Performance Analysis of Routing Protocols in Manets under Higher Density and Realistic Mobility

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Abstract: Mobile Ad Hoc Networks (MANETs) are self-organizing wireless systems without fixed infrastructure, widely applied in military operations, disaster response, and mobile collaboration. Their dynamic topology, high mobility, and varying node densities make routing highly challenging. This study evaluates the performance of the traditional Ad Hoc On-Demand Distance Vector (AODV) protocol and its machine learning–enhanced variant (ML-AODV) under realistic mobility patterns and high-density conditions. Simulations were conducted in NS-2.35 within a 2000 × 2000 m area using node densities of 100, 500, and 1000, three mobility models (Random Waypoint, Random Walk, and Levy Walk), and varying node speeds. Constant Bit Rate (CBR) traffic with 512-byte packets was used, and performance was assessed through Packet Delivery Ratio (PDR), throughput, end-to-end delay, routing overhead, and jitter. Results show that ML-AODV outperforms AODV in Random Waypoint and Random Walk scenarios, achieving up to 23% higher PDR, lower jitter, and more than 50% reduction in routing overhead. However, AODV performs better under the Levy Walk model at medium and high speeds, especially in dense networks, due to its lightweight route discovery mechanism. Overall, ML-AODV is more effective in unpredictable or human-like mobility environments, while AODV remains advantageous in dense and structured conditions.

Keywords*: High Density; Mobile Ad-hoc Network; Mobility; Routing; High Speed.*

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I. INTRODUCTION

Mobile Ad hoc Network (MANET) is a collection of wireless mobile nodes dynamically forming a temporary network without the aid of any established infrastructure or centralized administration [1]. They are self-configuring networks where nodes communicate directly with each other without relying on a fixed infrastructure. Due to their unique qualities, MANETs are increasingly being used in areas where it is not feasible to create standard infrastructure, such as military operations, search and rescue operations, healthcare services, and virtual conference [2].

Despite this increase in usage, MANET faces major challenges such as routing and mobility management, which seriously affect its performance. Many attempts are made by researchers to overcome these challenges like the work in[3], observes the advantages and disadvantages of the three groups of MANET routing protocols (Proactive, Reactive and Hybrid) protocols, by conducting a comparative analysis of their features and methods in terms of routing overhead, scalability and delay.

Also [4], investigate the performance of Ad-hoc On-Demand Distance Vector (AODV), Destination-Sequenced Distanced Vector (DSDV), and Machine Learning-enhanced AODV (ML-AODV) protocols using five metrics— throughput (TP), packet delivery ratio (PDR), average end-to-end latency (E2EL), packet loss rate (PLR), and energy consumption (EC).

However, the study is constrained with the use of only 50 nodes density and a speed of 30 m/s. This shows lack of generalizability, as performance can significantly vary with different node densities, mobility patterns, and speed ranges.

To address this limitation, this study will investigate and explore how variations in node density, speed, and mobility influence protocol performance, ensuring that the results can be reliably extended to broader MANET deployments.

II. RELATED WORK

Recent researches on Mobile Ad Hoc Networks (MANETs) focuses on evaluating the performance of routing protocols under varying mobility, density, and traffic conditions. These studies emphasize that routing strategies:

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Reactive, Proactive, and Hybrid offer different strengths and weaknesses depending on network dynamics.

➤ *Reactive Protocols*

A reactive protocol is a type of routing protocol used in networks, especially in Mobile Adhoc Networks (MANETs), where routes are created only when needed. This type of protocols does not have any pre-determined routing table; it is otherwise called On Demand Routing Protocols. In this type of protocols nodes initiate a route discovery process throughout the network, only when it wants to send packets to its destination [5]. Reactive protocols such as Ad Hoc On-Demand Distance Vector (AODV), Dynamic Source Routing (DSR), Dynamic MANET On-Demand (DYMO), discover routes on demand. Several studies such as [6] and [7] show that AODV and DSR achieve higher throughput and packet delivery than DSDV, and therefore are more efficient than DSDV and reasonably more proper for ad-hoc applications and projects. Also [8] and [9] highlight reactive protocols (AODV and DSR) strengths in high-mobility scenarios, while protocols like Dynamic MANET On-Demand (DYMO) demonstrate efficiency in obstacle-rich or failure-prone networks[10].

➤ *Proactive Protocols*

In proactive protocols, the routing process is based on predefined routing tables that contain routes to all destinations and a periodic update message is used to update these routes periodically [11]. While this ensures route availability, it introduces high overheads. Examples of proactive routing protocols include Destination-Sequenced Distance Vector (DSDV), Optimized link state routing protocol (OLSR), Dynamic source routing protocol (DSR), and Global State Routing (GSR). Comparative studies [12] and [13] show OLSR achieving superior throughput under low mobility, whereas DSDV performs better in small, stable networks.

