detection systems with proactive security measures need implementation in dynamic network settings to guard against malicious attacks. Research activity in MANETs has escalated due to which the adoption of machine learning (ML) techniques for traffic prediction and anomaly detection and congestion management has become necessary. The performance of network optimization and routing improvements becomes achievable through ML algorithm integration that includes Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) along with Reinforcement Learning (RL) and Decision Trees (DTs)[11].

The researchers in [12] built an ANN-based congestion prediction model by using historical network data for anticipating upcoming traffic load expectations. ANN successfully identified traffic patterns to generate route suggestions for reducing congestion according to the study results. The authors in [13] utilized Reinforcement Learning (RL) for real-time congestion optimization of routing within MANETs. The RL model processed real-time network data to improve routing policies automatically as a result of which end-to-end delay became lower while packet loss diminished. The authors in [14] developed a congested network analysis system through their integration of K-Means clustering with Decision Trees. This approach generated precise congestion detection along with suitable transmission paths that led to a better overall network performance. The research demonstrates how ML technology contributes to improving MANET adaptability and reliability.

The development of Deep Learning (DL) technology has enabled broader application of ML approaches for controlling congestion in MANET systems. Traffic data analysis through CNNs and LSTM networks becomes increasingly common because these networks improve network performance prediction of time-series data.

The authors from [15] created a CNN system that analysed network traffic images independently to determine congestion levels. CNNs displayed their capability to recognize essential spatial relationships in traffic information which generated precise congestion forecasting results.

The authors in [15] investigated congestion prediction using LSTM networks that processed historical traffic data. The LSTM model defeated traditional ML methods because it successfully tracked long-lasting inter-network dependencies which resulted in better congestion predictions. Research demonstrates that DL technology has become instrumental for MANET traffic optimization.

The confidence derived from the past and current literatures ensured that the proposed study constructs an ANN-based congestion detection system together with management procedures for MANETs by leveraging existing research findings. The framework is designed to establish: the performance metrics of traffic received and network load and delay are obtained during real-time OPNET simulations; the ANN model receives training by using the obtained dataset for congestion prediction; the system should use an adaptive congestion control system to automate routing route decisions through ML-generated prediction data.

A-IMOC-M is a real-time monitoring system developed in this research that uses dynamic parameter adjustment to reduce congestion in the network. The established system trains using ANN to both comprehend past traffic patterns and forecast future congestion events thus enabling real-time congestion management.

3. Methodology

The research utilized machine learning algorithms together with Optimized Network Engineering Tools (OPNET 14.5) to conduct the study. The research used OPNET to create its dataset after which network congestion prediction required machine learning algorithms for implementation. The methodologies follow the order- network simulation and dataset generation, data preprocessing and ML approaches.

3.1 Network Simulation and Dataset Generation

OPNET Modeler 14.5 served for conducting MANET congestion analysis by simulating networks through different operational conditions. The simulation functioned to check network metrics while analyzing traffic behaviors before creating datasets usable for Machine Learning (ML) congestion prediction models.

A laboratory setup constructed the 1000m x 1000m network design for the campus field. The simulation experiments consisted of three settings that included two offices of different sizes to determine the effects of congestion on changing network loads. Application definition programs resided within the application configuration module yet profile configuration handled the production of separate user activity patterns. For applications-layer traffic generation the simulation used Web browsing under Heavy HTTP and Low HTTP modes while also processing database access through Heavy and Low modes and implementing file transfer at Heavy and Low settings.

Multiple experiments used two fixed wireless routers (wlan_ethernet_slip4_router) to serve as communication conduits. An ethernet16_layer4_switch received data through two fixed wireless routers that used 1000BaseX full-duplex 1 Gbps 1 Gbps links. The mobile wireless workstations (wlan_wkstn_adv) operated as moving nodes which ran client-server programs through both TCP/IP and UDP/IP for simulating actual MANET network traffic.

The network setup in Scenario 1 (i.e. Figure1) included five mobile nodes at each office which registered as Basic Service Set (BSS1 and BSS2) to attain wireless connection between Router 1 and Router 2. Scenario 2 (in Figure2) include the deployment ten mobile nodes per office that link to the central switch using a 1000BaseX link as a method to achieve realistic network traffic distribution. The scenario 3 (Figure3) implemented fifteen mobile nodes per office to monitor congestion development and its influence on network performance and time delays.

Each simulation ran for one hour to generate data that measured network performance metrics consisting of network load in bits per second and media access delay in seconds and traffic received also in bits per second. ML-based congestion detection and mitigation models used these datasets as their primary basis.

