J. Integr. Sci. Technol. 2024, 12(1), 718

Journal of Integrated
SCIENCE & TECHNOLOGY

Optimization of energy consumption and routing in MANET using Artificial Neural Network

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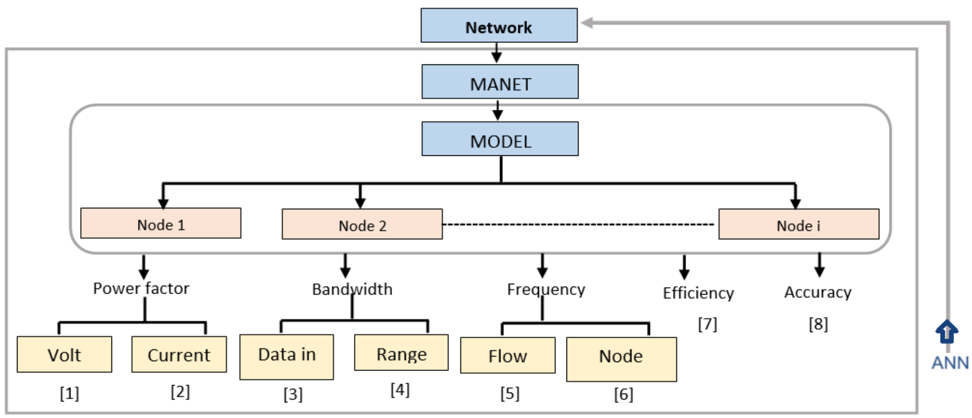
Received on: 20-Jun-2023, Accepted and Published on: 11-Sep-2023

Article

ABSTRACT



Mobile Ad Hoc Networks (MANETs) face challenges in optimizing energy consumption and routing due to their dynamic and decentralized nature. This paper presents a novel approach utilizing artificial neural networks (ANNs) to address these limitations. The study explores the potential of ANNs in making intelligent energy consumption decisions, considering factors such as node mobility, transmission power, and network traffic. Additionally, ANNs are employed for dynamic routing decisions based on node energy levels, link quality, and network congestion. To train the ANNs, relevant data is used to capture the complex relationships between the network parameters. The experimental evaluation demonstrates the superiority of ANNs compared to conventional methods, showcasing improved network efficiency, reduced energy consumption, and enhanced overall performance. By leveraging ANNs, MANETs can achieve optimized energy utilization, leading to prolonged network lifetime and reduced instances of service disruptions caused by node power exhaustion. The findings of this research contribute to the advancement of power-aware protocols for wireless networks by addressing the challenges specific to MANETs and improving their functionality in practical scenarios.

Keywords: Mobile Ad hoc Networks (MANETs), Optimization, Energy Consumption, Routing, Artificial Neural Networks (ANNs)

INTRODUCTION

Wireless networks have experienced significant growth in popularity over the past decades, with two primary variations: infrastructure networks and infrastructure-less networks. Infrastructure networks, such as cellular networks and wireless local area networks (IEEE 802.11), rely on centralized controllers to establish and maintain communications between terminals. In contrast, infrastructure-less networks, also known as wireless ad hoc networks, operate in a decentralized manner.[1] Terminals within an ad hoc network can autonomously establish connections and communicate with each other in a multi-hop fashion without relying on fixed infrastructure.[2] This inherent infrastructure-less property enables rapid deployment and robust operation, making ad hoc networks suitable for applications such as emergency services, disaster recovery, wireless sensor networks, and home networking.[3]

Effective communication plays a vital role in facilitating information exchange among individuals in various contexts and locations. Mobile Ad Hoc Networks (MANETs) are a collection of mobile nodes that form a network independently, without centralized administration.[4] However, as these mobile devices operate on batteries, extending their battery life has become a critical objective. Researchers have increasingly focused on developing power-aware and efficient protocols for MANETs to address the limited energy levels of mobile nodes.[5] Each mobile node in a MANET performs the routing function to establish communication with other nodes.[6] Therefore, even the depletion of

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Cite as: *J. Integr. Sci. Technol., 2024, 12(1), 718.*
URN:NBN:sciencein.jist.2024.v12.718

 ISSN: 2321-4635
http://pubs.thesciencein.org/jist

a few nodes' energy can result in service disruptions across the entire MANET.

