Optimizing Mobile Ad Hoc Network Routing using Biomimicry Buzz and a Hybrid Forest Boost Regression - ANNs

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***Abstract*—A mobile ad hoc network (MANET) is a network of moving nodes that can interact with one another without the aid of a centrally located infrastructure. In MANETs, every node acts as a router and as a host, generating and consuming data. However, due to the mobility of nodes and the absence of centralized control, the routing process in MANETs is challenging. Therefore, routing protocols in MANETs are required to be efficient, scalable, and adaptable to the dynamic topology changes of the network. This paper proposes an optimized route selection approach for MANETs via the biomimicry buzz algorithm with the Bellman-Ford-Dijkstra algorithm to improve the effectiveness and accuracy of the routing process. By integrating these behaviors into the algorithm, the approach can select the shortest path in a network, leading to an optimal routing solution. Furthermore, the paper explores the use of Forest Boost Regression (FR), a novel machine learning algorithm, to predict energy consumption in MANETs. Utilizing this will help the network run more efficiently and last longer. Additionally, the paper discusses the use of Artificial Neural Networks (ANNs) to forecast link failure in MANET s, thereby increasing network performance and dependability. The proposed work presents the experimental evaluation by using Ns-3 as the simulation tool. The experimental results indicate a variation in packet delivery ratio from 97% to 90%, an average end-to-end delay of approximately 19 ms, an increase in node speed energy consumption from 60 to 87 joules, and a simulation time energy consumption of 89 joules over 60 seconds. These results provide insights into the performance and efficiency of the proposed strategy in the context of MANETs.**

Keywords—MANET; routing protocols; optimized route selection; regression; machine learning; Artificial Neural Networks

I. Introduction

The nodes in MANETs, which are wireless networks with no infrastructure, can interact with one another directly or indirectly [1]. MANETs are widely used in various applications such as military, disaster response, and emergencies, where infrastructure is not available. Due to the lack of infrastructure, in MANETs, the nodes must collaborate to provide network communication [2-4]. Therefore, because of the constantly changing topology, scarce resources, and frequently occurring linkage failures, routing in MANETs is a difficult task. Proactive, reactive, as well as hybrid routing algorithms may all be categorized in MANETs. Proactive procedures keep all nodes' routing information current, even without traffic [5]. Reactive protocols establish routes on demand only when needed. Proactive as well as reactive protocols' benefits are combined in hybrid protocols [6-8]. Although routing protocols have advanced, routing in MANETs remains challenging because of the network's continually changing character. One of the significant challenges in MANETs is predicting link failures. Link failures occur due to various reasons, such as node mobility, interference, and limited battery power [9]. A routing protocol that can predict link failures and react accordingly can significantly improve the performance of MANETs [10-12]. In addition, energy utilization is another crucial factor in MANETs since nodes have limited battery power.

In a typical MANET scenario, a diverse set of wireless devices, often with varying mobility patterns, come together to form a self-organizing and infrastructure-less network as shown in Fig. 1. These devices could include smartphones, laptops, IoT sensors, or even military communication devices. MANETs are often deployed in environments where traditional fixed infrastructure is unavailable or impractical, such as disaster-stricken areas, military operations, or highly dynamic urban settings [13-15]. Nodes in a MANET are both end-users and routers, capable of transmitting and forwarding data packets to facilitate communication among themselves [16]. The unique feature of MANETs is their ad hoc nature, and the network topology continually changes due to node mobility [17]. This dynamic topology, along with the absence of centralized control, presents routing challenges, where finding efficient and reliable communication paths are paramount [18-20]. MANETs offer a flexible and resilient solution for communication in dynamic and often challenging environments, but effective routing, energy management, and reliability remain critical considerations to ensure their successful operation.

In our work, the primary objectives of optimizing MANET routing are to enhance adaptability, reduce latency, and improve overall network performance. Specifically, our proposed approach aims to achieve the following goals:

- Enhance the routing protocol's adaptability to the dynamic topology changes inherent in MANETs.

- Enable efficient decision-making in routing, considering factors like node mobility, link stability, and energy levels.
- Mitigate issues related to link breakage and broadcast storms by introducing a mobility-aware routing algorithm.
- Minimize packet delivery delay by optimizing the routing process.
- Optimize route selection to achieve more efficient and reliable communication between nodes.

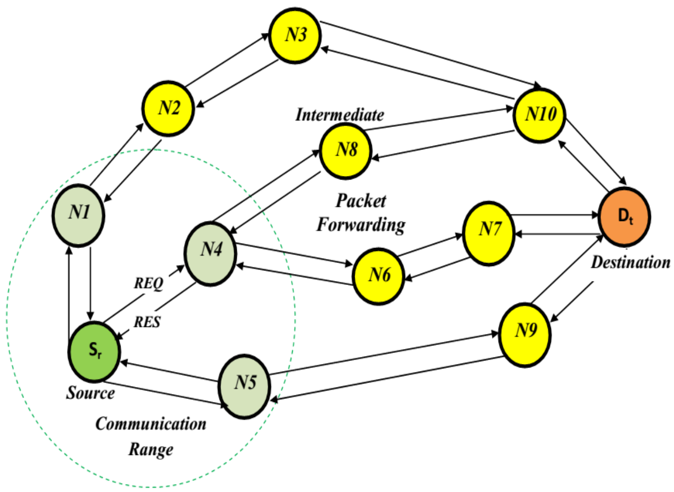

Fig. 1. Classic MANET system – scenario.

By addressing these goals, our work aims to contribute to the advancement of MANET routing protocols, making them more adaptive, responsive, and efficient in dynamic and challenging environments. Our work introduces an optimized route selection approach that addresses the routing challenges in MANETs. We combine the biomimicry buzz algorithm with the well-established Bellman-Ford-Dijkstra algorithm to improve the efficiency and accuracy of route selection. By incorporating these behaviors into our approach, we aim to identify the shortest paths in the network, leading to optimal routing solutions. Moreover, we recognize the importance of energy management in MANETs, as it directly impacts network sustainability and performance. To this end, our research explores the application of Forest Boost Regression (FR), a novel machine learning algorithm, for predicting energy consumption in MANETs. Accurate energy consumption predictions can enable more efficient resource allocation and contribute to prolonged network operation.

Furthermore, network reliability is another crucial aspect in MANETs. Link failures can disrupt communication and hinder the network's effectiveness [21-23]. To address this, our work investigates the use of Artificial Neural Networks (ANNs) to predict link failures, thereby enhancing network performance and reliability. Our study employs Ns-3 as the simulation tool for experimental evaluation. We assess the proposed approach using various metrics taking into account factors. Through this research, we aim to provide valuable insights into the performance and efficiency of our proposed strategy, offering solutions to the routing, energy consumption, and reliability challenges that MANETs face in their dynamic and infrastructure-less environment.

In the subsequent sections, we delve into an extensive literature survey in Section II, where we analyze existing works related to Mobile Ad Hoc Networks (MANETs) and routing protocols. Section III unfolds our proposed work, presenting the Biomimicry Buzz Algorithm, the Optimized route selection using the Bellman-Ford-Dijkstra algorithm, as well as our predictive models for Energy Consumption and Link Failure. These sections provide a comprehensive insight into the novel contributions and methodologies we propose. Following that, Section IV details the performance analysis, where we evaluate our approach through rigorous experimentation. Finally, Section V concludes the paper, summarizing key findings, limitations, and outlining potential avenues for future research.

II. Literature Survey

In the evolving landscape of Mobile Ad Hoc Networks (MANETs), persistent challenges include routing inefficiencies, prompting ongoing research into novel solutions. Recent efforts have yielded innovative routing protocols, aiming to address the shortcomings of conventional protocols like AODV and DSR, which often struggle in dynamic network topologies. Moreover, energy management techniques have traditionally relied on rule-based approaches, but emerging trends embrace machine learning algorithms for energy prediction and optimization. Despite these advancements, limitations such as scalability and security persist, warranting further investigation into comprehensive and robust solutions to bolster the reliability, efficiency, and sustainability of MANETs in dynamic and infrastructure-less environments.