➤ *Hybrid Protocols*

This type of protocols combines the advantages of proactive and reactive routing. The routing is initially established with proactive routing and then serves reactive routing for additionally activated nodes by flooding. Hybrid protocol is suitable for large networks where large numbers of nodes are present [14]. Hybrid routing protocols such as Zone Routing Protocol (ZRP), Temporally Ordered Routing Algorithm (TORA) and Machine Learning based Ad Hoc On-Demand Distance Vector (ML-AODV), combine proactive discovery with reactive adaptability. Recent works in [15] and [16] report that these approaches improve scalability but at the cost of higher complexity. Machine learning-based enhancements, such as ML-AODV [2], have been shown to improve packet delivery, reduce overhead, and mitigate attacks. Emerging strategies such as congestion-aware Adhoc On-Demand Multipath Distance Vector (AOMDV) [13] and multimedia-oriented protocols [14] further extend MANET applicability to critical scenarios.

➤ *Mobility Models*

A mobility model which represents movement behavior of considered application scenarios, is an important feature that may change characteristics of mobile nodes. It describes how speed, acceleration and direction of the node changes over time [1], and can significantly affect routing performance. The Random Waypoint (RWP) model has been widely adopted, with studies showing AODV outperforming DSDV in throughput and PDR [14]. Realistic human mobility patterns such as Levy Walk [15] better represent real-world scenarios, where reactive protocols adapt quickly to frequent topology changes. Comparative analyses [1] and [16] emphasize that protocol selection should be context-driven, matching node density, speed, and application requirements.

Prior studies confirm that while AODV and other reactive protocols excel under dynamic mobility, proactive schemes offer stability in low-mobility settings, and hybrid/ML-enhanced protocols hold promise for scalability and robustness. However, most evaluations remain limited to small node counts or simplified mobility models, underscoring the need for further analysis under higher densities and realistic mobility conditions—the focus of this study.

III. METHODOLOGY

The performance evaluation of Ad-hoc on-demand Distance Vector (AODV) and Machine Learning Ad-hoc On-demand Distance Vector (ML-AODV) routing protocols is conducted in NS-2 simulator, which is widely used in carrying out network research due to its flexibility, extensive protocol libraries, and its ability to simulate complex mobility patterns. The simulation environment is configured as follows:

Table 1 Simulation Parameters

PARAMETER	VALUE
Simulator	NS-2.35
Network size	2000 x 2000 meter
Number of Nodes	100, 500, 1000
Mobility model	Random way point, Random walk, Levy Walk
Speed Range	2ms, 15ms, 30ms
Traffic	Constant Bit Rate (CBR)
Packet size	512 bytes
Packet Rate	10 packets per second
Propagation Model	Two-ray ground
Transmission Range	300 meters

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Simulation Time	240 Seconds
Pause Time	10 Seconds

Note: Pause time is only applicable to RWP

The simulations were conducted in NS-2.35 within a 2000×2000 meter area, using node densities of 100, 500, and 1000. Three mobility models: Levy Walk, Random Walk, and Random Waypoint were applied with node speeds of 2, 15, and 30 m/s to capture realistic movement. Constant Bit Rate (CBR) traffic was generated between random source–destination pairs to model network load. Both AODV and ML-AODV were implemented under identical conditions. Performance was assessed using key metrics, followed by comparative analysis of results using excel.

➢ *The Evaluation Metrics And Methods*

- *Packet Delivery Ratio:*
  it is the ratio of the number of packets transmitted by the source to the number of packets successfully received by the destination.

- *Justification:*

PDR is a key indicator of routing protocol's dependability and efficiency. Maintaining a high delivery ratio becomes more difficult in dense and highly mobile MANET systems because of frequent link failures and network congestion.

- *Analysis:*

this measure sheds light on the routing protocol's capacity to deliver data consistently under pressure.

- *Method:*

PDR is calculated as:

$$\boldsymbol{PDR} = \left(\frac{\boldsymbol{Total\ packets\ received}}{\boldsymbol{Total\ packets\ sent}}\right) \times \mathbf{100\%} \ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Where:
Total Packets sent: All packets generated by the source node.
Total packets received: All packets successfully received at the destination node.

- *Average End-to-End Delay:*

This is the average amount of time it takes for a data packet to get across a network from its source to its destination.

- *Justification:*

Delay is essential in real-time applications (such as audio or video communication). Faster communication, particularly in situations where time is of the essence, is indicated by a lower end-to-end delay. This measure aids in assessing how fast the routing protocols can transmit data in dense and dynamic circumstances.

- *Method*:

For every packet that is successfully delivered, the delay is noted. The average is calculated as:

$$\boldsymbol{Average\ End\ to\ End\ Delay} = \frac{\sum_{i=1}^{n} \boldsymbol{Time\ Received_i} - \boldsymbol{Time\ Sent_i}}{\boldsymbol{n}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where:
n: Number of packets successfully delivered.
Time Received: Time stamp when the packet left the source.
Time Sent: Time stamp when the packet reached the destination.

- *Throughput:*

it is the rate at which data packets are effectively transmitted via a communication channel, and it is typically measured in bits per second (bps) or packets per second.

- *Justification:*

One crucial indicator of how well a network uses its available capacity is throughput. A high throughput indicates successful data transfer and shows how well the protocol works in real-world traffic scenarios with moving nodes.