One of the significant challenges in MANETs is the limited energy availability of the battery-driven mobile nodes.[7] Additionally, the dynamic nature of MANETs, where nodes are constantly moving, can lead to link breakages when a node moves out of the radio range of its neighboring node. Consequently, link breakages in MANETs can occur due to two primary reasons: energy exhaustion of nodes and nodes moving out of range.

Addressing the optimization of energy consumption and routing in MANETs is crucial to mitigating the impact of limited energy availability and node mobility.[8] This paper focuses on leveraging artificial neural networks (ANNs) to optimize energy consumption decisions and dynamic routing in MANETs. ANNs are capable of learning complex relationships from relevant data, enabling intelligent decision-making based on factors such as node mobility, transmission power, and network traffic.[9] By employing ANNs, the aim is to improve network efficiency, reduce energy consumption, and enhance overall performance compared to conventional methods.

The subsequent sections of this paper will delve into the methodology, experimental evaluation, and results, providing insights into the effectiveness of using ANNs for energy consumption optimization and routing in MANETs. The findings contribute to the development of power-aware protocols for wireless networks, addressing the specific challenges posed by MANETs and improving their functionality in practical scenarios.

LITERATURE REVIEW

Quevedo et. al.[10], noted that vulnerability and weaknesses in VANETS are the main problems. In addition to traditional network attacks, mANETs are influenced by modern threats based on the disruption of authentication and false information dissemination, such as threats by Sybil. This reported a system for detecting Sybil attacks in MANET.

Prema, S. et al.[11] discussed not only the architecture, elements, and operations of SDN-based VANETs but also how these VANETs provide better communication than conventional VANETs. We can lower the overall network load by managing the network as a whole from a single remote controller. SDN controllers can also keep track of security threats.

Hussein et al.[12], observed that many of the method's SDN adoptions are still hampered by many security issues. In this report, they analyzed security vulnerabilities, risks, and solutions in the current SDN stage. The capabilities of the SDN present a host of new challenges to the network.

Boutaba et. al.[13] presented a thorough overview of the limitations, difficulties, and threats in the architecture of the SDN in various de-facto scenarios. The authors also implemented an innovative approach to define and secure the SDN-based networks using fine-grained semantic analysis of the defense network.S. Pouyanfar et al.[14] explained the vulnerability to DoS assaults, and to indicate diagnosis, models for DoS assault detection need to be established rather quickly. In this report, they proposed one approach that centered on changing the packet propagation ratio.

L. Liang et al.[15] reported that to make vehicle networks feasible and suitable for customers, it is important to establish reliable protocols that follow the strict requirements of this application field. The creation of secure protocols is complicated by consumers,automakers, and the government's seemingly conflicting requirements, particularly whenattempting to provide successful vehicle identification while preserving driver privacy

