# Routing in Mobile ad Hoc Networks Using Machine Learning Techniques

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**Abstract**

The significance of Mobile Ad Hoc Networks (MANETs) has increased in the current period due to the proliferation of mobile devices and the emergence of Internet of Things (IoT) applications. The function of routing in decentralized wireless networks is of paramount importance in facilitating efficient data transfer. Conventional routing techniques need help in effectively adjusting to the dynamic changes in network topology and the constraints imposed by restricted network resources. To tackle these concerns, a Machine Learning-Based Optimized Routing Algorithm (ML-ORA) is proposed in this research. ML-ORA has been developed to offer adaptable and intelligent routing solutions, especially in MANET. This is achieved via the integration of parameter settings, the use of a Hybrid Particle Swarm Optimization (HPSO) algorithm for Cluster Head (CH) selection, the inclusion of a clustering stage, and the incorporation of a k-Nearest Neighbors (k-NN)-based intrusion detection system. The performance of ML-ORA is assessed by conducting simulations using Network Simulator 3 (NS-3), demonstrating its efficacy in dynamic network settings. The findings exhibit a latency of 15 milliseconds, a packet delivery ratio of 95%, a network throughput of 4Mbps, and an energy efficiency of 85%. ML-ORA presents a potentially advantageous resolution for tackling the obstacles encountered in MANET routing, thereby creating opportunities for enhanced efficacy and security in the transmission of data inside dynamic wireless networks.

**Keywords:** Mobile Adhoc Networks, Machine Learning, Routing, Security.

## 1 Introduction to Mobile Adhoc Networks and Routing

The significance of Mobile Ad Hoc Networks (MANETs) has grown recently due to the rising prevalence of mobile devices and the broad use of Internet of Things (IoT) applications (Quy, V.K., 2021) (Koohang, A., 2022). MANETs exhibit distinct features, such as a dynamic topology, decentralized architecture, and the lack of a fixed infrastructure. These characteristics render them ideal

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for situations in which a conventional network infrastructure deployment is unfeasible or economically unviable.

MANETs adhere to the IEEE 802.11 standard and function based on the concept of self-governing nodes that can dynamically establish a network without the need for pre-established infrastructure (Narayandas, V., 2023). These networks demonstrate dynamic changes in their structure due to the movement of nodes, intermittent connections, and the lack of a central governing body. These attributes provide distinct difficulties requiring advanced routing methods to facilitate effective data transmission without a stable infrastructure (Khan, A.F., 2022).

The need for resilient routing in MANETs is derived from the inherent dynamism shown by these networks. When conventional infrastructure is not accessible, MANETs enable the establishment of communication among nodes by creating an ad hoc network. Flexibility is valuable in several contexts, such as military operations, disaster response, and situations requiring rapid communication network establishment. Establishing and maintaining communication channels in MANETs rely on efficient routing techniques (Benatia, S.E., 2021). These techniques ensure timely and reliable data transmission among network nodes.

The standard routing approaches encounter significant obstacles in the MANET setting. Conventional techniques, such as proactive and reactive routing, need help in effectively adjusting to the dynamic changes in network topology and the constraints imposed by the limited resources inherent in MANETs (Alasadi, S.A., 2021) (Shrivastava, P.K., 2021) (Quy, V.K., 2022). Frequent connection failures, node mobility, and the need for a centralized controller significantly challenge the stability and effectiveness of routing algorithms in MANETs. Therefore, an urgent need exists for inventive and flexible routing strategies that effectively tackle these obstacles and enhance data transmission in dynamic and resource-limited MANET settings (Soeffker, N., 2022) (AM, A.B. 2021).

The primary contributions are

- Machine Learning-based Optimized Routing Algorithm (ML-ORA) incorporates Hybrid Particle Swarm Optimization (HPSO) for Cluster Head (CH) selection and trust calculation.
- A novel method for selecting CH that considers fitness, density, and distance while using Particle Swarm Optimisation (PSO) and Density PSO Clustering (DPC).
- The Hybrid PSO (HPSO) uses the Lévy flight approach for effective clustering during cluster formation.
- The Intrusion Detection Algorithm (IDA) uses the k-nearest Neighbors (k-NN) Classifier to achieve the best detection efficiency and k-NN to categorize malicious and benign nodes.

