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Adaptive Buffer Handling with Optimal Power Allocation-based QoS-Satisfied Multicast Routing Protocol

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Abstract:- Mobile Adhoc Networks (MANETs) commonly use innovative technologies to improve Quality-of-Service (QoS) while transporting different data speeds. Due to variations in the node's proximity, this type of network has a significant forwarding latency and inefficient data transmission rates. To combat this challenge, an Extending Lifespan and QoS-Satisfied Multicast using Multiple Learned rate (ELQSSM-ML)-based routing protocol was suggested which reduces the energy usage and allocates the transmit energy in an adaptive manner. But, the dynamics of the buffer were not considered, which causes the data loss and latency. Hence, this article proposes an Extending Lifespan and Enhanced QSSM-ML (ELEQSSM-ML)-based routing protocol to decrease the packet loss by applying an adaptive hop-aware buffer handling technique. First, the buffer size of all nodes in the network is partitioned into different segments according to the number of hops and QoS for multiple classes of packets. Then, the dimension of each segment is adaptively fine-tuned based on the traffic load and reliability thresholds. Here, the reliability thresholds for each class of packet are optimized by using the Reinforcement Learning (RL) strategy to defend the packet loss. Further, the simulation outcomes show that the ELEQSSM-ML-based protocol achieves superior efficiency in multicast routing compared to the traditional protocols.

Keywords:- *Multi-rate MANET, Multicast routing, ELQSSM-ML, Buffer handling, Hop count, Reinforcement learning.*

I. INTRODUCTION

MANETs are made up of multiple mobile nodes that have been established to communicate without the direction of a centralized infrastructure. Every node in the network can operate as a source or access point. These are very useful for a variety of applications, such as web servers, disaster relief, law enforcement, medical assistance, and so on. Scalable topological uncertainties such as energy demands, bandwidth, and latency often have an impact on total stability. The main problems in such topologies are collisions, traffic delays, and reliability threats. MANETs are being appropriately implemented by their requirements to overcome these problems and so boost dependability.

Yet, a strong path identification technique is required to choose the efficient route in data transmission since standard path preferences cannot achieve QoS objectives [1]. Routing algorithms are created by taking into account each node's unique address while building a route from a source to a destination node with many relay nodes. These methods are either unicast or multicast in terms of data delivery. Unicast routing sends packets to a specific target at a time, while multicast routing sends packets to several targets at the same time. Multicast communication is formed at the physical, network, and application levels of MANETs [2-3]. This connectivity reduces throughput, node capability, power efficiency, and transfer delay. However, today's real-world MANETs include multicast communication solutions for data delivery [4]. To enable this, a multicast tree was built to deliver data from one source to several targets individually. These cases require the use of delay-sensitive multicast protocols when any delay conditions of the required multicast solutions are to be met with certain reliability bounds, i.e., a defined number of packets with the least amount of latency.

Several latency-aware multicast routing techniques have been proposed over the decades to enhance system reliability. From this perspective, a Delay-Sensitive Multicast (DSM) protocol [5] was developed to improve performance in multi-rate MANETs. A 1-hop delay has been calculated using the busy/idle rate of the distributed data. Following that, a multicast tree was developed to reduce the average of the entire relaying duration of the nodes and the complete blocking interval of the compromised nodes by utilizing adjacent information. Besides, the data rates of the nodes were properly tuned to reduce resource usage, allowing numerous flows to be activated in the MANETs. But, other QoS parameters were required to boost bandwidth utilization even more.

To address this issue, the QoS-Satisfied Multicast using a Multiple rate-based (QSSM-M) protocol was developed, which reflects the throughput, packets lost, jitter and the delay estimated from each adjacent node for relaying [6]. After that, many QoS-satisfied multicast trees were created, with each tree ensuring a given set of QoS criteria. As a result, the cumulative delay and bandwidth usage were reduced while ensuring QoS for the intended flow and continuing flows. Further, a distributed system coding was used to discard superfluous packets, so that all targets received the unique coded packets via distinct paths. However, due to the utilization of multiple transfer zones, the transmission rate for the origin was not adequately determined.

So, a QSSM-ML routing strategy was developed with the aid of a Deep Convolutional Neural Network (DCNN) to determine an appropriate transmission rate for the sender [7]. Originally, the problem of determining the transmission rate for sources was viewed as a multiclass classification issue. Afterwards, several measures like frame payload size, path reliability and throughput for data transfer were assessed while maintaining the specified false positive rate. Additionally, the DCNN learned such parameters to forecast the appropriate data rate for the origin and accomplish successful routing. Despite greatly increasing network capacity, the network lifespan was not properly enhanced due to severe power usage.

As a result, an ELQSSM-ML-based routing protocol was developed to minimize energy consumption and increase the lifetime of MANETs [8]. An optimization problem was presented in this ELQSSM-ML protocol to maximize the MANET's lifespan while preserving energy usage, residual energy and route stability. Then, an asymmetric transmit energy approach was created to assign transmit energy adaptively at both the origin and intermediary nodes. As a consequence, this method successfully decreases energy depletion and increases the MANET's lifetime. On the other hand, the dynamics of the buffer were not considered, which influences the data loss and latency.

