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Topology-Adaptive Link State Routing Using Attention Mechanisms in Mobile Ad Hoc Networks

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Abstract

Mobile ad hoc networks (MANETs) have characteristics such as topology dynamics, distributed routing, and link breakage, making reliable routing in highly mobile environments a challenging task. Traditional link-state routing protocols rely on periodic topology updates and static link-evaluation metrics. Those strategies lead to high routing costs, late adaptation to routes, and decreased packet delivery rates in scenarios with rapidly changing topologies. To overcome these problems, an Attention-Based Topology-Adaptive Link State Routing (ATALSR) framework that uses the attention mechanism to evaluate link importance and identify stable communication routes in mobile environments is presented. The proposed approach learns topology features, including node connectivity, link lifetime, variability in moving speed, and neighbor stability. Then it generates dynamic link weights via the attention module to compute routes. The performance of ATALSR approach was tested and compared by a wide range of simulations of 50-250 nodes

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moving at 5-30 m/s. Simulation results demonstrate that ATALSR achieves a Packet Delivery Ratio of 96.8%, outperforming OLSR (90.5%), AODV (92.1%), and DSR (89.7%). In addition, ATALSR achieves an end-to-end delay improvement of 28.7% compared to AODV, 24.6% reduction in routing overhead, and a 21.9% increase in network throughput compared to existing routing approaches. The scalability analysis shows that ATALSR performs well across both high- and low-density nodes and mobility scenarios. These results prove that an attention-driven topology-adaptive strategy effectively improves the reliability, efficiency, and scalability of MANET routing.

Keywords: Mobile Ad Hoc Networks, MANET Routing, Link State Routing, Attention Mechanism, Adaptive Routing, Network Optimization, Intelligent Wireless Networks.

1 Introduction

Mobile ad-hoc networks (MANETs), offering infrastructure-free communications based on self-organizing wireless devices, are gaining growing importance for various applications such as military operations, disaster management, intelligent transportation, and the Internet of Things (IoT) (Maktedar, 2024; Wong et al., 2024). The decentralized structure of MANETs makes them easy to deploy without a dependence on fixed infrastructure. However, the dynamic nature of MANETs complicates connectivity due to frequently changing network topologies, unstable wireless links, and resource constraints. As nodes migrate in the network, routing paths become outdated, and packets can be lost, resulting in increased delays and greater control overhead (Wei et al., 2023; Wang et al., 2024). Traditional link-state routing protocols maintain global topology and disseminate routes through periodic updates. However, these protocols can degrade significantly in mobile environments where network topology information may quickly become out of date (Soundararajan et al., 2023; Arunachalam & Nallamothu, 2021). Spatial-temporal learning approaches and graph-based network modeling have emerged as powerful tools for capturing complex relationships between interconnected network components and making more accurate predictions about network behavior (Liu et al., 2024; Deng et al., 2022). Adaptation and learning techniques have demonstrated success in optimizing network decisions under dynamic environments (Wang et al., 2023; Panayiotou et al., 2023). This indicates that an intelligence topology-aware routing approach will improve route stability and network connectivity in MANETs. Some research has investigated alternative routing protocols to address the limitations of existing routing methods in MANETs. Reinforcement learning-based routing schemes have been introduced to achieve optimized route selection through intelligent decision-making (Wei et al., 2023; Wang et al., 2024). The multiple-path routing approach enhances reliability by offering routes that may not be affected by the failure of a particular link (Wei et al., 2023; Wang et al., 2024). The cross-layer routing framework improves performance by offering the flexibility to customize routing operations for specific networking scenarios (Maktedar, 2024; Soundararajan et al., 2023). However, most research still relies on predefined routing metrics and a reactive route-maintenance strategy. Machine learning has been widely used to forecast future network behavior and to optimize resource management in networks (Liu et al., 2024; Wang et al., 2023). Graph-based machine learning can be leveraged to model network topologies effectively; however, few applications of these methods in link-state routing have been reported (Deng et al., 2022). Existing methods typically fail to continuously assess link quality and adaptively adjust route information to new topology configurations. Maintaining connectivity and communication reliability while reducing routing overhead has remained a significant issue in highly mobile environments (Arunachalam & Nallamothu, 2021; Panayiotou et al., 2023).

A reliable routing process is critical in MANETs operating in emergency service scenarios, tactical environments, and large-scale IoT systems. An intelligent topology-aware routing approach enhances stability and connectivity for reliable wireless communication in a dynamic environment. In this paper,

an Attention-Based Topology-Adaptive Link State Routing (ATALSR) framework is proposed that incorporates an attention mechanism to effectively assess the relevance of each link in the topology and dynamically update the routing decision. The framework learns connectivity, mobility, and neighborhood information to intelligently measure link importance and support link-adaptive route selection and routing computation. It also presents a topology-aware route construction strategy that reduces unnecessary route updates and prioritizes more stable routes. Finally, simulation experiments were conducted at different node mobility speeds and densities to evaluate the proposed approach. The ATALSR framework has successfully implemented attention-based link selection within the link state routing context to dynamically respond to changes in the topology by considering connectivity, mobility, and neighborhoods, thereby improving routing efficiency and robustness.