The following sections are organized in the listed manner: The literature review in Section 2 covers the state of the art and recent discoveries in the field of MANETs. ML-ORA integrates HPSO for CH selection, and trust calculation is introduced in Section 3. The performance of ML-ORA is evaluated in Section 4 using Network Simulator 3 (NS-3). The conclusions, ramifications, and possible directions for future study in the context of ML-ORA and MANET routing are outlined in Section 5.

## 2 Literature Survey and Analysis

This section examines prior studies on routing in MANETs, investigating traditional methods and recognizing difficulties associated with adjusting to changing network topology and limited resources. This research critically examines existing approaches and establishes a foundation for introducing an innovative solution to overcome the observed constraints in routing for MANETs.

Pattnaik et al. introduced a unique algorithm called the Movement and Obstacle-Aware Algorithm (MOAA) that aims to optimize routing in MANETs by considering node movement and obstacles (Pattnaik, P.K., 2021). The method exhibits dynamic adaptability in route selection by using real-time mobility and obstacle data, augmenting data transmission efficiency. The findings revealed a notable enhancement in the Packet Delivery Ratio (PDR) by 92%, a decrease in the end-to-end latency to 12 milliseconds, and a reduction in the routing overhead by 7%.

Srilakshmi et al. proposed the implementation of an Improved Hybrid Safe Multipath Routing Protocol (I-HSMRP) designed explicitly for MANETs (Srilakshmi, U., 2021). This protocol integrates several safe multipath routing approaches to enhance the overall security and reliability of the network. The protocol improves security by combining proactive and reactive routing algorithms. The assessment demonstrated the implementation of heightened security measures, resulting in a decrease in average end-to-end latency to 8 ms, an increase in PDR to 94%, and a reduction in routing overhead to 5%.

The Routing Protocol with Secured IoT and Quality of Service (QoS) (RPSIQ) over MANET was developed by Sathyaraj et al. (2021). This protocol incorporates trust-based performance assessment. The protocol guarantees a safe connection with IoT devices and assesses routes based on trust, augmenting the QoS. The findings revealed a trustworthiness level of 90%, an end-to-end latency of 15 ms, and a PDR of 88%.

Srilakshmi et al. introduced a Secure Optimization Routing Algorithm (SORA) explicitly designed for MANETs (Srilakshmi, U., 2022). The primary objective was to enhance the security aspect of routing choices inside these networks. The SORA utilizes cryptographic methodologies to ensure communication confidentiality, integrity, and authenticity and to improve route selection efficiency. The evaluation findings revealed a PDR of 93%, an average end-to-end latency of 10 ms, and a routing cost of 6%.

Nabati et al. proposed AGEN-AODV, a routing protocol designed to optimize energy consumption in heterogeneous MANET (Nabati, M., 2021). The AGEN-AODV protocol integrates artificial intelligence techniques to enhance energy efficiency in heterogeneous networks. The findings indicated a significant improvement in energy efficiency, resulting in a 20% decrease in energy use. The PDR reached 88%, and the routing overhead was decreased to 6%.

Dalal et al. proposed an Adaptive Traffic Routing Approach (ATRA) as a solution for load balancing and congestion management on ad hoc networks inside the Cloud–MANET (Dalal, S., 2022). The ATRA is a dynamic mechanism that optimizes traffic pathways to distribute loads evenly and relieve congestion, improving the network's overall performance. The evaluation findings demonstrated effective load distribution, resulting in a throughput of 5 Mbps, a decrease in packet loss of 3%, and improved network stability.