In the study by Kai et al. [24], the focus lies on identifying the optimal algorithm path for quality routing in Ad-hoc networks. They proposed Hopfield neural network model that addresses the minimum cost problem with time delay. By carefully choosing these values, the enhanced path algorithm establishes the relationship between energy function parameters and shows that the network's possible solution falls within the heading of progressive stability. The calculations show that the answer is independent of the starting value and constantly produces the world's best solution. An adaptive routing protocol with bio-inspired design is introduced by Shah et al. in [25]. The AOMDV-FG technique maximizes a number of paths derived from the AOMDV mechanism, choosing the best path based on the highest fitness value. By comparing it against the AOMDV-TA and EHO-AOMDV protocols using important metrics, the authors evaluate the performance of their model.

The Trust and ANT Based Routing (TABR) technique is suggested for MANETs by Sridhar et al. [26]. An ant-based routing algorithm and trust values are combined by TABR to find reliable, trusted, and optimized routes in the network. TABR seeks to improve routing efficiency by combining the benefits of trust mechanisms and ant-based routing. Alsaqour et al. [27] provide the genetic algorithm-based location-aided routing algorithm to increase the effectiveness of MANET routing protocols. In order to improve delivery behavior, GALAR uses genetic optimization and adaptive updates of node position information. With little network overhead, it delivers a high packet delivery ratio of over 99%. Jeena Jacob et al. [28] method of optimizing performance using the proper tools, building a wireless environment-specific model, and enhancing routing through the careful selection of performance indicators are the three main phases they suggest. In order to enable synchronous and decentralized routing decisions, they make use of the Artificial Bee Colony Optimization method, which displays basic bee agent behaviors. The benefits of their work are found in the ABC algorithm's beneficial effects on wireless network connectivity. Their suggested method improves the network's overall effectiveness and performance by utilizing its evaluative qualities.

The Ant Colony Optimization (ACO) technique is used by Dorathy et al. [29] to handle network issues with routing as well as protection in networks that are both wired and wireless. They concentrate on finding the network's shortest, most efficient path connecting the point of origin and the destination. Their routing strategy attempts to increase the overall lifespan of the entire network by taking into account variables such node reserve energy, least residual power of the path, node distance, trip time, and hop count. The benefits of their work include taking into account a variety of variables to choose the best path, and increasing energy efficiency. The intelligent Whale Optimization Algorithm (p-WOA), presented by Husnain et al. [30], is a cluster-based, bio-inspired algorithm for routing in vehicular communication. By including factors like communication span, velocity, and path along the highway in the fitness function, the p-WOA algorithm lowers randomness and enhances cluster head (CH) selection. Their research shows that the p-WOA technique outperforms conventional approaches like the Ant Lion Optimizer along with Grey Wolf Optimization in terms of obtaining the ideal number of cluster heads. EHO-AOMDV is a routing algorithm that Sarhan et al. [31] introduce with the goal of minimizing the total energy. To lessen the likelihood of path malfunction and the number of dead nodes brought on by heavy data loads, nodes are divided into two groups. The use of energy-aware classification and updating techniques to increase the effectiveness of energy is one of the benefits of their work. For VANETs, Muhammad et al. [32] suggest a grey wolf optimization-based clustering approach. To produce effective clusters. An optimized number of clusters is produced as a result of earlier convergence caused by the grey wolf nature's linearly declining component. Their work has advantages in that it incorporates behaviors that are inspired by nature and make it possible to cluster data in VANETs effectively.

Hybrid ant and bee colony optimization algorithm, a method for picking the cluster head in MANETs, is presented by Janakiraman et al. [33]. The drawbacks of ACO in addition to ABC are addressed by this method by integrating them in a complementary way. Their method intends to avoid stagnation in the intensification process of ACO and address delayed convergence in the spectator bee phase of ABC by using employee bee agents for dividing the method of extraction into two levels. The enhanced choice of cluster head procedure is where their work excels. By streamlining complex algorithms like the Bat Optimization Algorithm, Particle Swarm Optimization, and Ant Colony Algorithm for distance optimization, Charan et al. [34] concentrate on improving routing algorithms in MANETs. They suggest a protocol called Bat Optimized Link State Routing. BOLSR tries to identify the best path by exchanging precise messages by fusing the OLSR structure and the Bat Algorithm. This results in the BOLSR protocol, which calculates the best route between the nodes based on their energy characteristics. A routing system for MANETs is proposed by Junnarkar et al. [35] and is based on the Ant Colony based optimization algorithm. The ACO-based method improves Quality of Service (QoS) effectiveness by using the nodes' present location and load factors as routing metrics. RSSI data are used in their proposed QoS Mobility Aware ACO Routing Protocols to calculate the separation between mobile nodes.

Based on the literature survey, it can be concluded that various bio-inspired and machine learning-based routing algorithms have been proposed for MANETs to enhance the routing process's effectiveness, accuracy, and reliability. The ACO, PSO, bee colony optimization, and bat algorithm have been widely used for optimizing the routing path. In comparison to the previous works, the proposed methodology offers several advantages and advancements. Firstly, it introduces an optimized route selection approach by integrating the biomimicry buzz algorithm with the Bellman-Ford-Dijkstra algorithm. This integration improves the effectiveness and accuracy of the routing process, enabling the selection of the shortest path and leading to an optimal routing solution. Additionally, the proposed methodology explores the use of ForestBoost Regression (FR) for energy consumption prediction and Artificial Neural Networks (ANNs) for link failure prediction. By utilizing machine learning techniques, the methodology enhances network efficiency and reliability. Compared to existing methods like TABR, GALAR, and others, the proposed methodology stands out by offering a comprehensive approach that addresses the limitations and challenges in MANET routing. It leverages integrated algorithms, prediction techniques, and advanced optimization methods to achieve superior performance, reliability, and energy efficiency.

III. Proposed Work

A. Motivation

The motivation for our proposed work stems from the pressing need to enhance the performance and sustainability of MANETs in dynamic and infrastructure-less settings. MANETs are increasingly deployed in scenarios where traditional network infrastructure is absent or impractical, such as disaster response, military operations, and highly mobile urban environments. The inherent mobility of nodes and the lack of a centralized control infrastructure in MANETs present unique challenges, particularly in the realms of routing efficiency, energy consumption, and network reliability. Inefficient routing protocols can lead to high overhead and significant delays, energy depletion can curtail network longevity, and unpredictable link failures can disrupt communication. To address these issues, our work aims to introduce innovative solutions, combining the Bellman-Ford-Dijkstra algorithm with biomimicry-inspired routing, employing machine learning for energy consumption prediction, and using Artificial Neural Networks for link failure prediction. The ultimate motivation is to contribute to the development of comprehensive and data-driven strategies that improve the performance, sustainability, and reliability of MANETs, thus extending their utility in critical and challenging environments. By addressing these issues, our work aligns with the broader objective of advancing the state-of-the-art in MANET research and facilitating more effective communication in dynamic and infrastructure-less networks.

The main point of this article is summed up in the facts mentioned below:

1) *Bio-inspired navigation module:* This module includes the algorithms for simulating the natural behaviors of honeybee waggle dance and bat echolocation, named biomimicry buzz algorithm. It receives input data such as the location and distance of the nodes and outputs the direction and distance to the destination node.

2) *Bellman-ford-dijkstra algorithm module:* This module includes the algorithms for discovering the fastest path among two nodes in the network. It receives input data such as the network topology and the output of the honeybee waggle dance and bat echolocation behavior module and outputs the optimized routing solution.