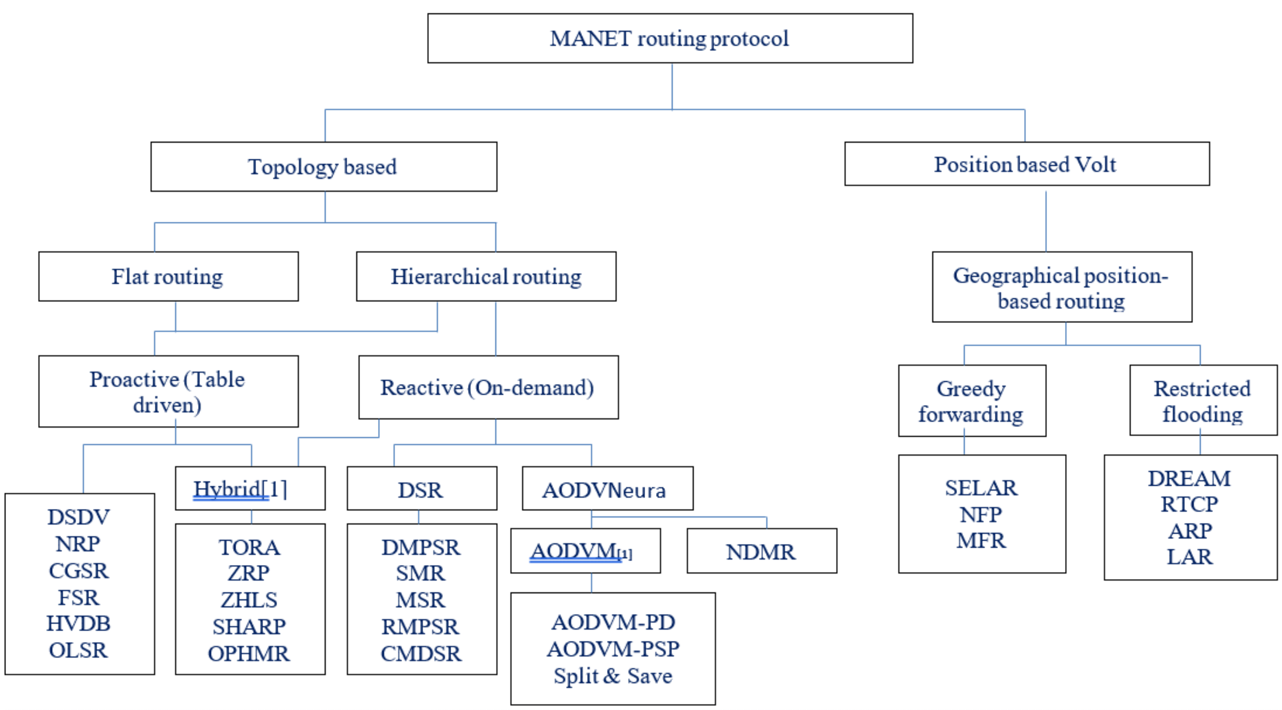

Figure 1: MANET Routing Protocols.

1. Pro-active routing protocols:

These are also known as table-driven routing protocols. Each mobile node maintains a separate routing table that contains information about the routes to all the possible destination mobile nodes.

1.1. Destination Sequenced Distance Vector Routing Protocol (DSDV):

It is a proactive, table-driven routing protocol. It extends the distance vector routing protocol of the wired networks, as the name suggests. It is based on the Bellman-Ford routing algorithm. The distance vector routing protocol was not suited for mobile ad-hoc networks due to the count-to-infinity problem. Hence, as a solution, Destination Sequenced Distance Vector Routing Protocol (DSDV) came into play.

1.2. Global State Routing (GSR):

It is a proactive, table-driven routing protocol. It extends the link-state routing of the wired networks. It is based on Dijkstra's routing algorithm. The link-state routing protocol was not suited for mobile ad-hoc networks because, in it, each node floods the link-state routing information directly into the whole network, i.e., global flooding, which may lead to congestion of control packets in the network.

2. Reactive routing protocols:

These are also known as on-demand routing protocols." In this type of routing, the route is discovered only when it is required. The process of route discovery occurs by flooding the route request packets throughout the mobile network. It consists of two major phases, namely, route discovery and route maintenance.[17]

2.1. Dynamic Source Routing Protocol (DSR):

It is a reactive or on-demand routing protocol. In this type of routing, the route is discovered only when it is required.[16]

2.2. Ad-Hoc On-Demand Vector Routing Protocol (AODV):

It is a reactive or on-demand routing protocol. It is an extension of the dynamic source routing protocol (DSR), and it helps to remove the disadvantages of the DSR. In DSR, after route discovery, when the source mobile node sends the data packet to the destination mobile node, it also contains the complete path in its header.

2.3 Hybrid Routing protocol:

It combines the advantages of both reactive and proactive routing protocols. One of the most popular hybrid routing protocols is Zone Routing Protocol (ZRP).