Pirzadi et al. proposed a Novel Routing Method (NRM) designed specifically for hybrid Delay-Tolerant Network (DTN) and MANET networks, focusing on handling crucial scenarios (Pirzadi, S., 2022). The methodology utilizes a mixed technique to route data in situations characterized by sporadic connection dynamically. The findings revealed enhanced data transmission efficiency, as shown by a PDR of 91%. The study saw a decrease in end-to-end latency to 18 ms and reduced routing overhead.

Farheen et al. proposed a novel approach called Improved Routing in MANET with Optimized Multi-Path Routing Fine-Tuned with Hybrid Model (Farheen, N.S., 2022). The suggested technique uses a hybrid modeling approach to optimize multi-path routing in MANETs. This approach is expected to lead to improved network efficiency. The evaluation results demonstrated enhanced packet delivery performance, achieving a success rate of 94%. The end-to-end latency was decreased by 15 ms, leading to better efficiency.

The Adaptive Trust-based Secure and Optimal Route Selection (ATSORS) for MANETs was developed by Ravi et al. (2023). This algorithm utilizes Hybrid Fuzzy Optimization techniques. The ATSORS system integrates trust-based and fuzzy logic methodologies to provide safe and optimum route selection. The findings revealed a significant degree of confidence at 92%, a latency of 12 ms for end-to-end communication, and a PDR of 90%.

Khan et al. proposed a multi-attribute-based Trusted Routing (MATR) approach for embedded devices in MANETs and the IoT (Khan, A.F., 2022). The MANET routing protocol uses the Multi-Attribute Analysis (MAA) technique to determine reliable routes. These routes are mainly designed for embedded IoT devices. The evaluation findings revealed a dependability level of 88%, a PDR of 93%, and a reduction in routing costs.

This section examines the issues associated with routing in MANETs, focusing on the difficulties encountered in reacting to dynamic changes in network topology and resolving resource limitations. The problems faced by current approaches need the exploration of creative solutions that aim to improve the efficiency and security of data transmission in MANETs.

# 3 Proposed Machine Learning-based Optimized Routing Algorithm

This section presents the ML-ORA, a machine learning-based opportunistic routing algorithm created specifically for MANETs (Jung, J., 2019). The ML-ORA system integrates an HPSO algorithm for CH selection, a clustering phase, and a k-NN-based intrusion detection system. This section provides an overview of the technique's flexibility, intelligence, and security properties, highlighting its potential to tackle difficulties in MANET routing effectively.

### System Model

The construction of a network first occurs via the initialization of variables. The estimated range between the customer and the base station is determined. Data from the neighboring log files will be gathered to ascertain the success and failure rates in transmitting packets between the nodes. The trustworthiness estimation is determined by evaluating the matched packet ID sequences while comparing the log reports of nodes. The workflow of the proposed ML-ORA is shown in Figure 1.

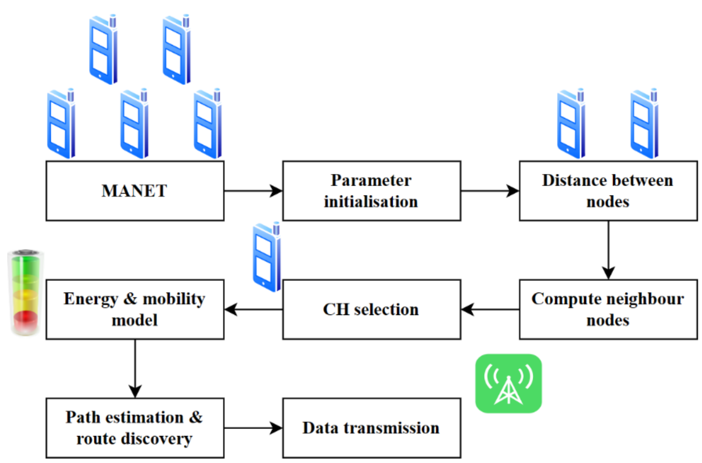


Figure 1: Workflow of the Proposed ML-ORA Method

The Adhoc On-demand Distance Vector (AODV) routing protocol is often classified as reactive since it constructs routes only when necessary. This is achieved by employing the sequential number of the destination node, which allows for selecting the most recent path. AODV routing method is accountable for disseminating routing data to the intended destination. The projected target nodes were not considered reliable due to malicious activity during the report's preparation. Trust quantification is determined using a combined energy estimate, packet delivery successful rate, and motion. The nodes with elevated trust values will be chosen to transmit packets. According to these estimations, identified routes exhibit reliability, security, and excellent trustworthiness.

