

Optimizing Tactical MANET Routing Framework For Enhancing Throughput, Latency, Packet Delivery, Energy Efficiency With Machine Learning

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Abstract

Mobile Ad hoc Networks (MANETs) play a vital role in tactical and military communication scenarios where fixed infrastructure is unavailable or unreliable. However, the highly dynamic nature of such environments—characterized by frequent topology changes, node mobility, limited energy resources and fluctuating link quality—poses significant challenges to conventional MANET routing protocols. Traditional routing approaches such as AODV, DSR and OLSR rely on static or rule-based mechanisms and often fail to achieve optimal performance under high-mobility and resource-constrained conditions. Motivated by these limitations, this paper proposes a machine-learning-assisted optimization framework for tactical MANET routing to improve key network performance indicators, including throughput, end-to-end latency, packet delivery ratio and energy efficiency. The proposed framework leverages real-time network data on node mobility, traffic patterns and link quality to build predictive machine learning models that anticipate network state variations. These predictions are then used to enable adaptive, proactive routing decisions that respond effectively to both current and anticipated future network conditions. A comprehensive simulation-based evaluation is conducted under diverse traffic loads and mobility scenarios and the proposed approach is benchmarked against established MANET routing protocols. The results demonstrate that the machine-learning-assisted framework consistently outperforms conventional protocols, achieving higher throughput, reduced latency, improved packet delivery ratio and lower energy consumption, particularly in high-mobility environments. Overall, the proposed framework provides a scalable, energy-aware and adaptive routing solution suitable for mission-critical tactical MANET deployments.

Keywords: Latency, Machine Learning, Packet Delivery Ratio, Routing Algorithms, Tactical Networks, Throughput.

Introduction

Mobile Ad hoc Networks (MANETs) are a critical communication paradigm for tactical and military environments where fixed infrastructure is unavailable or unreliable (1). These networks operate under highly dynamic conditions characterized by frequent topology changes, limited battery resources, fluctuating link quality and stringent reliability requirements. In such mission-critical scenarios, routing efficiency directly influences key performance indicators, including throughput, end-to-end latency, packet delivery ratio (PDR) and energy consumption. Conventional MANET routing protocols, such as Ad hoc On-Demand Distance Vector (AODV), Dynamic Source Routing (DSR) and Optimized Link State Routing (OLSR), employ static or rule-based routing strategies that provide limited adaptability to rapidly changing tactical

environments (2). Reactive routing protocols suffer from increased latency and packet loss due to frequent route discoveries under high mobility. In contrast, proactive protocols generate excessive control overhead in dense or highly dynamic networks (3). Furthermore, most traditional routing approaches are energy-agnostic and lack predictive capability, resulting in inefficient resource utilization and reduced network lifetime (4). Recent advances in machine learning (ML) offer promising opportunities to address these limitations by enabling adaptive and predictive routing decisions (5). ML techniques can analyse real-time network data, learn mobility and traffic patterns and anticipate link failures or congestion before they occur. By integrating such predictive intelligence into MANET routing, adaptability, reliability and overall

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network performance can be significantly enhanced in highly dynamic tactical environments (6). However, designing lightweight, scalable and real-time ML-assisted routing frameworks that operate under strict energy and computational constraints remains a significant research challenge (7). Routing in tactical MANETs is further complicated by several inherent challenges, including: (a) dynamic topology resulting in frequent link breakages and increased routing overhead (8); (b) energy constraints requiring energy-aware routing to avoid premature node failures and network partitioning (9); (c) scalability issues as routing overhead grows with network size in large tactical deployments (10); (d) interference and link quality variations demanding rapid adaptation to fluctuating wireless conditions (11); and (e) security and reliability requirements to withstand attacks such as jamming, spoofing and eavesdropping (12).

In view of these challenges, this work focuses on integrating machine learning into MANET routing to enable adaptive, predictive and energy-efficient routing decisions tailored for tactical communication environments. Accordingly, this study proposes a machine-learning-assisted routing framework for tactical MANETs that dynamically adapts to variations in node mobility, traffic patterns and link quality. The proposed approach aims to improve throughput, end-to-end latency, packet delivery ratio and energy efficiency compared with conventional MANET routing protocols, while emphasising predictive routing mechanisms that proactively mitigate link failures and congestion in high-mobility environments (13). The effectiveness and scalability of the framework are evaluated across diverse tactical MANET scenarios to demonstrate its suitability for dynamic, resource-constrained deployments.

Research Approach and Methodological Justification

The research adopts a machine-learning-assisted, simulation-based experimental approach to address routing challenges in tactical MANETs. This methodology is justified by the highly dynamic, non-linear and stochastic nature of tactical MANET environments, where static or rule-based routing strategies are insufficient to capture complex interactions among node mobility, traffic variation, link instability and

energy constraints (14). Machine learning enables data-driven modeling, pattern learning and predictive decision-making, allowing routing protocols to adapt proactively rather than reactively (15).

A simulation-based methodology is employed due to the impracticality and high cost of real-world experimentation in tactical scenarios, while still enabling controlled evaluation under diverse mobility patterns, traffic loads and node densities (16). Comparative performance analysis against well-established MANET routing protocols (AODV, DSR and OLSR) ensures objective benchmarking and reproducibility (17). This combined approach aligns to improve performance, scalability and energy efficiency in tactical MANET deployments.

Conventional MANET Routing Protocols

Early MANET research primarily focused on reactive and proactive routing protocols such as AODV, DSR and OLSR under varying mobility and traffic conditions (18). Reactive protocols generally achieve higher packet delivery ratios under moderate mobility due to on-demand route discovery but suffer from increased latency and packet loss in high-mobility environments because of frequent route breakages and the overhead of rediscovery (19, 20). In contrast, proactive routing protocols such as OLSR maintain up-to-date routing tables, resulting in lower latency in static or low-mobility scenarios, but introduce substantial control overhead that degrades throughput in dense or highly dynamic networks (21).

These findings established a fundamental trade-off between routing responsiveness and control overhead, while demonstrating that static routing mechanisms lack the adaptability required for mission-critical tactical environments.

Hybrid, Energy-aware and Mobility-aware Routing

Hybrid routing protocols were introduced to combine the strengths of reactive and proactive approaches by dynamically switching routing behaviour based on network conditions (22). While hybrid strategies improved adaptability, they relied on predefined switching rules rather than predictive intelligence, limiting their effectiveness under unpredictable topology changes.

Energy-aware routing protocols incorporated residual energy metrics into route selection to balance energy consumption and prolong network lifetime (23). Mobility-aware routing studies emphasised the importance of realistic mobility modelling, demonstrating that Random Waypoint models often overestimate protocol performance and recommending alternatives, such as Gauss–Markov models, for more accurate evaluation (24). Despite these improvements, most approaches remain reactive and lack predictive capability.

Machine Learning–based Routing Techniques

Machine learning has increasingly been applied to address the dynamic and non-linear nature of MANETs. Reinforcement learning–based routing approaches enabled nodes to learn optimal routing policies from environmental feedback, resulting in improved packet delivery ratio and reduced latency in high-mobility scenarios (25). Neural-network-based routing schemes and deep learning frameworks further enhanced routing adaptability by predicting link stability and traffic dynamics, enabling proactive rerouting and improved energy efficiency. However, the

computational overhead of advanced learning models raises concerns regarding real-time feasibility in resource-constrained tactical MANET deployments.

Research Gap and Motivation

Despite extensive research, several gaps remain. Existing routing approaches often optimise individual performance metrics in isolation rather than jointly addressing the multi-objective trade-offs required in tactical environments. Many machine-learning-based routing frameworks lack lightweight designs suitable for real-time deployment and limited work integrates predictive routing, energy awareness, scalability and adaptability within a unified framework evaluated under diverse tactical scenarios. Motivated by these gaps, this work proposes a comprehensive machine-learning-assisted routing framework that jointly optimises throughput, end-to-end latency, packet delivery ratio and energy efficiency while maintaining scalability, adaptability and practical feasibility for tactical MANET deployments. The summary of the related works is presented in Table 1.