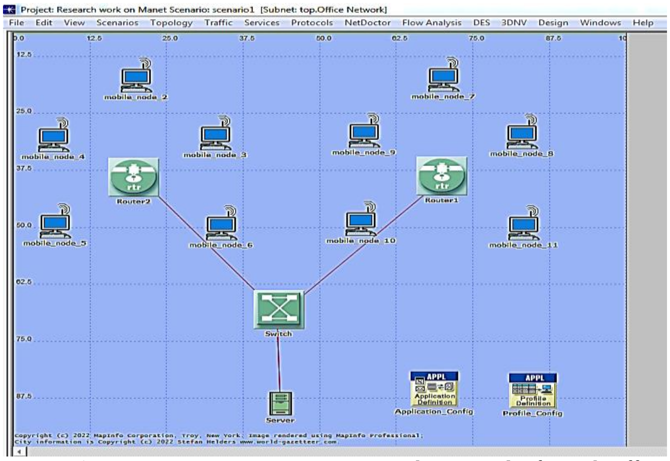

Figure 1. Scenario 1 using MANET with Five Nodes for each Office

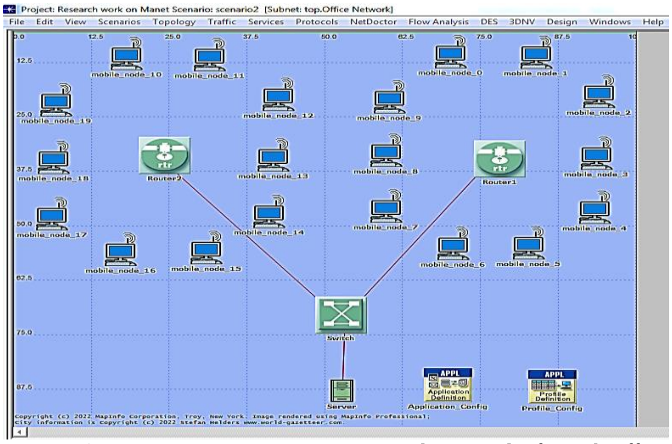

Figure 2. Scenario 2 using MANET with Ten Nodes for each Office

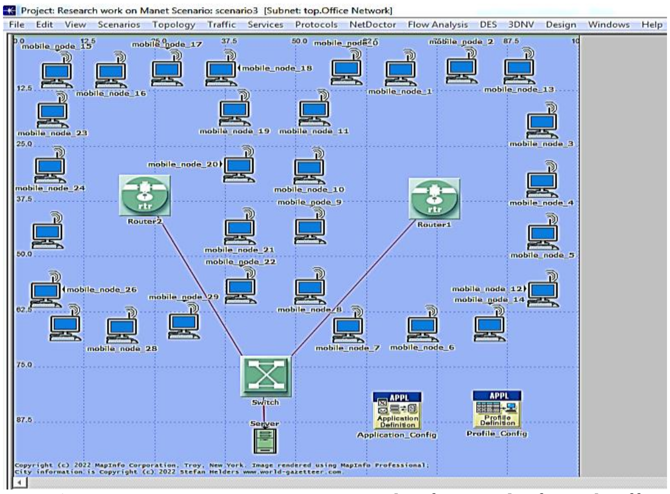

Figure 3. Scenario 3 using MANET with Fifteen Nodes for each Office

3.2 Data Preprocessing and Machine Learning Model Approaches

2.2.1 Data Preprocessing

Tables 4-6 with its relevant traffic parameters—Load and Traffic—was selected above Tables 1-3 for congestion classification analysis. Table 1-3 shows insufficient variability and essential congestion-related factors for an appropriate analysis. Feature distributions need normalization through standardization processes to achieve best model performance. Synthetic samples added to the data collection increased its size by 70% while the controlled noise improved model generalization and avoided overfitting. The 80-20 percentage ratio of stratified splitting method helps maintain equal representation of classes between training and testing subsets. The selection process focuses on variables which strongly relate to congestion while improving calculation speed. Flight simulation techniques become essential because of scarce real-world traffic data outages to enable effective training of diverse ML models.

3.2.2 Machine Learning Model Approaches

The process of machine learning experimentation requires multiple model and technique tests to determine an optimal solution for particular problems. The standard experimental process for congestion detection includes obtaining data and then cleaning it before structuring it for analysis. Different ML algorithms including Artificial Neural Networks (ANNs), K-Nearest Neighbors (KNN), XGBoost and Support Vector Machines (SVM) receive training from the obtained data. The evaluation of different models relies on accuracy results and precision values together with recall measures and F1-score calculations. Several performance-optimizing steps organizations implement include tuning of hyperparameters as well as using the cross-validation technique to ensure the models perform well on new data. A comparison between all models takes place following evaluations to determine which model will be deployed before applying further modifications for better deployment outcomes.