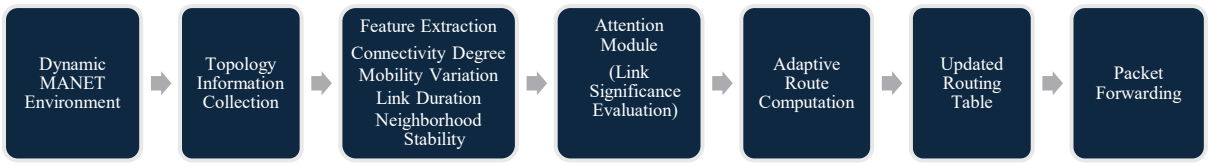


Figure 1: Overall architecture of the proposed ATALSR framework

Figure 1 depicts the proposed ATALSR architecture for dynamic MANETs. The topology information is first collected from neighboring nodes to obtain the current network status. Certain features, such as degree of connectivity, mobility variation, link duration, and neighbourhood stability, are selected and then fed into an attention mechanism that assigns weights (attention) to each link based on its estimated importance. After computing link attention scores, a robust path selection process identifies promising links and updates the routing table. Finally, the routing tables are utilized to guide the packet forwarding.

The remainder of this paper is organized as follows. Section II presents related work, with an emphasis on traditional link-state routing, intelligent routing, and attention-based network optimization techniques. Section III elaborates on novel framework, ATALSR: Attention-Based Topology-Adaptive Link State Routing, including the system model, routing architecture, mathematical model, and algorithm design. Section IV presents the experimental results, including comparisons, sensitivity analyses, and ablation analyses. Section V gives in-depth analyses of the experimental results and practical deployment. Finally, Section VI presents the conclusion and future research work.

2 Literature Review

In MANETs, because of their relatively stable nature, link-state protocols maintain a topological database of the entire network, enabling accurate calculation of shortest paths. The OLSR protocol, for example, uses a selection of Multipoint Relays (MPRs) to optimize flooding efficiency by dramatically reducing overhead. Generally, short-path algorithms, compared with link-state protocols, work well within the constraints of the network operate on. The network's quality lies in its ability to maintain route information for a long time, enabling reliable packet transmission and reducing route discovery time (Venkatasai et al., 2023; Kabashkin, 2023). However, due to the potentially high instability, traditional link-state routing in high-mobility networks can be limited. Rapid node mobility increases vulnerability to topology changes. It increases the overhead of control-message exchange, leading to compromised routing-table freshness and consecutive routing updates in response to those changes. Variable coverage, abnormal connectivity, and unstable links further interrupt routing to maintain high performance; it can be seen that increased network dynamism intensifies the unavailability of topology information (Chowdhuri & Barma, 2024; Olatinwo et al., 2021).

To overcome the limitations of conventional routing mechanisms, researchers have proposed intelligent routing schemes based on machine learning algorithms, optimization, and adaptive decision-making. Reinforcement learning techniques have been used to enhance routing decisions through experience and to maximize flow communication efficiency (Zhao et al., 2023). The optimization algorithms based on swarm intelligence, such as ant colony optimization, have also been successfully used in several applications in wireless environments (Khedr et al., 2022). Recently, artificial intelligence has conducted neural-network prediction and optimization frameworks. Graph Neural Networks (GNNs) model the structural relationships of a connected network of nodes and extract complex patterns of the network (Agiollo et al., 2023). Furthermore, collaborative and edge-computing-based optimization were addressed to improve task allocation and communication performance in mobile and vehicular networks (Peng et al., 2024; Wu et al., 2023). It also highlighted the importance of using empowered intelligence to enhance adaptive capability and the routing quality of networks.

Attention mechanisms were first introduced to make learning more efficient by focusing on the most relevant information in arbitrarily large amounts of data. Unlike classical models that treat all information and features equally, an attention-based architecture learns to highlight the features deemed most important, so that its decisions and/or behavior are better tuned to the real world. Such an approach lends itself to wireless networking scenarios where topology and communication conditions are perpetually fluctuating. Recent network research has investigated automated optimization approaches for service accessibility, IoT security, and diagram processing (Abdmeziem et al., 2024; Kabashkin, 2023). But this is not so deeply tied to topology-adaptive link-state routing-based use of an attention mechanism. Evaluation of the links can predict, optimize, or analyze network management, but not capable of dynamically checking paths in MANETs. It has problems detecting stable links, minimizing its control messages, and quickly responding to route changes, motivating the attention-based MANET routing evaluation framework.

