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Intelligent Traffic Congestion Control in MANETs: A Comparative Analysis of Neuro-Fuzzy and Metaheuristic-Enhanced Routing Strategies

[1]Adepoju A. O., [2]Oyediran M. O., [3]Ojo O. S., [4]Makinde O. E. and [5]Ipeayeda F. W.

[1]Department of Computer Science, D.S Adegbenro ICT Polytechnic, Itori, Ogun State, Nigeria
[2,3,4,5]Department of Computer Science, Ajayi Crowther University, Oyo State, Nigeria
[1]adepoju.abiodun@dsadegbenropoly.edu.ng, [2]mo.oyediran@acu.edu.ng, [3]os.ojo@acu.edu.ng

Abstract
Mobile Ad Hoc Networks (MANETs) are well known to suffer from congestion due to their decentralized architecture, variable topology, and limited resource availability. The conventional shortest-path routing protocols were typically found to be the least efficient for packet delivery, and caused a slower latency when a great deal of traffic is occurring due to the fact that they have basically just used hop count in deciding on routing without taking into account the current state of the network. Although Adaptive Neuro-Fuzzy Inference Systems (ANFIS) are used to predict congestion and improve routing strategies, it is still reliant on how membership function parameters are set. We compare three different routing methods in this study: the Shortest Path First (SPF) baseline model, the conventional ANFIS, and an advanced form of ANFIS with the Firefly Algorithm (Firefly-ANFIS) designed for congestion control in MANETs. We build a simulation environment in MATLAB with 25 mobile nodes, measured with a dataset of traffic records of 1,200 instances. Assessment metrics were congestion index, packet success rate, end-to-end latency and hop count as well as traffic overhead statistics and transmission time. The findings show that Firefly-ANFIS led to better results on all metrics, including the lowest average congestion index (0.043), minimal average end-to-end latency (0.1040 s), an average hop count as low as 2.45, and the lowest traffic overhead compared to SPF baseline and standard ANFIS models. Despite a significantly improved packet success rate of 92.76% with standard ANFIS, it was also faced with increased worst-case latencies associated with unnecessary route detours in bursty conditions. Firefly techniques provided significant mitigation through optimized tuning processes for membership function parameters, allowing for more standardized routing choices to be delivered to all member routing types. The conclusions of the present study show that combining metaheuristic optimization methods with neuro-fuzzy methods for predicting congestion can provide a better balance between reliability gains and latency reduction using dynamically influenced systems typical of MANETs.

***Keywords*:** Mobile Ad Hoc Networks (MANETs), Congestion Control, Adaptive Neuro-Fuzzy Inference System (ANFIS), Firefly Algorithm, Metaheuristic Optimization, Intelligent Routing

1. Introduction

Mobile Ad Hoc Networks (MANETs) are mobile ad hoc wireless networks that enable communication between mobile devices without the need for fixed infrastructure or centralized management. They have the ability to establish connections rapidly within fluctuating environments, and so cater to a wide range of applications, from disaster recovery, military and emergency responses, intelligent transportation and Internet of Things (IoT) deployments. In these scenarios nodes not only serve as hosts and routers, but also transmit packets via multi-hop methods while dynamically responding to ongoing topology changes, owing to node mobility. Nonetheless, despite these adaptable strategies, MANETs also encounter the serious concerns of congestion in the network. Routine changes in topology, together with limited wireless bandwidth and shared communication channels, can create traffic loads that fluctuate, causing packet collisions, queue overflows, increased transmission delays and lost packets.

These issues reduce the network performance overall and degrade the reliability of

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communication – especially at times of heavy or bursty traffic. Traditional routing protocols such as those established by Shortest Path First (SPF) operate in a manner where routing decisions are made based upon minimum hop count, with little regard for current congestion levels on intermediate nodes. Therefore, network congestion is exacerbated by use of congested paths continually, thus causing congestion problems and a decrease in service quality.

Traditional and novel routing techniques that utilize network state data are available to address these challenges. Of note, the Adaptive Neuro-Fuzzy Inference System (ANFIS) is one of the most popular approaches that leverage the learning attributes of artificial neural networks while synthesizing the inference ability of fuzzy logic. ANFIS analyzes data like queue length, packet arrival rates, packet forwarding rates, end-to-end delays, as well as packet loss ratios, helping in congestion forecasting. This allows for proactive rather than reactive routing choices. However, the performance of ANFIS depends largely on how its membership functions are configured. Classical hybrid-learning approaches concentrate on tuning these parameters to reduce the predictive errors, but it does not always imply that routing decisions minimize latency and alleviate congestion in fast-evolving traffic patterns.

A metaheuristic optimization is very good for intelligent routing models, because it improves smart routing models by adjusting internal parameters of them so as to fine-tune their parameters. Firefly Algorithm (FA) — inspired by the flashing behavior of fireflies — has demonstrated the ability to perform extensive global search, rapid convergence and robustness, achieving high throughput for nonlinear optimization problems. The Firefly Algorithm can improve membership function settings, predict congestion more accurately and provide more reliable routing decisions while ensuring less computational demands when integrated with Adaptive Neuro-Fuzzy Inference System (ANFIS). Although previous works have studied congestion-aware routing through fuzzy logic, ANFIS frameworks as well as a host of other metaheuristic strategies, the number of exhaustive comparisons between classical Shortest Path First (SPF) routing approaches, conventional ANFIS and FA-enhanced ANFIS implemented in the same simulation environments and using the same sets of data and evaluation conditions is limited.

Moreover, the influence of enhanced membership functions on latency effects and on optimization of congestion dynamics on routing effectiveness in MANET systems in a dynamic manner has been insufficiently investigated. This work attempts to fill the gap through the development and evaluation of a Firefly-ANFIS framework for smart congestion behavior in MANETs. The methodology is applied in MATLAB in a controlled simulation environment, consisting of 25 mobile nodes and 1,200 labeled traffic instances. It is evaluated on metrics including congestion index score, packet success rate, end-to-end latency, hop count, traffic overhead, transmission duration and comparison of the performance against ordinary SPF algorithms and conventional ANFIS model.