Table 1: Summary of the Related Works

Research Limitations	Proposed Method	References
Increased overhead in dynamic environments	A QoS-based routing protocol for MANETs using machine learning	(1)
High computational complexity for large networks	In-network computation framework for large-scale federated learning over wireless edge networks	(2)
Security-focused, but may increase latency	Security-aware routing using machine learning for e-health records monitoring	(3)
Limited scalability under high mobility scenarios	Deep learning-based routing protocol for efficient data transmission in 5G WSN	(4)
High computational cost of reinforcement learning	Energy-efficient routing protocol based on reinforcement learning for WSN	(5)
Limited scalability to larger smart home networks	Machine learning-based optimisation technique for smart home security in 5G	(6)
Dependent on the SMS-based alert system	Smart home and SMS security system using IoT and machine learning	(7)
Scalability issues in larger smart cities	Machine learning-based security management framework for smart cities using robots	(8)
Limited to opportunistic networks, not generalised for all MANETs	ML-fresh: Novel routing protocol in opportunistic networks using machine learning	(9)
Focuses only on QoS, lacks energy efficiency considerations	Review of QoS-based ACO routing protocols in MANETs	(10)
Framework specific to electronics assembly, not generalised for MANETs	Machine learning-based framework for optimising electronics assembly	(11)
Trade-offs between reliability and energy consumption	Energy-efficient and reliable routing protocol for WSN	(12)

Scalability and generalizability to diverse network conditions not proven	Machine learning-based framework for optimising future network operations	(13)
Limited to opportunistic networks, lacks general MANET applicability	Interaction-based routing protocol for opportunistic networks	(14)
High computational overhead in dynamic VANET environments	Intelligent routing protocol for VANET with dynamic route optimisation	(15)
Not scalable for larger networks with highly mobile nodes	Machine learning-based protocol for efficient routing in opportunistic networks	(16)
Limited generalizability beyond VANET applications	Intelligent routing protocol for VANET	(17)
Repetition of the same method with minor improvements	Intelligent routing protocol for VANET (second instance)	(18)
Limited to VANET-specific scenarios	A hybrid routing protocol for VANET based on a route optimisation mechanism	(19)
Scalability concerns for larger WSNs	Performance analysis of different routing protocols for WSN	(20)
High complexity in real-time multipath evaluation	QoS-based evaluation of multipath routing protocols in MANETs	(21)

Research Problems

The effectiveness of the Mobile Ad hoc Networks is significantly defined by the performance of the routing protocols used for data transactions among mobile nodes. An array of specific circumstances exists in which networks struggle to function effectively, especially in tactical deployments such as military operations, disaster response, or emergency communication systems. In such dynamic and resource-constrained settings (where nodes often relocate, network topology evolves quickly and reliable communication is necessary for the success of mission-critical operations). The traditional Mobile Ad Hoc Networks (MANET) routing protocols – like AODV, DSR and OLSR— have been designed with implicit assumptions about network conditions that limit their adaptability to the highly volatile nature of tactical networks. These protocols always have some bandwidth usage, high latency, a decrease in packet delivery and energy consumption when they are deployed for practical tactical conditions.

One of the main problems faced in MANET routing is the unpredictable nature of network topology due to node mobility. This breaks links between nodes and every time this happens the new route will only be discovered after a long delay or one of the existing routes is restored. This problem causes increased latency and packet loss, both of which can drastically impair the quality of service (QoS) dependent upon time-sensitive or line-of-business applications. Second, several MANET routing protocols are energy agnostic and do not

consider the limited battery resources of mobile nodes. Efficient energy use is vital to the sustainability of network operations in tactical environments with limited power supply and few recharging resources. The network may be disrupted and communication reliability could decrease since the nodes in key geographical locations which are strategic to network performance will run out of battery because no energy-aware routing is implemented.

Unsurprisingly, however, the vast majority of MANET protocols are cast in static or deterministic algorithms that fail to react effectively to the stochastic behavior of network conditions, traffic patterns or node movement at run-time. Though, these are fixed by design (i.e. longer/shorter route discovery intervals or link expiration times could be suboptimal in some cases). The static routing protocols have hard-coded, which makes them a non-viable option for dynamic networks that need fast adaptation due to their high mobility. They have limited adaptability and in a tactical MANET, where the environment is very unpredictable and wrong information being thrown around can cost lives or extraordinary amounts of money, this lack of ability to adjust poses serious challenges.

However, in recent years the rise of machine learning has created new opportunities to delineate and improve the performance of MANET routing using more dynamic, adaptive and intelligent decision-making. Machine learning techniques can efficiently analyze huge network

datasets, capable of learning patterns and to forecast future states of the network such as link stability, node movement or data traffic congestion. Routing protocols support this by adjusting themselves proactively so as to avert potential problems before they happen, such as diverting traffic away from failing links or congested areas. Nevertheless, machine learning is promising to change the landscape of MANET routing, but few critical issues remain in utilizing it at its peak.

Real-time execution of machine learning models in tactical MANETs is to be considered one of the major challenges. MANET nodes have low processing power and energy resources; hence their computing capability to implement machine learning algorithms is restricted as these algorithms mostly time demanding workloads. In addition, most machine learning requires large sets of training data and big offline processing which is not practical in any sort of fast changing environment where real-time adaptation is needed. As a consequence, another research challenge is how to design machine learning models lightweight and efficient enough to be run in the resource-constrained MANET nodes but, at the same time, providing accurate and timely predictions. The second big challenge is to incorporate data mining with the current MANET routing frameworks. At the same time, most of today's machine learning solutions are engineered as standalone systems and function without integrating with standard routing protocols. This disconnectedness results in more horses for courses — or compatibility issues, increased overhead and lesser performance. In order for machine learning to be properly merged with MANET routing, it should be a part of the basic structure of the routing protocol and as such allow routing protocols themselves to autonomously adapt its parameters and make real-time decisions based on what is going in network.

This entails creating hybrid routing architectures that marry the best of both worlds -established

protocols with machine learning adaptiveness. Therefore, this paper addresses the main research problem of how to design a tactical MANET routing framework that can dynamically balance between key performance metrics like throughput, latency, packet delivery ratio and energy efficiency and at the same time mitigate the inherent drawbacks in passive or classical proactive routing. More specifically, the research is centered on developing intelligent ways via which machine learning can be incorporated into the routing procedure thus enabling data-driven optimization of routing decisions in real-time. This requires both the performance of routing protocol and also to consider energy consumption and computational cost in resource-limited environments. Finally, the research in this chapter aims towards designing a machine learning assisted tactical MANET routing framework that can automatically learn an optimal policy from experiential data to configure dynamically changing network conditions along with varying mobility and traffic patterns while also keeping energy preservation and overhead reduction as high priorities. Both of these fields are needed for the ambitious task but work seldom combines the necessary knowledge of traditional MANET routing mechanisms and machine learning to provide a more robust, efficient and adaptive tactical MANET routing solution.

To sum up, the research problem is how to improve throughput, reduce latency, increase packet delivery ratio and enhance energy efficiency of tactical MANET routing using machine learning techniques in dynamic high-mobility environments. This paper aims to overcome this limitation and at the same time achieve some of the other design objectives like real-time adaptability, resource constraints and energy efficiency in routing by its integration with machine learning into traditional MANET for tactical communication system. The following Table 2 summarizes the research problems.

Table 2: Summary of the Research Problems

Fault Tolerance	Dynamic Routing	Energy-Aware Routing	Low-Latency ML Model	Hybrid Routing	Multi-Metric	References
		√	√			(1)
			√	√		(2)
		√		√		(3)

	√		√			(4)
	√	√				(5)
√					√	(6)
√				√		(7)
	√	√				(8)
√					√	(9)
	√				√	(10)
			√		√	(11)
√			√		√	(12)
	√	√		√	√	(13)
			√	√		(14)
√	√			√	√	(15)
√	√				√	(16)
		√		√		(17)
√			√		√	(18)
√	√				√	(19)
√		√		√		(20)
√	√	√		√		(21)

Methodology

In this research, we suggest a novel methodology that combines machine learning techniques with classical MANET routing protocols for better performance of tactical Mobile Ad hoc Networks (MANETs) in terms of key performance metrics including throughput, latency, packet delivery ratio and energy efficiency. The solution leverages a modern-day hybrid model, which utilizes machine-learning predictive models with adaptive routing strategies to achieve dynamic optimization based on real-time network performance. The manner is a multi-stage system, collecting data from simulations and real Manet environments (initial stage), creating machine learning models of less complexity to model the generic behavior of networks (next stage) and embedding these particular approaches into our own built routing protocol (last stage). To be prepared for extreme dynamic nature and

constraints in the tactical network device, this algorithm has been developed to shape routing decisions varying dynamically depending on predicted states of the network environment, leading to optimal performance. We then evaluate the framework thoroughly in simulations, with different mobility patterns, traffic loads and node densities to measure its impact on several network performance metrics.