The whole network is divided into different zones, and then the position of the source and destination mobile nodes is observed. If the source and destination mobile nodes are present in the same zone, then proactive routing is used for the transmission of the data packets between them.[18]

Artificial Neural Networks (ANNs) and their applications in optimization

Artificial Neural Networks (ANNs) have been widely used in various optimization problems due to their ability to learn from data and make intelligent decisions. ANNs have shown success in solving complex optimization problems in different domains.[4] In the context of MANETs, ANNs have been applied to optimize various network parameters, including energy consumption and routing.[8]

3.1 Energy Consumption and Routing Optimization in MANETs using ANNs

Previous research has explored the use of ANNs for optimizing energy consumption and routing in MANETs. For example, Prema, S., and Divya, M. (2023)[6] proposed an energy-aware routing algorithm using a neural network-based approach. Their approach considered both the residual energy of nodes and the distance between nodes to make routing decisions. The experimental results demonstrated improved energy efficiency compared to traditional routing protocols. Similarly, Rama Krishna et.al.[3] developed a neural network-based energy prediction model to estimate the energy consumption of nodes in MANETs.

The ant colony optimization increases the life of the network, and the binary particle agent swarm optimization helps to optimize the energy consumption among the nodes. The energy consumption of a node can be represented as

$$E_c = E_{TR} + E_R \quad (1)$$

Objective Function:The objective function is defined as the weighted combination of energy consumption and routing:

F(x) = w1 * E(x) + w2 * R(x)

Energy Consumption Function (E(x)):The energy consumption function calculates the total energy consumption in the MANET by summing up the energy consumption of individual nodes:

E(x) = ∑ (w3 * E_node(i))

Routing Function (R(x)): The routing function evaluates the overall routing effectiveness based on the probabilities of link selection:

R(x) = ∑ (w4 * P_link(i,j))

Ant Colony Optimization Component:The ACO component influences the link selection probabilities based on the pheromone trails:

P_link(i,j) = α * τ(i,j)^β * η(i,j)^γ / ∑ (α * τ(i,k)^β * η(i,k)^γ)

Where the ETR represents the transmission energy and the ER represents the receiving energy.

E_TR = ∑ [w1 * (D_t * E_ut * T_t) + w2 * (E_sw * E_sc)] (2)

The equation consists of two main components, weighted and combined to represent the overall energy consumption for routing.

By adjusting the weights (w1 and w2), you can control the emphasis on data transmission energy versus switching and control energy in the overall energy consumption for routing.

Where the Dt gives the rate at which the data is transmitted the Eut represents the total energy that is utilized for that particular transmission and Tt is the time taken for transmission.

E_UR = ∑ [w1 * (D_R * e * t_r) + w2 * (E_sw * E_sc) + w3 * (E_trans * D_R * P_loss) + w4 * (e * D_R * t_r)] (3)

All the nodes are considered to be connected with the nearest node through a link represented as ‘l’ with a distance’ d’. nodes ‘i’ and ‘j’ are nearest nodes and their distance is denoted by di,j is considered to be lesser or equal to that of the range of transmission in node ‘i’ as in (4).