- *Method*:

Throughput is calculated as follows:

$$\boldsymbol{Throughput} = \frac{\boldsymbol{Total\ Data\ Received\ (in\ bits)}}{\boldsymbol{Total\ Simulation\ Time\ (in\ seconds)}} \quad \ldots\ldots \ (3)$$

- *Routing Overhead:*

Routing overhead is defined as the number of control packets (RREQ, RREP, and RERR) used to establish and maintain routes in relation to the data packets transmitted.

- *Justification:*

High-density scenarios can cause network congestion, and efficient protocols try to reduce the number of control packets used, freeing up bandwidth for actual data transmission. Routing overhead is a metric that helps evaluate the scalability and efficiency of a routing protocol.

- *Method*:

Routing Overhead is calculated as follows:

- *Jitter:*

Jitter is defined as the variability in packet arrival times, or the difference in delay between successive packets reaching the destination.

- *Justification:*

It is measured to assess how stable and smooth a protocol's performance is over time. High jitter can seriously impair performance for applications that are sensitive to delays, such as VoIP and video conferencing. In mobile and high-density networks, jitter can increase due to frequent path changes and congestion.

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- *Method:*

Jitter can be calculated as follows:

$$\boldsymbol{Jitter} = \frac{1}{n-1}\sum_{i=1}^{n-1}|(T_i - T_{i-1})| \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4)$$

Where:
Ti: Arrival time of the i-th packet
T(i−1): Arrival time of the previous (i−1) packet
n: Total number of received packet

IV. RESULTS AND DISCUSSION

The performance of AODV and ML-AODV routing protocols was analyzed under varying node densities (100, 500, and 1000 nodes), mobility models (Random Waypoint, Random Walk, and Levy Walk), and speeds (2 m/s, 15 m/s, and 30 m/s). The evaluation metrics included Packet Delivery Ratio (PDR), throughput, average end-to-end delay, routing overhead, and jitter.

- *Packet Delivery Ratio (Pdr)*

The comparative results are illustrated in Figures 1**,** 2**,** and **3** on the Packet Delivery Ratio for 100, 500, and 1000 node densities respectively. In Figure 1 which shows the PDR at 100-node density, ML-AODV demonstrates consistently higher PDR values than AODV across RWP and RW mobility models. This indicates that the predictive behavior of ML-AODV helps maintain stable routes in moderately populated networks. As density increases to 500 nodes shown in Figure 2, ML-AODV continues to outperform AODV in RWP and RW. For instance, under the RW model at 30 m/s in Figure 2, ML-AODV reaches 79.23% PDR compared to AODV's 73.03%. This improvement is attributed to ML-AODV's predictive routing, which anticipates link stability and reduces packet losses.

However, in Figure 3, representing the 1000-node density, the trend reverses under the Levy Walk (LW) model at higher speeds. Here, AODV records 82.10%**,** significantly higher than ML-AODV's 58.90% at 30 m/s. This confirms that ML-AODV struggles with the irregular long jumps typical in LW mobility, while AODV adapts better to abrupt topology changes.

Overall, the Figures 1 & 2 confirm that ML-AODV is superior in structured or moderately random mobility (RWP and RW), whereas Figure 3 shows AODV remains more resilient under highly irregular Levy walk scenarios.

