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Minimizing Energy Depletion Using Extended Lifespan: QoS Satisfied Multiple Learned Rate (ELQSSM-ML) for Increased Lifespan of Mobile Adhoc Networks (MANET)

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Abstract: Mobile Adhoc Networks (MANETs) typically employ with the aid of new technology to increase Quality-of-Service (QoS) when forwarding multiple data rates. This kind of network causes high forwarding delays and improper data transfer rates because of the changes in the node's vicinity. Although an optimized routing technique to transfer energy has been used to lessen the delay and improve the throughput by assigning a proper data rate, it does not consider the objective of minimizing the energy use, which results in less network lifetime. The goal of the proposed work is to minimize the energy depletion in a MANET, which results in an extended Lifespan of the network. In this research paper, an Extended Life span and QSSM-ML routing algorithm is proposed, which minimizes energy use and enhances the network lifetime. First, an optimization problem is formulated with the purpose of increasing the network's lifetime while limiting the energy utilization and stability of the path along with residual. Second, an adaptive policy is applied for the asymmetric distribution of energy at both origin and intermediate nodes. In order to achieve maximum network lifespan and minimal energy depletion, the optimization problem was framed when power usage is a constraint by allowing the network to make use of the leftover power. An asymmetric energy transmission strategy was also designed for the adaptive allocation of maximum transmission energy in the origin. This made the network lifespan extended with the help of reducing the node's energy use for broadcasting the data from the origin to the target. Moreover, the node's energy use during packet forwarding is reduced to recover the network lifetime. The overall benefit of the proposed work is that it can achieve both minimal energy depletion and maximizes the lifetime of the network. Finally, the simulation findings reveal that the ELQSSM-ML algorithm accomplishes a better network performance than the classical algorithms.

Keywords: energy depletion; MANET; multicast communication; network lifetime path stability; QSSM-ML algorithm

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1. Introduction

MANETs involve several mobile nodes which have been deployed to collaborate together without guidance from a centralized network. The dual character of being a source and an access point is exhibited by nodes. This feature helps for multiple uses, including public networks, emergency regulation, armed forces, and rehabilitation services. The

flexible geometrical instabilities, including power requirements, throughput, and delay, have an effect on overall reliability.

Mobile Ad hoc Networks (MANETs) operate in a decentralized and constantly changing environment where the nodes are typically battery-powered and have limited energy sources. This makes energy consumption a critical concern in MANETs, as it can lead to node failures that impact the entire network. If a node exhausts its battery, it increases the likelihood of network partitioning, which can be detrimental to the network's longevity. Therefore, to extend the MANET's lifespan, energy-efficient approaches must be considered to reduce network energy consumption. One such method is to optimize energy utilization by making best use of leftover energy. By doing so, the energy depletion can be avoided, and the likelihood of network partitioning can be minimized. Deploying the methods described above shall help in decreasing energy depletion, but the lifetime of the network still becomes a question.

Collision, traffic delays, and integrity risks are the key concerns in such topologies. MANETs are properly implemented as per their necessities in order to combat these concerns and therefore increase reliability. Nonetheless, a robust route election strategy is crucial to determine the best path in packet forwarding because typical route opinions cannot meet the QoS functionalities [1].

To enhance the longevity of sensor nodes and networks, methods for energy preservation are often implemented to minimize energy usage. The literature has classified energy preservation strategies into three major categories: duty cycling, data-driven, and mobility-driven methods. Duty cycling aims to decrease idle listening when the node's radio is waiting for frames in vain, as well as overhearing when nodes remain active while listening to irrelevant frames. Data-driven methods employ certain data parameters to make energy-efficient communication decisions, while mobility-driven approaches consider the mobility of sink or relay nodes as a factor influencing network energy consumption. All the methods help in increasing the lifetime of a MANET, but they fail to address the critical issue of energy depletion.

Routing algorithms are developed by considering the node's unique addresses for forming the path between source and destination with numerous relay nodes. Regarding packet forwarding, such algorithms are either unicast or multicast. Unicast forwarding will distribute the packet to a single destination at a period, whereas multicast forwarding will share the packet to multiple destinations simultaneously [2,3]. Multicast channels of communication are introduced in all the layers of a given MANET. According to this communication, the throughput, node's ability, power consumption, and forwarding latency are decreased. However, the modern real-world MANET enables multicast communication services for packet forwarding [4]. To accomplish this, a multicast tree has been constructed for forwarding the packets from an origin to the different destinations separately. Such scenarios would need the delay-sensitive multicast algorithms if latency criteria of the desired multicast services were ensured with the particular trust ranges, i.e., a specified quantity of packets with the minimum delay.

A handful of research was found in the literature which addresses the issue of latency in multicast routing for enhancing the effectiveness of the network. In [5], the authors have proposed DSM for enhancing the throughput in multi-rate MANETs. Primarily, Hop latency was determined by taking the busy-to-idle ratio of the data being distributed, followed by the creation of multicast decision tree to minimize the summation of the total forwarding period of the relays and the sum of blocking time of all nodes that are obstructed by using the transfer data of neighboring nodes. Additionally, the data rates of the relays were precisely modified to lessen the resource consumption such that several flows were enabled in the MANETs. Conversely, additional QoS metrics were essential to further improve the network throughput.