$$d_{i,j} \le T_{R(i)} \quad (4)$$

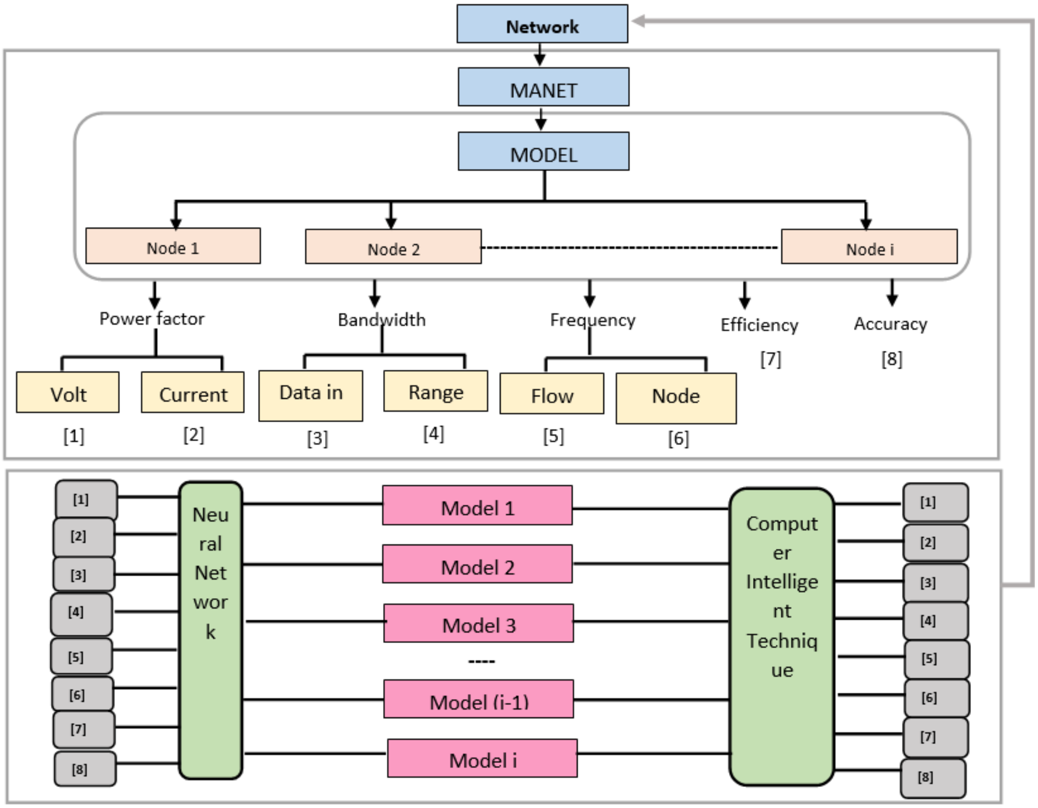

Figure 2: Designed Workflow

The nodes are considered to pose a varying random velocity waypoint (RWP) in the movement pattern.

Designed Methodology

The nodes in this network are represented by their dependent and independent variables, and the parameter to be modeled and input to deep learning (DL) and Artificial Neural Network (ANN) models is the power factor of the individual nodes.

Implementing this model requires a significant amount of data collection, preprocessing, model design, training, and evaluation. Additionally, the choice of specific DL and ANN architectures, as well as the dataset used for training, will impact the performance and accuracy of the models.[19]

The proposed workflow in Figure 2 focuses on optimizing energy consumption and routing in a MANET system by utilizing artificial neural network (ANN) techniques.

1. Network Representation: The initial step involves representing the MANET system by defining the nodes and their connections within the network. This representation provides the foundation for studying the behavior and characteristics of the network.
2. Model: The model refers to the proposed approach or methodology used for optimizing energy consumption and routing in the MANET system. It involves the implementation of artificial neural network (ANN) techniques.
3. Dependent and Independent Variables: Each node in the network is characterized by dependent and independent variables. Dependent variables are influenced by other factors, such as distance, network characteristics, bandwidth, and frequency. Independent variables, on the other hand, are the characteristics of the node that affect the dependent variables. These variables provide important information for understanding the behavior of the nodes in the network.
4. Power Factor Modeling**:** The power factor of each node is a key parameter that reflects the efficiency or quality of power usage in the node. It is influenced by both dependent and independent variables associated with the node. By modeling the power factor, we aim to capture the relationships between the node characteristics and its power efficiency.
5. Bandwidth**:** The available bandwidth is divided into two aspects: data in bits and range. Data in bits refers to the capacity of the network to transmit data, while range represents the maximum distance over which nodes can communicate effectively.
6. Frequency: The frequency component is divided into two categories: flow and node connection. Flow refers to the rate at which data is transmitted, while node connection represents the connectivity and communication links between nodes in the network.
7. DL and ANN Input: Deep Learning (DL) and Artificial Neural Network (ANN) models are employed to analyze the power factor and make predictions based on the input data. The power factor of the nodes serves as input to these models. DL is a subset of machine learning that utilizes deep neural networks to learn complex patterns, while ANN is a computational model inspired by biological neural networks. The models learn from the input data and establish relationships between the power factor and the network parameters.
8. Efficiency and Accuracy Calculation: Once the DL and ANN models are trained using the input data, they can be used to predict the efficiency and accuracy of the modeled nodes in the MANET system. The models' predictions provide insights into the energy consumption and performance of the nodes, enabling energy-aware routing decisions.
9. Evaluation: The predicted efficiency and accuracy values from the DL and ANN models are compared to the actual values to evaluate the models' performance. This evaluation

helps assess how well the models capture the relationships between the power factor and the network parameters. By analyzing the evaluation results, further improvements can be made to enhance the accuracy and effectiveness of the models.