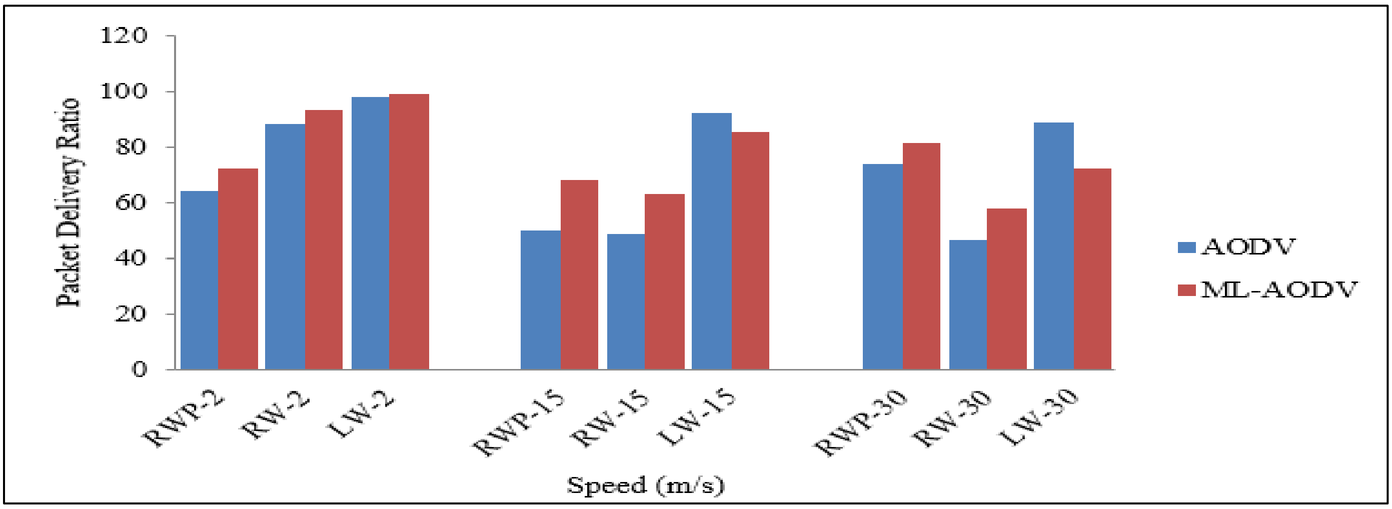

Fig 1 Packet Delivery Ratio (PDR) at 100 Node Density

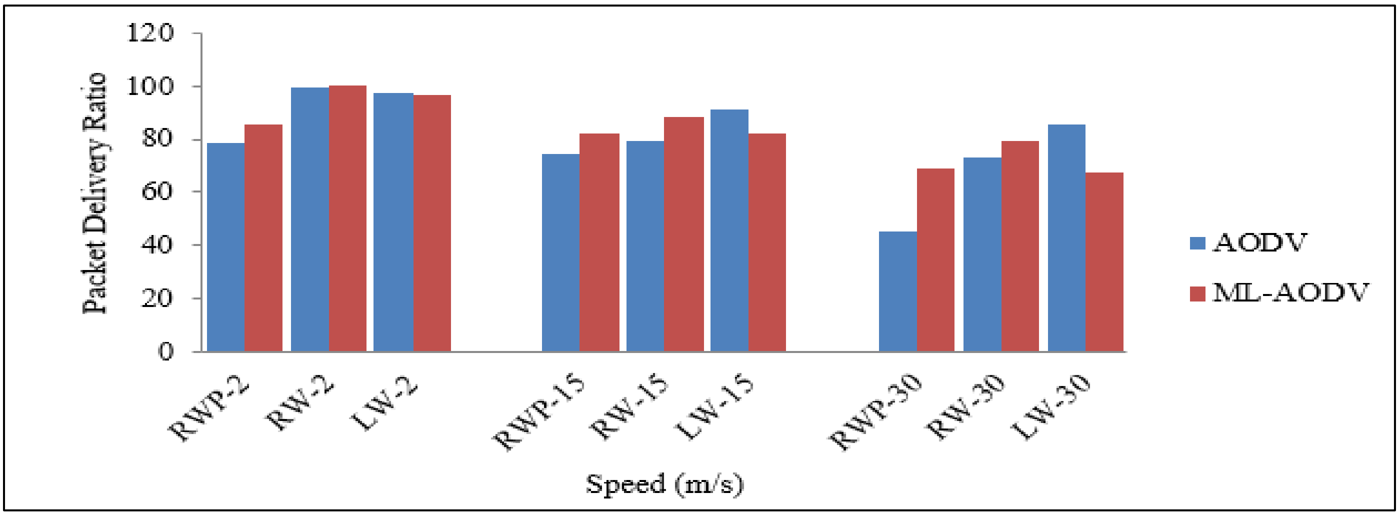

Fig 2 Packet Delivery Ratio (PDR) at 500 Node Density

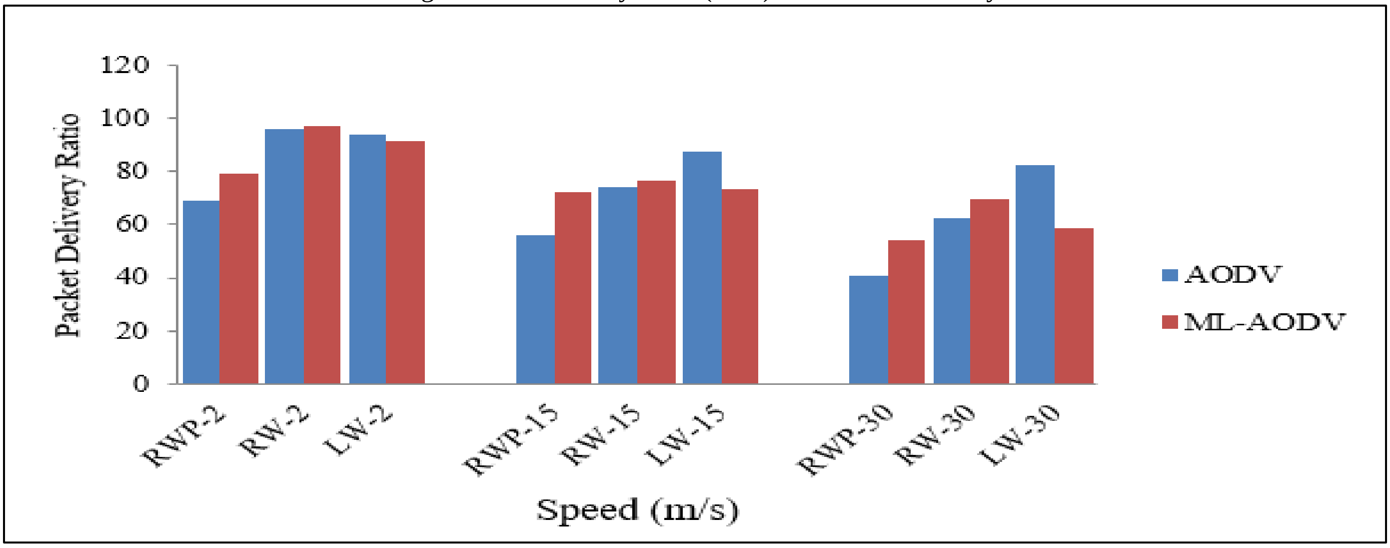

Fig 3 Packet Delivery Ratio (PDR) at 1000 Node Density

- *Throughput*

Throughput results for the three node densities are presented in Figures 4, 5, and 6, which illustrate the rate at which data packets are successfully delivered across the network under varying mobility models and node speeds. In Figure 4 (100-node density), ML-AODV consistently achieves higher throughput than AODV under both Random Walk (RW) and Levy Walk (LW) mobility models. For example, at 15 m/s in the LW model, ML-AODV delivers significantly higher throughput—an increase of more than 80% over AODV. This indicates that ML-AODV's predictive route selection reduces link interruptions and enhances data transmission efficiency in low-density and highly mobile environments.