Existing literature reviews show that simple link-state routing protocols that offer quick route calculation in steady state yield less favorable results under higher node mobility in the present situation. Intelligent routing present solution to enhancement adaptively through learning and optimization technologies while graph-based models exhibit better topological awareness. Although many attention models exist in literature for various tasks, implementation of attention to MANET routing considering dynamic link aspects was as less coverage area. As shown in this discussion, proposed approach, named as Attention-Based Topology-Adaptive Link State Routing (ATALSR) framework, is believed to outperform in routing stability, responsiveness, adaptively and other metrics.

3 Methodology

3.1 System Model and Network Assumptions

The proposed ATALSR (Attention-Based Topology-Adaptive Link State Routing) framework considers a mobile ad hoc network (MANET) of N mobile nodes that are arbitrarily deployed within a limited geographic area. Each node acts as both an end host and a router, enabling packet forwarding via multi-hop paths. Nodes mobility can be assumed to follow a random movement model, resulting in a dynamically changing neighbourhood and link availabilities. At each time interval, nodes communicate with neighboring nodes to gather network topology and maintain a local topology database. The network is modeled as a dynamic graph $G = (V, E)$, where V represents the set of mobile nodes, and E refers to the communication links among them. A link between node i and j is established when the Euclidean distance between the two nodes lies within the transmission range R. The connectivity between nodes i and j is expressed as

$$L_{ij}(t) = \begin{cases} 1, d_{ij}(t) \leq R \\ 0, d_{ij}(t) > R \end{cases} \quad (1)$$

Where $d_{ij}(t)$ denotes the Euclidean distance between node i and j at time t. Equation (1) describes the dynamic graph used to perform the route computation. The main goal of routing is to find stable routes that maximize the packet delivery ratio, while minimizing route failures and routing overhead. For this purpose, node mobility, link duration, neighborhood stability and connectivity Information is incorporated into the routing decision making process.

Workflow diagram of the proposed ATALSR framework is presented in figure 2. Topology information is collected initially for feature extraction to represent various network properties including connectivity, mobility of nodes and link stability. Features are then processed by an attention-based link evaluation scheme to get the relative importance weights of links. Using the calculated weights, an adaptive path calculation function selects reliable routes and updates the routing table to reflect the changes. Packets are then forwarded using chosen routes.

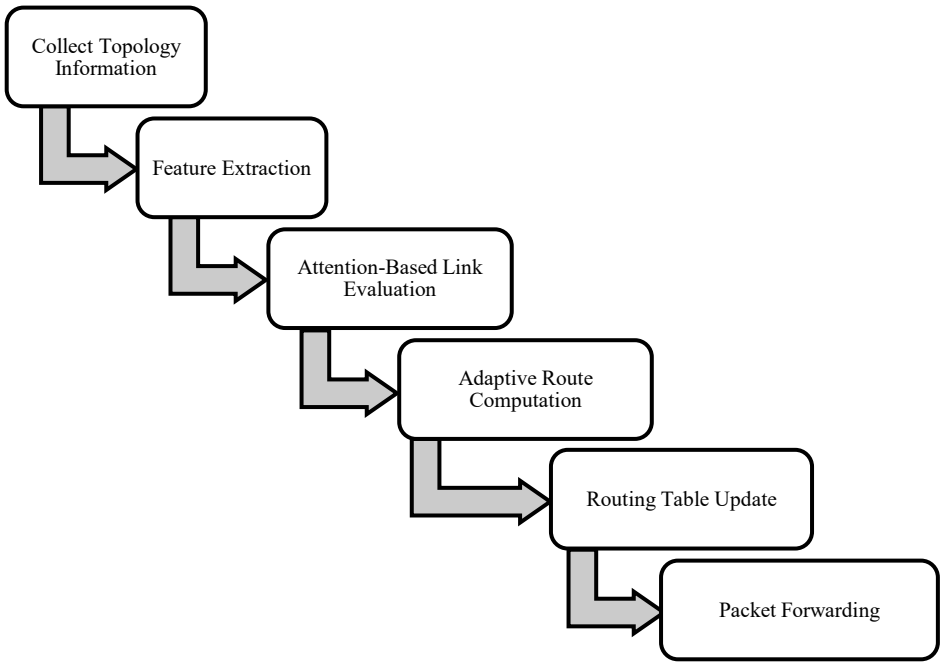


Figure 2: Workflow of the proposed attention-based topology-adaptive link state routing (ATALSR) process