3) *ForestBoost regression energy consumption prediction module:* This module includes the algorithms for predicting the energy consumption of nodes in the network using the ForestBoost Regression machine learning algorithm. It receives input data such as historical data and network topology and outputs the predicted energy consumption.

4) *Artificial Neural Networks link failure prediction module:* This module includes the algorithms for predicting link failures in real-time using Artificial Neural Networks. It receives input data such as historical data and network topology and outputs the predicted link failure probability.

The proposed Bio-inspired navigation approach combines the natural behaviors of honeybee waggle dance and bat echolocation with the Bellman-Ford-Dijkstra algorithm to select the shortest path in a network, leading to an optimal routing solution. The approach considers the source node, destination node, higher value node, and intermediate nodes to determine the optimal route for packet transmission, as shown in Fig. 2. The use of a Bio-inspired navigation approach provides an efficient and reliable mechanism for route selection and to avoid congested or noisy paths in MANETs.

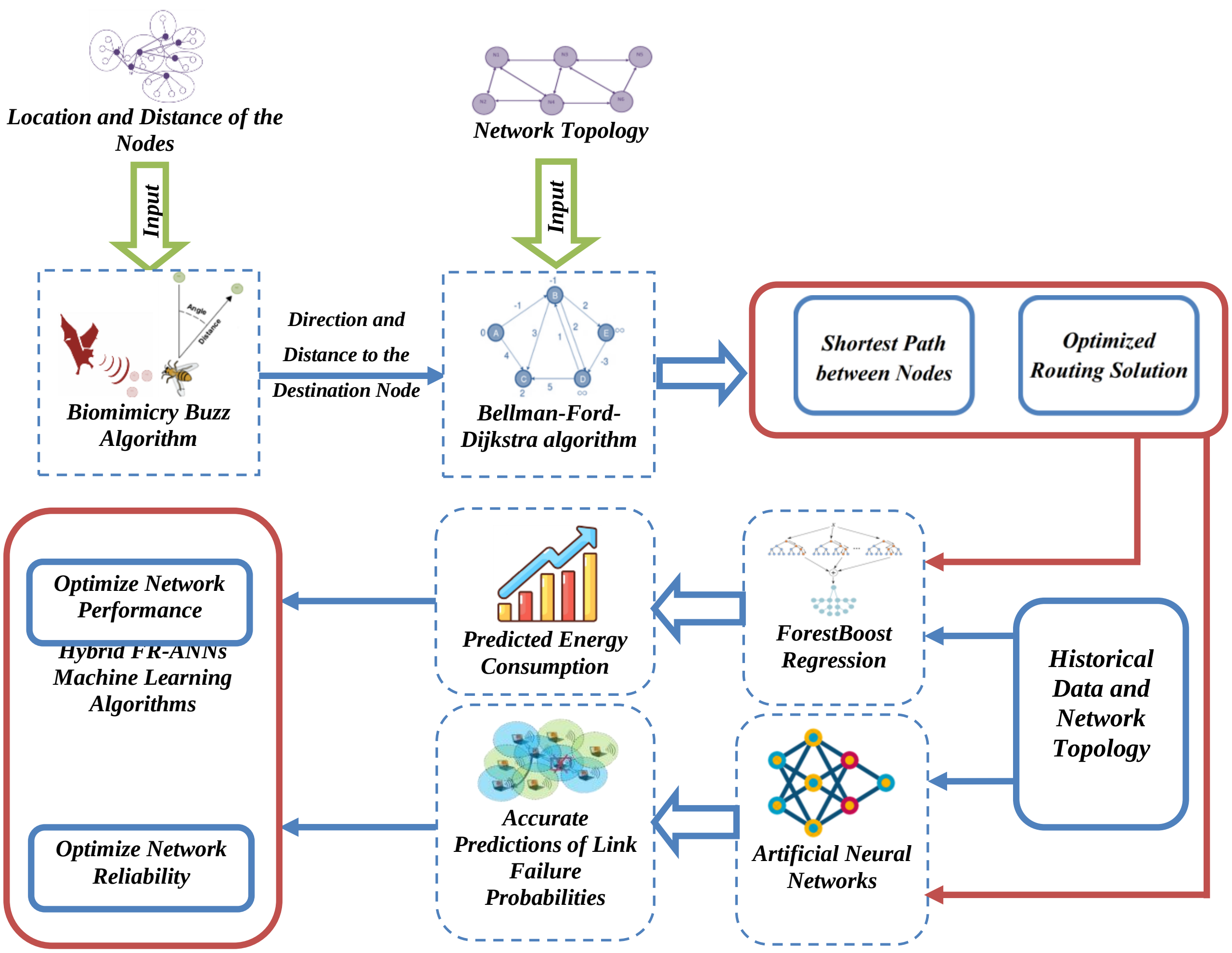

Fig. 2. Complete architecture of proposed model.

In addition, the paper explores using FR-ANN, a novel machine learning algorithm, to predict energy consumption and link failure in MANETs. FR-ANN can be used to optimize the network's energy usage, prolong the network's lifespan, and enhance the network's performance and reliability by predicting potential link failures before they occur. By predicting energy consumption and potential link failures, the network can use energy-efficient routes, resulting in longer battery life for nodes, preventing data loss, and improving network availability.

B. Biomimicry Buzz Algorithm

The honeybee waggle dance is a behavior used by honeybees to communicate the location of food sources to other bees in the hive. A bee that has found food returns to the hive and performs a dance, where the angle, along with the duration of the dance, is a sign of the direction plus distance of the food source, correspondingly. Other bees in the hive use this information to locate the food source. Bat echolocation is a behavior bats use to navigate and find food in the dark. Bats emit high-frequency sounds, which bounce off objects in their environment and create echoes. They listen to the echoes to determine the distance and location of things. To integrate these two behaviors for route selection, we could use the honeybee waggle dance to communicate the establishment of a destination, while bat echolocation could be used to navigate around obstacles and avoid collisions.

The echolocation method used by bats involves transmitting sound waves and detecting their reflection to locate prey based on the characteristics of the echo. Similarly, a device discovery algorithm uses a similar concept to find proximal devices within a specific search space. The discoverer device sends a signal or relies on the base station to determine the location of nearby devices. Mathematically, this technique can be expressed as follows: Let L denotes the position of a bat at time tm and s denotes the speed, which represents the rate of change in status. Consequently, the bat's position-refreshing method is determined in Eq. (1)

$$L_j(tm) = L_j(tm + 1) + s_j(tm) \tag{1}$$

Bats change their trajectory and pace depending on how far they are from their prey's location, as evidenced by their characteristics, which are represented in Eq. (2)

$$S_j(tm) = S_j(tm + 1) + (L_j(tm) – L') * fn_j \tag{2}$$

L′ deals with the location of the prey, whereas fn deals with the periodicity of natural waves. The following equation can be used to simulate the irrational behavior of bats, such as migration far from their identified prey via a degree of divergence in the range of loudness by employing Eq. (3)

$$L_{new} = L_{old} + \varepsilon * Sig^{tm} \tag{3}$$

The loudness evaluation algorithm indicates a uniform distribution, and Sigtm stands for signal strength by using the Eq. (4)

$$Sig_j(tm+ 1) = \tilde{e} * Sig_j(tm) \tag{4}$$

where, $Sigj(tm+ 1) \rightarrow 0$, where $tm \rightarrow \infty$, and $\tilde{e}$ the empirical value. Bats can determine how far they are from their target by varying the frequency associated with emanation. The emanation change occurs at the following frequency by using the Eq. (5)

$$c_j(tm + 1) = c_j(0)[1 - f^{(-d_* tm)}] \tag{5}$$

while $c_i(tm) \rightarrow c_i(0)$ as $tm \rightarrow \infty$, as well as d is the empirical constant.

Process Flow:

1) A node in the network needs to communicate with another node at a specific location.

2) The node sends a request to the network for the location of the destination.