When node density increases to 500 nodes, as shown in Figure 5, the same performance trend continues. ML-AODV maintains superior throughput in RW and LW scenarios across all speed levels. This suggests that ML-AODV scales effectively in moderately dense networks by mitigating frequent route failures that commonly arise in mobile ad hoc environments. However, under the RWP mobility model, the throughput gap between the two protocols narrows, indicating that pause time and structured movement favor a more reactive protocol like AODV

In the 1000-node scenario shown in Figure 6, a shift in performance emerges. AODV surpasses ML-AODV under the Random Waypoint (RWP) model, particularly at higher speeds. For instance, at 30 m/s in Figure 6, AODV achieves a throughput of approximately 200,000 bps, compared to 162,340 bps for ML-AODV. This drop in ML-AODV's throughput is linked to the increased computational and processing overhead required for learning-based route predictions in extremely dense networks. Meanwhile, AODV's simpler, on-demand mechanism responds more efficiently to frequent route breaks in RWP high-density conditions.

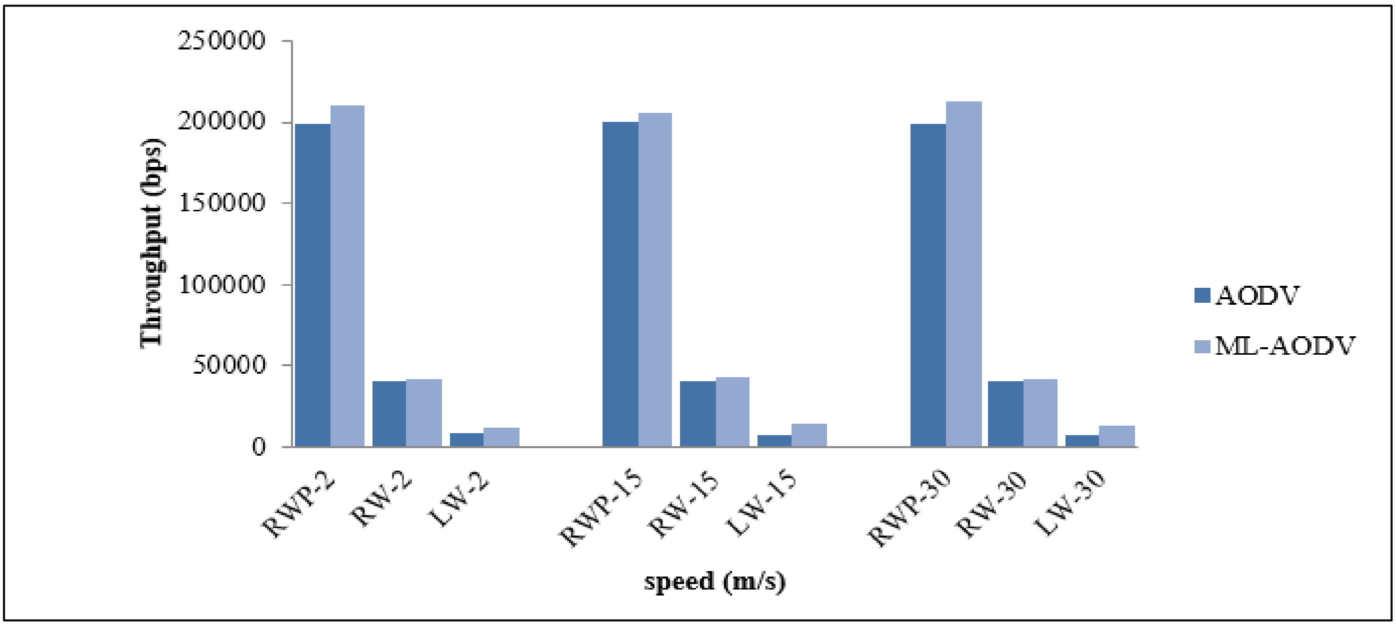

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Fig 4 Throughput at 100 Node Network Density