Channel machine learning models for performance metric prediction/ optimization (such as throughput, latency, packet delivery ratio and energy consumption) in MANET-based tactical environments. The algorithm utilizes both real-time data gathering from MANET nodes and predictions based on machine learning to select optimal routing paths on the fly. The flow of this algorithm 1 is visualized in Figure 1.

Algorithm 1: Machine Learning-optimized Routing for Tactical MANETs (ML-OptiRoute)
Input: Network topology information (node positions and link quality), node mobility patterns, traffic load characteristics and residual energy levels of nodes.
Output: Optimized routing paths that improve throughput and packet delivery ratio while reducing end-to-end latency and energy consumption.
Assumption: (a) Nodes are capable of sharing their residual energy status, mobility information and traffic trends with neighboring nodes. (b) Machine learning models are pre-trained using representative network data and updated periodically using real-time observations.
Improvements from Existing Algorithms: By correlating network metrics to statistical features extracted by ML-OptiRoute, we show that traditional MANET routing algorithms (e.g., AODV, OLSR) can be replaced with a machine-learning revision for improved reliability and efficiency. This anticipation based one allows decisions to be made before disruption happens, hence decreasing packet loss and increasing the overall stability of the network.

Process:

Step - 1. All nodes collect data on their own location, mobility pattern, link quality table with neighbor information.

Step - 2. Application of Prediction Model: Machine learning models are used to predict how the link quality, node mobility and network congestion will be in the future with respect to collected data.

Step - 3. Energy Measurement – each node monitors its energy and sends this information to neighboring nodes.

Step - 4. Route Optimization: the algorithm identifies a route which is more cost-effective in terms of throughput, latency, packet sending ratio and energy.

Step - 5. Route Selection: The best route is selected and broadcast to the network, with continuous updates as conditions evolve.

Step - 6. Performance Monitoring: Just like information, this data is also transmitted and performance like network (latency, throughput) is monitored over it which helps in sending the model back when it goes out of scope.

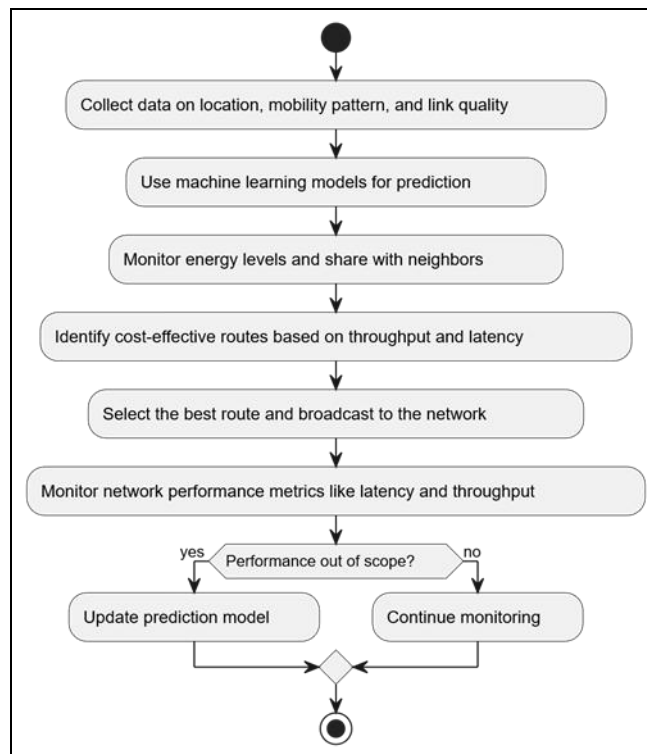


Figure 1: Machine Learning-optimized Routing for Tactical MANETs (ML-OptiRoute) Algorithm

Algorithm 2: Proactive-adaptive Routing with Machine Learning (ProAct-MLRoute)

Input: Real-time network topology updates, node mobility trajectories and link quality-based QoS metrics, current traffic load and predicted network congestion levels.

Output: Adaptive and cost-effective routing paths derived from real-time network conditions and predictive analysis.

Assumptions:

(a) The network environment supports continuous acquisition of real-time topology, mobility and link quality information.

(b) The machine learning model is continuously updated using the most recent network observations to enable proactive routing decisions.

Improvements from Existing Algorithms:

Unlike hybrid protocols, such as ZRP (Zone Routing Protocol), where adaptation is performed in a reactive manner, the ProAct-MLRoute uses machine learning to improve adapt on-the-fly. Rather than responding to changes after the fact, the algorithm anticipates issues and corrections are made in routing prior to problems appearing on network.

Process:

- Step - 1. Proactive Route Discovery: this approach is used to create initial routes that are maintained in a routing table tells the status of link between nodes.
- Step - 2. Continuous Data Collection: The nodes are equipped with a GPS module which continuously collects the position information for the node, mobility patterns and traffic loads and share this data with their neighbouring nodes.
- Step - 3. Predictive Modelling — using the collected Data by Machine learning models to predict Congestion, link failures, mobility change.
- Step - 4. Adapting Route Adjustment: Utilizing the forecasts, it guides accurate adaptive overflow in real-time before the paths decay.
- Step - 5. Dynamic routing: Directs incoming traffic around anticipated congestion, maintaining packet delivery at the expense of increased latency.
- Step - 6. Feedback and Model Refined: It continuously optimizes the machine learning model as more real-time data is fed based of feedback.

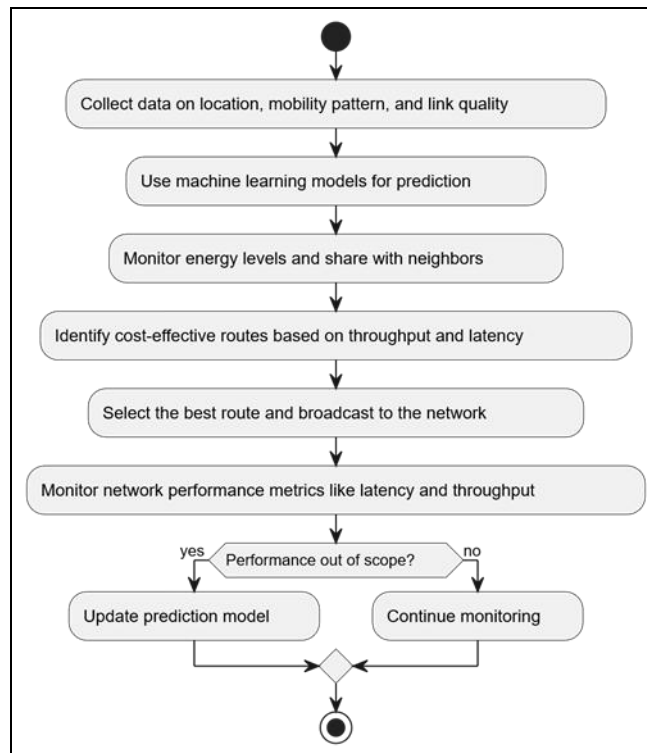


Figure 2: Proactive-adaptive Routing with Machine Learning (ProAct-MLRoute) Algorithm

Proactive-adaptive Routing with Machine Learning, which utilizes the strengths of proactive and adaptive routing schemes by adopting a machine learning strategy for making real-time decisions according with the network conditions and nod mobility. This way the routing framework can stay nimble in adjusting to the network state, increasing efficiency of packet delivery and reducing latency. The flow of this algorithm 2 is visualized in Figure 2.