3) Another node in the network, which has knowledge of the location of the destination, responds by performing a "waggle dance" to indicate the direction and distance of the goal.

4) The requesting node uses this information to navigate toward the destination using bat echolocation to detect obstacles and avoid collisions.

5) As the node gets closer to the destination, it can continue using bat echolocation to refine its navigation and avoid any obstacles.

Combining the honeybee waggle dance and bat echolocation can create a more robust and adaptive approach for route selection in a MANET. The honeybee waggle dance provides information about the location of the destination, while bat echolocation enables nodes to navigate around obstacles and avoid collisions in real time. This approach could be beneficial in situations where nodes are mobile, and the network topology is constantly changing.

C. Optimized Route Selection - Bellman-Ford-Dijkstra Algorithm

To determine the fastest path through a network of paths, the Bellman-Ford-Dijkstra procedure incorporates the Bellman-Ford algorithm and Dijkstra's algorithm. The network's negative cycles are initially detected along with removed using the Bellman-Ford algorithm, followed by the shortest route among the two nodes is determined using Dijkstra's algorithm. The algorithm effectively discoveries the shortest path in various network topological structures by integrating the advantages of each algorithm. For example, to incorporate honeybee waggle dance and bat echolocation into the Bellman-Ford-Dijkstra algorithm, we can use these behaviors to provide additional information about the network and guide the search toward the shortest path.

Use honeybee waggle dance to estimate the direction and distance of the destination node. Honeybees use this behavior to communicate the location of food sources to other bees in the hive. We can use a similar approach to estimate the location of the destination node in the network. Use bat echolocation to identify obstacles and congested areas in the network. Bats use echolocation to navigate in the dark and avoid collisions, and we can use a similar approach to help nodes navigate around obstacles and avoid congested areas. Utilize the Bellman-Ford method to find negative network cycles and eliminate them. Negative cycles are loops in the network with a negative weight, and they can cause the algorithm to enter an infinite loop. By detecting and eliminating negative cycles, we can ensure that the algorithm converges to a valid shortest path.

To determine the shortest route between two locations, use Dijkstra's algorithm. In most instances, the Dijkstra algorithm is better than the Bellman-Ford algorithm at choosing the shortest path. Using honeybee waggle dance and bat echolocation to guide the search toward the destination node and avoid obstacles, we can further optimize the search process and reduce the search space. Add the shortest route to the routing database among every network combination of points. Then, every node consults the routing database to identify the subsequent hop on the fastest way to the target node. By integrating honeybee waggle dance and bat echolocation into the Bellman-Ford-Dijkstra algorithm, we can create an optimized route selection approach that takes advantage of these natural behaviors to progress the excellent organization in addition to the accuracy of the routing process. Table I shows the example of a routing table with sample data, we have a network with six nodes, and the routing table demonstrates the shortest path between each and every pair of nodes. For instance, to reach node B from node A, the next hop is node C. The next hop is node E to reach node C from node D. Each node in a network may utilize the routing database to find the following route on the most convenient path to the target node. Note that this is just a sample table, and the routing table would be much larger and more complex in a real-world network. A regular update of the table was additionally required as the network's topography changed.

An optimized routing solution can provide essential input data for the ForestBoost Regression energy consumption prediction module and the Artificial Neural Networks link failure prediction module. The Bellman-Ford-Dijkstra module uses the output of the honeybee waggle dance and bat echolocation behavior module to determine the network's quickest route among two nodes, which results in an optimized routing solution. This optimized routing solution can be used as input for the ForestBoost Regression energy consumption prediction module to forecast the system's nodes' energy usage.

TABLE I. EXAMPLE OF A ROUTING TABLE WITH SAMPLE DATA

Source Node	Destination Node	Next Hop
A	B	C
A	C	F
B	A	C
B	C	D
C	A	F
C	B	A
D	A	B
D	C	E
E	A	C
E	B	A
F	A	C
F	B	D

Let S_p, αS_p, C_{pt}, C_{pr} indicate the power of the transmitted signal, the power of the amplifier, the power of the circuit at the transmitter, along with the power of the circuit at the receiver, respectively by Eq. (6) to Eq. (8).

$$S_p = \frac{(4\pi)^2 d_m^{\alpha'} M_l N_f}{G_t G_r \gamma^2} E_b R_b \tag{6}$$

$$\mathrm{C_{pt}} = \mathrm{P_{mix}} + \mathrm{P_{syn}} + \mathrm{P_{filt}} + \mathrm{P_{DAC}} \tag{7}$$

$$C_{pr} = P_{mix} + P_{syn} + P_{LNA} + P_{filr} + P_{ADC} + P_{IFA} \tag{8}$$

The amount of power used while transmitting in active mode (A_{pt}) is able to be determined by Eq. (9).

$$A_{pt} = S_p + \alpha S_p + C_{pt} = (1+\alpha)S_p + C_{pt} = \frac{\varphi}{\tau} S_p + C_{pt} \tag{9}$$

During reception (A_{pr}), the electricity used in the active phase is able to be provided by Eq. (10).

$$A_{pr} = C_{pr} \tag{10}$$

The ForestBoost Regression energy consumption prediction module utilizes historical data and network topology as input to predict the energy consumption of nodes. Using an optimized routing solution as input, the module can consider the energy consumption associated with specific routing decisions and provide more accurate predictions. Similarly, the Artificial Neural Networks link failure prediction module utilizes historical data and network topology to predict link failures in real-time. By incorporating an optimized routing solution as input, the module can consider the impact of routing decisions on the network's overall reliability and provide more accurate predictions of link failure probabilities.

Let E_e^i represent the starting energy concerning a node n_e and the amount of energy needed for transmission (E_e^{Tx}) or as reception (E_e^{Rx}) beginning at that node n_e. The specified L bits are actually by Eq. (11) and Eq. (12).

$$(E_e^{Tx}) = \mathrm{P_{tx}T_{tx}} = \frac{\varphi}{\tau}\mathrm{P_t P_{ct}} \tag{11}$$

$$(E_e^{rx}) = \mathrm{P_{rx}T_{rx}} = \mathrm{P_{cr}T_{rx}} \tag{12}$$

After transmitting L bits, the RE (E_k^{Tx}) at a node n_e is given by Eq. (13).

$$(E_e^R) = \begin{Bmatrix} E_e^i - E_e^{Tx} \\ E_e^i - E_e^{Rx} \end{Bmatrix} \tag{13}$$

When using the approach we suggest with Z hops, the total amount of energy used per iteration by the fastest route via the node's $n_l(n_{lo}, n_{l1}, n_{l2}, \ldots, n_{lz},)$ can be determined based on Eq. (14).

$$E_T = \sum_{l=0}^{Z-1} [(E_k^{Tx} + E_{l+1}^{Rx})] + \sum_{l=0}^{Z} [E_l^{idle} + E_l^{CPU} + E_l^{Bat} + E_l^{DC}] \tag{14}$$

where, $E_l^{idle} = P_{idle} T_{idle}$ at node n_l and $P_{sp} \approx 0$.

Optimized route selection - Algorithm
1. Let s be the source node along with t is the destination node. 2. Use the honeybee waggle dance to estimate the direction

and distance of the destination node. Let θ be the anticipated angles among the present point and the target node, along with let the d_s is the anticipated distance among the two nodes.

3. Use bat echolocation to identify obstacles and congested areas in the network. Let $w_t(e)$ be the edge-weight e in a network, which represents the cost of traversing that edge. If an obstacle or congested area is detected along edge e, then set $w_t(e)$ to a high value to discourage nodes from using that edge.