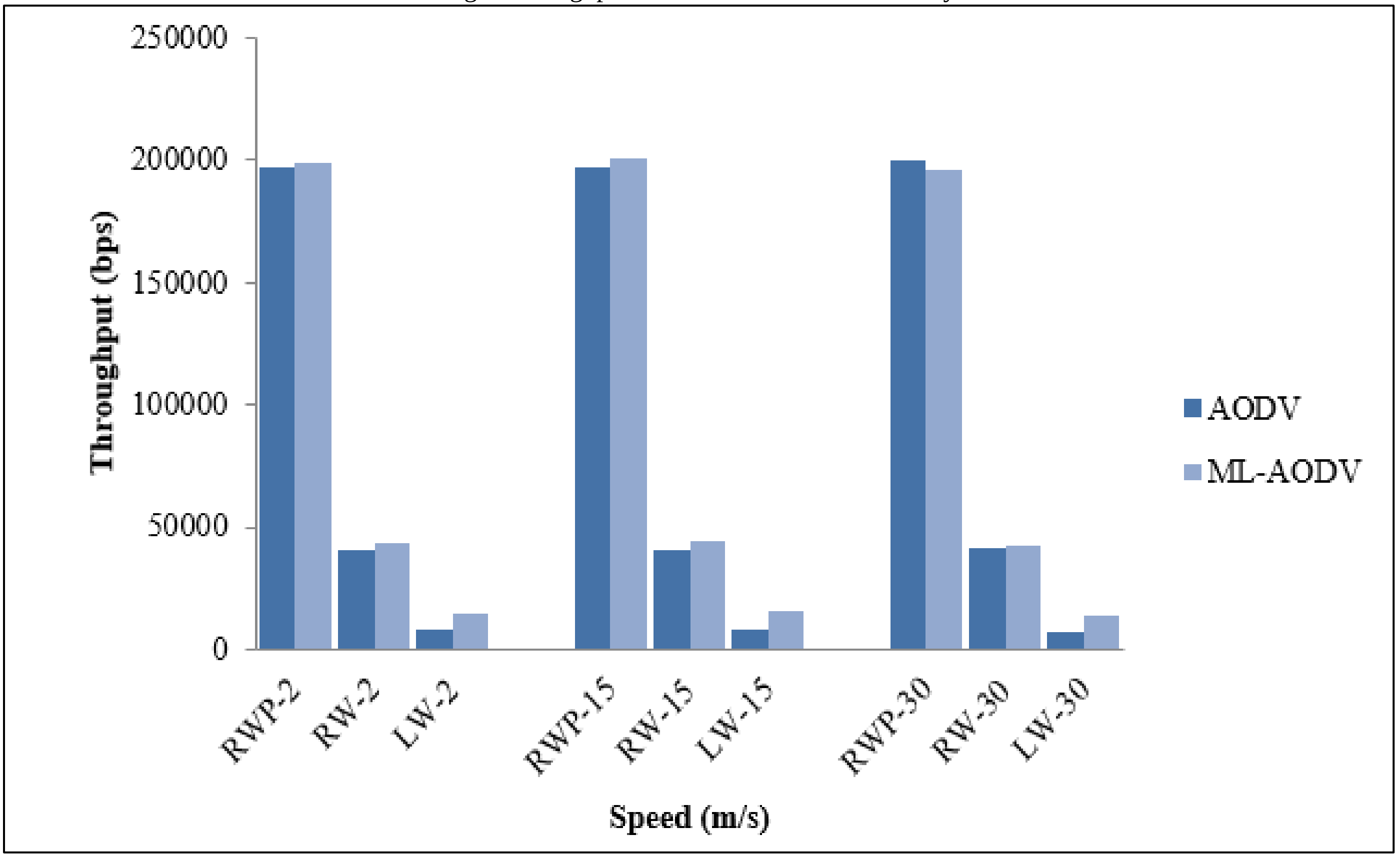

Fig 5 Throughput at 500 Node Network Density

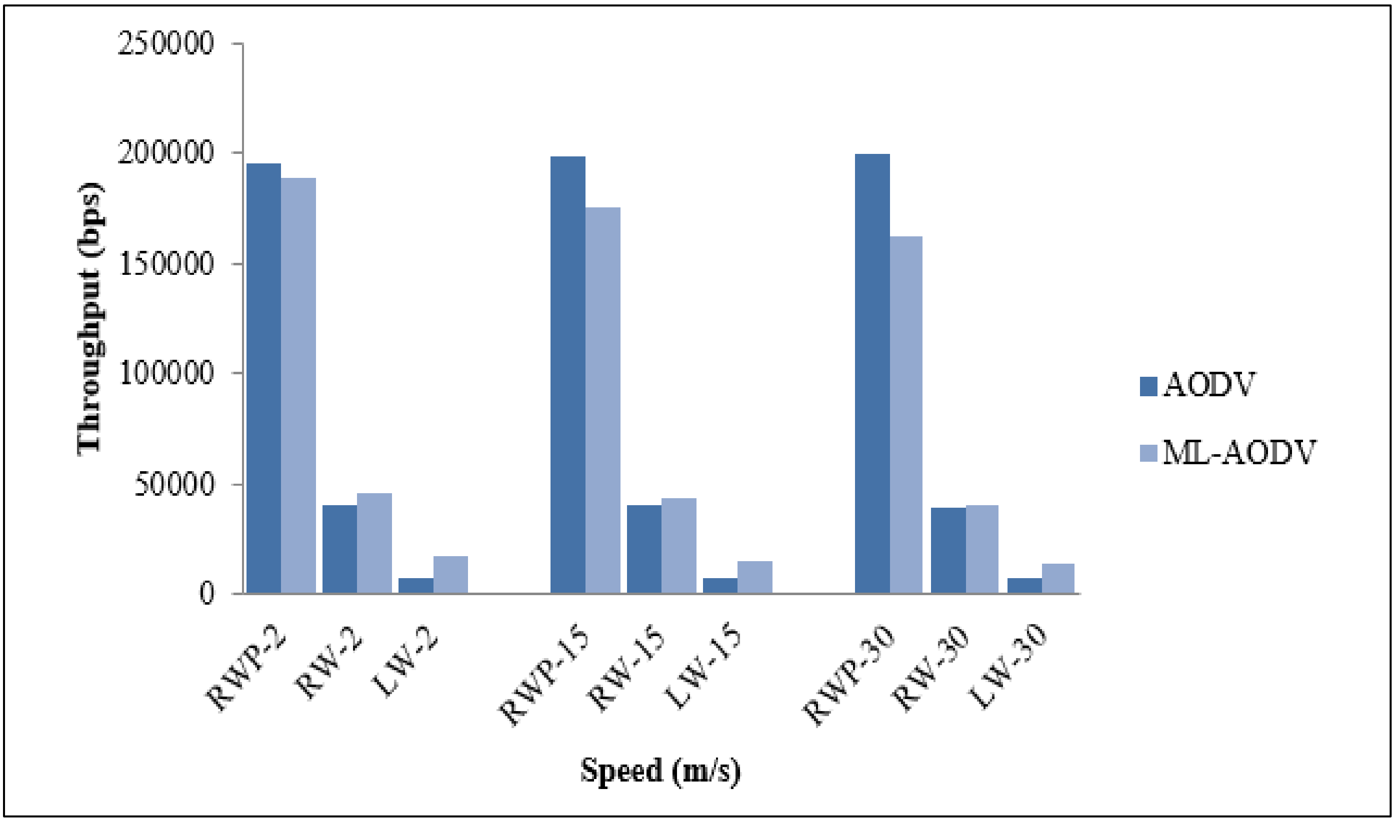

Fig 6 Throughput at 1000 Node Network Density

- *Combined Results For End-To-End