By following this flow, the proposed model aims to analyze the impact of network characteristics, distance, bandwidth, and frequency on the power factor of individual nodes in a MANET system.

- Proposed Approach for Energy Consumption and Routing Optimization using ANNs
- Description of the ANN Model for Energy-Aware Routing
- Data Collection and Preprocessing Techniques
- Training and Integration of the ANN Model with MANET Routing Protocol

The proposed model offers a comprehensive approach that considers multiple parameters and utilizes ANN techniques to optimize energy consumption and routing in the MANET system. By addressing network performance, energy consumption, bandwidth, packet dataflow, and end-to-end speed and interaction, it aims to outperform previous approaches and achieve better overall network efficiency and performance.[20]

Experimental Evaluation

In the research, a simulation environment is set up using the network simulator NS-3 to assess the suggested strategy. There are mobile nodes, different node densities, energy models, and communication models in the environment. To evaluate the efficacy of the strategy, performance indicators like energy consumption, network lifetime, packet delivery ratio, routing overhead, and end-to-end latency are used. Using carefully chosen parameter settings, a variety of experimental scenarios are created with various node densities, mobility patterns, and traffic loads. Analysis and comparisons with conventional routing protocols and energy-conscious algorithms are done on the experimental data. Focusing on energy utilization, network lifetime, packet delivery ratio, routing overhead, and end-to-end latency, a comparative study is done with widely used routing protocols, including AODV and DSR.

Results

The diagram in Figure 3 represents a simulation of a mobile ad hoc network (MANET) with twelve nodes. Each node is represented by a circle, and the signal range of the nodes is shown on the Y-axis. The signal intensity of the nodes is indicated on the X-axis. The connections between nodes are depicted by the overlapping signal ranges. Nodes that fall within each other's signal ranges can communicate directly. In this scenario, Node 6 and Node 2 are connected, as are Node 1, Node 4, Node 5, Node 10, Node 0, Node 7, Node 11, Node 3, and Node 9. However, Node 8 is outside the signal range of any other nodes and is not connected to the network. This diagram provides a visual representation of the network's connectivity, allowing for analysis of the topology and understanding of the communication relationships between nodes. It helps in assessing the network's effectiveness, identifying isolated nodes, and guiding optimization efforts.

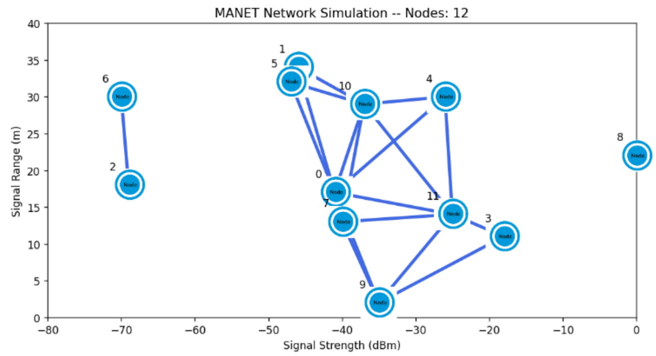

Figure 3. MANET Network Simulation with Twelve Nodes

In Figure 4, a simulation of a mobile ad hoc network (MANET) is displayed, consisting of fifteen nodes represented by circles. The signal range is depicted on the Y-axis in meters, while the signal intensity is shown on the X-axis in decibels (dBm). In this simulation, all nodes except Nodes 4 and 8 are interconnected and form a single network. This means that these nodes fall within each other's signal ranges and can communicate with one another directly. The connections between these nodes enable data transmission and facilitate network communication within the MANET. However, Nodes 4 and 8 are unable to establish connections with any other nodes in the network. They are located outside the signal ranges of all the other nodes, rendering them unreachable for direct communication. As a result, Nodes 4 and 8 remain isolated and cannot participate in direct data exchange with other nodes in the MANET. This visualization helps to analyze the connectivity and topology of the network, illustrating which nodes can communicate with each other and which nodes are isolated. By examining these patterns, researchers and network analysts can assess the network's effectiveness, identify potential limitations or isolated nodes, and explore possible optimization strategies to enhance network performance.