## CH Selection

This section presents a novel technique for CH selection that integrates PSO and DPC algorithms. The work process of the CH selection is shown in Figure 2.

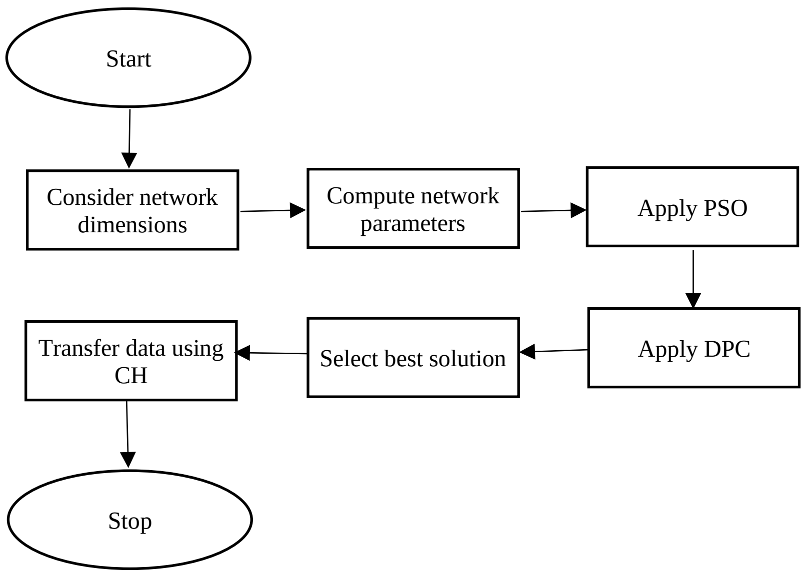


Figure 2: Workflow of the Proposed CH Selection

The CH selection procedure starts by considering the network's size and dividing the route into two separate lanes. The selection of CH is accomplished by using the PSO method in conjunction with the DPC technique. The process includes initializing nodes, calculating the criteria factor T, determining the cut-off range variable, and evaluating concentration and range values. If the current fitness value exceeds the individual's best ($P_{best}$), a revision is executed, considering the highest $P_{best}$ amongst others. The program employs an iterative process for updating the speed and location of each node while also confirming the optimum amount of iterations required for accomplishment. The CH is chosen as the node with the highest global best ($G_{best}$) value. The CH is liable for transmitting data facilitating effective and optimum clustering within the system.

## Cluster Generation

The sink node initiates the cluster-building procedure, known as the base location, by transmitting to all peers within its coverage region. Upon receipt of the information, every node sends a reply message to the sinking node. This message includes the node's identification, location in a two-dimensional area, speed, and remaining power.