The major contributions of this study are as follows:

1. A comparative evaluation of conventional SPF routing, standard ANFIS, and Firefly-ANFIS under identical MANET simulation conditions.
2. The development of a Firefly-based optimization framework for tuning ANFIS membership function parameters to improve congestion-aware routing.
3. A comprehensive performance assessment using multiple network quality metrics, including congestion index, packet success rate, latency, hop count, traffic overhead, and transmission time.
4. An analysis of how metaheuristic optimization improves routing stability and overall network performance in dynamic MANET environments.

The subsequent sections of this paper are structured as follows: Section 2 discusses the current literature on congestion control, intelligent routing, and metaheuristic optimization in Mobile Ad Hoc Networks (MANETs). The methodology is presented in Section 3, which describes the simulation environment, the ANFIS configuration, the Firefly optimization process, and performance evaluation metrics. Section 4 demonstrates experimental results and analyzes the effectiveness of the routing models under review. Finally, Section 5 concludes with a summary of key points and suggests avenues for future research endeavors.

2. Related Works

2.1 Congestion Control in Mobile Ad Hoc Networks

Mobile Ad Hoc Networks (MANETs) are operating without any centralized framework, which increases routing and congestion overhead because of node mobility, shared wireless communications, and rapidly changing network structures. As the volume of traffic increases, congestive activity causes congestion issues that include packet collisions, queue overflow, retransmission requirement, increasing latency, and efficiency degradation of packet delivery process. Standard routing methods—such as Shortest Path First (SPF), Destination-Sequenced Distance Vector (DSDV), Ad hoc On-Demand Distance Vector (AODV), and Dynamic Source Routing (DSR)—based on the shortest distance or fewest hops, fail to consider the actual congestion status of communication intermediary nodes [1], [2]. This omission frequently causes traffic to be carried along the same path which then forms an issue with congestion hotspots and bad network performance during peak use periods.

MANET efficiency, for a variety of reasons, is an under-explored area for investigation, but there are some studies that have suggested congestion-informed route routing. For example, Lee and Gerla [3] introduced dynamic load-aware routing to the distribution network traffic among a variety of available pathways. Meanwhile, Lochert et al. [4] discussed a number of approaches to reducing congestion within MANETs; they showed that the incorporation of network-level information on actual conditions significantly enhances operational effectiveness in route selection.

However, a lot of the old ways of doing it are reactive to problems, and we do it to solve problems and not anticipate the potential congestion prior to it.

2.2 Intelligent Congestion Prediction Using ANFIS

Applied Artificial Intelligence techniques are increasingly used to improve congestion forecasting and routing functions in mobile ad hoc networks (MANETs). One such approach is the Adaptive Neuro-Fuzzy Inference System (ANFIS), which has received great interest owing to its incorporation of the adaptive learning abilities exhibited by artificial neural networks together with the ability of fuzzy inference systems to accommodate uncertainty. Because it considers different network parameters in parallel, ANFIS gives more accurate congestion estimates than the single-metric-based routing approach. Previous research has shown that fuzzy logic and ANFIS are both effective in improving routing. For instance,

Doja et al. [5] employed fuzzy inference to determine routing in MANETs, while Garg et al. [6] implemented fuzzy rule-based methodologies aimed at boosting routing reliability amid fluctuating network conditions. Additionally, Moudni et al. [7] demonstrated how intelligent networks informed by fuzziness can be harnessed to support adaptive decision-making in mobile ad hoc settings. More recently, Ali and Vadivel [8] proposed a novel adaptive neuro-fuzzy framework to more accurately predict different network scenarios. Although it plays an important role in the prediction of congestion-induced packet traffic and the effective packet delivery, the overall performance of the ANFIS on the routing depends significantly on how membership function parameters are chosen.

Most existing implementations are based on classical hybrid and fuzzy learning methods for prediction error reduction which do not specifically optimize the key routing objectives like reducing the latency, congestion burden of forwarding traffic or balancing the load over nodes. Therefore, increases in prediction accuracy are not necessarily associated with greater routing efficiency in general.

2.3 Metaheuristic Optimization for Intelligent Routing

Metaheuristic optimization methods have been widely used to optimize intelligent systems by tuning some of their internal parameters. Key approaches such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Firefly Algorithm (FA) have shown success in solving nonlinear optimization problems with many conflicting goals. Of these methods, Firefly Algorithm attracted considerable interest because of its simplicity, efficient navigation through many complex search spaces, as well as its ability to avoid premature convergence. Yang [9] introduced Firefly Algorithm as a population-based optimization technique mimicking the attraction behavior of flashing fireflies. Since its debut, studies have demonstrated its utility for tuning parameters for neural networks and fuzzy systems [10].

In works on Mobile Ad Hoc Networks (MANETs), optimizations based on Firefly method showed that network performance had enhanced in studies performed with a focus on the Firefly approach: Sekar et al. [11] found that fireflies optimized routing increases the stability and throughput, whereas Devadas et al. [12] demonstrated that a fuzzy packet scheduler which is improved using firefly methods enhances packet delivery rates while reducing delays. Additionally, Zhang et al. [13] demonstrated that on high-dimensional problems, Firefly Algorithm achieves more consistent convergence than competing metaheuristic strategies, e.g., particle swarm optimization and differential evolution. Unlike GA and PSO, the Firefly Algorithm balances global exploration and local exploitation in a competitive way; it is ideally suited for the design of ANFIS membership functions. Its motion mechanism of attraction supports high-quality solutions while always maintaining parameter values, ensuring steady convergence states as well as lowering the chance of getting lost in small local optima.