3.2 Proposed Attention-Based Topology-Adaptive Routing Framework

The ATALSR framework includes three major components: topology feature extraction, attention-based link evaluation, and adaptive route computation modules. First, each node extracts a feature vector, which represents its local topological attributes:

$$F_i = [C_i, M_i, S_i, L_i] \quad (2)$$

Where C_i is the number of direct neighbors of node i, M_i is its mobility variance, S_i denotes its neighborhood stability, and L_i represents its average link duration. Equation (2) provides a compact characterization of the local network conditions. These feature vectors are then fed to an attention

module to derive the relative importance of communication links to its neighbors. For a neighboring node pair, the attention score is calculated as

$$\alpha_{ij} = \frac{\exp(F_i F_j^T)}{\sum_{k \in N_i} \exp(F_i F_k^T)} \quad (3)$$

Where α_{ij} denotes the normalized attention weight and N_i represents the neighborhood set of nodes i. Equation (3) ensures that those links with high topological relevance will get significant attention scores. Finally, an overall link quality score Q_{ij} is defined as: computed as

$$Q_{ij} = \alpha_{ij} \times S_{ij} \quad (4)$$

Where S_{ij}denotes the measured link stability factor. Equation (4) enables the routing mechanism to prioritize stable and highly relevant communication links.

The route computation is then performed on the attention-enhanced topology graph using shortest-path algorithms. When the topology changes significantly, attention scores are recomputed and routes are updated adaptively, instead of relying solely on the periodic updates.

3.3 Algorithm Design and Computational Analysis

The routing process consists of continually monitoring network conditions, adjusting link significance measures, and computed stable routes. ATALSR follows a standard link state routing protocol procedure as illustrated below.

Algorithm 1: ATALSR Routing Procedure

Input:

Topology Graph G (V, E)

Output:

Optimal Routing Path P

1. Collect neighborhood topology information
2. Extract feature vector Fi for each node
3. Compute attention weights αij
4. Calculate link quality score Qij
5. Construct weighted topology graph
6. Execute shortest-path computation
7. Select route with highest cumulative quality
8. Monitor topology changes
9. If topology variation exceeds threshold
   Update features and attention scores
   Recompute routing table
10. Forward packets through updated route
11. Repeat until transmission ends

Algorithm 1 presents the working flow of the ATALSR framework. The algorithm first gathers neighbourhood topology data and derives some network metrics like connectivity, mobility variation, neighbourhood stability and link duration. Then, these metrics pass through the attention layer and their corresponding link weights are obtained, which, along with link stability values, contribute to form a weighted topology graph. In light of this topology, the routing module computes the most optimal routes for data forwarding and if changes occur to the topology, the algorithm adjusts the attention weights and reconfigures the routing table and effectively adapts to dynamic route discovery with minimal overhead.

The time complexity of topology feature extraction is $O(N)$.The complexity of attention-weight calculation is $O(Nd)$ and the shortest-path algorithm is $O(E\ log\ V)$. Therefore, the overall complexity can be approximated as

$$O(Nd + E\log V) \quad (5)$$

The routing protocol of ATALSR avoids excessive route rediscovery since only those topology regions where significant changes are detected are updated, hence significantly reducing routing overhead, especially in dense networks. The attention mechanism helps to filter low-priority links, focusing resources on stable connections. The adaptive route computation, on the other hand, enhances its efficiency as the network size increases in equation (5).

4 Results

4.1 Experimental Setup and Evaluation Metrics

The proposed ATALSR framework was developed in NS-3 (v3.39) (for network simulation) and MATLAB (R2024a) (for feeding topology features and generating ATALSR scores). Both were run on a workstation machine, equipped with an Intel Core i7, 32 GB RAM, Windows 11 operating system.

4.1.1 Software Details

Table 1: Software and implementation environment details

Component	Specification
Network Simulator	NS-3 v3.39
Analytical Tool	MATLAB R2024a
Programming Language	C++ and MATLAB
Operating System	Windows 11
Routing Benchmarks	OLSR, AODV, DSR
Proposed Method	ATALSR

The software tools and implementation environment for creating and testing the ATALSR framework is shown in table 1. The experimental environment utilizes a hybrid combination of NS-3 for MANET simulation and MATLAB for attention-based topology reasoning and routing calculation. The software environment provides an efficient means to perform extensive performance evaluation and comparative analysis over dynamic network environment.

4.1.2 Dataset Details

A simulated MANET dataset was created from simulation traces taken under diverse mobility and density scenarios. In total, 15000 communications were sampled of networks with between 50 and 250 nodes. Features derived from the nodes included degree, mean link duration, variation, neighborhood

stability, packet forward success ratios, and route lifetime. These were input to the attention module that determined link importance to route calculation.