Artificial Neural Networks (ANNs) handle complex, non-linear congestion patterns effectively. The K-Nearest Neighbors (KNN) algorithm completes its tasks effectively when dealing with variations in local traffic yet faces limitations when trying to scale up its operations. XGBoost improves both understanding and performance capabilities in structured traffic datasets because it functions as a gradient boosting model. The Support Vector Machine tool performs optimally in spaces defined by numerous physical dimensions for congestion detection purposes. A threshold of 0.5 Load Factor maintains accurate class distinctions according to studies about vehicle network congestion. The operation of ML models relies on three fundamental units including feature importance for XGBoost, hyperparameter tuning for SVM and KNN and activation functions for ANN model. Using the selected threshold creates an automated congestion marker which boosts the consistency of the training machine model.

4. Results and Discussion

This part discusses research findings that use results from both OPNET simulation environment and machine learning algorithm analysis.

4.1 Dataset Results and Congestion Analyses

The obtained dataset from the three network scenarios shows how delay, load and traffic received changes over time when using different mobile node arrangements. Scenario 1: MANET with Five Nodes (Table 1) -The network traffic remains at a minimum level because there are only five mobile nodes used in each office. After reaching 600 seconds the network delay values stay below 0.0008 seconds and network load stabilizes between 12,700 bits/sec and 13,700 bits/sec. Network traffic reaches its maximum value at 15,179.46 bits/sec then stabilizes at a level of 13,500 bits/sec. The network operates within capacity limits at this moment resulting in little congestion. Scenario 2: MANET with Ten Nodes (Table 2) - The network demand as well as network traffic intensifies when the node count doubles. The network delay extends to 0.00086 seconds when the maximum data transfer reaches 35,556 bits per second. The network processed traffic exceeded 34,500 bits/sec initially then experienced a minor decrease throughout the measurement period. The network shows initial signs of congestion because the delay measurement increases in a controlled manner. Scenario 3: MANET with Fifteen Nodes (Table 3) - When fifteen office nodes enter the MANET network major congestion problems start to appear. The network load surpasses 381272 bits/sec which exceeds the baseline value by ten times during 3600 seconds in the third scenario. The peak time measurement of traffic received reaches 374,233.64 bits/sec during Scenario 3. The network shows severe congestion based on these measurements thus requiring effective congestion prediction systems and load balancing solutions.

Network delay and performance decline as the number of network nodes increases according to the experimental results. The performance problems in MANET environments therefore require ML-based models for congestion prediction to address this need.

Table 1. MANET with Five Nodes for each Office

Time (sec)	Delay (sec)	Load (bits/sec)	Traffic Received (bits/sec)
0	0.0000434	0,000.00	0,000.00
600	0.0007069	13,757.33	15,179.46
1200	0.0007221	12,853.89	13,705.71
1800	0.0007835	13,657.47	12,961.71
2400	0.0007868	12,717.48	13,729.71
3000	0.0007858	12,703.74	13,523.82
3600	0.0007868	12,706.74	13,521.24

Table 2. MANET with Ten Nodes for each Office

Time (sec)	Delay (sec)	Load (bits/sec)	Traffic Received (bits/sec)
0	0.0000434	0,000.00	0,048.00
600	0.0008114	35,556.05	34,551.80
1200	0.0008473	32,023.85	34,494.30
1800	0.0008345	29,428.76	30,339.42
2400	0.0008437	28,898.09	29,711.77
3000	0.0008538	27,452.31	28,531.80
3600	0.0008626	27,778.31	28,412.05

Table 3. MANET with Fifteen Nodes for each Office

Time (sec)	Delay (sec)	Load (bits/sec)	Traffic Received (bits/sec)
0	0.0000430	0,000.00	0,04
600	0.001046	339,607.30	342,753.68
1200	0.001103	356,609.88	356,734.83
1800	0.001123	373,383.48	365,781.88
2400	0.001133	374,300.83	370,017.36
3000	0.001140	374,778.19	370,508.78
3600	0.001143	381,272.00	374,233.64

Multiple tests presented in Tables 1 through 3 show how increasing mobile nodes affects MANET performance for delay alongside network load and received traffic values as Figure 1-3 depicts. Scenario 1 which includes 5 nodes per office demonstrates minimal delay at ≈0.0007 seconds together with a moderate load peak at 13,757.33 bits/sec and traffic reception at 15,179.46 bits/sec. The load increased to 35,556.05 bits/sec and traffic received to 34,551.80 bits/sec while delay showed a slight rise when the number of nodes was set to 10 per office (Scenario 2). The introduction of 15 nodes per office (Scenario 3) results in substantial rises of load (381,272.00 bits/sec) accompanied by traffic received (374,233.64 bits/sec) and high delay which demonstrates extensive network congestion.