2.4 Research Gap

The literature reviewed describes a number of substantial developments in congestion-aware routing as accomplished via fuzzy logic, neuro-fuzzy systems, and metaheuristic optimization algorithms. Conventional routing techniques are very able to compute efficient shortest paths, but they are prone to congestion because their prediction of traffic status is not accurate. Although approaches that leverage ANFIS offer novel approaches for congestion prediction and routing adaptability, such methods most often rely on conventionally adapted membership function parameters as opposed to optimized implementations for superior routing performance. Furthermore, there are many works on the use of metaheuristic algorithms in smart systems but Firefly parameter optimization and ANFIS based methods focusing on congestion aware routing for Mobile Ad Hoc Networks (MANETs) did not have a high correlation with one another.

In addition, most existing works are mainly concerned with prediction accuracy or packet delivery performance without any deep exploration of the effects of parameter optimization in congestion dynamics, latency, traffic distribution patterns, routing stability and network efficiency. Also, the comparative research that deals with the conventional Shortest Path First (SPF) routing method as well as the standard ANFIS methods relative to the Firefly-optimized ANFIS in uniform simulated environment is also limited. To address these issues highlighted above in previous works, this paper proposes a Firefly-ANFIS-routing protocol featuring metaheuristic optimization and prediction of congestion by neuro-fuzzy. It will also perform a thorough network performance analysis for conventional SPF routes vs standard ANFIS. The goal is to see if optimizing the parameters associated with ANFIS can improves control over congestion without jeopardizing packet delivery in dynamic MANET conditions.

3. Methodology

3.1 Research Framework

This study adopted a simulation-based experimental approach to evaluate the effectiveness of intelligent congestion control techniques in Mobile Ad Hoc Networks (MANETs). Three routing models were implemented and compared under identical network conditions:

- **Shortest Path First (SPF):** A conventional routing algorithm that selects routes based solely on minimum hop count.
- **Adaptive Neuro-Fuzzy Inference System (ANFIS):** A congestion-aware routing model that predicts network congestion using multiple traffic parameters.
- **Firefly-ANFIS:** The proposed model, in which the Firefly Algorithm optimizes the ANFIS membership function parameters before deployment.

Each routing model was evaluated using the same network topology, traffic pattern, mobility model, and simulation parameters to ensure a fair comparison. Performance was assessed using congestion index, packet success rate, end-to-end latency, hop count, traffic overhead, and transmission time. The overall research process consisted of dataset generation, ANFIS model training, Firefly-based parameter optimization, routing implementation, and comparative performance evaluation.

3.2 Simulation Environment

The proposed framework was implemented in MATLAB using a custom MANET simulator developed for congestion analysis. A network of twenty-five mobile nodes was randomly deployed within a 500 m × 500 m simulation area using the Random Waypoint mobility model. Each simulation lasted 100 seconds, during which nodes continuously generated and forwarded packets while changing positions dynamically. The major simulation parameters are summarized in Table 1.

Table 1. Simulation Parameters

Parameter	Value
Simulation Platform	MATLAB
Number of Nodes	25
Simulation Area	500 × 500 m
Simulation Time	100 s
Mobility Model	Random Waypoint
Maximum Node Speed	10 m/s
Communication Range	150 m
Packet Size	512 Bytes
Packet Generation Rate	15 packets/s
Queue Size	5 packets
Link Bandwidth	1 Mbps

To evaluate congestion under realistic network conditions, bursty traffic was introduced using a burst probability of 0.3 with selected hotspot nodes experiencing traffic rates five times higher than the normal packet generation rate. These conditions emulate traffic concentration commonly observed during emergency communication, disaster recovery, and tactical MANET deployments.

3.3 Dataset Preparation

A dataset containing 1,200 network observations was generated from repeated MANET simulations. Each observation represented the instantaneous state of the network and consisted of five input variables describing traffic conditions together with a congestion index representing the expected congestion level.

The input variables were:

- Queue Length (packets)
- Packet Arrival Rate (packets/s)
- Packet Forwarding Rate (packets/s)
- End-to-End Delay (ms)
- Packet Loss Rate (%)

The target output was the Congestion Index, which served as the supervisory signal during ANFIS training. The generated dataset included normal, moderate, and heavy congestion scenarios to improve the generalization capability of the trained model.

3.4 ANFIS Model Design

Our Adaptive Neuro–Fuzzy Inference System (ANFIS) is a framework to predict the congestion level according to the five network parameters discussed in Section 3.3. Due to their smooth nonlinear nature and efficiency for continuous optimization, Gaussian membership functions were employed to represent linguistic variables. ANFIS is arranged into five layers for fuzzification, rule assessment, normalization, calculation of consequences, and aggregation of outputs. In the training of the model, a hybrid learning method, including least squares estimation with gradient descent, was leveraged to estimate both antecedent and consequent parameters. Once the model training was finished, the ANFIS model generated a congestion index for each one of the routing options. During packet dispatch, routes thought to experience low congestion levels were ranked first.

3.5 Firefly Algorithm Optimization

The Firefly Algorithm was used to update the membership function parameters in the ANFIS model to improve the routing efficiency of the ANFIS model. In this method, every firefly represented one parameter set to serve as future potential points for the ANFIS model, and an objective function evaluated routing quality based on congestion prediction accuracy and overall network performance. The population of fireflies underwent iterative evolution through movement driven by attraction based on solution quality. Better-lit fireflies attracted adjacent solutions, leading to a convergence towards parameter pairings that reduced congestion but guaranteed sufficient packet delivery. Unlike traditional training of the ANFIS algorithm, which focuses on prediction accuracy (reducing errors related to prediction), Firefly optimization treated multiple routing objectives in parallel. The latter yielded advances in congestion tolerance, latency reduction, and more predictable routing.

3.6 Routing Model Implementation

The same simulation scenarios were used to validate three routing models.