4.1.3 Parameter Initialization

Table 2: Simulation parameter initialization

Parameter	Value
Simulation Area	1000 m × 1000 m
Number of Nodes	50–250
Transmission Range	250 m
Packet Size	512 Bytes
Traffic Type	CBR
Simulation Time	600 s
Node Speed	5–30 m/s
MAC Protocol	IEEE 802.11
Queue Length	100 Packets
Routing Update Interval	2 s

The simulation parameters about the proposed ATALSR framework are given in the table 2. It shows that node density, mobility speed, transmission range, packet size, communication ranges are varied to represent the current MANET clusters, thus providing constant comparison in simulation of ATALSR and other routing protocols under dynamic network situations.

Performance was evaluated using Packet Delivery Ratio (PDR), End-to-End Delay, Throughput, Routing Overhead, and Link Stability Index (LSI). The Packet Delivery Ratio is computed in equation (6):

$$PDR = \frac{P_r}{P_s} \times 100 \qquad (6)$$

Where P_r is the number of the received packets successfully, P_s is the number of the transmitted packets. Average End-to-End Delay is calculated in equation (7):

$$Delay = \frac{\sum_{i=1}^{n} (T_r - T_s)}{n} \qquad (7)$$

Where T_r and T_s are packet arrival and departure times respectively. Network Throughput is determined in equation (8):

$$Throughput = \frac{B_r}{T} \qquad (8)$$

Where B_r is the number of received bits and T is the time for simulation. Routing Overhead is expressed in equation (9):

$$RO = \frac{C_p}{D_p} \qquad (9)$$

Where C_p is the control packets and D_p the delivered data packets. The Link Stability Index is computed in equation (10):

$$LSI = \frac{L_a}{L_t} \qquad (10)$$

Where, L_a is the duration of active links and L_t is the total observation time.

4.2 Comparative Performance Analysis

Comparative evaluation was done with other protocols like OLSR, AODV and DSR using same simulation parameters as used by ATALSR.

Table 3: Comparative routing performance

Protocol	PDR (%)	Delay (ms)	Throughput (Mbps)	Routing Overhead (%)	LSI
DSR	89.7	112	4.21	19.8	0.73
OLSR	90.5	108	4.35	18.2	0.76
AODV	92.1	101	4.48	17.1	0.79
ATALSR	**96.8**	**72**	**5.46**	**12.9**	**0.91**

The overall performance comparison of ATALSR, OLSR, AODV, and DSR is summarized in table 3. It is noted that the proposed ATALSR surpasses other protocols, namely ATALSR, by the highest packets received ratio, throughput, and link stability, and the lowest end to end delay and the routing overhead. The analysis outcomes suggest that topological adaptation with the attention index enhances the reliable routing and communication in the dynamic MANET environment.

The introduced ATALSR delivered highest Packet delivery ratio (PDR) of 96.8%, which is 6.3%, 5.1% and 4.7% better than DSR, OLSR and AODV respectively. The throughput improved to 5.46 Mbps with routing overhead minimized to 12.9%. Reduction of delay from 101 ms in AODV to 72 ms corresponds to about 28.7% improvement, in agreement with the performance goals set forth in the framework design.