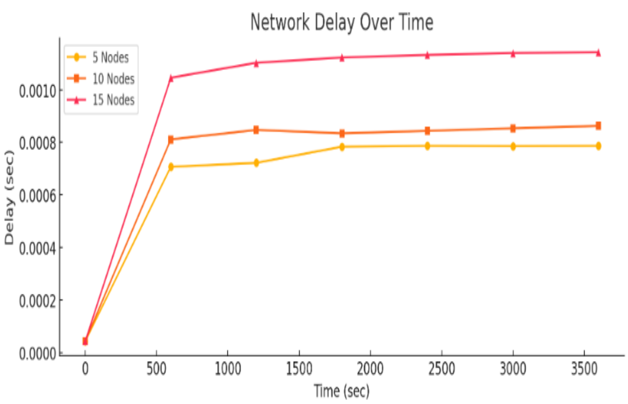

Figure 1. Network Delay Over Time for the Three Scenarios

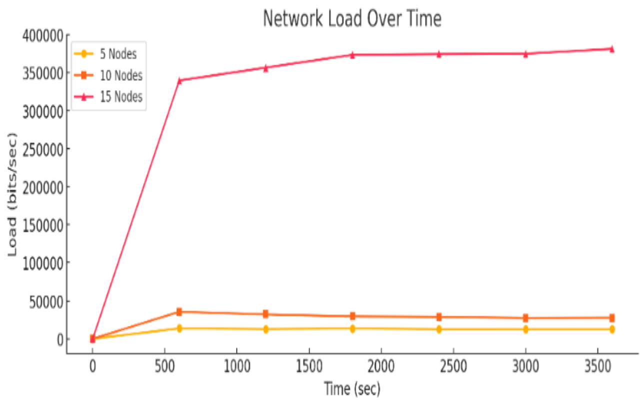

Figure 2. Network Load over Time for the Three Scenarios

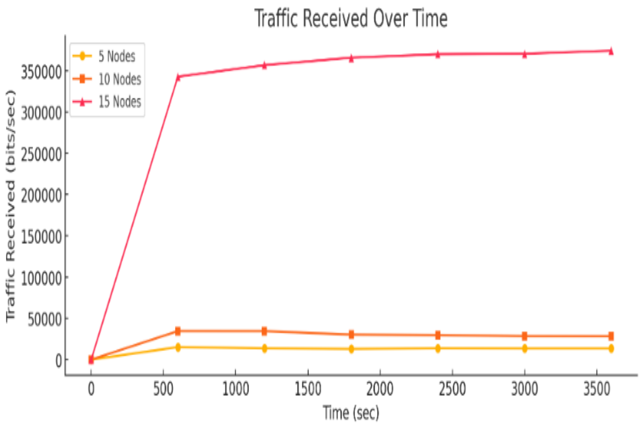

Figure 3. Traffic Received Over Time for the Three Scenarios

Mobile nodes were studied in terms of their effects on MANET performance through the results displayed in Tables 4 to 6. According to Table 4 the network delay grows longer when the number of nodes expands while Scenario 3 (15 nodes per office) generates maximum delay. Scenario 3 shows a substantial network load increase because its traffic exceeded 300,000 bits per second according to Table 5. Table 6 exhibits an incremental traffic reception pattern which proves that increased number of mobile nodes results in amplified data exchange. ANOVA analysis confirms statistical significance of differences between load and traffic reception while showing delayed changes are insignificant between the scenarios.

The performance evaluation in Tables 4–6 demonstrates how Mobile nodes affect the function of MANET systems. Table 4 demonstrates that network delay extends as the total number of nodes expands which generates maximum delay in Scenario 3 containing 15 nodes per office. The network load exhibits an essential rise according to Table 5 especially in Scenario 3 when traffic reaches above 300,000 bits/sec. Table 6 presents evidence through its proportional data which demonstrates that increased node density creates more data exchange opportunities. Results from ANOVA analysis demonstrate both statistically significant differences between the scenarios for load and traffic reception while showing no significant effect on delay measurements.

Table 4. Delay (sec) Comparison of the Three Scenarios

Time (sec)	Delay (sec)	Delay (sec)	Delay (sec)
0	0.0000434	0.0000434	0.0000430
600	0.0007069	0.0008114	0.001046
1200	0.0007221	0.0008473	0.001103
1800	0.0007835	0.0008345	0.001123
2400	0.0007868	0.0008437	0.001133
3000	0.0007858	0.0008538	0.001140
3600	0.0007868	0.0008626	0.001143

Table 5. Load (bits/sec) Comparison of the Three Scenarios

Time (sec)	Load (bits/sec)	Load (bits/sec)	Load (bits/sec)
0	0,000.00	0,000.00	0,000.00
000	13,757.33	35,556.05	339,607.30
1200	12,853.89	32,023.85	356,609.88
1800	13,657.47	29,428.76	373,383.48
2400	12,717.48	28,898.09	374,300.83
3000	12,703.74	27,452.31	374,778.19
3600	12,706.74	27,778.31	381,272.00