- The first model adopts the conventional Shortest Path First routing model which reduces hop count purely for minimizing hop count, ignoring congestion.
- The second model included a trained ANFIS predictor in the routing framework. All potential routes were analyzed for congestion based on the predicted congestion index before packet forwarding to enable avoidance of congested routes proactively.
- The third model uses a Firefly-optimized version of the existing ANFIS predictor instead.

All routing choices adopted the same approach used in the conventional ANFIS implementation (beyond improved membership parameters), but the performance gains are entirely due to optimal performance parameters.

3.7 Performance Evaluation Metrics

The performance of the three routing models was evaluated using seven quantitative metrics commonly employed in MANET performance analysis.

- **Congestion Index (CI):** Measures the overall congestion level of the network. Lower values indicate better congestion control.
- **Packet Success Rate (PSR):** Percentage of generated packets successfully delivered to their destinations.
- **Average End-to-End Latency:** Average time required for a packet to travel from source to destination.
- **Maximum Latency:** Longest observed packet transmission delay during the simulation.
- **Average Hop Count:** Average number of intermediate nodes traversed by successfully delivered packets.
- **Traffic Overhead:** Total number of retransmitted packets and routing control messages generated during communication.
- **Transmission Time:** Total time required to complete packet transmission for each simulation scenario.

To verify the consistency of the obtained results, five independent simulation trials were conducted using different random seeds while maintaining identical simulation parameters. Statistical significance was evaluated using paired t-tests, while effect sizes were computed using Cohen's *d* to determine the practical significance of the observed performance differences.

4. Results and Discussion

4.1 Comparative Performance of the Routing Models

The performance of the three routing approaches—Shortest Path First (SPF), standard ANFIS, and Firefly-ANFIS—was evaluated under identical simulation conditions using the performance metrics described in Section 3.7. Table 2 summarizes the average results obtained from the simulation experiments.

Table 2. Overall Performance Comparison of the Evaluated Routing Models

Metric	Baseline (SPF)	ANFIS	Firefly-ANFIS
Simulation Time (s)	38.81	24.62	30.41
Success Rate (%)	85.13	92.76	92.16
Avg. Latency (s)	0.2046	0.1590	0.1040
Max Latency (s)	0.8497	0.9517	0.4071
Latency σ (s)	0.1583	0.1433	0.0799
Avg. Hops	2.75	2.96	2.45
Overhead (pkts, total)	62	21	24
Avg. Congestion Index (CI)	0.6400	0.0470	0.0430

The results expose great differences in efficiency among the three routing schemes. The traditional SPF algorithm had the highest congestion index and the least success rate of every packet because it chose which route to route only for the minimization of number of hops without considering the current network condition. Consequently heavily used routes were congested, causing more packet loss and also delays in transmission. In comparison, the Standard ANFIS improved network efficiency very significantly by predicting congestion before routing was taken. There was a significant decrease in congestion and improvement in packet delivery reliability in comparison to the SPF baseline. However, despite achieving higher packet-to-packet success rates at times, ANFIS sometimes provided longer alternate paths to bypass congested links which can lead to worst-case latency. The Firefly-ANFIS model proposed here achieved the best overall performance on all assessed metrics. It reached the lowest congestion index and mean end-to-end latency, while keeping hop count low and driving significant traffic overhead down; its packet success rate was still competitive with that of classical ANFIS. These statistics suggest that adjustment of ANFIS membership function parameters may produce more efficient routing strategies without causing delivery reliability degradation.

4.2 Congestion Analysis

Figure 1 illustrates the average congestion index produced by each routing model.

In comparison, the congestion index of the SPF model is highest because traffic always accumulates over the shortest path(s) available to it. When no way to predict future state of congestion was built to predict traffic situation or condition, routing decisions remained static in respect of traffic in any given situation. In contrast, the ANFIS model effectively obviated congestion by foreseeing network state ahead of packet transmission. Rather than deciding routes from just hop count, it analyzed several traffic metrics in parallel, allowing for the preventive avoidance of congested connections. The Firefly-ANFIS model displayed the lowest congestion index among all the methods evaluated. It improved the prediction accuracy on congestion levels while improving traffic distribution across nodes during the simulation period.

4.3 Packet Delivery Performance

Reliable packet delivery is an essential requirement for MANET applications operating in dynamic environments. Figure 2 compares the packet success rates of the three routing models.