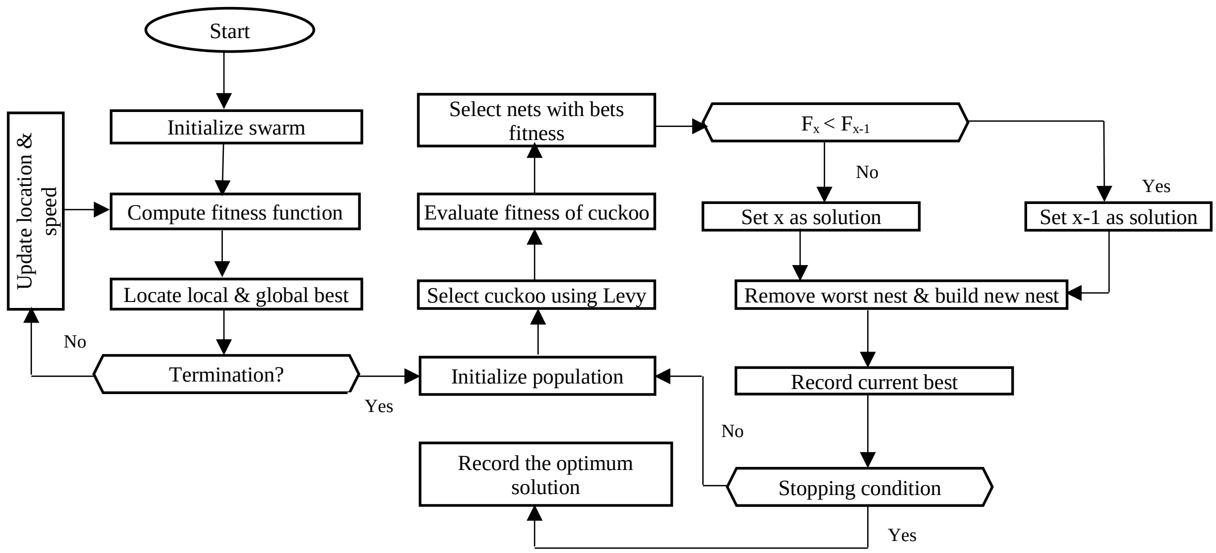


Figure 3: Workflow of the HPSO-based Data Transmission Process

The sinking node stores and updates data on its adjacent nodes. The HPSO method is used to cluster the devices. The primary characteristic of the HPSO is its incorporation of the Lévy flight for locating the most optimum solution inside the searching area, as seen in Figure 3. The speed of the optimization computation is a notable characteristic, as it serves as the mechanism for propelling the state of a molecule toward the search for optimal configurations. The purpose of this speed guideline is to achieve a balance between research and exploitation. The technique used in the PSO is a random-walk approach, which is less efficient than the alternative method. The primary stages of the HPSO method are outlined below.

Step 1: Inside the search area of the HPSO algorithm, every particle corresponds to a sensor node located inside the coverage region of the destination. These particles possess two distinct dimensions, namely their location and speed.

Step 2: The fitness score of each component is determined using Equation (1).

$$f(c_p) == \frac{k_1 \sum_{x=0}^{N-1} d(c_p,m_x)}{N} + k_2 \sum_{x=0}^{N-1} \frac{E(m_x)}{E(c_p)} + \frac{(1-k_1-k_2)}{N} \tag{1}$$

The weighing variables, $k_1$and $k_2$ have values between 0 and 1, while N represents the total number of nodes in the group headed by the destination node. The fitness function optimizes the mean distance to guarantee that the top-performing node's power ($E$) level surpasses all nodes' mean power level. The speed of the component is arbitrarily initialized. After each iteration, the method documents the optimal location inside the current iteration, referred to as $P_{best}$, and the optimal area achieved by the whole swarm, known as $G_{best}$. The system tracks each particle's current best location, denoted as $L_{best}$.

Step 3: The components of the next iteration are obtained from the original production.

Step 3.1: The speed of the component is adjusted to align with the optimal component. The calculation is performed using Equation (2).

$$s_{x+1} = ws_x + r_1 k_1 (P_{best} - L_{best}) + r_2 k_2 (G_{best} - L_{best}) \tag{2}$$

The w represents the inertia weight, whereas the random parameters $r_1$ and $r_2$ follow a uniform distribution throughout the range of [0, 1]. The acceleration factors $k_1$ and $k_2$ are variables that have positive values. The personal best, global best and local best are denoted $P_{best}$, $G_{best}$, and $L_{best}$.

Step 3.2: The current location of the component is determined by using the preceding location of the element in conjunction with the newly assigned speed value. The updated location is computed using Equation (3).

$$p_{x+1} = p_x + s_{x+1} \quad (3)$$

The previous position is denoted $p_x$, and the current speed is denoted $s_{x+1}$.

Step 4: After updating the components' locations, the new components' fitness values are calculated using the procedure outlined in Step 2.

