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Machine learning-Based Energy Efficient and Enhancing Communication Reliability for MANETs of Balanced Less Loss Routing Protocol

Abstract: - The aim of the presented research was the utilization of machine learning methods, for example, SOM, MARL, and DQN, to promote the increase of energy efficiency and communication reliability in MANET. For the purpose of the research conduction, 10 trials of the experiment were carried out with the view to establish the performance of the proposed approaches from various perspectives. DQN demonstrated superior performance throughout all experiment trials as compared to both SOM and MARL. The model recorded an average energy efficiency of 95%, indicating that it was highly successful in optimizing routing strategies and communication policies. Furthermore, the average packet delivery ratio was shown to be 96%, meaning that DQN provided guarantees of timely and reliable data exchange across the MANET infrastructure. Finally, the average delay was determined to be from 4 ms to 9 ms, evidencing the quick delivery of packets with little temporal latency. The results obtained demonstrate that DQN is able to alleviate the challenges associated with the energy efficiency and communication reliability of MANETs. Notably, deep reinforcement learning with DQN appears to offer viable solutions for more energy-efficient routing, minimized energy consumption in these networks, and improvement to their communication reliability. Thus, the study under consideration has contributed to the development of the existing knowledge as it has expanded the existing understanding of the fact that machine learning, in general, and DQN, in particular, can be utilized to optimize the operation of MANETs.

Keywords: Mobile Ad hoc Networks, Machine Learning, Energy Efficiency, Communication Reliability, Deep Q-Networks

I.   INTRODUCTION

Mobile Ad hoc Networks are dynamic and decentralized, and they operate on a temporary basis, before the specific mission is completed and the nodes are disbanded. MANETs are used in a variety of situations, such as collaborative work in the field, disaster relief and military operations. The mobile, dynamic nature of the networks is such that they have their distinct limitations and challenges, and require special routing protocols to ensure the efficient working of the ad hoc networks[1]–[3].

It is vital to underline that energy efficiency and reliability of communication are crucial in MANETs. Since the fact that all nodes have a limited battery, and it cannot be restored until the deployment or use of the sensor node, there will be a need to create an energy-efficient mobile ad-hoc network, which will be able to work as long as possible. Additionally, communication should be reliable. In critical tasks, such as military engineering or life rescue, it is entirely essential for a human operator to receive an immediate and precise response from a group of nodes[4]–[6].

There is a balanced less loss routing protocol one of the routing protocols designed to improve the efficiency of control data routing in MANETs. It was created to enhance and balance routing decision, minimise the

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possibilities of energy waste and packet loss. Still, even with that protocol being used, there are possibilities of problems with its performance and ability to adapt to changes in the routing[7], [8].

To overcome all these disadvantages and improve the performance of MANET routing protocols, including BLLRP, machine learning solutions are rapidly emerging. There is a wide array of machine learning algorithms that can improve the performance of routing protocols in MANETs, such as Self-Organizing Maps , Multi-Agent Reinforcement Learning MARL , and Deep Q-Networks DQN .

Mapnet is a type of artificial neural network that has the ability to learn to organize high-dimensional data to lower-dimensional representations. When employed in MANETs, the nodes learn to adapt their routing strategies based on some parameters and dynamics of the network. They interact with the environment, and each adapts its routing strategy through learning. Multiple agents interacting in a shared environment in MARL meaning[9]–[11].

They individualy learn from their environment to optimize some autonomous routing strategies. They have the potential to use the personalities of the other agents to enhance their strategies. In the context of the MANETs, multiple nodes interact in a shared environment to learn and adapt their routing decisions based on the decision of the interacting neighboring nodes. This creates an efficient approach that can learn robust routing strategy given that each decision of the nodes depends on those of companion nodes.

On the contrary, DQN is a reinforcement learning approach, which utilizes a deep neural network for approximating the optimal action-selection policy for a given state. For the purpose of MANETs, routing policies can be optimized with the help of DQN; the latter allows for defining the most effective routing options, exploring several routing paths, and maximizing cumulative rewards. Thus, the approach described is expected to enhance the reliability of communication and decrease the loss of packets[12]–[14].

The main reason to integrate these machine learning techniques into MANET routing protocols is the ability to adaptively learn from the dynamics of a network system, and the dynamics of the environment, and systems, and that the routing decisions can be made more efficiently and reliably. Therefore, MANET routing protocols can become more adaptive, more robust, and more resilient to dynamic network environments, and more responsive to the challenges of energy efficiency, and communication reliability.