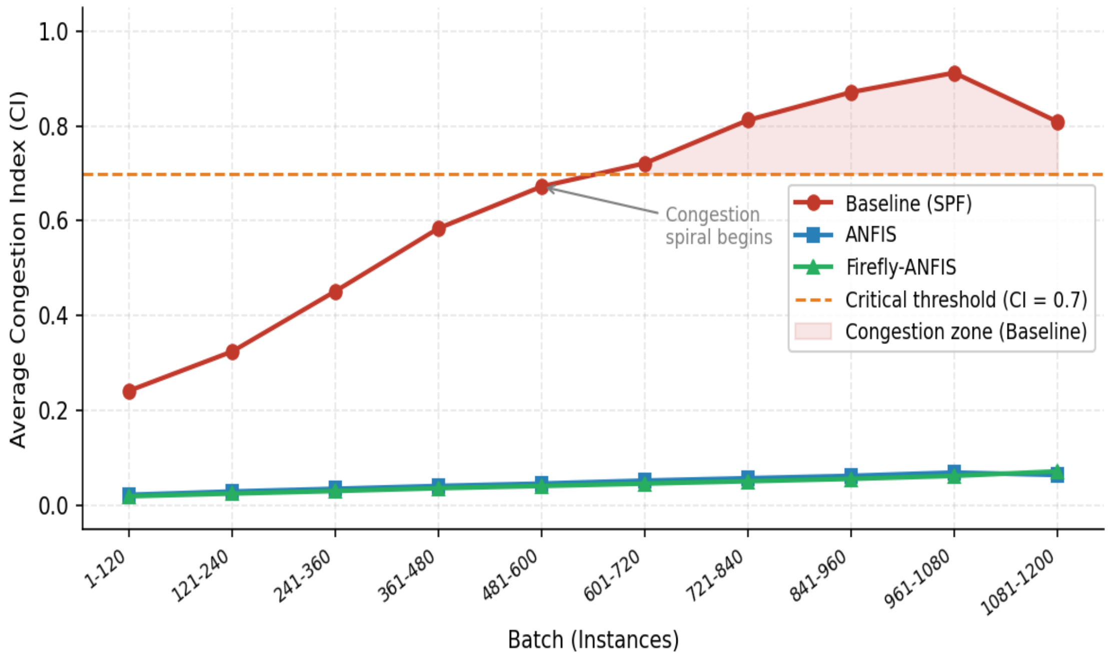


Figure 1. Average Congestion Index of the Evaluated Routing Models

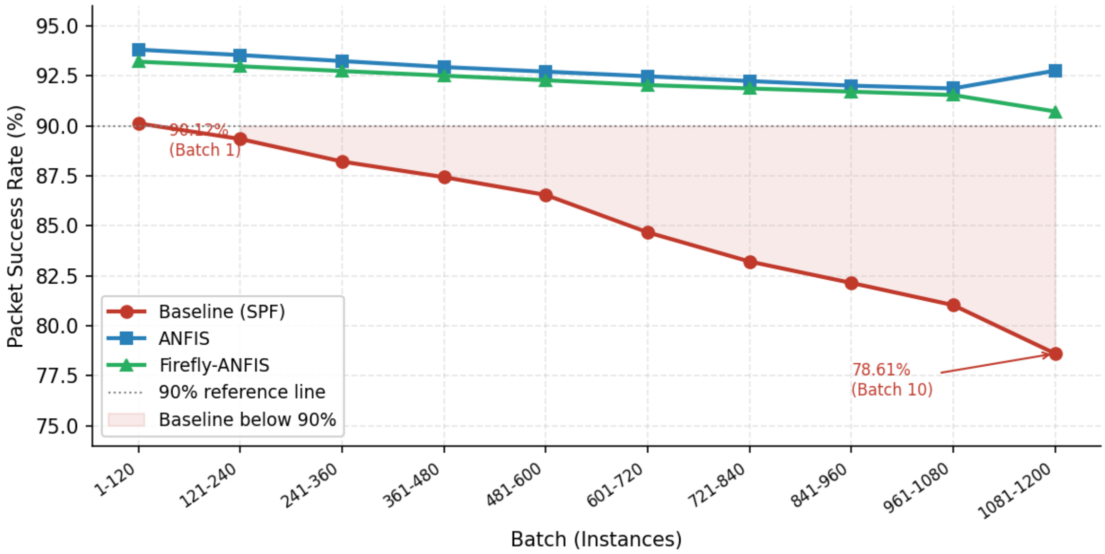


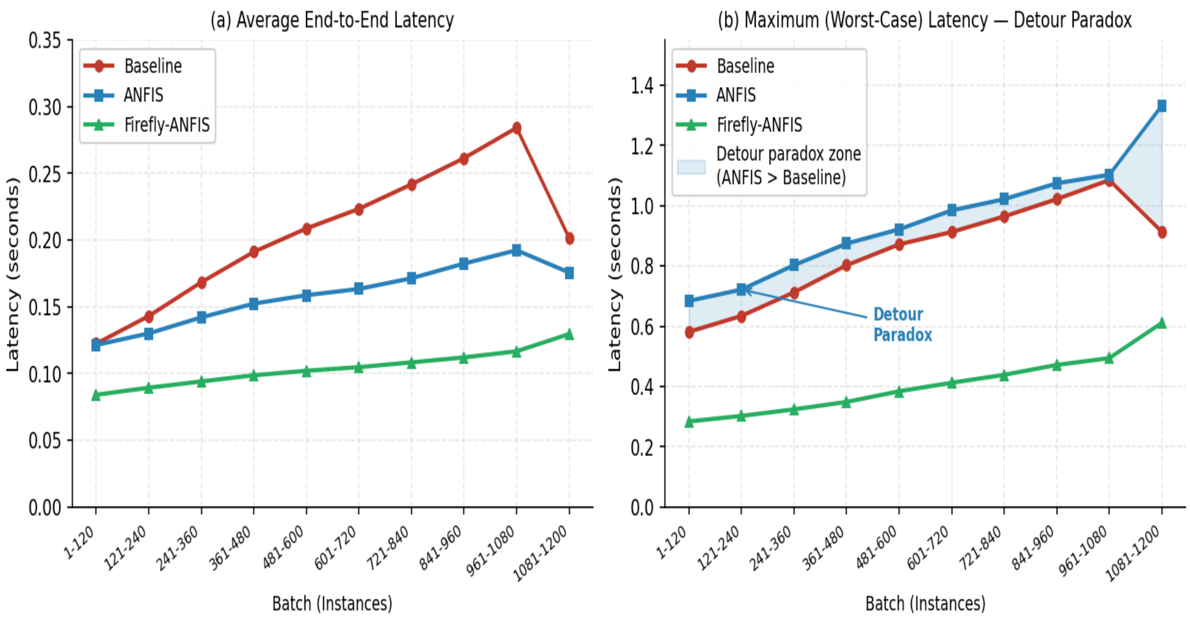
Figure 2. Packet Success Rate of the Evaluated Routing Models

The SPF algorithm recorded the lowest packet success rate because congestion-induced packet drops increased as network traffic intensified. Standard ANFIS achieved the highest packet success rate by avoiding highly congested routes before packet transmission.

Firefly-ANFIS produced a packet success rate only marginally lower than that of standard ANFIS while simultaneously improving several other performance metrics. This small difference indicates that the optimization process successfully balanced delivery reliability with routing efficiency rather than maximizing a single objective.