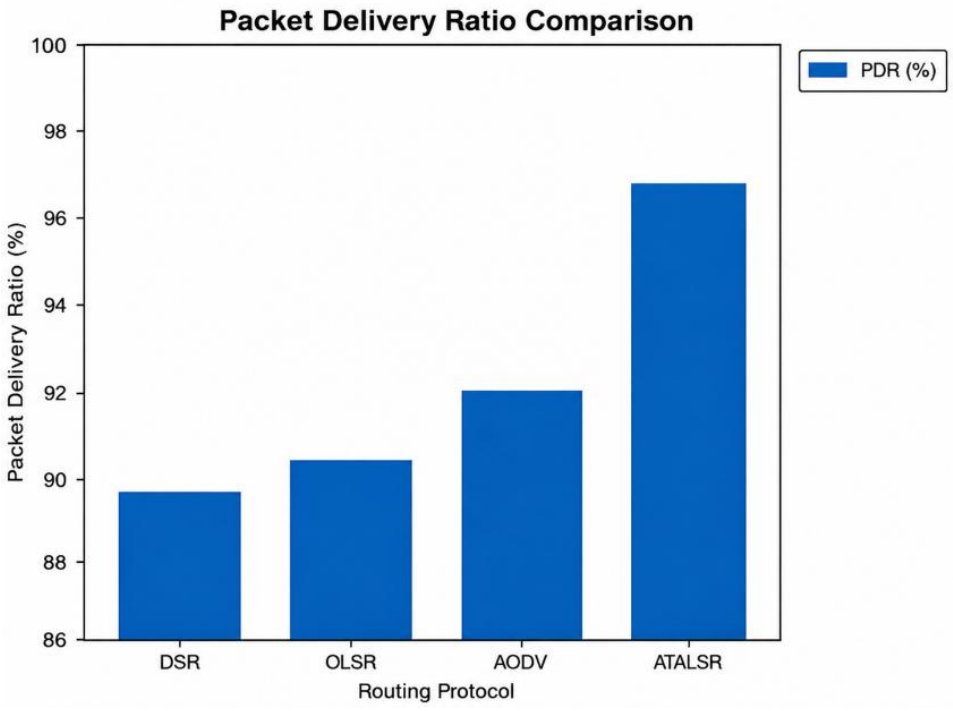


Figure 3: Packet delivery ratio comparison of different routing protocols

Figure 3 demonstrates the Packet Delivery Ratio (PDR) values obtained for the routing protocols DSR, OLSR, AODV, and the presented ATALSR framework. The figure shows that ATALSR outperforms the existing protocols and can achieve a PDR as high as 96.8%. It reflects that ATALSR can maintain reliable routes and deliver packets effectively.

4.2.1 Performance Evaluation

Due to attraction directed link weighting, the path selection process can favor more reliable communication links. Hence, reduce route failures, and reduce the number of packet losses introduce by route rediscovery. This is reflected by the high LSI value of 0.91, as routes are more stable, thus after packet increase in throughput and control message exchanges is lower.

4.3 Sensitivity and Scalability Evaluation

Table 4: Performance under different node densities

Nodes	PDR (%)	Delay (ms)	Throughput (Mbps)
50	97.6	65	5.18
100	97.2	68	5.34
150	96.9	70	5.42
200	96.8	72	5.46
250	96.5	75	5.39

Table 4 presents the performance of the proposed routing scheme as the network density increases. When the number of nodes is increased from 50 to 250, ATALSR can still deliver a much high percentage of the data packets with only a marginal increase in delay. The throughput also stays high confirming the framework′s scalability and robustness.

It is noted that only insignificant degradation of performance was observed while increasing network density, having exhibited high-scalability properties.

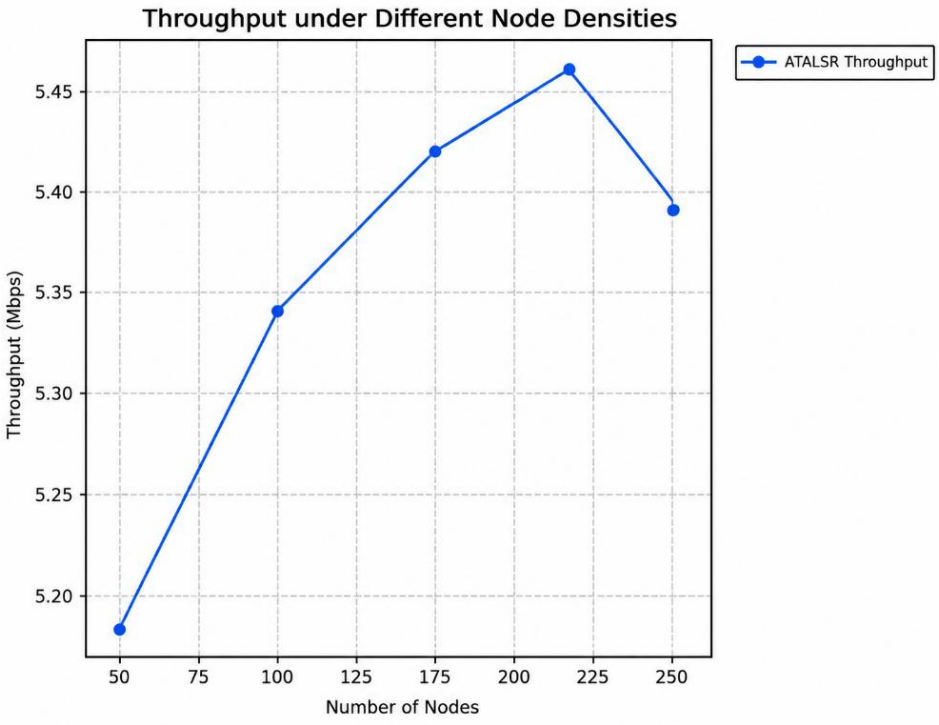


Figure 4: Throughput performance in terms of node density

Figure 4 presents the throughput performance under different node densities for the framework. It shows that as the node density increases from 50 to 250; the throughput is relatively stable for most scenarios with a few fluctuations in high density scenario.