Delay, Routing Overhead, And Jitter*

The combined results for EED, RO and Jitter are presented in Figure 7 below.

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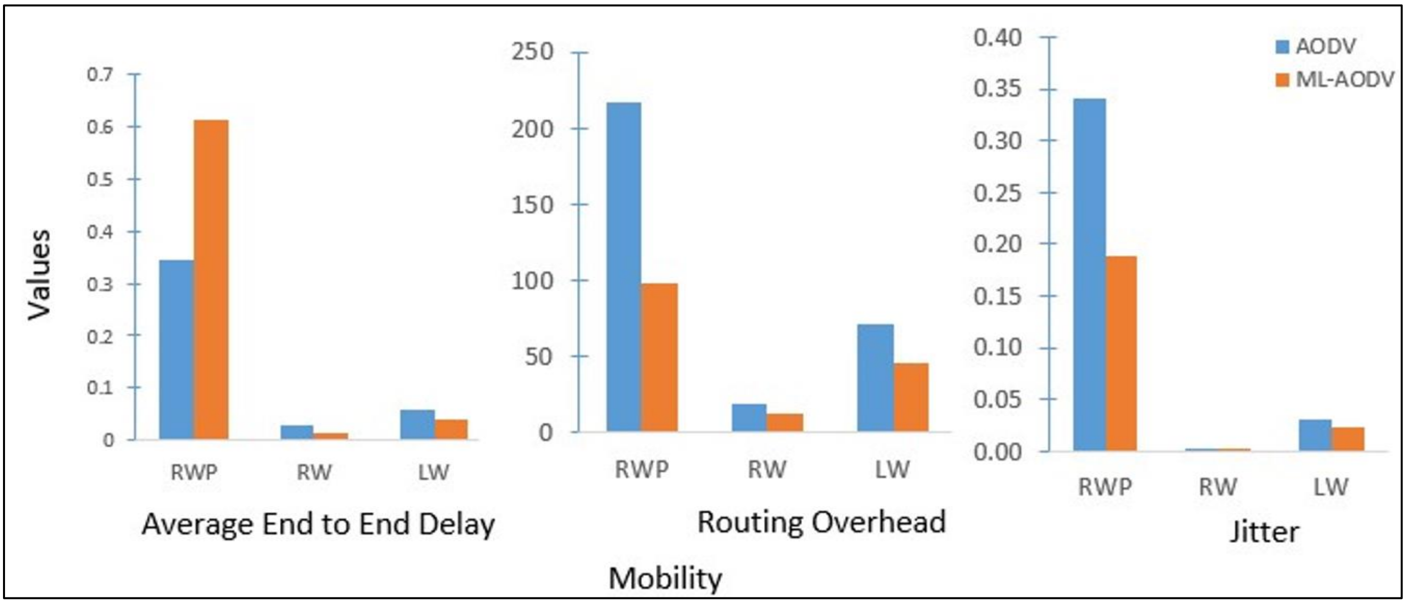