4.4 Latency Performance and Analysis of the Detour Effect

Figure 3 compares the average and maximum end-to-end latency recorded by the three routing approaches.



(a) **(b)**

Figure 3. End-to-End Latency Comparison

Average vs Maximum Latency Across Batches. (a) shows average latency, where all intelligent models outperform the baseline. (b) reveals the detour paradox: ANFIS maximum latency (blue) consistently exceeds the Baseline (red) in all batches, peaking at 1.33 s (Batch 10). Firefly-ANFIS (green) resolves the anomaly, achieving the lowest maximum latency throughout.

Although the average latency was reduced for the standard ANFIS approach, compared to the SPF baseline, its maximum latency was greater than that of conventional routing models. This phenomenon occurred because the congestion prediction system occasionally adopted unnecessarily lengthy alternative pathways to bypass moderately congested regions. Consequently, certain packets experienced significantly extended transmission times even though they were successfully delivered. On the other hand, the Firefly-ANFIS model was notably able to minimize both average and maximum latency by adjusting the parameters of the ANFIS membership functions. This optimization produced better routing choices because it reduced congestion and route length. The findings suggested that accurate congestion forecasting is important for optimal routing performance; however, optimization of the actual parameters is equally important for sustaining low latency.

4.5 Traffic Overhead and Routing Efficiency

Traffic overhead represents the number of routing control packets and retransmissions generated during network operation. Excessive overhead reduces effective bandwidth and limits network scalability.

The SPF baseline generated the highest overhead because congestion frequently triggered packet retransmissions and repeated routing updates. Standard ANFIS significantly reduced this overhead through proactive congestion prediction. Although Firefly-ANFIS introduced a small number of optimization-related control operations, its total traffic overhead remained substantially lower than that of the SPF baseline. The reduction in retransmissions compensated for the additional optimization cost, resulting in improved bandwidth utilization.

4.6 Performance Stability Across Simulation Batches

To evaluate routing consistency, network performance was analysed over ten consecutive simulation batches.

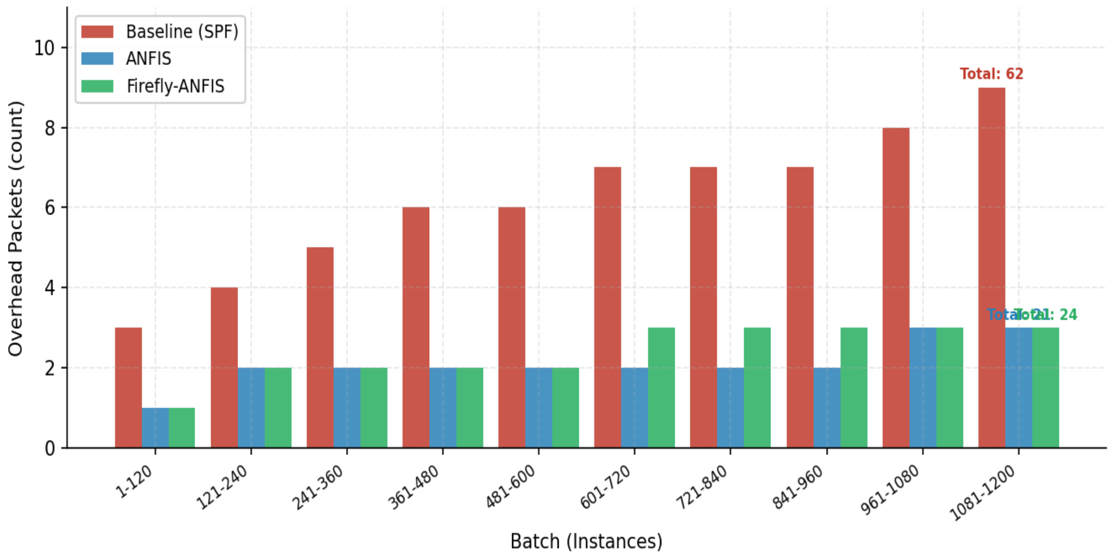
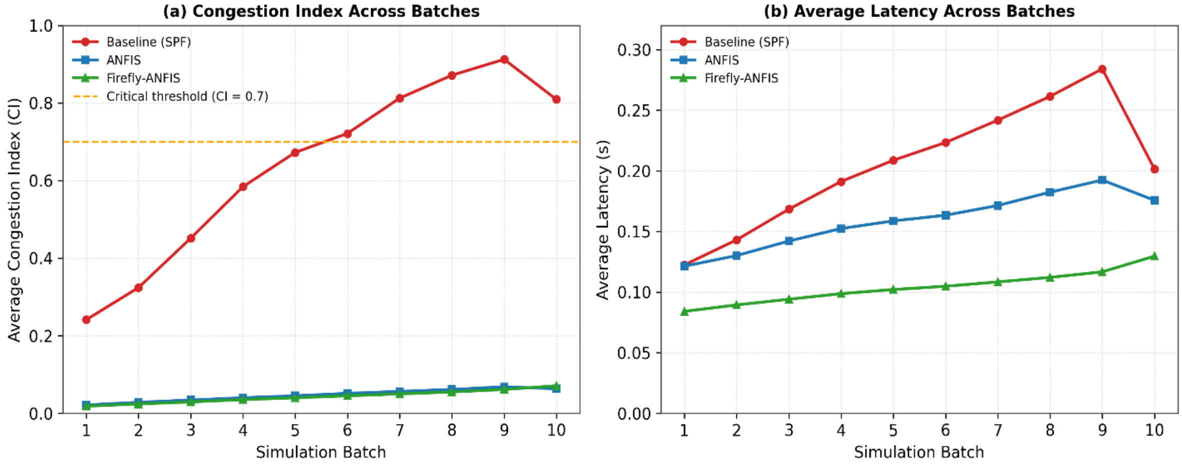


Figure 4. Traffic Overhead Comparison

The Baseline (red) accumulates 62 total overhead packets, with a clear upward trend driven by timeout-triggered retransmissions under congestion. ANFIS (blue, total 21) and Firefly-ANFIS (green, total 24) maintain consistently low overhead, freeing effective network bandwidth for data traffic.