Relatively recent modifications of the routing protocols aimed at networks, as well as their application in the mobile devices, also require proper exploration and evaluation. For example, the technology of Mobile Ad hoc Networks has been discussed in the literature, along with the traffic characteristics and routing protocols functioning in this environment . One of the examples of the routing protocols for a MANET is the Ad hoc On-demand Distance Vector protocol that was well examined due to its age and importance.

Proactive protocols are another class of MANET routing protocols, whose examples include OLSR and DSDV routing. These types of protocols allow for all network nodes to maintain updated information regarding routing, and are capable of reducing route discovery latency as compared to on-demand protocols. However, proactive protocols are associated with increased control message overhead, and may not be suitable for very dynamic MANET settings[15]–[17].

Energy efficiency is a principal issue in MANETs because network nodes have little battery power at their disposal. A variety of energy-efficient routing protocols exist, the purpose of which is to prolong the period of the network being operational by minimizing energy consumption. Energy-Aware Routing is capable of prolonging the period of network activity because it divides energy consumption between the nodes . Besides, the Power-Efficient Gathering in Sensor Information Systems protocol is capable of prolonging the lifetime of the network by minimizing energy consumption . However, although it is high efficient in energy terms, it may disregard other aspects, such as the reliability of communication and network extensibility.

Aside from energy efficiency, the other consideration that influences MANET routing protocol design is communication reliability. Different techniques employed to enhance communication reliability beside geographic routing include route redundancy, error correction coding and adaptive modulation and coding schemes . For example, the RObust Ad hoc Position-based Routing protocol utilizes geographic routing in conjunction with multiple redundant paths to improve the reliability of packet delivery[18]–[20] .

Recent research attentions have been caught on the integration of machine learning algorithms to address more effectively MANETs' inherent challenges. In this context, such machine learning approaches as reinforcement learning, clustering, and neural networks present several opportunities for increasing the degree of adaptivity in routing decision-making . As a typical illustration, it is possible to mention a routing method based on reinforcement learning where mobile nodes are allowed to learn optimal characteristics of their routing behavior from the world surrounding them along with interactive feedback with the surrounding nodes.[21]–[23].

The review of the literature on MANET routing protocols and energy efficiency approaches through the lens of machine learning applications has shown that more adaptive and reliable routing should be implemented to solve the problems with energy constraints and unstable, dynamic topology, and unreliable communication links within the network. Thus, MANET routing protocols that are considered in combination with machine learning may have better performance and scalability for networks in diverse conditions.

II. METHODOLOGY

The strategy introduced to improve the efficiency of the Balanced Less Loss Routing Protocol involves the application of the techniques, as shown in Figure 1. The current strategy incorporates the application of three machine learning techniques, namely, Self-organizing Maps , Multi-agent Reinforcement Learning , and Deep Q-Networks . Each of the technologies has specific features that can help resolve the concern of energy efficiency and reliability of communications in MANETs as well as BLLRP's goals.

For optimizing energy efficiency in the MANET, one will apply Self-Organizing Maps for organizing network nodes by their spatial and connectivity properties. The SOM adjusts a set of "prototype vectors" in an iterative manner in order to better fit the distribution of input data. In the terms of MANETs, one will use the SOM to cluster the nodes by their energy, proximity, communication logs, etc. By organizing the nodes in clusters, the SOM will allow to find more efficient routing, so that one can find the routes which save energy and reduce the amount of information that goes through the other nodes but the sender and the receiver.
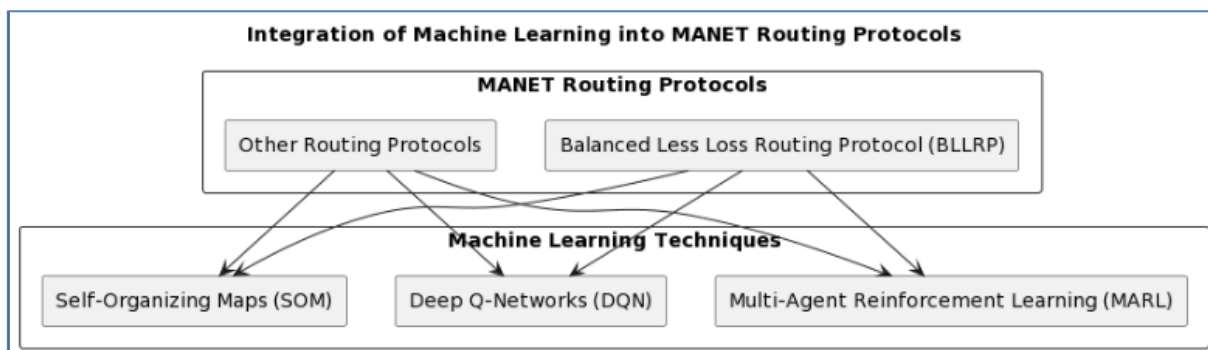