Fig 7 Comparative Analysis of End-to-End Delay, Routing overhead, and Jitter

- *End-To-End Delay*

The result shows that ML-AODV consistently achieves lower end to end delays in RW and LW models. In a dense network with node density of 500 nodes, the average delay recorded is 0.015s for ML-AODV compared to 0.029s for AODV. This indicates that ML-AODV effectively minimizes route discovery latency and enhances data delivery efficiency under moderate mobility conditions.

However, with the RWP with pause time, the result shows that AODV performs better, particularly in a highly dense network (1000 nodes), where ML-AODV experiences higher processing delays (0.612s vs. 0.345s). This suggests that the learning mechanisms in ML-AODV introduces computational overhead under heavy traffic and complex topologies.

- *Routing Overhead*

The result shows that ML-AODV generates significantly fewer control packets than AODV across most scenarios. In highly dense network under (1000 nodes) under RWP, ML-AODV requires 98.45 control packets compared to 216.65 for AODV. This demonstrates higher bandwidth efficiency and reduced routing congestion achieved by ML-AODV, particularly in environments with frequent topology changes.

- *Jitter*

The result shows that ML-AODV provides greater transmission stability in dense and highly dense network conditions. In the highly dense network (1000 nodes) under RW, jitter is recorded 0.001s for ML-AODV compared to 0.003s for AODV. This improvement reflects ML-AODV's ability to maintain more consistent packet intervals, a feature crucial for delay-sensitive applications such as VoIP and real-time video communication.

➢ *General Discussion*

The results presented in Figures 1–7 show that routing performance in MANETs depends strongly on node density, mobility model, and speed. The superior performance of ML-AODV under the Random Walk (RW) and Random Waypoint (RWP) models aligns with earlier studies that highlight the benefits of machine learning–based routing in improving packet delivery and stability in dynamic environments [2,3]. These results also agree with findings reported in [5,8], where reactive protocols such as AODV and DSR demonstrate strong adaptability to mobility-driven topology changes.

In contrast, the performance degradation of ML-AODV under the Levy Walk (LW) model—particularly at high speeds and high node densities—is consistent with observations in human mobility research. Levy Walk is known to produce long, unpredictable movement patterns that make link prediction more difficult [15]. This explains why AODV, with its lightweight reactive route discovery, performs better than ML-AODV under such irregular mobility conditions. Similar behavior has been reported in comparative MANET studies, where simpler reactive schemes outperform enhanced protocols in highly unstable networks [10,11].

The reduction in routing overhead achieved by ML-AODV across most scenarios corresponds with previous work showing that intelligent route selection reduces control traffic and improves bandwidth efficiency [2]. Moreover, the lower jitter values observed for ML-AODV support findings in multimedia-oriented MANET evaluations, where stability in packet arrival times is essential for maintaining application-level QoS [14].

Overall, the present results reinforce the consensus that no single routing protocol is universally optimal. Instead, protocol performance depends on mobility characteristics, topology size, and traffic dynamics, consistent with the broader MANET literature [1,3,12]. ML-AODV is most effective in moderately dense, highly dynamic environments, whereas AODV remains favorable in highly dense or highly irregular mobility scenarios.

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V. CONCLUSIONS

The study concludes that no single routing protocol is universally optimal across all MANET conditions. ML-AODV offers significant advantages in reducing routing overhead, delay, and jitter, making it more effective in unpredictable, random, and human-like mobility environments. Conversely, AODV proves more stable in high-density networks with structured mobility, particularly under the Levy Walk model, due to its straightforward on-demand route discovery mechanism.

Thus, the result shows that the choice or selection of a routing protocol in MANET deployments should be guided by specific network characteristics:

- ML-AODV is recommended for highly mobile, unpredictable, and low-to-medium density networks where adaptive learning enhances route reliability.
- AODV remains suitable for dense and structured mobility environments where scalability, predictability and reduced learning overhead are essential.

RECOMMENDATION

Based on the findings, the following recommendations are proposed to guide future work:

➢ *Hybrid Routing Strategies:*

Future research should focus on developing hybrid models that integrate AODV's reactive adaptability with ML-AODV's predictive intelligence, ensuring balanced performance across diverse MANET conditions.

➢ *Extended Mobility Scenarios:*

Additional realistic mobility models (e.g., Gauss-Markov, Manhattan Grid) should be explored to further validate results in urban and vehicular MANET settings.

➢ *Scalability Testing:*

Simulations with more than 1000 nodes and longer simulation durations are required to evaluate the long-term scalability and stability of ML-AODV in large-scale networks.

➢ *Real-World Validation:*

Beyond simulation, deploying these protocols in testbeds or real-life environments (e.g., disaster recovery, vehicular ad-hoc networks or IoT networks) is recommended to assess the protocol's performance under practical operational constraints

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