To overcome this problem, the QSSM-M algorithm [6] has been designed, which reports the bandwidth, packets dropped, and jitter together with the latency determined from every nearby node for relays. Then, several QoS-satisfied multicast trees were formed,

where all trees guarantee the fixed range of QoS criteria. So, the total latency and bandwidth use was lessened if guaranteeing the QoS to the present and desired flow. Moreover, a randomized code for the network is applied to reject the packets that are not relevant so that all destinations receive the novel coded packets through different routes. Nonetheless, the data transfer rate for the source was not properly decided because of using different transfer areas. To decide a proper data transfer rate for source node, the EECRM routing algorithm [7] has been presented, which uses the advantages of Deep Neural Networks. Here, the dilemma of multi-label classification for deciding the data rates was taken as a primary challenge. Then, different metrics such as payload size of transfer frames, transfer route efficiency, and throughput were measured whilst ensuring the predetermined false error rate. Further, such metrics were learned by the DCNN to predict the proper data rate for the source and achieve effective forwarding. Though it enhances the network throughput significantly, the network lifetime was not adequately increased because of high energy depletion. The EECRP-PSO method took the problem of energy utilization and life span as an optimized problem. The Particle swarm optimization was deployed for optimal usage of energy. However, the method could not prove to be scalable when more nodes are taken for experiments. A large deviation in the performance was noticed when the number of nodes was increased in the order of 400.

In this research work, a machine learning-based routing technique has been presented for minimizing energy usage and for improving the life of a MANET. Here, a maximization problem is framed, keeping the objective to increase the lifetime of a network amidst maintaining the optimal use of energy and stability of the path. Second, a strategy is adopted for energy transmission in an asymmetric manner. Adaptive transmission of energy both at the origin and intermediate nodes is performed. The proposed method significantly reduces energy depletion and increases the lifetime of the MANET. The proposed method produces significant results in terms of 1-Hop Latency, End-to-End Latency, Success rate, Admission Rate, and Control Byte Overhead.

2. Existing Methods

Zhang et al. [8] proposed a cluster-centric optimization using a cross-layered approach LEACH-CLO technique for reducing the power usage in Wireless Sensor Networks (WSNs). In this technique, the physical layer, link layer, and network layer were combined to provide the cross-layer optimization framework of WSN. First, the ring isomorphism forecasting region was created, and the optimum cluster nodes transfer method was developed based on the optimized hierarchical mechanism. However, its robustness and consistency were not effective for large-scale networks.

Leao et al. [9] proposed a geocentric multicast model for routing, which considered the trade-off between the delay and the lifetime of the network. A linear combination of metrics was used for decision-making while determining the next hop. Data were transmitted to the entire sink, which simultaneously identifies and removes duplications of data during transmissions. Moreover, the highest power use was considered as a sign of network lifespan. However, the mean delay and the computational difficulty were moderately high.

Papna et al. [10] proposed an EELAM path decision scheme with the help of an adaptive genetic algorithm. It depends on the tree topology that differentiates other trees in accordance with the multicast routing topologies by adapting a genetic algorithm. Based on this scheme, an optimized number of intermediary nodes with the maximum residual energy and the minimum energy depletion were decided. However, it was time-consuming.

Banerjee et al. [11] designed a Weight-based Energy-Efficient (WEEM) protocol in MANETs. In this WEEM, if multiple routes were predicted to stay active till the multicast session, then the weight was allocated to the routes by the target node. The route having the maximum weight was decided as the best. This weight was determined by considering the remaining power and multicast data transfer ability of nodes in the route, including the number of multicast targets situated in that route. If multiple routes have equal weights,

then the route with the minimum latency was assigned a higher priority. But the control overhead was not efficiently reduced.

Riasudheen et al. [12] developed Energy-aware cloud-based routing method for minimizing energy depletion in MANET. The proposed method has less energy consumption through efficient local route discovery among the nodes. Backup nodes were deployed in case of failure in connection. As the proposed method did not consider multicast routing, there were control overheads while transferring data.

Shivakumar et al. [13] developed an Energy-Efficient Cross-layer Routing Protocol with Particle Swarm Optimization (EECRP-PSO) to reduce the energy consumption problem in MANETs. The proposed method estimated the metrics such as the success rate of data transfer, the mobility of a node, and the associated power of residue in advance. Then, the PSO algorithm was performed to create robust and power-effective routes. Further, the connection in the network was identified through the MAC layer and from the contention windows. Although efficient, the number of packets dropped, and the routing overhead was still very high.

Shah et al. [14] suggested a novel centralized method that evaluates the network's power use for optimizing the node duty cycles. In this method, a busy/idle mode to every node was assigned by the sink node regularly for the successive network cycle through pairing the remaining power, overall busy period, and the probable coverage region to lessen the power usage. However, it was not a completely distributed method and needed to analyze the effect on increasing the network life.

Although the various literature has proved the possibility of addressing Energy depletion and lifespan issues in a MANET, there is no literature found to address these in a combined manner. Table 1 shows the state-of-the-art proposals for addressing the issue.

Table 1. Comparison of existing methods.