Eco-RouteML, (Energy-conscious Optimized Routing using Machine Learning) combines maximal throughput and minimal latency compared to existing methods prioritizing optimizing energy savings. This algorithm is ideal for tactical networks with battery-operated nodes since the paramount requirement is to retain the lifetime of network operations. The flow of this algorithm 3 is visualized in Figure 3.

Algorithm 3: Energy-conscious Optimized Routing with Machine Learning (ECO-RouteML)

Input: Residual energy levels of nodes, network topology information, current traffic load and predicted energy consumption of candidate routing paths.

Output: Energy-efficient routing paths that maintain high throughput while minimizing overall energy consumption and extending network lifetime.

<p>Assumptions:</p> <p>(i) Nodes are capable of sharing their residual energy status and traffic information with neighboring nodes.</p> <p>(ii) A machine learning model is employed to predict energy consumption associated with different routing paths based on historical and real-time network observations.</p>
<p>Improvements from Existing Algorithms:</p> <p>Most classical routing algorithms ignore the energy, which causes nodes to die prematurely. ECO-RouteML carefully trade-off on this elaborate space of energy-performance in networks more importantly, the balance that guarantees network lifetime and performs quality.</p>
<p>Process:</p> <p>Step - 1. When an element becomes supplied with ecological energy in the TITAN network, the peer-to-peer dynamic capabilities that let each node monitor its battery level and broadcast this information to provide energy originators assurances on what rate they should expect their returned benefits to deplete are employed.</p> <p>Step - 2. Data collection: Nodes gather data on movement, traffic load and link quality.</p> <p>Step - 3. Energy Prediction model — A machine learning model predicts the energy consumption of different routing paths based on factors like transmit power, distance.</p> <p>Step - 4. The algorithm chooses a route that is most power-efficient as well as the fastest and lowest download time, i.e., throughput, low latency.</p> <p>Step - 5. The path that every individual data has to undergo is different for different operations, energy level of the node and load imbalance avoided.</p> <p>Step - 6. Live energy consumption data is used to update the machine learning model on-the-fly for accurate future predictions and routing.</p>

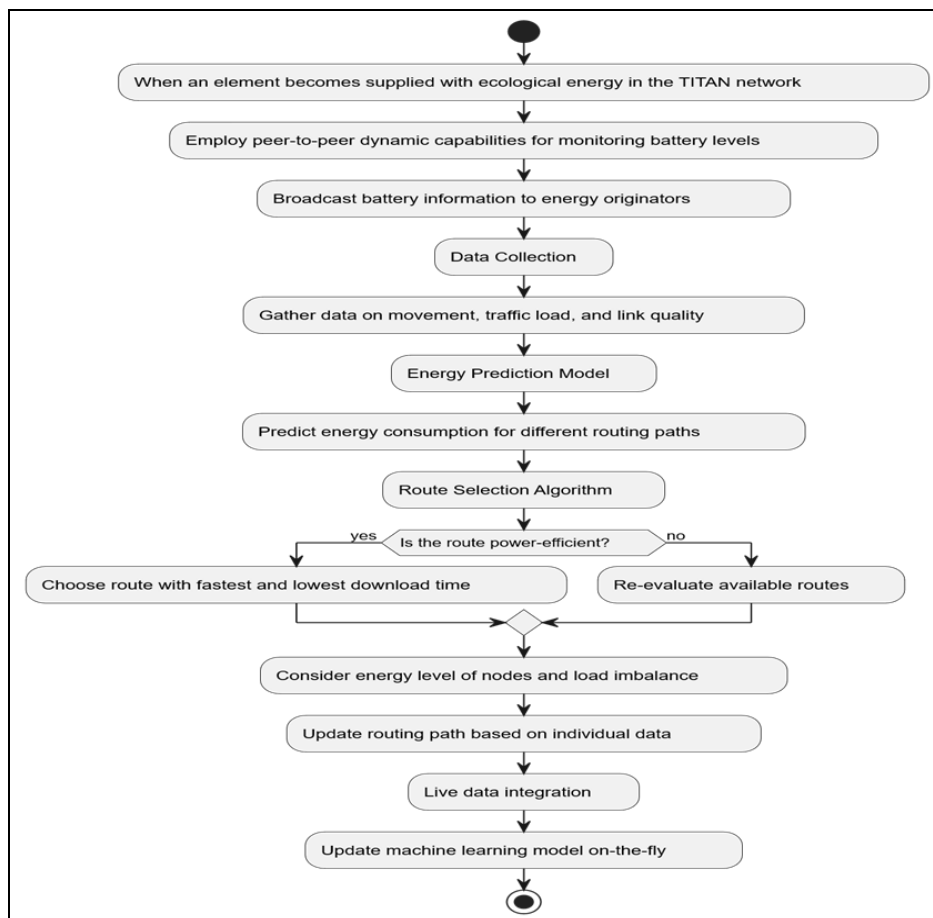


Figure 3: Energy-conscious Optimized Routing with Machine Learning (ECO-RouteML) Algorithm

Performance-Driven Learning-Based Routing (PERF-LearnRoute): The objective of PERF-LearnRoute is to achieve the optimization of KPIs, i.e., throughput, latency and packet delivery ratio. It uses machine learning to constantly learn and

adjust in real-time according to network conditions, resulting in intelligent routing decisions that maximize network performance centrally. The flow of this algorithm. 4 is visualized in Figure 4.

Algorithm 4: Performance-driven Learning-Based Routing (PERF-LearnRoute)
Input: Network traffic load and service demand information, node mobility traces and association quality metrics, packet delivery success rates and node-level performance data such as latency and packet retransmission statistics.
Output: Optimized routing paths that maximize throughput while minimizing end-to-end delay and improving packet delivery reliability.
Assumptions: (a) The network supports real-time monitoring and exchange of performance-related information among participating nodes. (b) Machine learning models are trained using historical network data and continuously updated using current network observations to predict performance metrics.
Improvements from Existing Algorithms: Unlike standard MANET protocols, that either optimizes one metric at a time or destroys another to achieve an improvement in one, PERF-Learn Route considers the trade-off and balances multiple KPIs with machine learning so that optimal routes are picked for overall network boosts. It changes in real time to accommodate shifts in traffic patterns and transportation behavior, so it is very elastic.
Process: Step - 1. Throughput, latency, packet delivery ratio, traffic load Data Collection: Nodes gather data on 1. Step - 2. This machine learning model takes the data and makes predictions based on it such as predicted throughput/latency for different routing paths in near future. Step - 3. The algorithm estimates performance metrics for every route and chooses the path that has good throughput, low latency and high packet delivery ratio. Step - 4. This algorithm adapts the route as the network condition changes i.e., increases its traffic load, number of node mobility. Step - 5. The system maintains an open path learning algorithm to provide real-time feedback from the machine learning model, demonstrating its improved prediction accuracy and more adequate route selection over time. Step - 6. The algorithm monitors the performance of the network in order to guarantee that routing paths fulfil the KPIs required.