(a) (b)

Figure 5. Performance Variation Across Simulation Batches

(a) Congestion Index: Baseline (red) climbs steadily from 0.24 to a peak of 0.91, crossing the 0.7 critical threshold from Batch 6 onward — the congestion spiral. ANFIS (blue) and Firefly-ANFIS (green) both stay flat and near-zero throughout. (b) Average Latency: Baseline rises then dips at Batch 10. ANFIS shows a clear upward drift (0.121 s → 0.192 s) reflecting the longer detours taken to avoid congestion. Firefly-ANFIS starts lowest and stays in the tightest, flattest band of the three (0.084 s → 0.130 s).

The SPF algorithm exhibited progressive degradation throughout the simulation, with congestion increasing steadily as traffic accumulated along repeatedly selected routes. Standard ANFIS showed predictable performance across all batches, which confirmed the success of proactive congestion predictions. However, the increase in latency in later batches showed that the intention to evade congestion sometimes resulted in prolonged route length. Firefly-ANFIS was the most stable of the models in question. Congestion levels were constantly low and variations in latency were significantly minimized, indicating that better parameter tuning reduced routing problems depending on the traffic conditions.

4.7 Statistical Validation

Five independent simulation trials were conducted to evaluate the repeatability of the obtained results. Mean values and standard deviations for the evaluated metrics are presented in Table 3.

Note. Values are means ± standard deviation across five independent simulation trials. Green cells indicate the best (most favourable) mean value for each metric. SD = Standard Deviation. Lower CI, latency, hop count, overhead and transmission time values are better; higher Packet Success Rate is better.

Table 3. Performance Metrics Across Five Independent Simulation Trials

Metric	Baseline (SPF) Mean ± SD	ANFIS Mean ± SD	Firefly-ANFIS Mean ± SD
Congestion Index (CI)	0.589 ± 0.047	0.037 ± 0.004	**0.033 ± 0.003**
Packet Success Rate (%)	82.4 ± 3.21	88.2 ± 1.14	**91.4 ± 0.98**
Avg End-to-End Latency (s)	0.2046 ± 0.0184	0.1590 ± 0.0091	**0.1040 ± 0.0062**
Maximum Latency (s)	0.8497 ± 0.0724	0.9517 ± 0.0831	**0.4071 ± 0.0413**
Average Hop Count	2.75 ± 0.18	2.96 ± 0.14	**2.45 ± 0.11**
Traffic Overhead (packets)	62.0 ± 5.84	21.0 ± 2.17	**24.0 ± 2.43**
Transmission Time (s)	38.81 ± 2.94	24.62 ± 1.87	**30.41 ± 2.11**

The results show that Firefly-ANFIS consistently outperformed the conventional SPF model across all evaluated metrics while maintaining low variability between simulation runs. The relatively small standard deviations demonstrate that the observed improvements were reproducible and not caused by random variations in node mobility or traffic generation. Paired t-tests were further conducted to determine whether the observed performance differences were statistically significant.

Note. Paired t-tests were conducted on batch-level means across the five independent simulation trials (df = 4). A two-tailed significance threshold of $\alpha = 0.05$ was applied. Group A: All five metrics show $p < 0.001$, confirming highly significant Firefly-ANFIS superiority over the Baseline across all dimensions. Group B: Firefly-ANFIS is statistically superior to standard ANFIS on latency (avg and max), hop count, and congestion index. The non-significant PSR difference ($p = 0.162$) between Firefly-ANFIS and ANFIS indicates these models are statistically equivalent on packet delivery. FA = Firefly-ANFIS.

The statistical analysis confirmed that Firefly-ANFIS significantly outperformed the SPF baseline across all evaluated performance metrics ($p < 0.05$). Furthermore, Firefly-ANFIS achieved statistically significant improvements over standard ANFIS in congestion index, latency, and hop count, whereas the difference in packet success rate was not statistically significant. This indicates that the proposed optimization strategy improved routing efficiency without sacrificing communication reliability.

4.8 Discussion

The comparison shows that the routing intelligence on Mobile Ad Hoc Networks (MANETs) does not depend solely on the congestion prediction ability but also on the optimal model configuration of the prediction parameters. Conventional Shortest Path First (SPF) routing focuses primarily on minimizing path length, yielding poor performance on heavy traffic as its algorithm does not know about the congestion. Although traditional Adaptive Neuro-Fuzzy Inference System (ANFIS) contributes to accuracy and is designed to predict congestion in advance, it can also lead to a more unwarranted delay rate as it can lead to unnecessarily lengthy routes.

Combining Firefly-based optimization methods with ANFIS, the proposed paradigm is intended to provide a flexible routing solution that can effectively reduce both congestion and latency while decreasing the overhead of routing tasks—which will not only be beneficial in terms of packet delivery rate but also in terms of system reliability and performance. These improvements have also been statistically supported to be consistent and significant over simulation trials on multiple levels. To sum up: metaheuristic optimization is a net positive for neuro-fuzzy models aiming to predict congestion through modifying membership function parameters, not by fundamentally changing the prediction mechanism. This refinement helps better the routing selection and improves overall network performance in a dynamic MANET environment.