S.No	Method	Advantage	Disadvantage
1	EECRM	Low cost Less energy wastage	Do not address Lifespan issue The residual energy is not used
2	EECRP-PSO	Optimized energy usage The Source node is always backed up with energy	The time taken for message delivery is long The algorithm has huge implementation cost
3	QSSM-ML	The source and sink had equal energy distribution The average waiting time for a node to get energy is less	Implementation cost The problem of local minimal optimization

3. Proposed Algorithm

The proposed algorithm ELQSSM—ML is discussed in this section. Initially, the Multi-Rate Mobile Adhoc Network is developed where each node is deployed with an Omni-directional aerial and posse's similar radio specifications. Let the MANET consists of N arbitrarily circulated relay nodes $r_n, n \in \{1, \ldots, N\}$, situated in the vicinity of the origin and target nodes. Every node distributes a similar transmission channel and transmit the packet at a consistent rate. The data transfer is at a higher rate when compared to the direct transfer from a given origin to a destination. The nodes are normally disseminated, with the origin containing the data being forwarded to the target. Moreover, N relay nodes will help to send the accurately decoded data to the target at the minimum transfer cost, and so the total throughput is increased.

All of the nodes help to identify the gain in channel among self and target nodes through the SN Ratio of the packets that arrive, which are measured in terms of distance, the loss in energy of a particular route, and the fade factor for correct decoding of data. The channel between the two nodes is considered to be independent. All the nodes are half-duplex with a condition to exhibit a high level of energy during transfer. The IEEE802.1 standard is adopted in the physical layer that assists multi-rate ability among the transfers.

Each node is defined by an equal primary power, and the current power of every node is produced in a random way prior to the transfer task for representing the real-world

quality of the node's energy range in the network. In the collaborative transfer mode, the origin forwards its data to the target through the elected optimum relay node in a dual-hop fashion. Moreover, the highest rate collaborator is applied at the target for decoding the arriving data at the PHY layer if many independent paths collaborate.

3.1. Extending Lifetime and QSSM-ML Algorithm

In this ELQSSM-ML algorithm, the network lifetime is extended by minimizing the transfer power. This is accomplished by adjusting the transfer energy as follows:

$$E = \min\{E_S - E_t^S T, E_{r_1} - E_t^{r_1} T, \ldots, E_{r_n} - E_t^{r_N} T\} \tag{1}$$

In Equation (1), E refers to the node's least remaining power, which would remain after probably contributing in collaboration, E_S refers to the origin's present remaining power, E_t^S refers to the predicted transfer of energy at the origin, $\{E_t^{r_1}, \ldots, E_t^{r_N}\}$ denote the predicted transfer energy subgroup of the amount of contributing relay nodes for minimizing the power used at transfer time t, E_{r_n} denotes the present power of individual nodes, and T refers to the predicted overall transfer period. The predicted power used (E_S^D) between origin (S) and target (D) for direct transfer is represented by

$$E_S^D = (E_{t-max} + E_{rp} + E_c)T_{Con} + (E_t^S + E_{rp} + E_c)T_{data\_S,D} \tag{2}$$

In Equation (2), E_{t-max}, E_{rp} and E_c are the highest transfer energy for control frames at 1 Mbps, the reception energy and the processing energy, correspondingly, T_{Con} is the time required to transfer all control frames and $T_{data\_S,D}$ is transfer time between source and destination. Moreover, the predicted power used $(E_{r_n}^C)$ if the relay node collaborates is provided as follows:

$$E_{r_n}^C = (E_{t-max} + E_{rp} + E_c)(T_{Con} + T_{srt}) \ldots + (E_t^S + E_{rp} + E_c)T_{data\_S,r_n} \ldots + (E_t^{r_n} + E_{rp} + E_c)T_{data\_r_n,D} \tag{3}$$

$$T_{Con} = T_{RTS} + T_{CTS} + T_{ACK} \text{ and } T_{i,j} = \frac{8(L + L_H)}{R_{i,j}} \tag{4}$$

In Equations (3) and (4), T_{srt}, T_{RTS}, T_{CTS}, and T_{ACK} are the time required to transfer the Supporter-Ready-to-Transmit (SRT), *RTS*, *CTS*, and *ACK* frames, correspondingly, T_{data_S,r_n}, and $T_{data\_r_n,D}$ are the time needed to transfer the data between origin and relay, as well as relay and target, accordingly, $R_{i,j}$ is the transfer rate from the path i to j,L_H refers to the header data in bytes, and L is the total number of bytes to be forwarded by the origin. Additionally, the power use of the direct transfer is evaluated with that of collaborative transfer prior to the relay node is served as a supporter node. Evaluating (3) and (4), obtain $E_S^D - E_{r_n}^C \neq 0$, which should be a non-zero range for realizing the power gain. It defines the power used by any of the collaborator nodes, which should be lower when compared to a direct transfer owing to the distance between the origin and its corresponding target.

3.2. Optimized Transfer Energy Distribution

To determine the optimum energy which can increase the network lifespan, the overall energy criteria should satisfy $E_t^S + E_t^{r_n} \leq E_{overall}$, which is a linear optimization dilemma. Let a network with relay nodes, $r_n, n \in \{1, \ldots, N\}$, the major goal is to increase the network lifetime and maintain a greater throughput in the MAC layer when minimizing the overall power use during data transfer. The optimized energy distribution will increase the possible rates and guarantee fairness among the relay nodes by certifying that the overall transfer energy using collaboration is lower than the direct transfer energy and then increase the network efficiency. The neighboring data are essential by every node in the MANET for lessening the overall transfer of energy while collaborating. Because the transfer rate is related to the transfer energy, multiple relay nodes will have an equal possible rate; however, at many transfer energies. This means that an asymmetric transfer energy strategy is applied, and the overall power use is reduced than the utilization of

the same energy at all nodes and its root selections for adhoc networks are represented in Algorithm 1.