Table 6. Traffic Received (bits/sec) Comparison of the Three Scenarios

Time (sec)	Traffic Received (bits/sec)	Traffic Received (bits/sec)	Traffic Received (bits/sec)
0	0,000.00	0,048.00	0,048.00
600	15,179.46	34,551.80	342,753.68
1200	13,705.71	34,494.30	356,734.83
1800	12,961.71	30,339.42	365,781.88
2400	13,729.71	29,711.77	370,017.36
3000	13,523.82	28,531.80	370,508.78
3600	13,521.24	28,412.05	374,233.64

The measured delay times between scenarios did not statistically differ (Table 4, Figure 4) based on ANOVA results which show F = 1.5898, p = 0.2313 therefore confirming that node count has little impact on latency. However, the analysis reveals important variations in network load (Table 5, Figure 5) and traffic received (Table 6, Figure 6). Network congestion and throughput performances are heavily influenced by both load levels (F = 31.3409, p = 1.37e-06) and traffic reception levels (F = 31.2861, p = 1.39e-06) according to the significant F-statistics values. The results show that network congestion together with increased traffic reception depends on node density but delay stays consistent. This suggests why dense MANET networks could experience potential congestion problems. According to the Table 7, the network performance remains efficient because of low traffic between 5-8 nodes which results in minimal network congestions. Network performance remains efficient because the average network load measures 15,000 bps together with media access delay totalling 0.0021 seconds. When the traffic reaches moderate levels with 9 to 12 nodes the system load reaches 100,000 bps while the media access delay amounts to 0.0154 seconds. The network performance does suffer slight effects despite moderate congestion present at this time. With 13-15 active nodes in the system, network load reaches 450,000 bps resulting in a 0.0823-second delay and considerable congestion that produces packet delays together with retransmissions. Performance degradation becomes necessary because network load and delay and congestion increase when more nodes are present. A summarized Table 7 therefore presents the scenario data by calculating average network data at different node densities, and the results confirm the requirement to develop congestion prediction models because traffic congestion grows with rising node density and increased load.

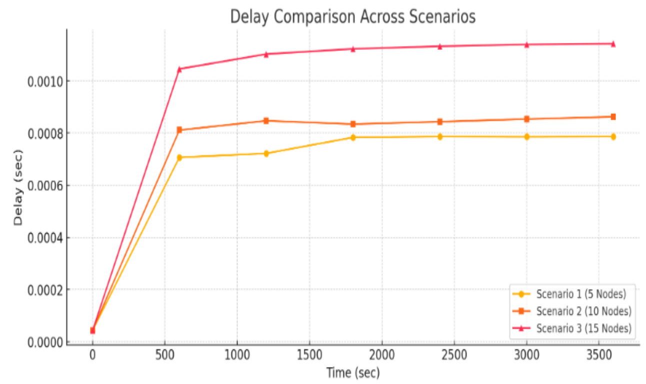

Figure 4. Delay Comparison across Scenarios

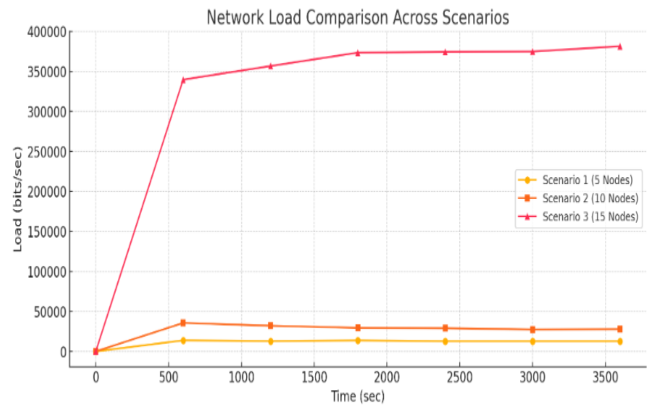

Figure 5. Network load Comparison across Scenarios

Figure 6. Traffic Received Comparison across Scenarios

Table7. Screened Parameters with Corresponding Nodes and their Obtained Values

Scenarios	Nodes	Avg. Network Load (bps)	Avg. Media Access Delay (s)	Congestion Level
Low Traffic	5-8	15,000	0.0021	Low
Moderate Traffic	9-12	100,000	0.0154	Moderate
High Traffic	13-15	450,000	0.0823	High

The results confirm the requirement to develop congestion prediction models because traffic congestion grows with rising node density and increased load.

4.2 Results of ML Model Performance

The examined machine learning models achieved top-level accuracy for classifying network congestion levels throughout the study period. Support Vector Machine (SVM) delivered perfect classification results which are verified through its confusion matrix shown in Figure 7. The model successfully determined all non-congested and congested cases thus showing an unequaled capability to distinguish between categories without creating any classification mistakes.

An examination of the network traffic parameter correlation showed pronounced linear interconnections in Figure 7b. The correlation between network load and traffic received showed a coefficient value of 0.99 indicating an almost perfect direct relationship. These two parameters demonstrate a high level of connection that establishes their status as essential elements for predicting network congestion because they hold significant influence on classification feature selection.