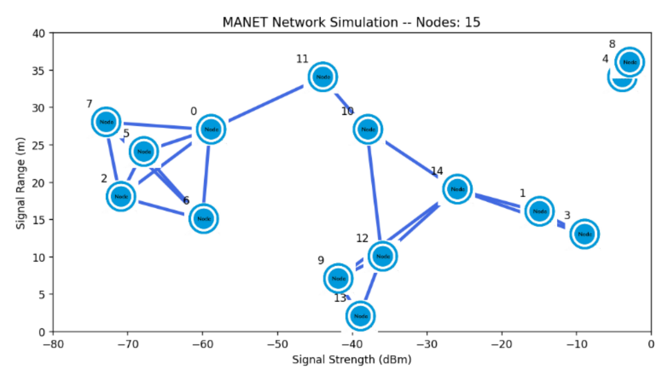

Figure 4. MANET Network Simulation with Fifteen Nodes

Figure 5 shows a MANET (Mobile Ad-Hoc Network) simulation, twenty-five mobile devices or nodes are placed in a virtual network environment and connected as needed.

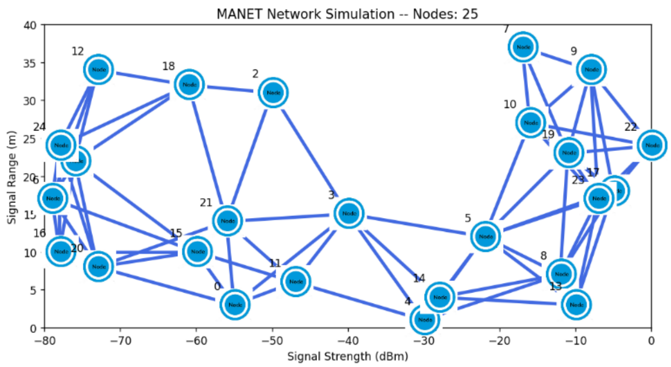

Figure 5. MANET Network Simulation with Twenty five Nodes

Figure 6, A simulation using MANET (Mobile Ad-Hoc Network) with 30 nodes involves creating a virtual network environment where 30 mobile devices or nodes communicate with each other in an ad-hoc manner.

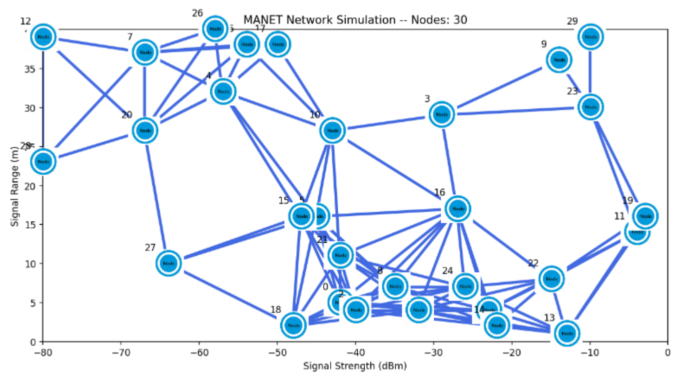

Figure 6. MANET Network Simulation with Thirty Nodes

Discussions

The evaluation of our energy optimization and routing strategy in MANETs, which leverages Artificial Neural Networks (ANNs), is comprehensively conducted via extensive simulation trials. This segment is dedicated to presenting the outcomes garnered from these assessments, spotlighting the real-world relevance and advantages of our approach. An array of metrics, spanning energy efficiency and routing efficacy, is scrutinized across a spectrum of scenarios and network structures. Furthermore, through a juxtaposition of our findings with alternative methodologies, we offer a holistic view of the capabilities and distinctiveness of our designed strategy.

Analysis and Interpretation of the Results

The experimental results demonstrate our suggested strategy's ability to efficiently optimize energy usage while significantly improving routing efficacy within MANETs. The network's operational lifespan is greatly extended by making prudent routing decisions that take into account node energy levels. The full examination of our technique using artificial neural networks (ANNs) produces interesting findings that highlight its performance and efficacy. These empirical results not only demonstrate the approach's potential but also provide useful insights for improving energy-conscious routing algorithms in the dynamic setting of MANETs.