An optimization dilemma is formulated for increasing the network lifetime:

$$\max_{E_t^S + E_t^{r_n} \geq 0, n \in N} E_{\text{overall}} \tag{5}$$

$$\text{s.t } E_t^S + E_t^{r_n} \leq E_{\text{overall}}, \forall n \in N \tag{5a}$$

$$R \leq C, \forall n \in N \tag{5b}$$

$$E_S - E_t^S T_{S,r_n} \geq E_{min}, \forall n \in N \tag{5c}$$

$$E_{r_n} - E_t^{r_n} T_{r_n,D} \geq E_{min}, \forall n \in N \tag{5d}$$

$$0 \leq E_t^S \leq E_{t-max}, \forall n \in N \tag{5e}$$

$$0 \leq E_t^{r_n} \leq E_{t-max}, \forall n \in N \tag{5f}$$

The fitness factor, as mentioned in (5), is obtained from (2). Here, Max_E^S denote the ratio of maximum energy at the source S and the energy at time t. E^{rn} denote the energy of the relay node. N denote the total node, and E_{overall} denote the maximum energy threshold that a network can accommodate, and the same is constant for a given number of nodes.

The criteria for overall energy transfer are as per (5a). Here, s.t is the product of source and time, n denotes the node at the instance, and N denotes the total number of nodes. E_{overall} denotes the maximum energy threshold.

The optimal Shannon capability is arrived at using (5b). The Shannon capability, or the channel capacity C, is the theoretical tightest upper bound on the information rate of a message that can be communicated in a network N at an arbitrarily low error rate R using an average received nodes n through a multi-hop collaborative transfer,

The remaining power after the present transfer is depicted in (5c) and (5d) at the origin and relay nodes, accordingly, and the highest transfer energy is depicted in (5e) and (5f).

The solution to this optimization dilemma is achieved by discovering the optimum transfer energy at the origin and relay nodes. To find the best decision, the Lagrangian operation is applied as follows:

$$\mathcal{L}\{E_t^S, E_t^{r_n}, \lambda, \mu, z, u, \sigma, \rho\} = E - \lambda\left(E_t^S + E_t^{r_n} - E_{overall}\right) \ldots \mu(R - C) - z\left(E_{min} - E_S + E_t^S T_{S,r_n}\right) \ldots u\left(E_{min} - E_{r_n} E_t^{r_n} T_{r_n,D}\right) - \sigma\left(E_t^S - E_{t-max}\right) \ldots \rho\left(E_t^{r_n} - E_{t-max}\right) \tag{6}$$

In Equation (6), $\lambda, \mu, z, u, \sigma, \rho$ are the Lagrangian multiplier operators for the overall transfer energy criteria, possible collaboration rate, origin, and relay remaining power after contributing in collaboration; the origin forwards energy and relay nodes forward energy criteria, accordingly.

In an asymmetric scenario, consider that $E_t^S \neq E_t^{r_n}, d_{S,r_n} \neq d_{r_n,D}$ and $|h_{S,r_n}|^2 \neq |h_{r_n,D}|^2$ are not equal for the 2-hop; however, it has an equal data transfer rate because of the IEEE802.11 PHY multi-rate facility. Taking the first derivative of (6), i.e., $\frac{\partial \mathcal{L}\{\cdot\}}{\partial E_t^{r_n}}$, the optimal decision is obtained for the prediction of energy transfer in a relay node after arriving at RTS and CTS packets. Then, the predicted best transfer energy at the relay nodes is computed as follows:

$$E_t^{*r_n} = \left(\psi - \frac{2^{2R} N_0}{|h_{r_n,D}|^2 d_{r_n,D}^{-\alpha}}\right)^+ \tag{7}$$

where $\psi = \frac{\mu}{2\ln 2(\lambda + \rho + T(1+\mu))}$.

After this, this predicted $E_t^{*r_n}$ is piggybacked in the SRT frame, forward through the engaging optimum node which has its backoff timer die earlier during the contention relay choice task.

Additionally, the optimum-elected relay distributed energy should fulfill the energy criteria if the primary term is assigned to the range higher than the second term and $(\cdot)^+ = \min\left(E_t^{r_n}, E_{t-max}\right)$, or else the criteria are not fulfilled. Subsequently, the origin determines its best transfer of energy E_t^{*S} as a factor of $E_t^{*r_n}$. By considering the first-order derivative of (6) with respect to E_t^S i.e., $\frac{\partial \mathcal{L}\{\cdot\}}{\partial E_t^S}$, get

$$E_t^{*S} = \left(\zeta - \frac{E_t^{*r_n}|h_{r_n,D}|^2 d_{S,r_n}^{-\alpha}}{|h_{S,r_n}|^2 d_{r_n,D}^{-\alpha}}\right)^+ \tag{8}$$

where $\zeta = \frac{\mu}{2\ln 2(\lambda+\sigma+T(1+z))}$

The optimum distributed energy at the origin has to fulfill the criteria with $(\cdot)^+ = \min\left(E_t^S, E_{t-max}\right)$. It creates the reliable and independent distribution of the direct transfer energy, so power efficacy is increased. The best decision of the asymmetric strategy in (7) and (8) are achieved iteratively through modifying the Lagrangian multipliers in (9) based on the Karush Kuhn–Tucker (KKT) criteria from (6) with ε decided to be a limited step size.