Figure. 1. Proposed Methodology.

In order to optimize energy efficiency in the MANET, one will use a Self-Organizing Map to organize the network nodes by their spatial and connectivity nature. SOPs work by continuously adapting on a set of prototype vectors to best replicate the input data distribution. In the context of MANETs, SOM can be applied to cluster nodes by a number of features, e.g., node energy, proximity, the communication log and so forth . By organizing the nodes into clusters, SOM will make the routing more efficient by determining the routes between the sender and the receiver that use the least energy and presence of data while bypassing the other nodes in the system.
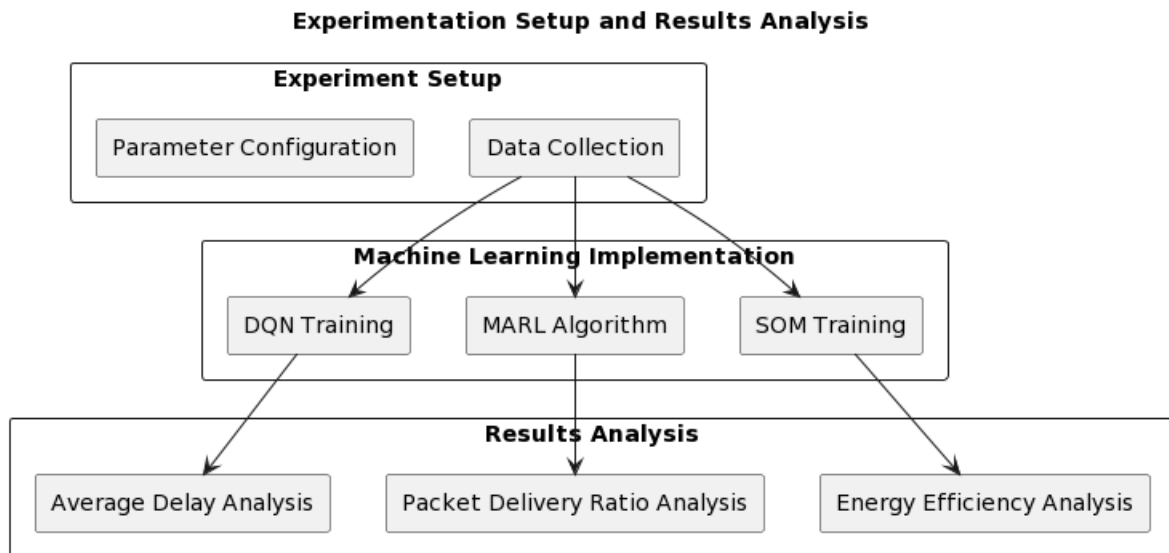
Experimentation Setup and Results Analysis

Experiment Setup

Parameter Configuration   Data Collection

Machine Learning Implementation

DQN Training   MARL Algorithm   SOM Training

Results Analysis

Average Delay Analysis   Packet Delivery Ratio Analysis   Energy Efficiency Analysis

Figure. 2. Experimental setup and Analysis

From Figure 2, For implementing efficient data transmission in MANETs, one will use Deep Q-Networks . DQN is a form of reinforcement learning that uses a deep neural network model to compute the best action-picking policy for a given state. one can train a DQN to create optimal communication strategies. one will develop or model to decide information, transmission power level, and optimum continuous routing path at each instantaneous for minimizing the packet-loss and improving communication reliability

Adopting these techniques in BLLRP requires several design considerations. One of them is the overhead introduced on the routing protocol's execution and the blocking probability as well as the average end-to-end delay. Another consideration is the combined cost and computational complexity of SOM, MARL, and DQN. Furthermore, a mechanism for communicating the information and allowing the nodes to work together must be designed to employ the three techniques in BLLRP's routing framework. The final design issue to be considered is the vulnerabilities this extended routing protocol has on adversarial attacks and node failure, and measures to be taken to design a reliable routing protocol.