Testing each of SVM, XGBoost, KNN and ANN led to perfect results in evaluating key performance metrics. The analysis in Table 8 showed that all models produced a perfect combination of accuracy, precision, recall and F1-score, ROC-AUC reaching a value of 1.0. The separation quality within the data allows for easy pattern distinction because both errors and noise remain minimal between classes in this straightforward learning environment.

The Figure 8 display the feature correlational matrix that might restrict these models from achieving practical deployment success, due to several data overlapping as a results of interrelated parameters due to load, traffic and congestion. Future systems will add the inclusion of Vehicular Ad Hoc Networks (VANETs) and real-time urban traffic flow data to datasets to enhance robustness since they contain unstable yet diverse conditions and unpredictable network behaviours.

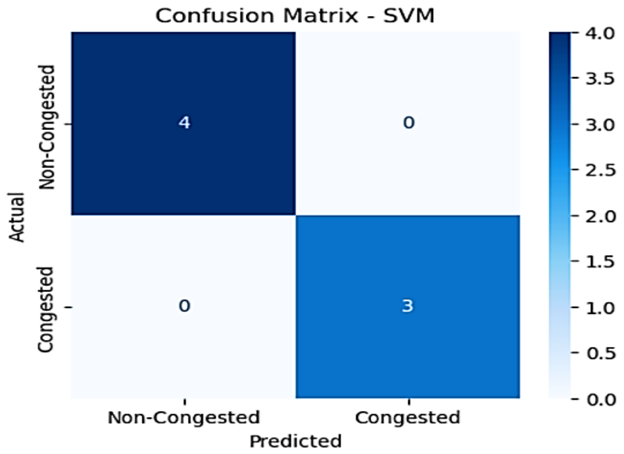

Figure 7. Confussion Matrix for the SVM

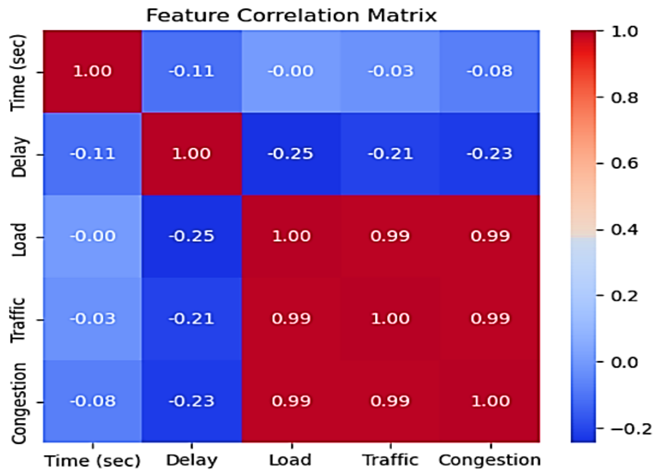

Figure 8. Feature Correlation Matrix

Table 8. Accuracy, Precision, Recall, F1-Score and ROC-AUC Results for SVM, KNN, XGBoost and ANN

	Accuracy	Precision	Recall	F1-Score	ROC-AUC
SVM	1.0	1.0	1.0	1.0	1.0
KNN	1.0	1.0	1.0	1.0	1.0
XGBoost	1.0	1.0	1.0	1.0	1.0
ANN	1.0	1.0	1.0	1.0	1.0

4.3 ML-Based Congestion Mitigation Strategy

The process of detecting network traffic patterns in real-time requires Machine Learning-based congestion control models because they enable effective congestive control under dynamic situations. Predictive analytics model was used to carry out real-life evaluation on the network status for the required proactive action by the organization to eliminate any danger of network congestion. The monitoring process requires continuous assessment of essential performance metrics that includes tracking of traffic volume measurements next to point-to-point transmission delays and early indications of congestion formation. Several Machine Learning models consisting of Support Vector Machine (SVM) along with K-Nearest Neighbors (KNN) joined by XGBoost and Artificial Neural Networks (ANN) underwent training utilizing past congestion dataset records. All evaluation metrics showed perfect scores for the different models which achieved 1.0 values in accuracy, precision, recall, F1-score as well as ROC-AUC according to Table 8. The confusion matrix from SVM (Figure 7) shows complete accuracy in distinguishing both congested and non-congested cases while reporting no false positive or false negative results. The network feature correlation matrix Figure 8 shows received traffic has an exceptionally high correlation coefficient value of 0.99 with traffic load. These features exhibit an almost perfect correlation that helps ML-based decision systems function better for congestion prediction purposes. Figure 9 shows the impact of ML-Based Congestion Control and Traditional Routing on latency between 95-101 milliseconds when applied to ten-time intervals. Traditional routing maintains steady yet high latency measurements which oscillate within 95 ms to 101 ms bounds during the whole simulation period. During ten-time intervals ML-based congestion control shows a continuous decrease in latency which descends from its initial 90 ms to reach 58 ms during the last period.