Every possible supporter executes this process to acquire their optimum ranges in (7) and (8), which is applied to deciding the optimum supporter.

$$\begin{aligned}
\lambda(i+1) &= \left[\lambda(i) + \varepsilon\left(E_t^{*S} + E_t^{*r_n} - E_{overall}\right)\right]^+ \\
\mu(i+1) &= \left[\mu(i) + \varepsilon\left(\left(2^{2R}-1\right) - \gamma_{S,r_n}^* - \gamma_{r_n,D}^*\right)\right]^+ \\
z(i+1) &= \left[z(i) + \varepsilon\left(E_{min} - E_S + E_t^{*S}T\right)\right]^+ \\
u(i+1) &= \left[u(i) + \varepsilon\left(E_{min} - E_{r_n} + E_t^{*r_n}T\right)\right]^+ \\
\sigma(i+1) &= \left[\sigma(i) + \varepsilon\left(E_t^{*S} - E_{t-max}\right)\right]^+ \\
\rho(i+1) &= \left[\rho(i) + \varepsilon\left(E_t^{*r_n} - E_{t-max}\right)\right]^+
\end{aligned} \tag{9}$$

Algorithm 1 Refs. [10,11]

Begin
Initialize $N, E_{t-max}, \alpha, T, R, N_0, E_0, I$ (maximum iteration) and the Lagrange multipliers such that $\lambda, \mu, z, u, \sigma, \rho \geq 0$;
for (*each node*, N)
  Create d_{S,r_n} and $d_{r_n,D}$ such that r_n is situated in the collaborative area from origin to the target such that $d_{S,r_n} \neq d_{r_n,D}$ and E_{r_n};
  Obtain $E_{min} = \min\{E_S, E_{r_1}, \ldots, E_{r_n}\}$;
  for $(eachiteration, I)$, Create $h_{S,D}, h_{S,r_n}$ and $h_{r_n,D}$ in a random manner;
    if $\left(|h_{S,r_n}|^2 \geq |h_{r_n,D}|^2, |h_{r_n,D}|^2 \geq |h_{S,D}|^2, d_{S,r_n} \neq d_{r_n,D}\right)$
  Calculate and modify (7) & (8) by their suitable Lagrange multipliers in (9);
    Else
      No possible supporters that fulfil (7);
    End if
  End for
  Find the best $E_t^{*r_n}$ and E_t^{*S};
  end for; **End**

Thus, this ELQSSM-ML algorithm can reduce the energy use of each node in the network by optimizing the transmitted energy, and thus, the network lifespan is increased efficiently.

4. Experiments

4.1. Experimental Setup

NS2 Simulator is used for analyzing the efficiency of the proposed method. The results are compared with state-of-the-art algorithms discussed in Section 2. The comparison is made based on metrics such as End-End Latency, 1-HOP Latency, CB-overhead, Rate of success, and admission rate. Table 2 describes the parameters set up for the simulation.

Table 2. Experimental Setup.

Parameter		Description
Region of Simulation		100×100 m^2
Total nodes considered		1000
Media Access Control (MAC)		IEEE 802.11
Channel		Wireless
Antennas		Single-way
Propagation method		Two-way
Bandwidth		300 Kbps
Data Header		20 bytes
Payload		256 Bytes
Factor of multiplication		2.4
Queue		128 bits
Type of traffic		CBR
Refreshing rate		8
Length of Simulation		100 S
Size of Packet	*hai*	64 Bytes
	Query	20 bytes
	Reply	150 bytes
	$identified_{path}$	10 Bytes

4.2. Metrics

Hop Latency

It is the duration needed to broadcast the packet from one node to another node.

$$l_n = MAC\_l_n \times Exp\_data_n \tag{9}$$

where

$$MAC\_l_n = \left(Exp\_bf\_slot_n \times \left(1 + \frac{b}{n}_{\_rate_n} \right) + Exp\_slot_n \right) \times Exp\_effort_n \tag{10}$$

$$\left(\frac{b}{n} \right)^f_{\_rate_n} = \frac{b\_slot_n + b\_slot\_occp_f}{n\_slot_n - b\_slot\_occp_f} \tag{11}$$

In Equation (10), l_n is the 1-hop latency of nth node, MAC_l_n is the MAC access latency of a packet forwarded by n and Exp_data_n is the predicted quantity of packets in the MAC queue of $n$at a constant interval.

In Equation (11), $Exp\_bf\_slot_n$ is the predicted quantity of backoff interval slots of $n$at a constant interval, $\frac{b}{n}_{\_rate_n}$ is the engaged/free channel ratio found by $n$at a given interval, Exp_slot_n is the predicted quantity of interval slots required for n for broadcasting the packet at a given interval and Exp_effort_n is the predicted number of transmission efforts

by $n$at a given interval. In Equation (6), $\left(\frac{b}{n}\right)^{f}_{\_rate_n}$ is either the channel ratio of a free or an engaged node, and it is determined by n for a period of the desired interval. The desired traffic/packet (f) agreed, b_slot_n is the count of intervals that are engaged, n_slot_n depict the count of intervals that are free.

4.3. End-to-End Latency

It is the time taken for broadcasting a packet from source to destination and is measured in Seconds. Figure 1 depicts the comparative analysis of the End–End latency of the proposed method with other methods.