4. Initialize the distance estimates as well as predecessor nodes for each node in the network as follows:

$d_s[s] = 0$

$d_s[v] = \infty$ for all other nodes v in the network

p[v] = null for all nodes v in the network

5. Utilize the Bellman-Ford method to find negative network cycles and eliminate them. Iterate over all edges e in the network |V|-1 times (where |V| represents the network's total number of connections), and update the distance estimates and predecessors as follows:

if $d_s[v] > d_s[u] + w_t(e)$ then:

$d_s[v] = d_s[u] + w_t(e)$ p[v] = u

If after |V|-1 iterations, there exists an edge e with $d[v] > d[u] + w_t(e)$, subsequently a negative cycle exists in the network and terminates the algorithm.

6. Using Dijkstra's algorithm, find the quickest route among the starting node s along with target node t. Initialize a priority queue Q with all nodes in the network, ordered by their distance estimates $d_s[v]$. Set $d_s[s] = 0$ and insert s into Q. Then, whereas Q is not empty, extract the node u with the smallest distance estimate d[u] from Q and relax all its outgoing edges e as follows:

if $d_s[v] > d_s[u] + w_t(e)$ then: $d_s[v] = d_s[u] + w_t(e)$ p[v] = u

If v = t, then the shortest path has been found and the algorithm terminates.

7. If a path does not connect the source node s along with the target node t, then the algorithm terminates and returns "no path".

D. Energy Consumption Prediction

Energy consumption prediction is an essential aspect of optimizing route selection in MANETs. By predicting the energy consumption of different routes, we can choose the route that requires the least amount of energy, thereby conserving battery power and extending the life of the network's components. In the approach that integrates honeybee waggle dance and bat echolocation into the Bellman-Ford-Dijkstra algorithm, we use Random Forest Regression as a hybrid machine learning algorithm to predict the energy consumption of each route. This is done by training the algorithms on historical energy consumption data for different routes and using the trained models to predict the energy consumption of new routes. The predicted energy consumption values are then integrated into the Bellman-Ford-Dijkstra algorithm to find the route with the lowest energy consumption. This route is then selected as the optimized route for data transmission in the network.

E. Random Forest Regression

An effective machine learning approach called Random Forest Regression may be utilized to anticipate energy consumption. A collaborative algorithm for learning called Random Forest Regression builds several decision trees and integrates their forecasts to create a more precise and trustworthy approach. It is well-suited for handling high-dimensional data and can control categorical and continuous variables. Gradient Boosting Regression is another ensemble learning algorithm that builds models sequentially. It is capable of handling several kinds of data and has been shown to be effective in predicting energy consumption.

Let $T_b(i)$ denotes the predicted output of Decision Tree T_b, for sample i. To forecast at a fresh location p:

$$\text{Regression: f\^{}rf B (p)} = f_{rf}^{B}(p) = \frac{1}{B}\sum_{b=1}^{B} T_b(p) \quad (15)$$

Classification: Let $C_b(p)$ is the class predicted of b^{th} random-forest tree.

$$\text{Then } C_{rf}^{B}(p) = majority\ vote\{C_b(p)\}_1^B \quad (16)$$

A constant value is determined for every one of the discontinuous sections that make up the input space. There are j leaf nodes in each random forest regression tree. The $g_m(p)$ values for the Random Forest Regression tree is achieved based on Eq. (17) to Eq. (19).

$$\text{gm(p)} = \sum_{j=1}^{j} (b_{jm} I), p \in R_{jm} \quad (17)$$

$$I(p \in R_{jm}) = \begin{Bmatrix} 1, p \in R_{jm}; \\ 0, other; \end{Bmatrix} \quad (18)$$

$$Z(L, f(p)) = \sum_{i=1}^{n} (L - f(p))^2 \quad (19)$$

Step 1: Initialization of Model:

$$\text{fo(p)} = \text{argmin} \sum_{i=1}^{n} Z(y_i, p) \quad (20)$$

Step 2: R random Forest regression trees are generated iteratively, with r denoting the r^{th} tree to stay r=1 to R:

(1) J represent the j^{th} selection for j = 1 to N. Finally, the loss function's low gradient number is determined, along with the result can be utilized to measure the residual r_{jr}:

$$r_{jr} = \left[\frac{\partial Z(yj, f_{r-1}(p_j))}{\partial f_{r-1}(p_j)}\right]_{f(p)} = f_{r-1}(p) \quad (21)$$

(2) A random Forest regression tree gm(p) is produced on behalf of the enduring created in the preceding phase. The amount of steps for gradient decline is subsequently established by dividing the input space regarding the r-tree towards J distinct regions, designated as D_{1r}, D_{2r}, :::, and D_{jr}:

$$p_{r,} = \text{argmin} \sum_{j=1}^{n} Z(y_j, f_{r-1}(p_j) + pg_r(p_j)) \quad (22)$$

Step 3: Refresh the parameters of the approach, in which lr stands for the learning rate, aims to reduce the impact of each basic model on the result and prevent the framework from being overfit.

$$f_r(p) = f_{r-1}(p-1) + lr * pg_r(p) \quad (23)$$

To combine these two algorithms for energy consumption prediction, we can use a technique called stacking. In stacking, the predictions from multiple machine learning models are combined into a single model that produces more accurate predictions than any of the individual models.

The overall workflow for using Random Forest Regression for energy consumption prediction:

1) *Collect* and preprocess energy consumption data, including relevant features such as temperature, humidity, and time of day.

2) *Create* training and validation groupings for the data.

3) *Create* a Random Forest Regression model using the training set, and then generate forecasts by applying it to the testing set.

4) *Create* a Gradient Boosting Regression model using the training set, and then generate forecasts by applying it to the testing set.

5) *Combine* the predictions from the Random Forest and Gradient Boosting models using stacking.

6) *Analyze* the stacked model's results on the test set.

7) *Fine-tune* the hyperparameters of the models to improve their performance, if necessary.

8) *Once* the models are trained and optimized, they can be used to forecast energy usage based on newly acquired data.

In the Random Forest Regression algorithm, numerous decision trees are built, and the predictions from each tree are combined to produce the final forecast. A randomized subgroup of the training information and a randomly selected portion of the features are used for training every decision tree. The algorithm then averages the predictions of all the decision trees to get a final prediction. Mathematically, the forecast for a new input x can be written as Eq. (24).

$$p = \frac{1}{Nd} * \sum_{j=1}^{Nd} p_j(y) \quad (24)$$

where, Nd symbolizes the amount of decision trees along with $p_j(y)$ symbolizes the prediction of the j^{th} decision tree for the input y. The algorithm also constructs multiple decision trees, but instead of averaging their predictions, it combines them using gradient descent. In this algorithm, each decision tree is trained on the residuals (the discrepancy among the prior tree's anticipated result along with the actual output) of the previous tree. Mathematically, the prediction for a new input y can be written as Eq. (25).

$$p = \sum_{1}^{M} f_m(y) \quad (25)$$

where, M represents the number of decision trees, along with $f_m(y)$ is the prediction of the m^{th} decision tree for the input y. Random Forest Regression utilized to predict the energy consumption for a given set of features (such as distance, obstacles, and congestion) and can be integrated into the proposed routing algorithm to reduce the network's consumption of energy as much as possible.

F. Link Failure Prediction

In the integrated approach using honeybee waggle dance and bat echolocation with the Bellman-Ford-Dijkstra algorithm, link failure prediction can be obtained through various methods. One possible approach is using statistical analysis and machine learning algorithms to analyze network data, including node connectivity, traffic load, signal strength, and other relevant parameters. Applying supervised machine learning - SML strategies like Artificial Neural Networks (ANNs) can help predict link failure based on historical data and other network features. Moreover, integrating honeybee waggle dance and bat echolocation can provide additional inputs for link failure prediction. For instance, the honeybee waggle dance can be used to estimate the distance and direction of the destination node, which can help identify potentially congested areas and bottleneck links along the path. Similarly, bat echolocation can be used to detect obstacles and other obstructions that may affect signal strength and link quality.