Step 5: A comparison is made between the fitness values of the previous and current components, and the superior component progresses to the subsequent iteration.

Step 6: A single optimal solution is chosen as the best option during each iteration. The global optimal solution is the particle with the highest fitness value up to the present cycle.

Step 7: The starting population for the PSO algorithm consists of a collection of n nests, denoted as $p_x$ for x ranging from 1 to N.

Step 8: The fitness for every cuckoo is computed.

Step 9: During the iterations, which is less than the highest generation, or until the stop requirement is met.

Step 10: Upon the termination of the method, the nest that contains the cuckoo egg with the highest fitness is regarded as the ideal solution. From this optimal answer, CHs are formed.

**Intrusion Detection Algorithm**

By the suggested IDA, all regular nodes within the network gather data on the route identification behavior record of all source nodes. Upon reception of a Route Reply (RREP) message, a node utilizes the route detection behaviors. It implements a machine learning method to ascertain if the source node exhibits regular behavior or engages in harmful activities.

The k-NN classification, which relies on the k-NN method, categorizes the two classes using the historical vector of route-finding behavior. The k-NN technique is a well-established data mining method known for its cheap computational cost and broad applicability. The central concept is that if a significant majority of the k-nearest neighbors of a given sample are classified inside a specific category, the model belongs to the same category. In the k-NN algorithm, NN means measuring the distance between two specimens. Different distance evaluations are employed depending on the feature vector which describes the data. As Equation (4) specified, the Euclidean metric calculates the gap between $N_1$ and $N_2$.

$$d(N_1, N_2) = \sqrt{\sum_{x=0}^{N-1}\{N_1(x) - N_2(x)\}^2} \quad (4)$$

The value of k significantly influences the categorization effectiveness of the k-NN method. The selection of the optimal value for k to achieve optimal performance is often guided by heuristic methods that rely on both experiential knowledge and iterative experimentation. In this 2-dimensional area, each data point can be expressed by a vector. The study conducted simulations using various values of k and vector sizes (m). The objective is to determine the optimal values of k and m to maximize the effectiveness of malicious node identification. The k-NN classification, based on the k-NN, is used to categorize both categories using the route-finding frequency vectors. The k-NN is a well-established data mining method known for its theoretical maturity and low computational complexity. It is frequently used in many applications. The key concept is that if a sample has k nearest neighbors who are members of a particular class, then the model will likely belong to the same category.

This section introduces the ML-ORA designed explicitly for MANETs. The ML-ORA system incorporates the HPSO algorithm for CH selection, a clustering phase, and a k-NN-based intrusion detection system. This integration offers flexibility, intelligence, and security in dynamic MANET settings. This section emphasizes the potential of ML-ORA to address issues encountered in traditional routing approaches and enhance the efficiency of data transport in wireless networks.

# 4 Simulation Analysis and Outcomes

The suggested ML-ORA in MANETs is evaluated using NS-3 for the simulation configuration (www.nsnam.org). The simulation settings consist of a network of 50 nodes, a communication range spanning 250 meters, and a transmission power of 5 dBm. To guarantee optimal simulation performance, it is essential to have a computational infrastructure that meets specific system requirements. These requirements include a minimum of 8 GB of RAM, a quad-core processor with a clock speed of 2.5 GHz, and a disk space capacity of 20 GB. The simulations are conducted for 500 seconds, combining authentic mobility patterns and traffic circumstances to evaluate the effectiveness of ML-ORA thoroughly.