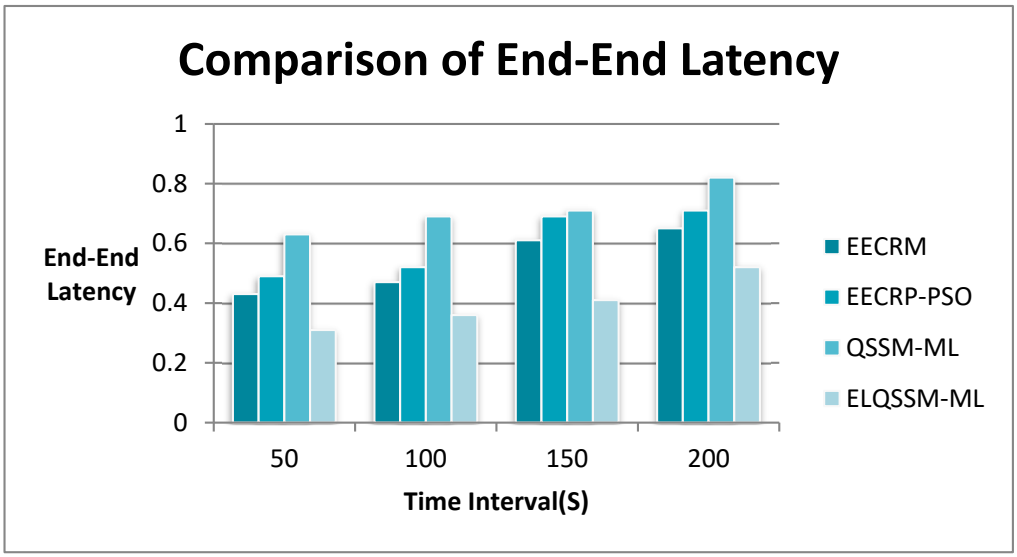

Figure 1. Comparison of End–End Latency.

4.4. Success Rate

It is measured as the percentage of the packets that are arriving successfully at D to that of the total packets that are broadcasted from source S. In common, it is termed as packet delivery ratio. Figure 2 shows the comparison of the Success rate of the proposed method to that of the other methods.

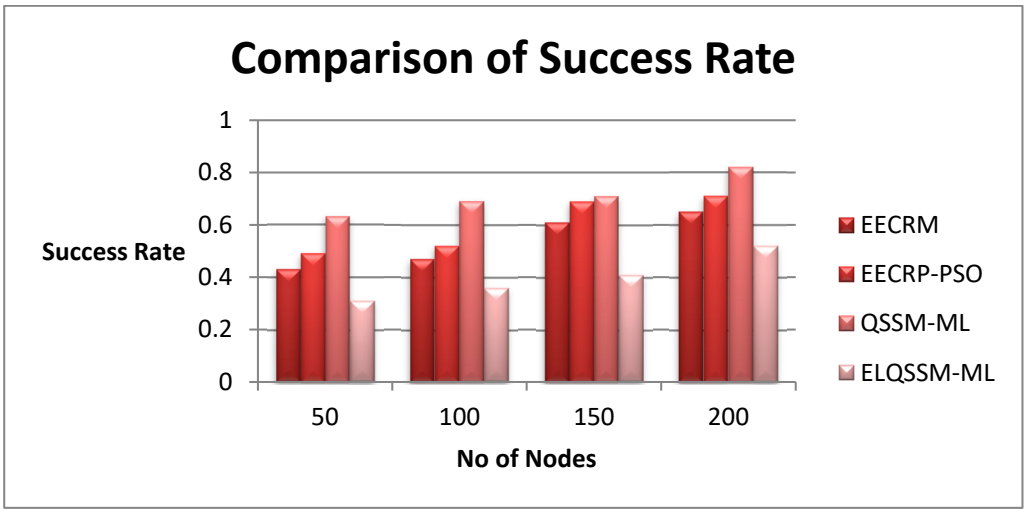

Figure 2. Success rate comparison.

4.5. Admission Rate

It is the ratio of the quantity of tolerable multicast traffic to that of the quality of traffic in demand while multicasting.

4.6. Control Byte Overhead

It is measured as the number of bytes that are controlled and forwarded as and when a packet arrives.

4.7. Experimental Results

The criteria taken to validate the results are as follows:

1. The experiment is subject to a constant increase in the number of nodes, and the experiment is run for different time intervals.
2. Testing one-hop latency involves measuring the time it takes for data to travel from one point to another in a single hop or transmission. To perform this test, a source device sends a packet of data to a destination device, both of which are connected to the network. The time it takes for the packet to reach the destination device is recorded and measured using a network latency tool. The test is repeated multiple times to obtain an average value and to identify any outliers or anomalies.
3. Testing end-to-end latency involves measuring the round trip time (RTT) of a packet. A source device is made to send a packet to a destination device, and the time taken for the packet to make the round trip is recorded and measured using a network latency tool. The test was repeated multiple times to obtain an average value.
4. Success rate testing is performed by measuring the packet delivery ratio (PDR) and the end-to-end delay of the data packets. The data obtained from testing the success rate of a MANET are used to optimize the network's performance and identify any potential issues that may affect the network's ability to deliver data packets.
5. The admission rate is tested by simulating the addition of new nodes to the network and measuring the network's throughput and delay. The results obtained from testing the admission rate are used to optimize the network's performance, such as adjusting the maximum number of nodes that the network can support and determining the network's ability to handle high traffic loads without experiencing congestion or delay.
6. The experiment is carried out to simulate the network's traffic load and measure the amount of control traffic generated by the routing protocols. The test is performed by varying the network's traffic load and measuring the control traffic generated at each traffic load level for obtaining CBO.