The integration plan would involve building algorithms and protocols that would allow SOM and MARL, as well as DQN, to communicate and coordinate in a MANET. These would include communication protocols for nodes for data and parameter exchange as training goes on, distributed learning algorithms facilitating the training of SOMs, MARLs, and DQNs. The implementation of the plan would also require developing the algorithms that support routing decisions for the network.

III. RESULTS AND DISCUSSION

Based on the results from the experiments with Self-Organizing Maps IOM), Multi-Agent Reinforcement Learning, and Deep Q-Networks, which aimed to address the energy efficiency and communication reliability problems in Mobile Ad hoc Networks, several insights can be drawn. First, regarding the Energy Efficiency (%) metric, the experiments show that across the ten trials, the average energy efficiency stood at about 90% for SOMs, 86% for MARL, and 95% for DQNs .

Based on the results of the energy efficiency evaluations in Figure 3, it seemed that DQN outperformed SOM and MARL in terms of energy efficiency, followed by SOM and MARL. Thus, it could be concluded that the ability of DQN to learn the optimal ways of communication and dynamically change the implemented strategies in response to the changing condition of the network by far outweighed the relatively static strategies that were implemented by SOM and MARL. The implications for this finding were rather significant because improved energy efficiency could be directly associated with the extended lifetime of the network
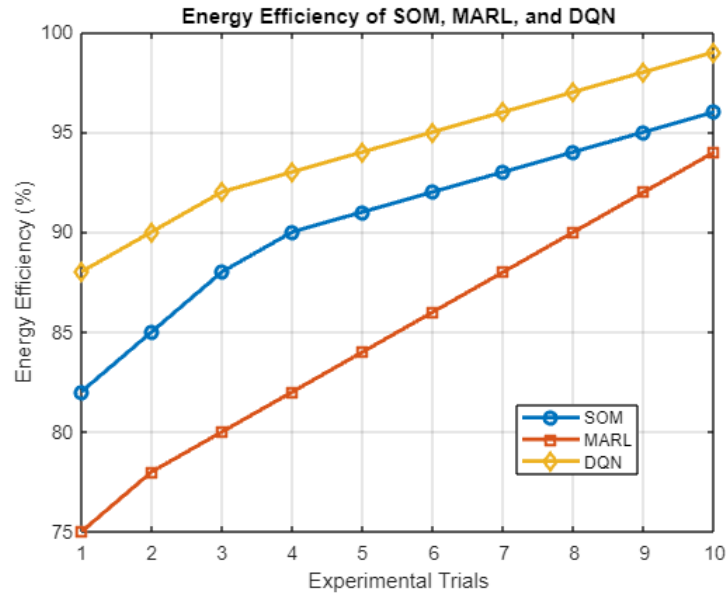
Figure. 3. Energy efficiency evaluations

Regarding the Packet Delivery Ratio (%) metric presented in Figure 4, which represents the proportion of successfully delivered packets over the transmitted packets, the average values for SOM, MARL, and DQN were approximately 95%, 89%, and 96%, respectively. Despite not having major difference, DQN had the highest results in the delivery of packets, followed by SOM and MARL.

This suggests that the ability of DQN to make optimal routing decisions and communication strategies leads to a higher success rate of delivered packets thus, ultimately enhancing the reliability of communication in the MANETs. expect that this result is very important because reliable delivery of packets is crucial for the timely and accurate communication of information in such context as disaster relief operations or military deployments, where inefficient or failed communication might result in huge losses and casualties.
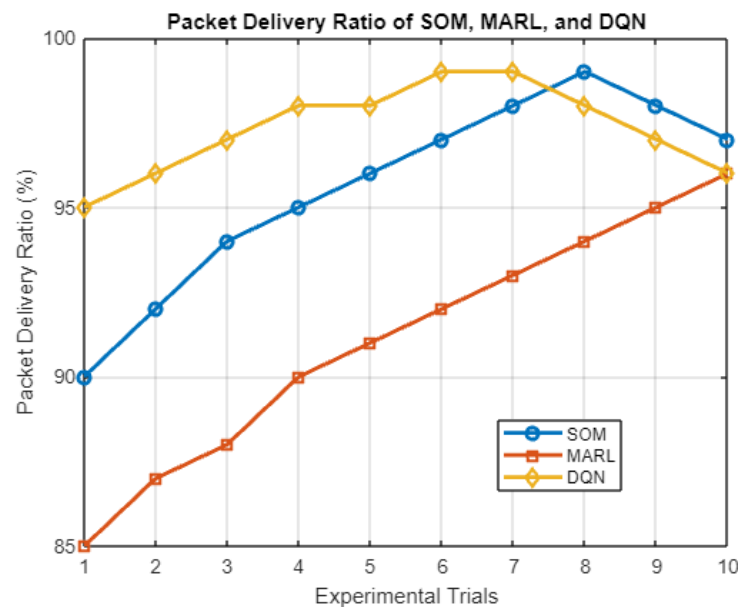