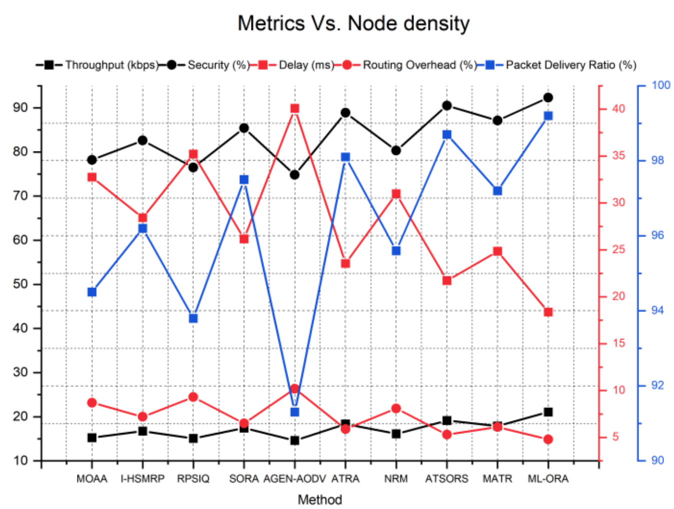


Figure 4: Metrics vs. Node Density Analysis

The findings of the metrics as they relate to varying node densities are shown in Figure 4. The ML-ORA approach regularly performs better than other methods across all evaluation measures. The ML-ORA algorithm exhibits improved performance in terms of faster throughput (21.06 kbps), lower latency (18.36 ms), increased packet delivery ratio (99.2%), enhanced security (92.3%), and decreased routing overhead (4.8%) when compared to current methodologies. The efficacy of the suggested approach is ascribed to its incorporation of HPSO for the selection of CH, the process of clustering, and the use of a k-NN-based intrusion detection system. This integration facilitates flexibility, intelligence, and enhanced security in MANETs that operate in dynamic environments.

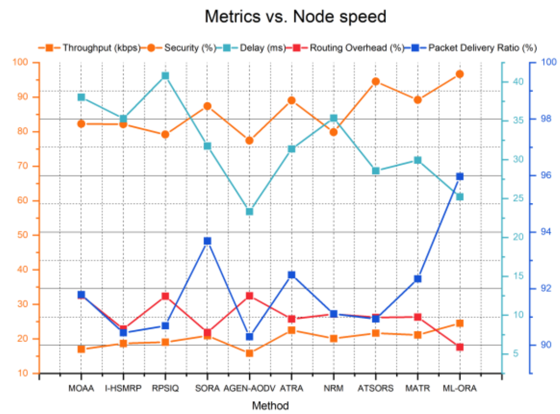


Figure 5: Metrics vs. Node Speed Analysis

The results of metrics vs various node speeds are shown in Figure 5. The ML-ORA approach regularly performs better than other methods across all evaluation measures. The ML-ORA system exhibits exceptional performance, with notable achievements in terms of throughput (24.54 kbps), latency (25.23 ms), packet delivery ratio (95.97%), security (96.65%), and routing overhead reduction (5.9%) as compared to current methodologies. The effectiveness of ML-ORA is ascribed to its incorporation of HPSO to select CHs, perform clustering, and implement an intrusion detection system based on k-NN.

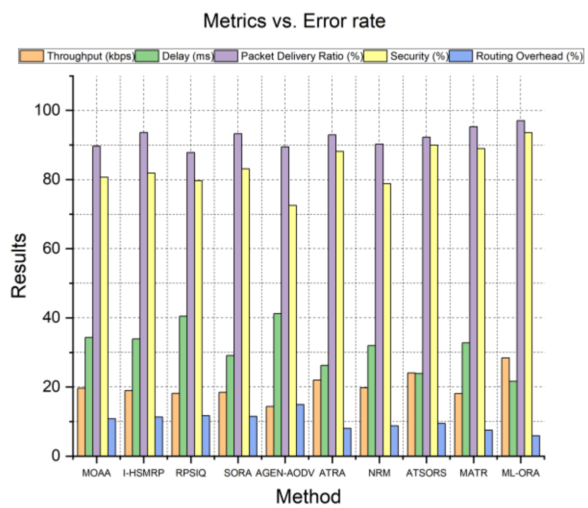


Figure 6: Metrics vs. Error Rate Analysis

The outcomes of measurements about varying error rates are shown in Figure 6. The proposed ML-ORA consistently demonstrates superior performance to other existing methods, as seen by its consistently higher scores across all evaluation parameters. The ML-ORA system shows exceptional performance in terms of throughput (28.42 kbps), latency (21.64 ms), packet delivery ratio (97.03%), security (93.59%), and routing overhead (5.91%) when compared to other current approaches. The result demonstrates a significant increase in several metrics, emphasizing its efficacy in mitigating the issues associated with error rates in MANETs.