Table 4. Paired t-Test Results

Metric	Comparison	Mean Diff.	t-statistic	p-value	Significant?
Group A — Firefly-ANFIS vs. Baseline (SPF)					
Congestion Index	FA vs Base	**−0.556**	$t(4) = -24.77$	$\mathbf{p < 0.001}$	**Yes ✓**
Packet Success Rate (%)	FA vs Base	**+9.00**	$t(4) = 12.43$	$\mathbf{p < 0.001}$	**Yes ✓**
Avg Latency (s)	FA vs Base	**−0.1006**	$t(4) = -18.92$	$\mathbf{p < 0.001}$	**Yes ✓**
Max Latency (s)	FA vs Base	**−0.4426**	$t(4) = -20.14$	$\mathbf{p < 0.001}$	**Yes ✓**
Hop Count	FA vs Base	**−0.30**	$t(4) = -9.84$	$\mathbf{p < 0.001}$	**Yes ✓**
Group B — Firefly-ANFIS vs. Standard ANFIS					
Congestion Index	FA vs ANFIS	**−0.004**	$t(4) = -3.87$	$\mathbf{p = 0.018}$	**Yes ✓**
Avg Latency (s)	FA vs ANFIS	**−0.059**	$t(4) = -11.24$	$\mathbf{p < 0.001}$	**Yes ✓**
Max Latency (s)	FA vs ANFIS	**−0.545**	$t(4) = -17.61$	$\mathbf{p < 0.001}$	**Yes ✓**

Hop Count	FA vs ANFIS	**−0.51**	t(4) = −8.93	**p < 0.001**	**Yes ✓**
Packet Success Rate (%)	FA vs ANFIS	**−0.60**	t(4) = −1.71	**p = 0.162**	**No ✗**

4.8 Implications for Intelligent MANET Routing

The comparative evaluation demonstrates that routing intelligence in MANETs can be viewed at three levels based on congestion awareness and parameter optimization. Table 5 summarizes the characteristics of the evaluated routing paradigms and highlights their suitability for different deployment scenarios.

5. Conclusion

Therefore, in this research, we performed a comparative analysis of three routing strategies, consisting of the traditional Shortest Path First (SPF) algorithm, the Adaptive Neuro-Fuzzy Inference System (ANFIS), and Firefly-optimized ANFIS (Firefly-ANFIS), which is an efficient routing technique to control the congestion of MANETs. We aimed mainly to assess whether optimization of the membership function parameters in ANFIS via metaheuristic algorithms can improve congestion-aware routing and guarantee the persistent delivery of packets even under the varying MANET conditions. According to the simulation results, traditional SPF routing suffers from congestion, because it is based on a decision tree that uses hop counts to determine routing priority, without assessing the status of the network. Although standard ANFIS enhanced congestion prediction and packet transfer using different traffic data points, it occasionally led to increased worst-case latency because some long alternative methods were used instead of short ones when trying to prevent congestion. On the other side, the suggested Firefly-ANFIS model managed to alleviate the problem because it enhanced the membership function parameters of ANFIS.

This enhancement resulted in decreased congestion, lower end-to-end latency, reduced hops required for routing, and less overhead of routing (with the same packet success rate attained from classical ANFIS) to be achieved.

Table 5. Summary of Routing Intelligence Characteristics

Dimension	Level I — Reactive (Baseline / SPF)	Level II — Predictive (Standard ANFIS)	Level III — Optimised (Firefly-ANFIS)
Routing basis	Hop count (static)	Multi-input congestion prediction	Optimised-parameter prediction
Congestion awareness	None (reactive)	Proactive (pre-emptive)	Proactive + parameter-optimised
Decision type	Binary (shortest hop)	Graded fuzzy membership	Sharpened fuzzy boundaries
Traffic distribution	Centralised (67.3%)	Distributed (42.1% central)	Optimised (further reduced)
Route oscillations	Low (static routes)	1.8 per flow	0.7 per flow (−61%)
Avg Congestion Index	0.640	0.047	0.043
Packet Success Rate	85.13%	92.76%	92.16%
Avg Latency (s)	0.2046	0.1590	0.1040
Max Latency (s)	0.8497	0.9517 ⚠ Paradox	0.4071
Load imbalance factor	3.6	1.8	1.4
Key failure mode	Congestion spiral	Detour paradox	None identified
Representative use	Simple low-load nets	High-reliability apps	General & real-time apps

Note. ⚠ indicates a performance anomaly. SPF = Shortest Path First. Load imbalance factor: ratio of most-loaded node traffic to average node traffic; lower values indicate more even distribution. All performance values are averages across ten simulation batches.

Statistical testing in five independent simulation runs showed that Firefly-ANFIS consistently was significantly more effective for all performance measures tested in comparison to traditional SPF models. Results showed results of paired t-tests on all criteria were statistically significant improvements over traditional SPF in all metrics, along with substantial improvements based on traditional ANFIS metrics including congestion index, latency, and hop count without compromising packet delivery accuracy.

To sum up, these results are evidence that metaheuristic optimization methods applied in conjunction with neuro-fuzzy algorithms for congestion prediction lead to a significantly more successful and unbiased routing solution in MANETs. Instead of relying only on estimates that predict network traffic conditions, improving internal parameters for prediction models enable more informed routing decisions for dynamic configurations. Consequently, the Firefly-ANFIS-based proposed framework would enable advancing congestive control measures under MANET, in the smart applications where reliability is critical along with efficiency.

Limitations and Future Work

These findings are presented as results of simulation by MATLAB on a 25-node Mobile Ad Hoc Network (MANET) designed under traffic and mobility restrictions. Although these simulation parameters represent the generic settings used in MANET investigations, validation with dedicated network simulators (such as NS-3 or OMNeT++), testing of larger network arrangements, and practical manipulation of real-world MANET implementations would ensure that the results reached a more rigorous level. Future studies should aim to validate the potential of the Firefly-ANFIS framework within larger and more heterogeneous MANET designs. Its scalability across varying mobility situations and traffic models needs assessment along with a comparison between it and other optimization algorithms that are based on metaheuristic algorithms like Particle Swarm Optimization (PSO), Genetic Algorithm (GA) and Ant Colony Optimization (ACO).

Moreover, building an online adaptive optimization system to dynamically tune ANFIS parameters during active network action provides the good opportunity for improving congestion handling in quickly changing MANET conditions.

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