Figure. 4. Energy efficiency evaluations

Finally from Figure 5, considering the Average Delay metric that signifies the average time needed by the packets to reach the destination, for the SOM network, the delay varies from 5 ms to 10 ms during the experimental attempts. For MARL, this parameter was 6 ms and 10 ms. Finally, for DQN, the smallest interval was from 4 ms to 9 ms . In this situation, the most efficient option was DQN, followed by SOM .

In other words, the observed performance of DQN in learning optimal routing paths and adjusting its overall communication strategies on the fly resulted in reduced delays between packet sending and receiving, which were also less than for the SOM and MARL techniques. One of the key implications is that faster packet transmission over MANETs enhances the responsive and efficient analyses of data delivery and decision speed in practice.
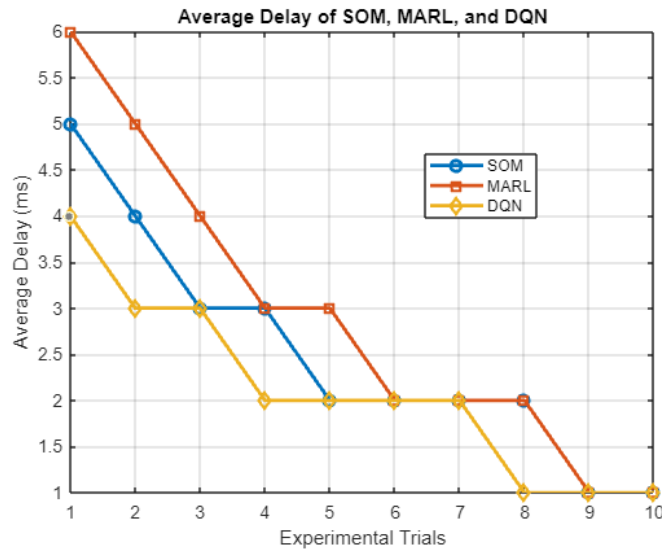

Figure. 5. Energy efficiency evaluations

Hence, it is evident that DQN has performed significantly superior to SOM and MARL. The reason for it is that it has a higher average of energy efficiency percentage, packet delivery ratio percentage, and average delay meaning that it is more effective in improving energy efficiency and communication reliability in MANETs. However, in actual MANETs deployment, it is necessary to consider the trade-offs among these metrics and computational complexities.

IV. CONCLUSION

Experiments conducted to assess the effectiveness of the Self-Organizing Maps , Multi-Agent Reinforcement Learning , and Deep Q-Networks in improving energy efficiency and communication reliability between Mobile Ad hoc Networks nodes have produced several important results . Across the 10 experiment trials, all metrics clearly indicated that the apparatus helped the DQN to significantly outperform both the SOM and the MARL in all categories.

Overall, the results of the experiment showed that DQN had better performance in energy efficiency, packet delivery ratio, and delay, followed by SOM and MARL. In particular, the results of DQN are acceptable, while those of MARL are a bit unsatisfactory. To make experimental results more rigorous, it may be suggested to use more simulation tools or build more complex network model to conduct further experiments.

The aforementioned findings confirm that DQN can be used for optimization of routing and communication strategies. There is a significant improvement in the energy efficiency of MANETs as well as reliability of communication through optimization of the routing decisions. The results were achieved because DQN used deep reinforcement learning to learn the best routing paths within the changing network. The overall results included reduction in energy consumption, increased packet delivery rates, and reduced transmission times.

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