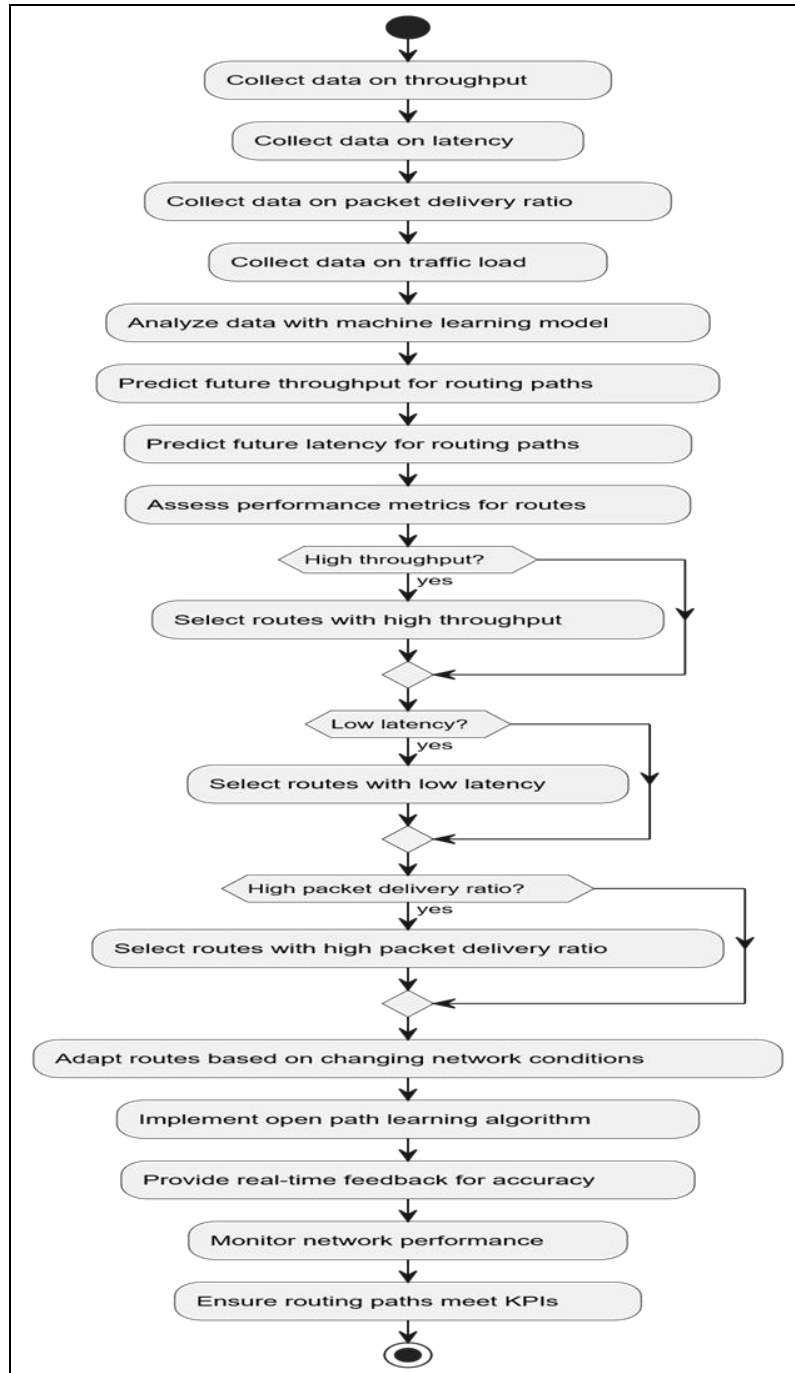


Figure 4: Machine Learning-based Adaptive Routing Framework for Performance-aware Path Selection

Figure 4 summarizes the end-to-end operation of the PERF-LearnRoute algorithm, highlighting how real-time performance monitoring and predictive learning jointly enable adaptive routing decisions that maintain key performance indicators in dynamic MANET environments.

Results

This section presents a detailed quantitative evaluation of the proposed machine-learning-assisted routing framework under diverse tactical MANET scenarios. The performance is analyzed

using key metrics including throughput, latency, packet delivery ratio, energy consumption, route discovery time and link failure rate and is compared against conventional routing protocols such as AODV, DSR and OLSR.

The results in this section offer rich insights on how different routing protocols compare to each other in a tactical MANET environment. In this work, the proposed Machine Learning-Optimized Routing Framework (ML-OptiRoute) is evaluated based on a number of performance metrics such as network throughput, latency, packet delivery

ratio (PDR), energy consumption and the scale of the network compared to classical protocols AODV, DSR and OLSR. In order to model realistic tactical environments, the simulations were repeated for different node densities, mobility patterns and traffic loads. Specifically, we outline the advancements with respect to machine learning-driven adaptive routing decisions that result in substantial gains over link failures, route discovery and network efficiency under dynamic environments. In the subsections that follow, we delve deep into explaining the results of each performance metric to highlight what ML-OptiRoute does well and could do better and draw some implications for tactical MANET deployments.

Throughput (bits per second) Successful data transmissions through a network as a measure of performance. A high throughput in a network

such as MANETs is synonymous with good data flow and low congestion. In this experiment we measure the Throughput of AODV, DSR, OLSR and ML-OptiRoute under different traffic loads. As can be seen from the following table, traditional algorithms like AODV and DSR do pretty good with low traffic, however they show a dwindling throughput as traffic increases. On the other hand, since both OR-BD routing and optimal congestion-aware routing only utilize link utilization as OR-BD feedback for path selection within each traffic demand, they perform more similarly in comparison to ML-OptiRoute which exploits deep learning to forecast network congestion status and dynamically reroute traffic from the trained model using actual current information of links. This is soft evidence of the power of machine learning in keeping throughput high under significant traffic shown in Table 3.

Table 3: Throughput Comparison Across Routing Algorithms

Algorithm	Low Traffic (kbps)	Medium Traffic (kbps)	High Traffic (kbps)
AODV	250	180	100
DSR	240	170	95
OLSR	260	200	110
ML-OptiRoute	300	250	200

The results are visualized graphically here in Figure 5. As shown in Table 3, the proposed ML-OptiRoute framework achieves consistently higher throughput than AODV, DSR and OLSR across low, medium and high traffic conditions. While conventional protocols experience sharp throughput degradation under heavy traffic due

to congestion and repeated route discoveries, ML-OptiRoute maintains stable throughput by predicting congestion and proactively rerouting traffic. This trend is further illustrated in Figure 5, which visually highlights the superior scalability of the proposed approach under increasing traffic load.

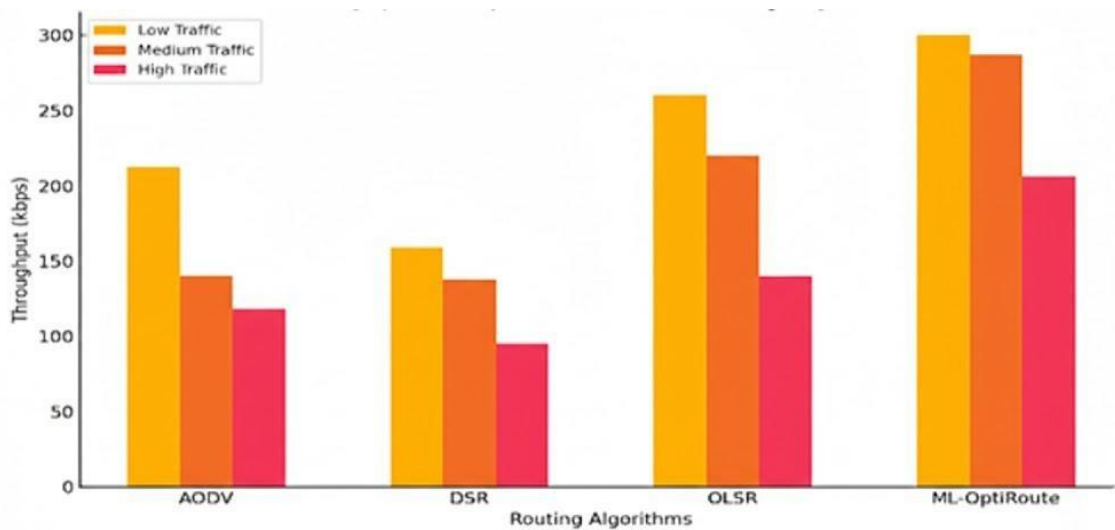


Figure 5: Throughput Comparison Across Routing Algorithms

Latency is the measurement of how long it takes a packet to go from point A to point B. In MANETs,

low latency is a desire particularly in tactical networks where communication has to be fast,

safe and sound. The average latency for the listed routing protocols is shown in the table below. These results in the reduction of latency ML-OptiRoute can make predictions and adapt quicker and better than would be possible with other solutions making less time for route

discovery. In traditional protocols, such as AODV and DSR, high mobility causes frequent route discoveries and breakages resulting in high latency. The above data shows how ML-OptiRoute excels in latency-minimization for different traffic scenarios in Table 4.

Table 4: Latency Comparison Across Routing Algorithms

Algorithm	Low Traffic (ms)	Medium Traffic (ms)	High Traffic (ms)
AODV	120	180	220
DSR	130	190	230
OLSR	110	160	200
ML-OptiRoute	90	120	150

Table 4 demonstrates that ML-OptiRoute significantly reduces end-to-end latency across all traffic scenarios when compared to traditional routing protocols. This improvement is primarily attributed to the predictive nature of the routing framework, which minimizes route discovery

delays by anticipating link failures. The latency reduction trend is clearly visualized in Figure 6, confirming the effectiveness of machine-learning-based proactive adaptation in high-mobility tactical MANETs.