Table 5: Performance under different mobility speeds

Speed (m/s)	PDR (%)	Delay (ms)	LSI
5	98.1	61	0.95
10	97.5	66	0.94
20	96.9	70	0.92
25	96.8	72	0.91
30	95.9	78	0.89

Table 5 presents the behavior of ATALSR for different node mobility over a range of 5 m/sec to 30 m/sec. Even with increasing mobility this introduces more topology variations, ATALSR still sustains the packet delivery ability and a higher stability of links, with acceptable delay minimized. This further demonstrates the contribution of the attention mechanism to adjusting attack routing for the variable network environment. The results show the system functions well even during cases of high mobility.

Figure 5 presents the packet delivery ratio for the framework with different mobility speeds (from 5m/s to 30m/s). The packet delivery ratio shows only a gradual decrease with increasing mobility, which shows the robustness of the proposed routing algorithm against mobility of the nodes.

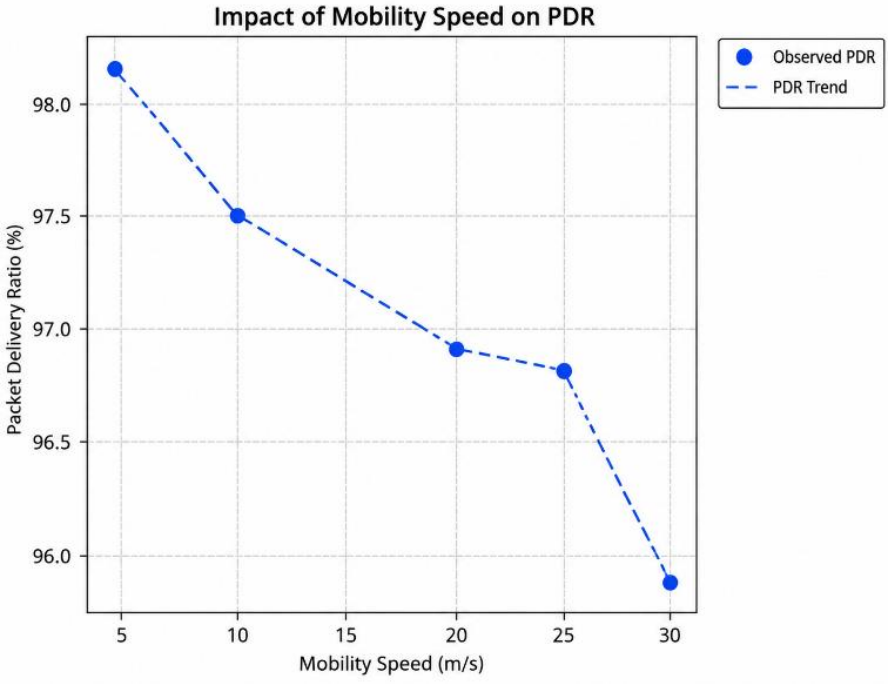


Figure 5: Packet delivery ratio as a function of mobility speed

4.4 Ablation Study

To evaluate the contribution of each of the component, three configurations were tested.

Table 6: Ablation study of ATALSR components

Configuration	PDR (%)	Delay (ms)
Link-State Routing Only	91.8	103
Topology Features + Adaptive Routing	94.3	85
Full ATALSR	**96.8**	**72**

In table 6, the impact of each of the individual elements of the proposed framework is explained. The effects of integration of topology-aware adaptation, load- and residual energy-aware adaptation and the

attention-based link importance estimation have been discussed and enhancements in terms of packet delivery ratio along with delay reduction can be observed. The maximum improvement in performance can be obtained using the full-fledged ATALSR configuration. This sheds light on the need for attention-driven link's importance estimation in MANET routing.