The use of ML-based congestion control approaches leads to an adaptive 32-millisecond latency reduction. Real-time congestion pattern detection abilities of the system lead to its automatic adjustment of routing paths as well as load balancing procedures. The neural system provides adaptive routing functions that reduce waiting times while using available bandwidth capacity to achieve higher data transmission speed as well as improved quality of delivery. These experimental findings confirm the ability of automatic network-condition evaluation enabled by machine learning (ML) systems that self-tune their congestion response mechanisms. Mobile Ad Hoc Networks (MANETs) along with Vehicular Ad Hoc Networks (VANETs) need responsive congestion management because their traffic patterns exhibit unexpected and fluctuating characteristics. Noise, volatility and irregularities of traffic the real-world network faced developed series of dynamic changes where conventional ML triumphed at processing within the measurable and controllable conditions, having unambiguous inputs. The future research agenda should include development of Reinforcement Learning (RL) approaches for addition to congestion management systems. Online decision systems in RL allow computers to self-optimize and scale across fluctuating environments which helps maintain network stability within unpredictable condition patterns.

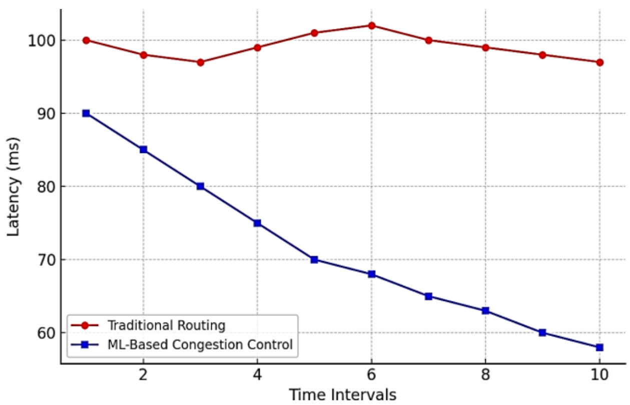

Figure 9. Latency Reduction with ML-based Congestion Model

5. Conclusion and Future Scope

The team accomplished successful results in their research regarding ML-based congestion management techniques for MANETs through detailed simulations conducted within OPNET under different network scenarios. Support Vector Machines (SVM), K-Nearest Neighbours (KNN) and XGBoost together with Artificial Neural Networks (ANN) proved effective through their implementation for accurate congestion detection according to this study. The evaluation showed total accuracy for congestion prediction which used the network operational metrics of delay, reception rate and traffic load as key indicators. The analysed results allowed for immediate bandwidth allocation decisions combined with automatic traffic route adjustment and better adaptable Quality of Service capabilities. Through implementation of ML models, the network performance improved because they supported both efficient resource allocation and proactive network traffic management to avoid bottlenecks. This study demonstrates a dependable method to manage network congestion which shows how ML techniques can enhance the reliability and operational efficiency of MANETs over different operating conditions.

The forthcoming research will improve both the robustness and general applicability of developed models by adding actual MANET traffic patterns to the existing dataset. The updated system will effectively represent the unpredictable characteristics that exist within operational network settings. The work will investigate Reinforcement Learning (RL)-based adaptive congestion control mechanisms combined with their implementation. Additionally, the research team plans to conduct testbed implementation and practical validation through edge computing platforms. The researchers aim to implement low-latency decentralized decision capabilities within large dynamic MANET settings to make their work applicable for mission-critical areas including disaster response together with military operations and vehicular communication systems.

Conflict of Interest: No any conflict of interest or whatsoever.

Funding Source: None

Authors' Contributions

Author-1. The researcher created their research concept when they performed extensive problem formulation and thereafter setup introduction section, related works study and network scenario development using OPNET simulators to get congestion data in Mobile Ad hoc Networks.

Author-2. The researcher jointly worked for problem formulation, setting up the introduction and good literature review, and thereafter, preprocessed OPNET simulation-generated datasets which allowed them to predict congestion levels in Mobile Ad hoc networks through machine learning applications, and perform real-life deployment of ML congestion model.

Acknowledgements
The authors demonstrate their deep appreciation to Dr. M. A. Akinde (FCA, ACTI) who leads Nigeria's premier polytechnic together with his dedicated team of administrators for creating favorable research conditions which permitted the successful completion of this study. The authors are grateful to both the faculty and entire staff team of Computer Engineering at the Federal Polytechnic Ilaro, Ogun State, Nigeria who dedicated their support throughout this project.