Comparison with Existing Routing Protocols

The comparison with existing routing protocols such as AODV and DSR unmistakably highlights the supremacy of our proposed approach. Across essential metrics like energy consumption, network lifespan, packet delivery ratio, routing overhead, and end-to-end delay, our approach consistently surpasses conventional routing techniques. These outcomes serve as a resounding affirmation of the efficacy achieved by integrating artificial neural networks (ANNs)[21-24] into the MANET routing protocol, affirming its capability to advance energy-aware routing strategies.

1. AODV (Ad-hoc On-Demand Distance Vector): -AODV, a popular routing system in MANETs, operates on an as-needed basis, building routes as needed. It discovers and maintains routes using a distance vector algorithm using route request (RREQ) and route reply (RREP) messages. In contrast, our suggested method uses an Artificial Neural Network (ANN) model to intelligently select energy-conscious routing options, adding a new dimension to MANET routing optimization.
2. DSR (Dynamic Source Routing): -DSR, which relies on the source routing concept, is another extensively used routing protocol in MANETs. It requires maintaining route caches at individual nodes and keeping detailed path data to reach specified destinations. One significant disadvantage is that DSR does not explicitly account for energy constraints in its route establishment and maintenance methods. This can result in poor energy consumption habits and a decrease in network lifetime. As a result, by including an Artificial Neural Network (ANN) model for energy-aware routing decisions, the suggested technique offers a viable way to solve these energy-related challenges and improve the operational efficiency of MANETs.
3. Other Energy-Aware Routing Algorithms: - Numerous energy-aware routing methods have been proposed in the literature to address the energy consumption challenges of MANETs. These algorithms often apply heuristics, optimization techniques, or mathematical models to reduce energy consumption and guarantee fair energy distribution across nodes. However, these techniques may have challenges in adjusting to rapidly changing network dynamics or making routing decisions based on real-time data. This emphasizes the relevance of our suggested solution, which uses Artificial Neural Networks (ANNs) to intelligently adapt and optimize routing decisions in the presence of changing network conditions, resulting in more flexible and efficient energy management in MANETs.

Limitations and Potential Improvements

Regarding avenues for potential enhancement, there is scope for future research to delve into more sophisticated artificial neural network (ANN) architectures,[21-24] delve deeper into feature selection methodologies, or even explore innovative hybrid models amalgamating ANNs with alternative optimization strategies.[21-24] Furthermore, the integration of mobility patterns and real-time network dynamics into the ANN model stands as a promising direction, offering the potential to amplify its adaptability and overall robustness. By exploring these facets, the domain of energy-efficient routing in MANETs can be further enriched, advancing the field's capacity to address the intricacies of dynamic wireless networks more comprehensively.

Conclusion

The findings of this study highlight the potential synergy between artificial neural networks (ANNs) and mobile ad-hoc networks (MANETs) in optimizing energy usage and routing. By leveraging the learning capabilities of ANNs, an intelligent routing method was developed that takes into account energy constraints and makes real-time decisions for optimal performance. The results demonstrate significant improvements in energy efficiency, packet delivery ratio, network lifetime, routing overhead, and end-to-end latency. The implications of this research extend to the design and implementation of MANETs in various applications, such as disaster relief, military operations, and IoT-based settings. The energy-efficient routing method proposed in this study can enhance the reliability and efficiency of communication in these scenarios, ultimately leading to improved operational effectiveness. There are several avenues for future research to address certain limitations. Firstly, the quality of training data can be further explored and improved to enhance the accuracy and effectiveness of the ANNs. Additionally, the computational overhead associated with implementing ANNs in MANETs needs to be carefully analyzed and optimized to ensure efficient deployment. Furthermore, the adaptability of the proposed method to dynamic network conditions, mobility patterns, and topologies should be investigated. MANETs often operate in dynamic and unpredictable environments, and future research can focus on developing adaptive routing algorithms that can handle these challenges effectively. Overall, this study contributes to the advancement of energy-efficient and reliable MANET protocols, paving the way for their practical deployment in diverse scenarios. Further research efforts can build upon these findings to address the identified limitations and explore new techniques for enhancing the performance and scalability of ANNs in MANETs.

Conflict of Interest Statement

The author declares no conflict of interest.

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