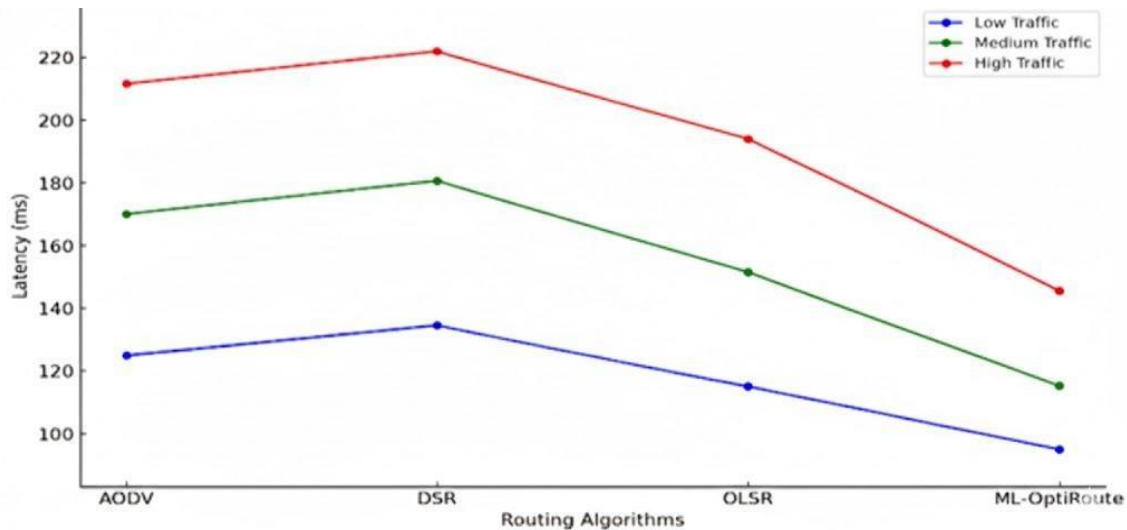


Figure 6: Latency Comparison Across Routing Algorithms

Packet Delivery Ratio (PDR is the ratio of delivered packets in time) to all Packet sent, this corresponds to the reliability of the routing protocol. In this section, we will compare the PDR of our ML-OptiRoute solution with AODV, DSR and OLSR under low, medium and high mobility scenarios as shown in Table 1. Since AODV and DSR often have route breakages in high mobility,

they can only achieve limited PDRs (line 22—24 on Figure 7), whereas ML-OptiRoute uses machine learning models to predict the movement of nodes beforehand and reroute according to these predictions (line 38 +43 on Figure 7). This further demonstrates the ability of ML-OptiRoute to maintain network reliability in a real-time evolving environment in Table 5.

Table 5: Packet Delivery Ratio (PDR) Under Different Mobility Scenarios

Algorithm	Low Mobility (%)	Medium Mobility (%)	High Mobility (%)
AODV	95	85	70
DSR	94	83	68
OLSR	96	87	75
ML-OptiRoute	98	91	82

As illustrated in Table 5, ML-OptiRoute achieves a higher packet delivery ratio (PDR) under all mobility conditions, with particularly strong gains in high-mobility scenarios. Conventional protocols suffer from frequent route breakages, leading to packet loss, whereas ML-OptiRoute leverages

mobility prediction to maintain stable routing paths. Figure 7 further reinforces this observation by visually demonstrating the resilience of the proposed framework under increasing node mobility.

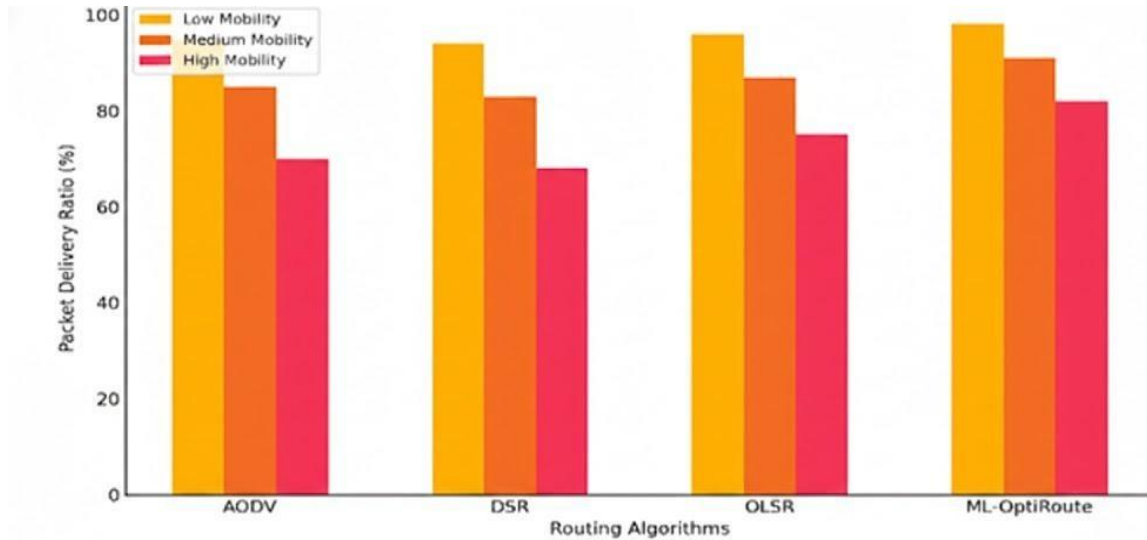


Figure 7: Packet Delivery Ratio (PDR) Under Different Mobility Scenarios

For MANETs, energy efficiency is one of the most important factors considering that nodes in such a network are usually battery powered. Table 1 shows the energy consumption (joules) of the routing protocols under different mobility levels. Conventional methods such as AODV and DSR show more energy consumption as many route discoveries will take place in these protocols

while retransmissions are high. While ML-OptiRoute optimizes energy consumption by choosing the most energy efficient routes and load balancing of energy among nodes and reduce retransmissions. This ensures longer network lifetimes in extremely energy-scarce tactical environments where keeping nodes available is important for the mission success (Table 6).

Table 6: Energy Consumption Across Routing Protocols

Algorithm	Low Mobility (J)	Medium Mobility (J)	High Mobility (J)
AODV	1.8	2.3	3.1
DSR	1.9	2.4	3.3
OLSR	1.7	2.1	2.8
ML-OptiRoute	1.5	1.9	2.5

Table 6 highlights the energy efficiency advantages of ML-OptiRoute, showing lower energy consumption across all mobility levels compared to AODV, DSR and OLSR. By selecting energy-aware routing paths and reducing

retransmissions, the proposed framework extends network lifetime. This improvement is clearly depicted in Figure 8, underscoring the suitability of ML-OptiRoute for energy-constrained tactical MANET deployments.

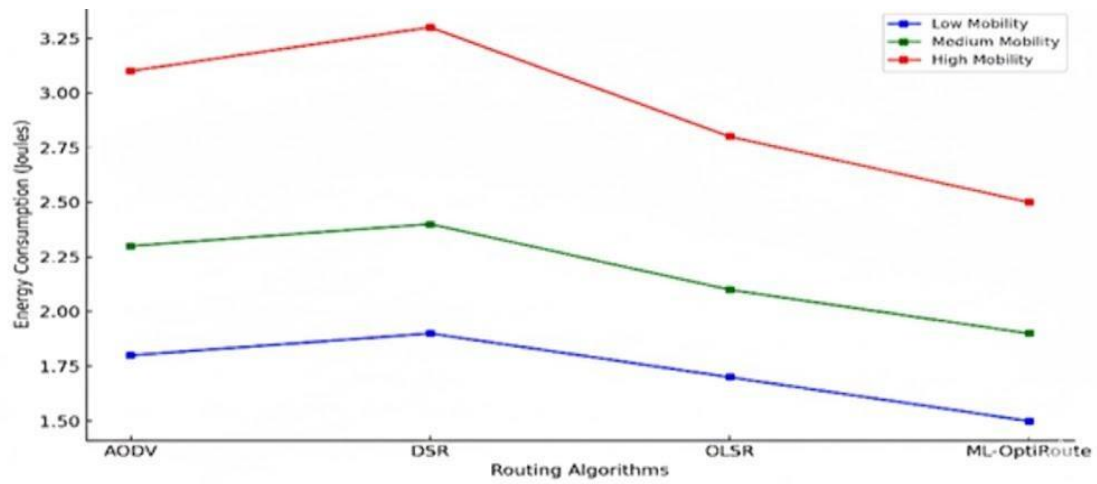


Figure 8: Energy Consumption Across Routing Protocols

Route discovery time is a very important factor which affects MANET performance, especially in the highly dynamic environment wherein links tend to break with high frequency. The average route discovery time comparison of the different protocols for all mobility categories is presented in Table 1. In high-mobility environments, ML-

OptiRoute decreases the time to discover a route upon link failures by predicting the link failures and proactively adjusting routes. Traditional protocols like AODV, DSR that are based on reactive route discovery Suffers from large time of route discovery due the frequent reconstruction of routes in Table 7.