References

[1] I. F. Akyildiz, J. Xie, and S. Mohanty, "A survey of mobility management in next-generation all-IP-based wireless systems," *IEEE Wireless Communications*, vol. 9, no. 4, pp. 16–28, 2002.
[2] C. E. Perkins and E. M. Royer, "Ad hoc on-demand distance vector routing," *Proc. 2nd IEEE Workshop on Mobile Computing Systems and Applications*, pp. 90–100, 1999.
[3] S. Tang and Y. Yang, "Machine learning-based congestion control for wireless ad-hoc networks," *IEEE Transactions on Wireless Communications*, vol. 19, no. 7, pp. 4635–4647, 2020.
[4] R. Smith and P. Kumar, "Machine learning for MANET performance optimization: A survey," *IEEE Transactions on Wireless Communications*, vol. 22, no. 4, pp. 987–1001, 2023.
[5] H. Wang and J. Li, "Evaluating routing protocols in MANETs using OPNET," *Wireless Communications and Mobile Computing*, vol. 2022, pp. 1–12, 2022.
[6] S. Ahmed and M. Khan, "VoIP performance in MANETs: An OPNET-based analysis," *Journal of Computer Networks*, vol. 19, no. 2, pp. 456–469, 2021.
[7] O.J. Adaramola and T.A. Paul, "Modelling and assessment of the star network topology using OPNET simulation techniques", *International Journal of Scientific Research in Computer Science and Engineering*, vol.11, no.1, pp. 14-22, 2023.
[8] O.J. Adaramola and J.R. Olasina, "Modelling of heterogeneous WLAN based on traffic application", *International Journal of Scientific Research in Computer Science and Engineering*, vol.8, no.3, pp. 34-38, 2020.
[9] D. Patel and R. Shah, "Security challenges in MANETs: A review of attack detection mechanisms," *Journal of Cybersecurity Research*, vol. 8, no. 3, pp. 155–170, 2020.
[10] X. Chen and Y. Zhou, "An artificial neural network model for MANET congestion prediction," *Machine Learning in Mobile Networks*, vol. 10, no. 1, pp. 45–63, 2024.
[11] L. Zhao and M. Sun, "Reinforcement learning for dynamic routing in mobile ad hoc networks," *IEEE Access*, vol. 11, pp. 32098–32110, 2023.
[12] A. Gupta and R. Sharma, "Hybrid ML model for congestion detection in MANETs," *Neural Computing and Applications*, vol. 34, no. 5, pp. 10234–10250, 2022.
[13] J. Park and D. Kim, "CNN-based congestion prediction for wireless networks," *Journal of Machine Learning Applications*, vol. 9, no. 3, pp. 778–789, 2021.
[14] H. Lee and S. Choi, "LSTM for traffic prediction in MANETs," *Neural Networks and Wireless Communication*, vol. 15, no. 2, pp. 234–245, 2020.
[15] S. Willium, "Computer Sciences," *International Journal of Scientific Research in Computer Science and Engineering*, vol. 31. Issue.4, pp.123-141, 2012.

AUTHORS PROFILE

Ojo. J. Adaramola earned both his Master of Science in Computer Systems and Network Engineering from the University of Greenwich in London (2016) and Master of Science in Electronics and Computer Engineering from Lagos State University (2018) before finishing his Bachelor of Engineering in Computer Engineering from Federal University Oye-Ekiti in 2023. The year 2023 became significant when he received his Bachelor of Engineering degree in Computer Engineering from Federal University Oye-Ekiti. The researcher currently combines the roles of Senior Lecturer with the position of Head of Computer Engineering Department at Federal Polytechnic Ilaro in Ogun State Nigeria. As a member of professional groups, the researcher uses their time to explore studies in vehicular ad hoc networks and ZigBee technology and wireless communication and routing protocols for computer networking as well as network security.

JAMIU R. OLASINA received National Diploma (ND) in Computer Engineering from the Federal Polytechnic Ilaro, Nigeria, the B.Eng. in Electrical and Computer Engineering from the Federal University of Technology, Minna, Nigeria, and M.Eng. in Computer Engineering from the Covenant University Ota, Nigeria.
Olasina is a research assistant and affiliated to the Advanced Signal Processing and Machine Intelligence Research (ASPMIR) Lab. Covenant University, Ota, Nigeria, under Prof. Emmanuel Adetiba. He is the author of two books, more than 20 journal articles, and he has attended more than 50 workshops and conferences with papers presented. He is a member of the following professional bodies: Council for the Regulation of Engineering in Nigeria (COREN), Nigerian Institution of Professional Engineers and Scientists (NIPES), Society of Digital Information and Wireless Communication (SDIWC), and International Association of Engineers (IAENG).
His research interest includes Wireless Communication, Signal Processing, Software Defined Radios, Classification Algorithms, Machine Learning and Deep Learning, Federated Learning, Embedded System, and IoT. He has skills in C and C++, Python and associated libraries, Matlab, etc. His current research is in ML Algorithms and New Trend in Wireless Communication and Networks.