G. Artificial Neural Networks (ANNs)

The structure and the human brain's operation motivate a computational model called an 'Artificial Neural Network'. It is made up of several linked, layered processing nodes or neurons. The layer that produces the result generates the prediction result, and the data that is the input layer gets the input data. The hidden layers perform intermediate processing on the input data to extract relevant features and patterns. The input data is represented as a vector x with n components: $x = [x_1, x_2, ..., x_n]$. Each component x_i represents a feature of the input data. Each neuron in the data layer gets a portion of the input vector as the input information is fed through the input layer. To create an output, each neuron in the layers that are concealed performs a weighted compilation of its inputs along with applying an activation procedure. Where $h_{i,j}$ represents the j^{th} neuron's outcome in the i^{th} buried layer. The activation function usually incorporates nonlinearity through the network structure through a nonlinearity.

The ultimate forecast is generated by feeding the final result of the last layer that is concealed through the output layer. Y_k stands for the outcome of the k-th neuron in the yield layer. The yield layer may have multiple neurons, each corresponding to a different output class or regression value. The weights and biases of the neurons are learned during the training phase of the network. A cost function that calculates the disparity between the outcomes predicted along with the outcome actually produced is what training aims to minimize. Using an optimization method like gradient descent or Adam, the weights are refreshed. In predicting link failure, ANNs can be used to predict the probability of link failure based on historical data and other features such as traffic load, weather conditions, and network topology. The input vector x symbolizes the features of the link; in addition to the output, y represents the probability of link failure. The biased and weighted elements of the neural network are modified to minimize the discrepancy across its projected likelihood alongside the actual possibility of link failure after it has been trained on the data set consisting of previous link failure occurrences. By the present status of the input characteristics, the ANN can be utilized for instantaneously predicting the likelihood of failure of the link once it has been trained. If the predicted probability exceeds a certain threshold, a link failure is predicted, and the network can take appropriate action to reroute traffic and avoid network disruption.

Steps:

1) Data collection: Collect data related to network topology, traffic, and energy consumption. This data includes features such as link distance, bandwidth, traffic volume, and energy consumption.

2) Feature engineering: Determine pertinent features from the gathered information, including statistical measures such as mean, variance, along with standard deviation.

3) Data preprocessing: Normalize the data to a common scale to remove any bias towards features with larger values. Also, divide the data into training, validation, and test sets.

4) Training ANNs: Use the training data to train ANNs for link failure prediction. ANNs are powerful machine learning algorithms that can learn the underlying patterns as well as make predictions based on new input data. In this case, the ANNs will learn to predict link failures based on the input features.

5) Validation and hyperparameter tuning: Verify the trained ANNs' effectiveness using the validation collection and tune the hyperparameters of the ANNs to improve their performance.

6) Testing: Test the final ANN models on the test set to evaluate their performance.

7) Integration with energy consumption prediction: Finally, integrate the ANN-based link failure prediction model with the previously developed energy consumption prediction model that uses Random Forest Regression and Gradient Boosting Regression with honeybee waggle dance and bat echolocation optimized route selection using the Bellman-Ford-Dijkstra algorithm. This integrated model will now be able to predict both link failures and energy consumption and use this information to optimize the process of routing in the network.

Optimized route selection approach In MANET using " honeybee waggle dance and bat echolocation for route selection, Bellman-Ford-Dijkstra algorithm to find the shortest path in a network, By integrating honeybee waggle dance and bat echolocation into the Bellman-Ford-Dijkstra algorithm, we can create an optimized route selection approach that takes advantage of these natural behaviors to improve the efficiency and accuracy of the routing process, ForestBoost Regression is a novel machine learning algorithms that can be used for energy consumption prediction, Artificial Neural Networks provides more accurate and timely predictions of link failure in MANETs, improving the performance and reliability"

Algorithm for Optimized route selection and Link Failure Prediction

1. Data preprocessing:

Input: Energy consumption data (X), network topology data (G), and link failure data (Y)

Output: Normalized energy consumption data (X_{nor}), normalized network topology data (G_{nor}), and binary link failure data (Y_{bin})

The data preprocessing step involves normalizing the energy consumption data X and the network topology data G, and converting the link failure data Y into binary form. Mathematically, we can represent this step as follows:

$$X_{nor} = (X - \text{mean}(X)) / \text{std}(X) \tag{26}$$

$$G_{nor} = (G - \text{mean}(G)) / \text{std}(G) \tag{27}$$

$$Y_{bin} = 1 \text{ if } Y > 0, \text{ else } 0 \tag{28}$$

where, mean(.) and std(.) represent the mean as well as standard deviation of the data, respectively.

2. Honeybee waggle dance and bat echolocation:

Input: Normalized network topology data (G_{nor})

Output: Estimated distance to destination node (d) and estimated angle to destination node (λ)

The honeybee waggle dance and bat echolocation steps use the normalized network topology data G_{nor} to estimate the distance d and angle theta to the destination node. Mathematically, we can represent this step as follows:

d, λ = honeybee_waggle_dance_and_bat_echolocation(G_{norm}) (29)

where, honeybee_waggle_dance_and_bat_echolocation (.) represents the function that estimates the distance and angle using the honeybee waggle dance and bat echolocation techniques.

3. Bellman-Ford-Dijkstra algorithm with link failure prediction:

Input: Normalized network topology data (G_{nor}), estimated distance to destination node (d), estimated angle to destination node (λ), and binary link failure data (Y_{bin})

Output: Shortest route between source and target nodes (P)

The Bellman-Ford-Dijkstra algorithm with link failure prediction step takes as input the normalized network topology data G_{nor}, the estimated distance towards the target node d, the estimated angle to the destination node theta, along with the binary link failure data Y_{bin}, and outputs the shortest route between source and target nodes. This step consists of two sub-steps: Bellman-Ford algorithm and Dijkstra's algorithm.

3.1 Bellman-Ford algorithm:

Input: Normalized network topology data (G_{nor}), estimated distance to destination node (d), estimated angle to destination node (λ), and binary link failure data (Y_{bin})

Output: Distance estimate ($d_s[x]$) as well as predecessor node ($p_s[x]$) for each node in the network

The Bellman-Ford algorithm takes as input the normalized network topology data G_{nor} , the estimated distance to the destination node d_n, the estimated angle to the destination node theta, and the binary link failure data Y_{bin}, and outputs the distance estimate $d_n[x]$ and predecessor node p[x] for each node x in the network. Mathematically, we can represent this step as follows:

Initialize $d_n[x]$ = infinity, $p_s[x]$ = null for all x in G

Set $d_n[\text{source}] = 0$

For i = 1 to |X|-1 do

For each edge (u, x) in G do

if $Y_{bin}[u,x] == 0$ then

if $d_n[x] + w_t(u,x) < d_n[x]$ then

$d_n[x] = d_n[x] + w_t(u,x)$

$p_s[x] = u$

where, |V| is the number of nodes in the network.

IV. Performance Analysis

An arbitrary collection of origins nodes was replicated with sizes varying from 25 to 125 nodes using the simulation platform, as shown in Table II, to test the efficacy of the suggested mechanisms. These node sources were configured to transmit CBR data packets, which are the nodes' transmission range of 250 seconds, at arbitrary speeds increasing from 25 m/s to a maximum of 30 m/s between arbitrary standstill intervals ranging from 0 to 50 s. The RWP technique is used to generate various nodes. 700s of simulation time is adequate to determine network congestion, latency, and complexity. The optimal path parameter, or "OPI," is generated for each alternate route based on the values of parameters like Movement Indication, Network Access, Path Accessibility, as well as Link Duration. In a MANET, the route with the highest Path selection factor is considered for data transfer across the intermediary nodes towards a target node.