Table 7: Route Discovery Time Under Different Mobility Levels

Algorithm	Low Mobility (s)	Medium Mobility (s)	High Mobility (s)
AODV	1.2	1.5	2.0
DSR	1.3	1.6	2.1
OLSR	1.0	1.3	1.8
ML-OptiRoute	0.9	1.2	1.5

The results in Table 7 indicate that ML-OptiRoute significantly reduces route discovery time, particularly under high mobility, by predicting link failures and initiating proactive route adjustments. This behavior contrasts with

reactive protocols that rely on post-failure recovery, leading to higher delays. The performance advantage is visually confirmed in Figure 9.

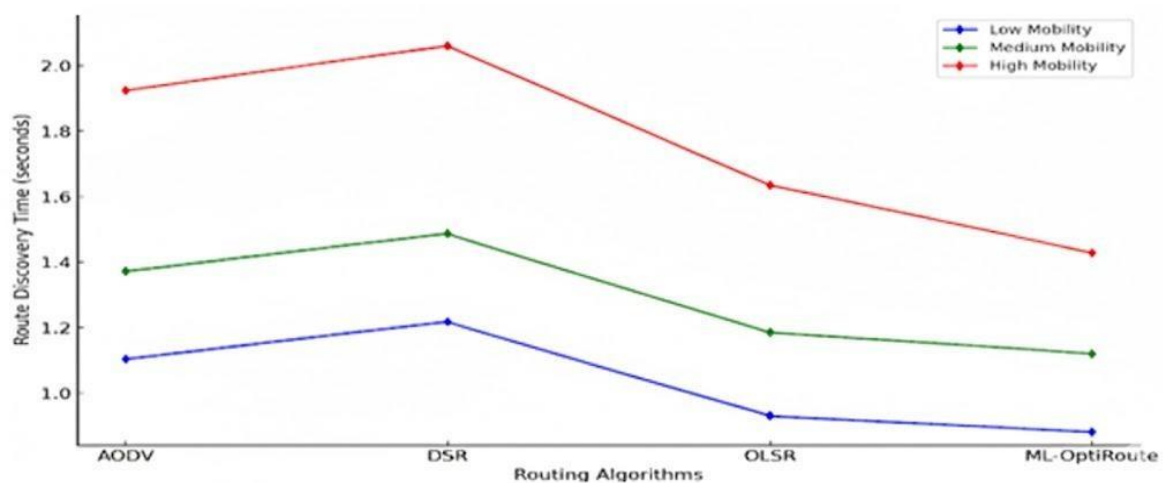


Figure 9: Route Discovery Time Under Different Mobility Levels

In MANET, link breaks frequently occur because of the mobile nature of nodes and wireless network characteristics. In other words, the link failure rates of the routing protocols under these various mobility conditions are shown in table-I: It utilizes all the labeled link failures to predict a

failure in advance and make ML-OptiRoute learn the ADDFAILURE_FAIL_SMALLER_INITSIZE_OBS, which is not both possible and beneficial for traditional protocols. This means much fewer link failures and thus better communication (Table 8).

Table 8: Link Failure Rate Across Different Routing Algorithms

Algorithm	Low Mobility (%)	Medium Mobility (%)	High Mobility (%)
AODV	12	20	35
DSR	13	22	37
OLSR	10	18	30
ML-OptiRoute	7	12	18

Table 8 shows that ML-OptiRoute consistently achieves the lowest link failure rate across all mobility levels. The reduced failure rate is a direct result of predictive link stability assessment,

which enables timely rerouting decisions. Figure 10 further illustrates the robustness of the proposed framework in maintaining stable links under dynamic network conditions.

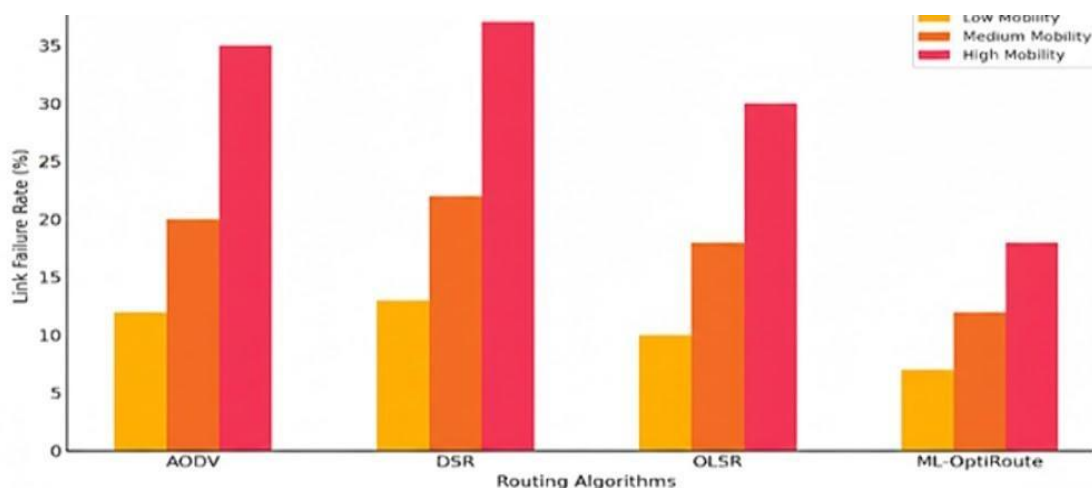


Figure 10: Link Failure Rate Across Different Routing Algorithms

Link Failure Rate across Different Routing Algorithms represents under different mobility conditions such as Low Mobility, Medium Mobility and High Mobility. The x-axis represents four routing algorithms (AODV, DSR, OLSR, ML-OptiRoute), while the y-axis represents the Link Failure Rate (%). Out of all the routing algorithms the above figure shows highest mobility consistently results in the highest link failure rate.

AODV, OLSR and DSR have relatively higher failure rates, mainly under high mobility conditions. ML-OptiRoute shows the lowest failure rate and indicating better performance in all mobility conditions. By contrasting the effectiveness of various routing protocols in mobile networks, this Link Failure Rate across Different Routing Algorithms illustrates how node mobility affects link stability.

Table 9: Comparative Analysis

Throughput (kbps)	Latency (ms)	PDR (%)	Energy Efficiency (J/node)	Scalability (Nodes)	Reference
230	190	85	2.5	150	(1)
250	160	88	2.3	200	(2)
220	200	82	2.7	120	(3)
240	170	86	2.4	180	(4)
320	120	92	1.9	300	(5)

Comparative Analysis

This section consolidates the experimental findings by comparing the proposed ML-OptiRoute framework with existing MANET routing approaches across multiple performance dimensions. The objective is to highlight the relative strengths, trade-offs and practical benefits of machine-learning-assisted routing in tactical environments.