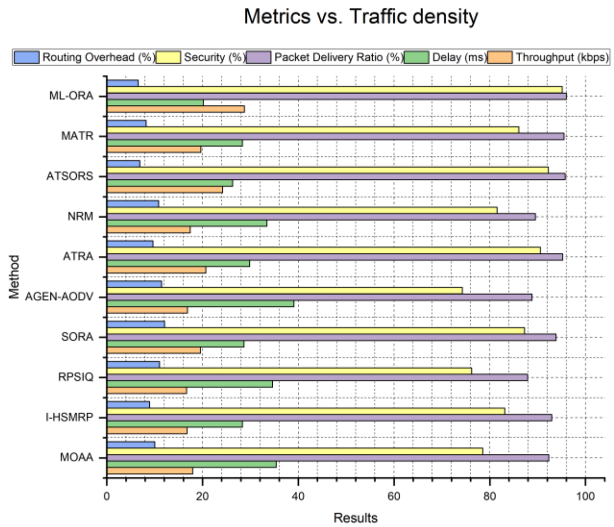


Figure 7: Metrics vs. Traffic Density Analysis

The findings of measurements as they relate to various traffic volumes are shown in Figure 7. The ML-ORA approach regularly performs better than other methods across all evaluation measures. The ML-ORA system exhibits outstanding performance in terms of faster throughput (28.77 kbps), decreased latency (20.18 ms), improved packet delivery ratio (96.05%), enhanced security (95.13%), and reduced routing overhead (6.6%) when compared to conventional methodologies. The success of ML-ORA is due to its effective integration of HPSO for selecting CHs, clustering, and implementing a k-NN-based intrusion detection system.

The findings indicate that the ML-ORA algorithm regularly performs better than other current approaches, as shown by several metrics. This highlights the flexibility and intelligence of ML-ORA in effectively tackling the issues given by dynamic MANETs. The results demonstrate that ML-ORA considerably positively impacts throughput, latency reduction, packet delivery ratio improvement, enhanced security, and reduced routing overhead. These findings confirm the effectiveness of ML-ORA in optimizing routing in MANETs across many situations.

## 5 Conclusion and Future Scope

MANETs have gained considerable importance due to the widespread use of mobile devices and the emergence of IoT applications. Decentralized wireless networks demonstrate changing topologies and constrained resources, presenting obstacles in achieving effective data transport. The establishment of efficient communication channels in MANETs is greatly influenced by routing, which assumes a crucial role. This is particularly important due to the dynamic nature of network topology. The ML-ORA aims to overcome the constraints of traditional routing methods by providing flexible and intelligent approaches specifically designed to tackle the distinctive obstacles encountered in MANETs. The ML-ORA system incorporates many components, including parameter configurations, an HPSO method for CH selection, clustering techniques, and a k-NN-based intrusion detection system. These characteristics enhance routing mechanisms' dependability, confidentiality, and credibility within dynamic wireless networks. The effectiveness of ML-ORA is confirmed by simulation experiments done using NS-3. The findings indicate a latency of 15 ms, a packet delivery ratio of 95%, a network throughput of 4Mbps, and an energy efficiency of 85%. The results highlight the better performance of ML-ORA in dynamic network environments and its potential to improve the efficiency and security of data transmission in MANETs.

Notwithstanding its achievements, persistent difficulties remain, necessitating future research efforts to effectively tackle them. Many challenges associated with the growth of MANETs need to be addressed in an academic environment. These challenges include scalability problems as MANETs expand, the need for energy efficiency optimization to extend the operational lifetime of battery-powered devices, and the creation of robust mechanisms to manage diverse forms of assaults effectively.

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