To substantiate the effectiveness of our proposed strategy, we recognize the critical importance of employing diverse and representative datasets that encapsulate various scenarios and environmental conditions inherent in MANET operations. Our dataset selection criteria prioritize factors pivotal to MANET performance, encompassing node mobility, signal strength, and network traffic. For node mobility, we intend to incorporate datasets that emulate a spectrum of mobility patterns and scenarios, including different speeds, pause times, and movement trajectories. The datasets related to signal strength will account for real-world fluctuations, considering interference, obstacles, and varying distances between nodes. Additionally, our approach involves simulating diverse network traffic scenarios, encompassing varying loads, sudden spikes, and fluctuations in traffic. This comprehensive dataset strategy aims to ensure the validity and generalizability of our experimental evaluations, evaluating the adaptability and responsiveness of the proposed MANET optimization strategy across a wide array of realistic conditions. The selected metrics for evaluation include node mobility metrics, signal strength metrics, network traffic metrics, and metrics related to topology changes, providing a holistic assessment of our strategy's performance and its real-world applicability.

TABLE II. SIMULATION PARAMETERS

Parameters	Values
Speed of the node	[25-30]m/s
Number of Nodes	25 - 125
Packet size	512 bytes
Simulation Time	700s
Traffic category	CBR
Protocol used for Routing	RIFA
Mobility Model	Random
Pause Time (s)	10s
Wireless Range of Transmission	250s
Area of Simulation	1200m
Node Assignment	Random

A. Discovery Signal Delivery Probability

To evaluate the performance of the proposed approach for optimized route selection in MANETs, one metric that can be used is the discovery signal delivery probability. This metric measures the ability of the routing protocol to deliver packets to their intended destination. Meeting chance refers to the likelihood that a relay entity will move into conversation with a destination entity. According to the algorithm above, the relay node's choice of the transmitted finding signal is based on the probability's variant value combination. The probability that a signal will be transferred successfully via object Rd to the other device Dd is represented by the Prob(Rd, Dd) symbol. The following procedures are provided for upgrading the detection delivery of messages probability Prob(Rd, Dd): As meeting frequency along with contact time grows, the likelihood of acquiring a signal rises. Therefore, whenever the two devices come together, they will transmit a likelihood table based on the provided mathematical framework, updating the discovery signal by employing Eq. (30) and Eq. (31)

$$Prob(Rd,Dd) = Prob(Rd,Dd)_{Prev} + (1 - Prob(Rd,Dd)_{Prev}) * Prob_{orig} * z^{\frac{T_{RdDd}}{T_r+T_d/2}} \quad (30)$$

$$T_{RdDd} = \sum_{q=1}^{l} t_{RdDd}(q) = \sum_{q=1}^{l} (t_{RdDd_{end}}(q) - t_{RdDd_{start}}(q)) \quad (31)$$

The entire contact time across the relay unit Rd along with the destination unit Dd. t is indicated by the symbol T_{RdDd}. The end, followed by the q[th] connection start times link among relay devices Rd along with recipient device Dd are denoted by $t_{RdDd_{end}}(q)$ in addition to $t_{RdDd_{start}}(q)$, respectively. In addition, $T_{Rd} = \sum_{q=1}^{n} t_{Rdq}$ represents the period of time during which the relay unit Rd is in communication with other network nodes, and $T_{Dd} = \sum_{k=1}^{n} t_{Ddk}$. The overall amount of time during which that device Dd is in communication with any other device on the same network is nt_Ddk. The duration of contact among devices Rd along with Dd is measured as $\frac{T_{RdDd}}{T_{Rd}+T_{Dd}/2}$ in terms of the mean impact rate $(T_r + T_d)/2$.

To evaluate the discovery signal delivery probability, the proposed approach can be compared to other existing routing protocols for MANETs using NS-3 simulation tool. The simulations can be designed to mimic real-world scenarios and measure the percentage of packets that successfully reach their destination. To evaluate the ForestBoost Regression algorithm's performance, the proposed approach can be compared to existing algorithms used for energy prediction in MANETs, such as ANNs or Support Vector Regression (SVR). The performance can be evaluated based on the accurateness of the energy prediction along with the energy consumption optimization achieved by the algorithm. Similarly, the ANN-based approach for predicting link failure in MANETs can be compared to other existing approaches, such as probabilistic models or machine learning-based models. The evaluation can be based on metrics such as prediction accuracy and false positive/negative rates.

B. Packet Delivery Rate

The proportion of the amount of packets sent by upper layers in relation to the amount of packets that arrived at the destination is known as the packet delivery rate. This standard represents the degree of the suggested way from a starting point to a target. With faster data packet delivery, the suggested technique becomes more effective. Let PDR stand for the data packet delivery efficiency, which can be calculated by applying Eq. (32)

$$\text{Packet Delivery Rate} = \frac{\mathrm{N_{pr}}}{\mathrm{N_{ps}}} * 100\% \qquad (32)$$

where, N_{pr} stands for the quantity of received packets whereas N_{ps} for the quantity of transmitted packets. The packet delivery ratio - PDR fluctuation for the protocols RRP [12], CHNN [14], and MAR [17] is shown in Fig. 3. The packet delivery ratio declines as node speed rises.

The proposed strategy falls from 97% to 90%, the RRP from 92% to 83%, and the MAR from 93% to 88%. The proposed method has a more excellent packet delivery ratio than previous protocols. The most dependable path to the destination is selected by the recommended routing protocol. In comparison to other options, the selected path can have the highest energy level, require the least amount of energy, and cover the greatest distance. By doing this, the likelihood of a node failure is lower, and data loss is reduced.

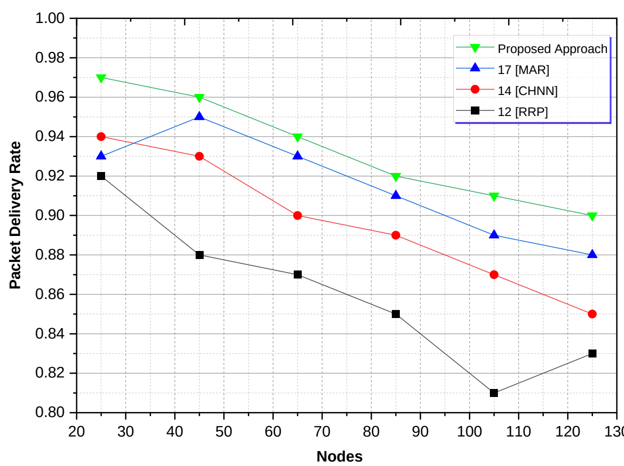

Fig. 3. Variation of packet delivery ratio.

C. Average End-To-End Delay – E2ED

The averaged E2E latency is the duration that it takes for a data packet to arrive which effectively voyage since solitary place to a new. To describe the typical end-to-end delay, we use E2ED. The computation process represented in Eq. (33)

$$\mathrm{E2ED} = \frac{1}{\mathrm{Tdp}} \sum_{\mathrm{a}=1}^{\mathrm{Tdp}} \left(\mathrm{T_{pt}(a)} - \mathrm{T_{pr}(a)}\right) \qquad (33)$$

Fig. 4 compares the suggested approach's average E2E delay to that of the RRP [12], CHNN [14], and MAR [17] range from 10 to 60 minutes. As the amount of time grew, the end-to-end latency shrank. As a result, the suggested method produced a significant latency of roughly 19 ms whenever the pause period was the 60s; however, as the pause time climbed, it dropped due to the lower transportation and likelihood of node failures.