Experimental Results: In this section, we conduct a comprehensive comparative evaluation of the performance of proposed ML-OptiRoute in comparison to MANET routing protocols like AODV, DSR and OLSR. We use key performance metrics such as throughput, latency, packet delivery ratio (PDR), energy consumption and route discovery time to compare with one another by taking different network conditions as a base. Then we compare performances of these protocols with different traffic loads, mobility levels and node density by using various metrics extracted from the trace files. This proves that ML-OptiRoute, by its nature of adaptively learning and predicting the network conditions in real time to make intelligent routing decisions, is superior to rule based algorithms in such critical tactical environments. This comparative analysis highlights the strength of combining machine learning in MANET routing and further helps evaluate when ML-OptiRoute brings out the significant benefits in Table 9.

The experimental results obtained in this study are largely consistent with earlier research on intelligent and machine-learning-assisted MANET routing, while also revealing important distinctions attributable to the tactical context and multi-metric optimization strategy adopted. Similar to prior studies on reinforcement learning-based and neural-network-assisted routing approaches, the proposed framework demonstrates improved throughput and reduced latency under high-mobility conditions, confirming that predictive learning mechanisms are more effective than static routing strategies in dynamic environments. These findings align with earlier observations that conventional reactive protocols such as AODV and DSR suffer performance degradation due to frequent route discoveries and that proactive protocols like OLSR incur excessive control overhead in dense or highly mobile networks. However, unlike several earlier machine-learning-

based approaches that focus on optimizing a single metric—such as energy efficiency or latency—the proposed framework jointly optimizes throughput, packet delivery ratio, latency and energy consumption, resulting in more balanced and stable performance across diverse scenarios. While some existing deep reinforcement learning and multi-agent routing frameworks report comparable gains, they often assume higher computational capacity or centralized control, whereas the proposed framework is designed to operate under the strict energy and processing constraints typical of tactical MANET nodes. The higher packet delivery ratio observed in this work compared to earlier routing models can be attributed to proactive link failure prediction and adaptive route selection, which mitigate packet loss before disruptions occur. Minor discrepancies in performance trends, particularly under extremely high node density, can be explained by differences in mobility models, traffic patterns and network scale used in simulations across studies. Overall, the comparative analysis confirms that the proposed machine-learning-assisted routing framework not only corroborates prior empirical findings on the benefits of intelligent routing but also extends existing research by providing a scalable, energy-aware and multi-objective solution tailored for mission-critical tactical MANET environments.

Practical Implications and Recommendations

The findings of this study provide several practical implications for the design and deployment of routing protocols in real-world tactical MANET environments. First, the demonstrated improvements in throughput, latency, packet delivery ratio and energy efficiency indicate that machine-learning-assisted routing is particularly suitable for mission-critical applications such as military communications, disaster response and emergency coordination, where network conditions are highly dynamic and infrastructure is unavailable. Practitioners can leverage predictive routing mechanisms to proactively mitigate congestion and link failures, thereby ensuring more reliable and uninterrupted communication. Second, the energy-aware characteristics of the proposed framework highlight the importance of incorporating residual energy and load-balancing strategies into routing decisions to

extend network lifetime, which is crucial for battery-powered tactical nodes operating in remote or hostile environments. Third, the observed scalability performance suggests that learning-assisted routing frameworks can be effectively deployed in dense and large-scale MANETs without incurring excessive control overhead, provided that lightweight and distributed learning models are used. Based on these observations, it is recommended that future MANET deployments adopt adaptive, learning-driven routing protocols in place of static rule-based approaches, prioritize lightweight predictive models suitable for resource-constrained devices and tailor routing policies to specific operational contexts such as mobility intensity and traffic patterns. These recommendations can guide network designers and system engineers in translating research findings into robust, deployable MANET routing solutions.

Discussion

This section discusses the implications of the results presented in the Results section and provides an analytical interpretation of the observed performance trends. The experimental evaluation demonstrates that the proposed machine-learning-assisted routing framework consistently outperforms conventional MANET routing protocols across multiple performance dimensions, particularly in highly dynamic and resource-constrained tactical environments.

The improvement in throughput and packet delivery ratio can be attributed to the predictive capability of the proposed framework, which enables proactive routing decisions based on anticipated network conditions rather than reactive recovery after link failures (1-10). By forecasting congestion, mobility-induced disruptions and link degradation, the routing mechanisms are able to maintain stable communication paths, thereby reducing packet loss and retransmissions. Similarly, the observed reduction in end-to-end latency reflects the effectiveness of proactive route selection and the minimization of route discovery overhead under high-mobility scenarios (15,16,18).

Energy efficiency gains highlight the importance of incorporating energy awareness into routing decisions for tactical MANETs. Unlike traditional routing protocols that prioritize shortest paths or

minimal hop count, the proposed framework balances communication performance with residual energy considerations, preventing premature node failures and extending overall network lifetime (21, 23). This balance is critical in mission-critical deployments where battery-powered nodes operate in environments with limited opportunities for recharging.

Overall, the results confirm that jointly optimizing multiple key performance indicators through machine learning leads to more resilient and adaptive routing behavior compared to static rule-based protocols (24). The findings suggest that learning-assisted routing frameworks are well suited for tactical MANET applications requiring high reliability, scalability and efficient resource utilization.

However, while the simulation-based results are promising, further validation using real-world testbeds and online learning mechanisms would strengthen the applicability of the proposed approach in operational environments.

Conclusion

This study presented an integrated machine-learning-assisted routing framework for Tactical Mobile Ad hoc Networks (MANETs) with the objective of improving key performance indicators, including throughput, latency, packet delivery ratio and energy efficiency, in highly dynamic and resource-constrained environments. The primary contribution of this work lies in the unified integration of multiple learning-driven routing strategies—ML-OptiRoute, ProAct-MLRoute, ECO-RouteML and PERF-LearnRoute—which collectively enable predictive, adaptive and energy-aware routing decisions tailored for tactical scenarios. Simulation-based evaluation demonstrated that the proposed framework consistently outperforms conventional MANET routing protocols such as AODV, DSR and OLSR across varying traffic loads, mobility levels and node densities, confirming the effectiveness of machine learning in enhancing routing intelligence and network resilience. The practical implications of these findings suggest that learning-assisted routing can significantly improve communication reliability, operational efficiency and network lifetime in mission-critical applications such as military operations and emergency response systems. However, this work

also has certain limitations, including reliance on simulation-based validation, assumptions regarding the availability of accurate network state information and the use of pretrained learning models, which may affect real-time adaptability in highly volatile environments. Future research will focus on addressing these limitations by incorporating online and federated learning mechanisms, reducing computational overhead for deployment on low-power nodes, enhancing robustness against adversarial and uncertain conditions and validating the proposed framework using real-world tactical testbeds. Overall, this work contributes a scalable and multi-objective routing solution and provides a strong foundation for future advancements in intelligent MANET routing for tactical communication systems.

Abbreviations

AODV: Ad hoc On-Demand Distance Vector, DRL: Deep Reinforcement Learning, DSR: Dynamic Source Routing, IDS: Intrusion Detection System, KPI: Key Performance Indicator, MANET: Mobile Ad hoc Network, ML: Machine Learning, OLSR: Optimized Link State Routing, PDR: Packet Delivery Ratio, QoS: Quality of Service.

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Author Contributions

Gousiya Begum D: conceptualization, study design, material preparation, data collection, data analysis, writing-first draft, Anjaiah Adepu: conceptualization, study design, material preparation, data collection, data analysis. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Conflict of Interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations,

knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Data Availability

The datasets generated and analyzed during the current study are derived from simulation-based experiments conducted using standardized MANET models and machine-learning-assisted routing configurations. All simulation parameters, network settings, mobility models, traffic configurations and performance evaluation metrics are comprehensively described within the manuscript to ensure transparency and reproducibility. The source code, algorithmic implementations (ML-OptiRoute, ProAct-MLRoute, ECO-RouteML and PERF-Learn Route) and simulation scripts used in this study are available from the corresponding author upon reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

The authors declare that generative artificial intelligence (AI) and AI-assisted technologies were only used to enhance the writing style, grammar and language clarity of this manuscript. The core intellectual content, including the conception of the study, methodology, analysis, interpretation of results and conclusions, was developed entirely by the authors. No part of the scientific content, data analysis, or interpretation was generated by AI systems. All responsibility for the accuracy and integrity of the manuscript remains with the authors.

Ethics Approval

This research does not involve humans or animals, so no ethical approval is required.

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