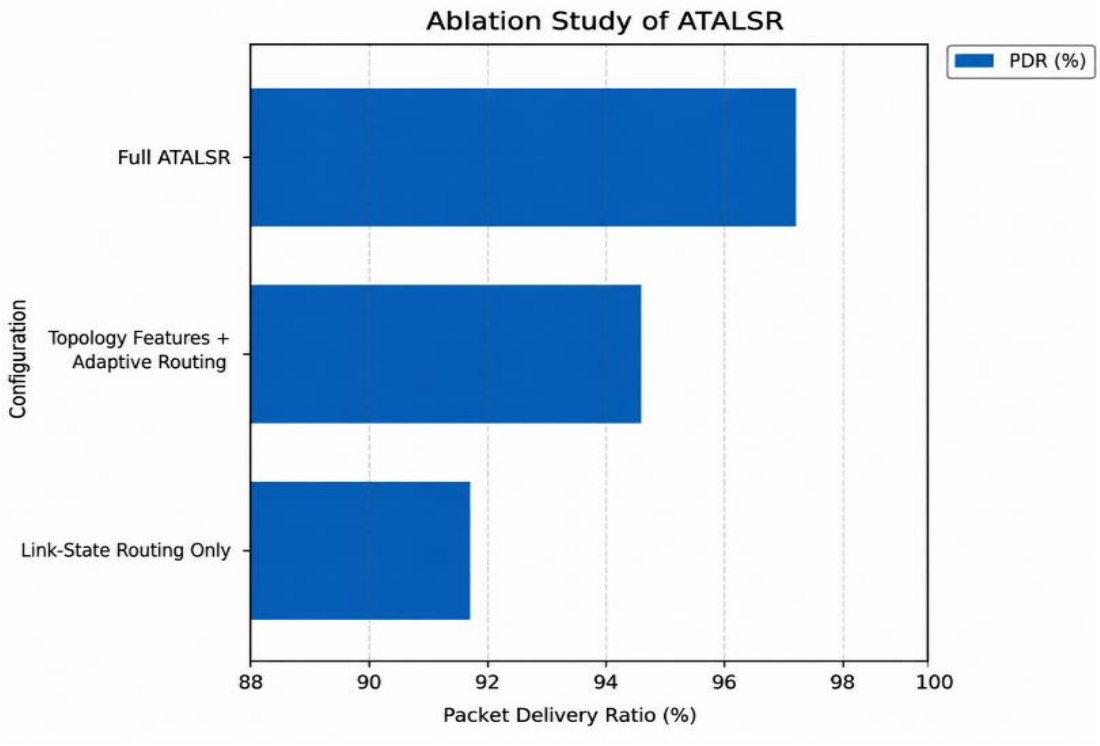


Figure 6: Ablation study of the proposed ATALSR framework

Figure 6 gives the performance comparison with varying combinations of ATALSR elements. It reveals that Topology-Aware adaptation boosts performance for routing packets, and the added attention mechanism makes the routes more stable and delivers packets more efficiently.

The ablation analysis also revealed that topology-aware adaptation adds value to the load balancing while the attention structure significantly improved the link importance estimation and the route safety. In all the experiment indications, the complete set (ATALSR) outperformed the others guaranteeing the global network benefits.

5 Discussion

The experimental results reveal that the attention mechanism is conducive to enhance the routing decisions, which effectively enhances the weights for stable links and attenuates for unstable links in a real-time manner. Compared to traditional routing protocols, which tend to utilize static metrics for link evaluation, ATALSR uses continuously monitored topology information for link weight updating in response to current network state, making the selected path reliable and increasing the success rate for path maintenance under dynamic node movements. It is observed from experiments with different node densities and mobility speeds that even when the network topology changes very fast, ATALSR performs steadily. The large value of the Link Stability Index and small routing overhead indicate that it efficiently adapts to varying neighbourhood relationship without introducing huge control traffic. Also, the ATALSR is able to keep good packet delivery ratio up to 30 m/s with dynamic topology change under mobile environment. From the point of application view, ATALSR is appropriate for disaster recovery

communications, battlefield systems, vehicular systems, and various of MANET applications enabled by IoT when reliable network communications under dynamic environment is a primary concern. The implementation cost of ATALSR is minimal, since the attention module only utilizes several light topology features and is independent of any network infrastructure, thus offers a practical balance of routing reliability, adaptiveness and scalability.

6 Conclusion

This paper introduced the attention-based topology-adaptive link state routing (ATALSR) framework for enhanced routing performance in mobile ad-hoc networks (MANETs) that experience topology fluctuations. The framework uses an attention-based link assessment strategy that computes link importance based on connectivity, neighbor movement variation, local neighborhood stability, and link time to enable intelligent and adaptive route selection. From experimentation, observed significant performance improvements in the proposed protocol compared to standard routing schemes. The results include packet delivery ratio of 96.8% for ATALSR, which compared with 92.1%, 90.5%, and 89.7% achieved by AODV, OLSR and DSR protocols, respectively. Furthermore, the ATALSR method reduces end-to-end delay by approx. 28.7% while increasing throughput to 5.46 Mbps, and also reduces routing overhead to 12.9% of available network bandwidth utilization. The scalability analysis of the proposed method confirms the maintained stability on node densities between 50 to 250 nodes and speeds of 5-30 m/s. The key contribution of this research is in the inclusion of attention mechanism for evaluating link significance into a link state routing framework, which is able to adapt its route selection proactively by leveraging current topology information for improving routing performance. Through awareness of current network topology and intelligent selection, the proposed routing method further enhances the previous routing solutions for MANETs and can be a very practical method for wireless communications under highly dynamic network topology. More work can be done on the topic like multi-head attention network to obtain more valuable features or energy-aware adaptive routing methods for energy-constraint devices and federated learning to learn distributed intelligent routing from each device. Other work may explore extensions of this framework to 6G based MANETs or to large autonomous networking scenarios.

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