D. Energy Consumption

Energy consumption is the sum of the energy network nodes consumed throughout the scenario. This is accomplished by calculating the energy level of every single node during the end of the trial and accounting for its residual energy. Energy consumption will be represented by the Eq. (34).

$$Econs = \sum_{a=1}^{B} (Ei(an) - Er(an)) \qquad (34)$$

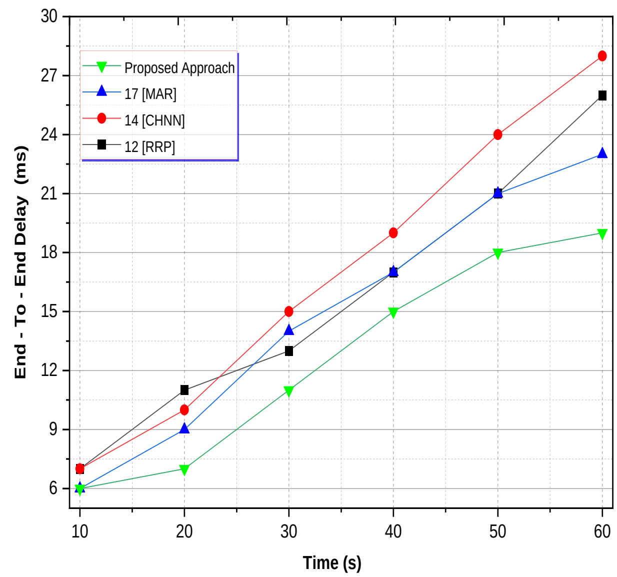

Fig. 4. Average end-to-end delay of the proposed approach.

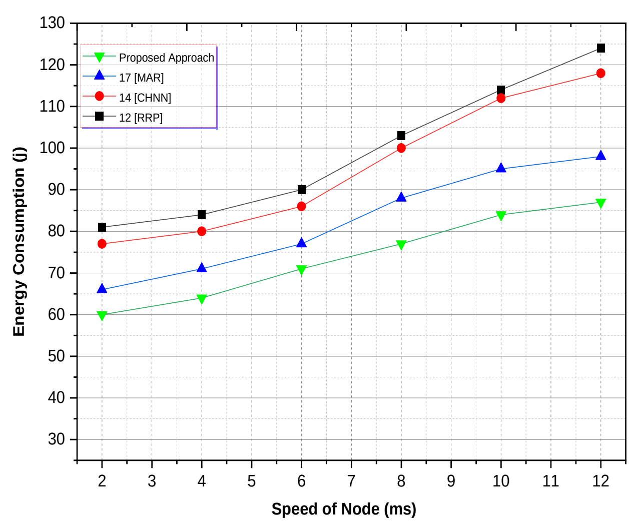

Fig. 5. Energy consumption - node speed.

RRP [12], CHNN [14], and AMR [17] are the three proposed approaches, and the variance in energy usage for each is shown in Fig. 5 (MAR). The energy usage rises as the node speed does. The suggested approach results in an increase of 60 to 87 joules, whereas RRP experiences an increase of 38 to 97 joules, CHNN experiences an increase of 31 to 107 joules, as well as MAR experiences an increase of 35 to 127 joules. The recommended protocol uses less energy than other protocols.

The proposed method groups the routes that eventually reach the desired destination based on their energy levels. The point of origin scatters the data packets while transferring it via pathways with an elevated energy level as well as the normal one in order to equally spread the load on numerous routes. Compared to sending the traffic across just one path, this process uses less energy. RRP, CHNN, and MAR are the recommended approaches, and their energy usage is shown in Fig. 6. In contrast to other protocols, which use more than 30 joules for 10 seconds as well as 90 joules over 60 seconds, the recommended technique uses 29 joules over 10 seconds along with 89 joules over 60 seconds. As a result, the recommended method uses limited energy compared to some alternative methods.

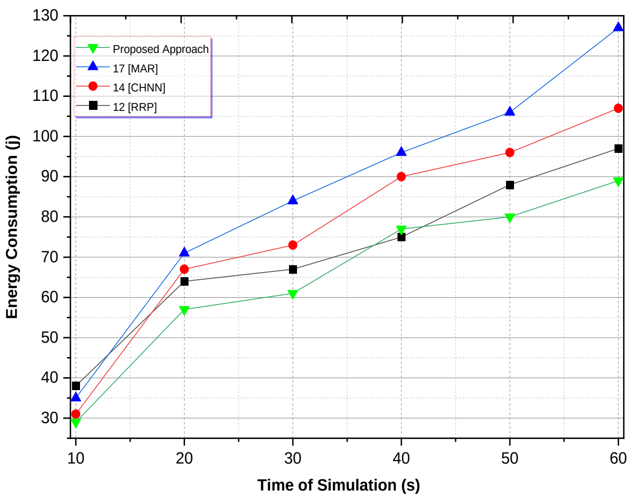

Fig. 6. Energy consumption - simulation time.

The optimization approach proposed for MANET routing offers benefits in improved adaptability, reduced latency, and enhanced energy efficiency. Integrating biomimicry-inspired algorithms and predictive models contributes to dynamic route selection, quicker data transmission, and optimized energy usage. Link failure prediction enhances network reliability. However, challenges include algorithmic complexity, dependence on dataset quality, and considerations for real-world implementation such as hardware constraints and scalability issues. Addressing these limitations is crucial for practical feasibility and efficacy in diverse MANET scenarios.

V. Conclusion and Future Work

In conclusion, the optimization of the routing process in MANETs is a crucial task for enhancing the performance and reliability of these networks. The proposed approach, which integrates the biomimicry buzz algorithm with the Bellman-Ford-Dijkstra algorithm, provides a promising solution for this task. By using these behaviors, the nodes can quickly converge on the optimal route to the destination, leading to an efficient and accurate routing solution. Additionally, the use of advanced machine learning techniques such as ForestBoost Regression and ANNs can further optimize the network's energy consumption and predict link failure, improving the network's performance and reliability. These techniques have the potential to revolutionize the routing process in MANETs, enabling them to operate more efficiently and reliably, even in dynamic and unpredictable environments. The proposed approach has the potential to improve the performance and reliability of MANETs, which serves numerous distinct applications in areas such as disaster relief, military operations, and sensor networks. The use of natural behaviors and advanced machine learning techniques is an innovative approach to optimizing the routing process, and further research in this area could lead to even more sophisticated solutions for MANETs.

The proposed optimized route selection approach, coupled with innovative applications of machine learning in predicting energy consumption and link failure, opens avenues for future research and development in the realm of Mobile Ad Hoc Networks (MANETs). The following areas represent potential directions for future exploration:

Further exploration and refinement of biomimicry algorithms, beyond the proposed biomimicry buzz algorithm, could yield enhanced routing strategies. Investigating the application of other bio-inspired algorithms may lead to more efficient and adaptive routing solutions in dynamic MANET environments. Continuous advancements in machine learning techniques can be leveraged to optimize the prediction accuracy of energy consumption and link failure. Exploring deep learning architectures or ensemble methods may enhance the precision of predictions, contributing to more reliable network management. Research into mechanisms for dynamically adapting the proposed algorithm to varying network conditions and node behaviors is essential. The ability to self-adjust based on real-time factors, such as traffic patterns or node density, would enhance the algorithm's adaptability and overall effectiveness.

Incorporating robust security measures within the routing protocol is crucial in MANETs. Future work could focus on integrating advanced security mechanisms to fortify the proposed algorithm against potential security threats, ensuring secure and reliable communication. Translating the proposed strategy from simulations to real-world implementations is a significant future avenue. Evaluating its performance in actual MANET deployments, considering factors like hardware constraints and varying environmental conditions, will validate the practicality and effectiveness of the proposed approach. Enhancing energy prediction models by considering dynamic factors such as node mobility patterns, terrain variations, and changing environmental conditions could further refine energy consumption predictions. Future work might involve developing energy models that adapt to real-time context changes. Extending the experimental evaluation to larger network sizes and assessing the scalability of the proposed approach will provide insights into its performance under more extensive MANET scenarios. Investigating how the algorithm scales with an increasing number of nodes is vital for its practical applicability. Exploring cross-layer optimizations that integrate routing, energy management, and link failure prediction could yield holistic solutions. Collaborative decision-making across multiple protocol layers may enhance the overall efficiency and reliability of MANETs.

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