Table 3 displays the comparative analysis of 1-hop latency, End–End Latency, Success rate, Admission rate, and Control Byte Overhead of the proposed method with that of the state-of-the-art methods in the literature. Column 2 in the table denotes either the Time interval or the number of nodes taken for the experiment, and it is interpreted based on the metric.

In order to test the scalability and consistency of the proposed method, experiments were conducted by increasing the number of nodes of the order of 500, and the results are tabulated as in Table 4. It is seen from the results that the proposed algorithm has a difference of 0.10 in terms of 1-hop latency when the no of nodes is increased from 500 to 2000. The End–End latency is found to have a total difference of 0.12 when the no of nodes is changed from 500 to 2000. Similarly, consistency is maintained for the Success rate, admission rate, and CBO with a tune of 0.7, 0.9, and 0.5 when the nodes increase from 500 to 2000, which proves the scalability and stability in the performance of the proposed method.

Figure 3 displays the comparative analysis of the 1-Hop latency of the proposed method to that of the state-of-the-art methods discussed in Section 2. It is seen that the proposed ELQSSM-ML has the least latency time of all the other methods. The proposed method reduces the latency by 26.22% when compared to EECRM, 18.2% when compared to EECRP-PSO, and 8% of that of the QSSM-ML method.

Table 3. Comparative analysis of performance metrics.

Method	Time Interval(s)/No of Nodes	1-Hop Latency	End–End Latency	Success Rate	Admission Rate	CBO
EECRM	50	0.43	0.54	0.44	0.54	0.76
	100	0.47	0.61	0.39	0.51	0.78
	150	0.61	0.72	0.31	0.49	0.78
	200	0.65	0.81	0.29	0.32	0.81
EECRP-PSO	50	0.49	0.63	0.25	0.65	0.67
	100	0.52	0.71	0.51	0.61	0.61
	150	0.69	0.81	0.49	0.59	0.58
	200	0.71	0.89	0.44	0.54	0.54
QSSM-ML	50	0.63	0.65	0.36	0.71	0.46
	100	0.69	0.69	0.31	0.68	0.49
	150	0.71	0.78	0.30	0.65	0.51
	200	0.82	0.89	0.29	0.63	0.57
ELQSSM-ML	50	0.31	0.41	0.81	0.87	0.21
	100	0.36	0.47	0.81	0.86	0.21
	150	0.41	0.51	0.80	0.86	0.23
	200	0.52	0.59	0.80	0.85	0.23

Table 4. Comparison of metrics for node range 500–1000.

Method	Time Interval(s)/No of Nodes	1-Hop Latency	End–End Latency	Success Rate	Admission Rate	CBO
ELQSSM-ML	500	0.61	0.65	0.88	0.89	0.27
	1000	0.64	0.68	0.91	0.93	0.29
	1500	0.69	0.71	0.93	0.95	0.31
	2000	0.71	0.77	0.95	0.98	0.32

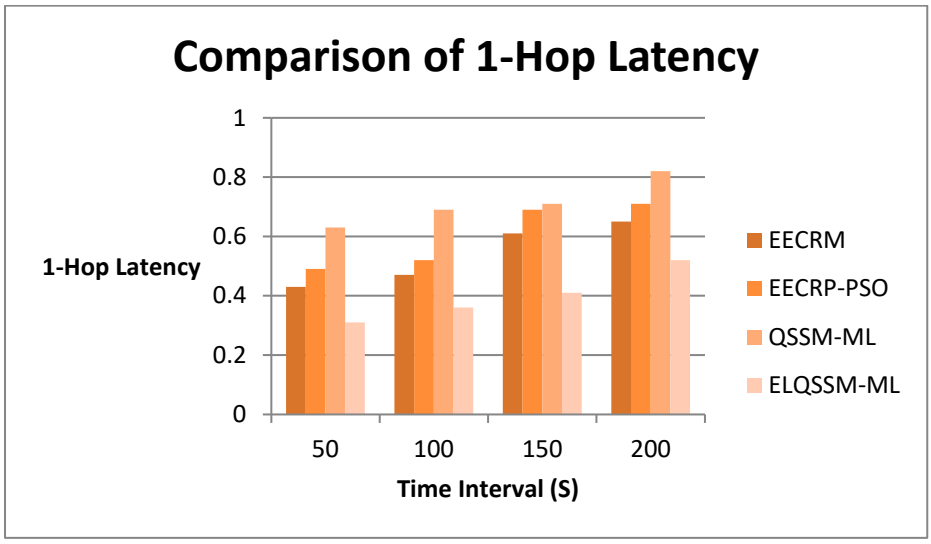

Figure 3. Comparison of 1-Hop Latency.

It is noted from Figure 1 that there is a consistency of the delay being kept minimum while increasing the time interval in the proposed ELQSSM-ML method. The End-End latency of the proposed method is 34.1% less than EECRM, 28% less than EECRP-PSO, and 18% less than the QSSM-ML method when the time for simulation is recorded for 150 s.

It is evident from Figure 3 that the success rate is high for the proposed method when compared to that of all the other methods taken for comparison. For the given number of nodes as 200, the success rate of the proposed method ELQSSM-ML is 31% more than the EECRM, 29.2% more than EECRP-PSO, and 11% more than the QSSM-ML.

Figure 4 depicts the comparative analysis of the Admission rate, and it is seen that the rate of admission for the proposed method is high and consistent even if the number of nodes is increased. It is seen that the proposed method ELQSSM-ML has 86% of admission rate when the no of nodes is 50 and 100 and an 87% admission rate when the no of nodes is 150 and 200, respectively, which is relatively better than other methods.

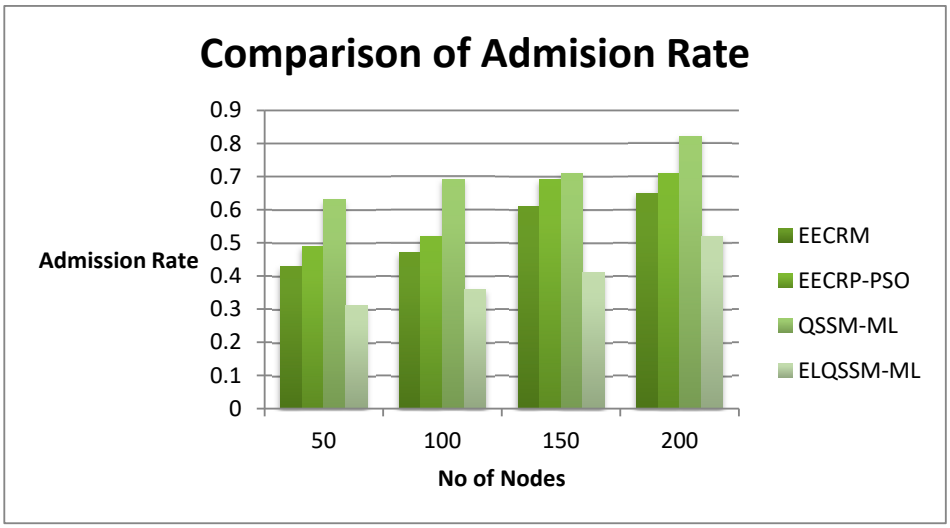

Figure 4. Comparison of Admission Rate.

Figure 5 shows that the CBO of the proposed method ELQSSM-ML has surpassed the other methods with a different number of nodes. It is seen that the proposed method can significantly decrease CBO by 29.8% when compared with EECRM, 17.6% when compared with EECRP-PSO, and 14.2% when compared with the QSSM-ML method.

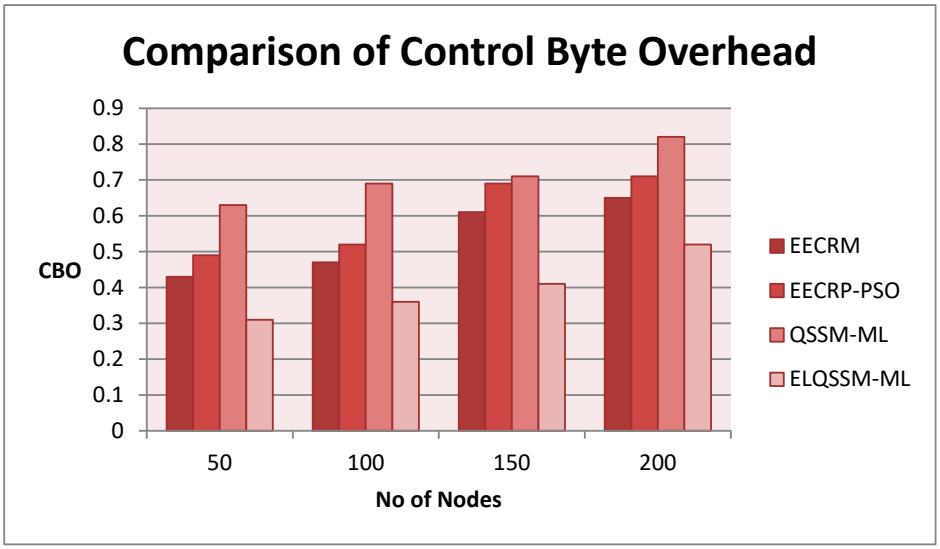

Figure 5. Comparison of CBO.

5. Conclusions

In this study, an ELQSSM-ML-based routing algorithm was presented to decrease power depletion and boost the network lifespan. An optimization dilemma was devised to extend the network's lifespan if constraining the power use, remaining power, and route reliability. Then, an asymmetric transmit energy strategy was designed for adaptively allocating the best transmit energy at the origin and relay nodes. So, the network lifespan was extended with the help of reducing the node's energy use for broadcasting the data from the origin to the target. The proposed method reduces the latency by 26.22% when compared to EECRM, 18.2% when compared to EECRP-PSO, and 8% that of the QSSM-ML method. The End–End latency of the proposed method is 34.1% lesser than EECRM, 28% lesser than EECRP-PSO, and 18% lesser than the QSSM-ML method. The success rate of ELQSSM-ML is 31% more than the EECRM, 29.2% more than EECRP-PSO, and 11% more than the QSSM-ML. The proposed method ELQSSM-ML has an 86% admission rate when the no of nodes is 50 and 100 and an 87% admission rate when the no of nodes is 150 and 200, respectively. It is also seen from the results that ELQSSM-ML significantly decreased CBO by 29.8% when compared with EECRM, 17.6% when compared with EECRP-PSO, and 14.2% when compared with the QSSM-ML method. The scalability and stability of the proposed method are also proven by increasing the number of nodes to the tune of 500 till 2000. To conclude, the simulation findings ensured that the ELQSSM-ML algorithm for multirate MANETs has increased success and admission rate, reduced 1-hop latency and end-to-end latency compared to the existing algorithms, which ensures minimum energy depletion and maximization of the life span of the network. The future work shall include enhancing the proposed method by incorporating bio-inspired optimization techniques.

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