Therefore, in this paper, an ELEQSSM-ML-based routing protocol is proposed which integrates an adaptive hop-aware buffer handling mechanism to avoid packet loss effectively. In this protocol, the buffer size of each node is partitioned into different segments according to the number of hops and QoS for multiple classes of packets. After that, the dimension of each segment is adaptively fine-tuned based on the traffic load and reliability thresholds. To avoid packet loss efficiently, the reliability thresholds for each class of packets are optimized by the RL strategy. Thus, this ELEQSSM-ML protocol can minimize packet loss, bandwidth usage, latency and increase the success rate significantly. The remainder of this manuscript is assembled as follows: Section II summarises previous research on buffer handling protocols in wireless networks. Section III describes the ELEQSSM-ML protocol in MANET, and Section IV shows how effective it is in modeling. Section V summarizes the entire study and makes suggestions for further improvements.

II. LITERATURE SURVEY

Aamir & Zaidi [9] presented a novel method of buffer management to control packet queues in MANETs for static and mobile nodes. In this method, efficient queuing in the buffer of a centrally interacting MANET node was achieved using an active queue management policy via allocating adaptive buffer space to each adjacent node in a fraction of the number of packets delivered by adjacent. But, its total processing overhead was high. Also, it needs to analyze its efficiency under high mobility and fluctuations of flow arrival rates.

Subramaniam & Tamilselvan [10] designed an Efficient Buffer Management Protocol (EBMP) to transmit data in multicast groups. The continuous requested video data was buffered in the mid-nodes along the multicast tree from the origin to the targets. If data was delivered, it was split into real and non-real-time. The total weight of the data in the real-time buffer was measured according to the number of hops, deadline and waiting period. According to the measured weight range, transfer priorities were allocated. The buffer space was adaptively optimized based on the number of mid-nodes along the multicast tree. But, its latency was high since the traffic density was high if the number of target nodes was high.

Liu et al. [11] developed a common model for the appropriate throughput ability of a class of buffer-constrained MANETs with the 2-hop relay. Initially, an analysis was presented to know how the throughput ability of such a MANET was computed by its Relay-buffer Blocking Possibility (RBP). According to the embedded Markov chain theory and queuing theory, an enhanced theoretical model was designed to facilitate the RBP and closed-form expression for appropriate throughput ability to be derived. But, its computation burden was high.

Petreska et al. [12] developed a delay-bound-based protocol to reduce the transmit energy and increase the network lifespan of multi-hop heterogeneous wireless systems. First, the minimum required to transmit energy was calculated at every hop such that a considered statistical latency limit was not violated. Then, the transmit energy among each source along the corresponding route were distributed such that the network lifespan was increased. But, it considers a single flow whereas it needs to analyze the multiple flows in networks.

Capone et al. [13] investigated the problem of transfer scheduling and routing to reduce the end-to-end latency under the Signal-to-Interference and Noise-Ratio (SINR) framework for multi-hop networks. Initially, the classical scheduling scheme was modified by analyzing end-to-end latency and discarding the limitation of frame periodicity. Then, this scheme was extended by featuring collaborative transmission and forward interference removal. But, it has high computational complexity and delay.

Wang et al. [14] formulated a service function chain mapping challenge, also known as the multicast-oriented virtual network function localization challenge. The objective function was determined by considering end-to-end delay, resource usage with bandwidth demands. To solve this issue, a 2-step method was presented. Initially, Dijkstra's algorithm was adopted to create the multicast tree. Then, a new estimation of distribution algorithm was designed to map a considered service function chain over the multicast tree. On the other hand, it needs to consider other QoS metrics to increase network efficiency.

Rana & Harsoor [15] developed a new traffic controlling framework for effectively controlling the routing overhead in MANET. Initially, the network traffic was determined by the probable node-link life to suggest the traffic controlling procedure. Depending on the node-link life, this framework can estimate how long the link was functioning and recreation was applied to reduce the overhead. A queue manager was designed to execute the traffic detection at each node and a mobility prediction method was derived to estimate the node-link life. But, the routing overhead was still high.

Cao et al. [16] considered a multiple Unmanned Aerial Vehicles (UAV) forwarding wireless network where Buffer-Aided UAVs create a Multi-hop aerial Forwarding (BAMF) network to offer stable wireless transfer facilities for ground terminals where a direct transfer connection was not available. The mean throughput was increased according to the buffer limits, the path choice restraints, the transfer energy restraints and the UAV mobility restraints. Moreover, an iterative algorithm was presented to effectively acquire the suboptimal solution. But, it has a high computation difficulty due to the use of mixed-integer non-convex programming.

III. PROPOSED METHODOLOGY

In this section, the ELEQSSM-ML-based protocol is explained briefly. Initially, the multi-rate MANET structure is built wherein all nodes are equipped with an Omni-directional antenna and have related radio configurations. Consider N number of relay nodes that are randomly distributed between the origin and target nodes. All nodes maintain a unique communication channel and disseminate the control packets at a specified rate of 1Mbps. Also, the data is broadcast at a rate which is greater than the direct communication rate between an origin to the target nodes. The broadcasted data packets are then categorized depending on the various conditions: (i) data group (Real-Time (RT) or Non-RT (NRT)) and (ii) number of hops M that the data traversed between its origin and a mid node.

When $H = 1, \dots, m$ is the arbitrary parameter represents the number of hops from origin to the target, the expected number of hops $E[H]$ that the data traversed from its origin to the target is defined as $E[H] = \sqrt{M/\log M}$, where m denotes the highest amount of hops in the network. According to the data group, the range of $M$and $E[H]$, this arriving data at the mid nodes is categorized as: (i). Extended Hop RT (EHRT) or Group-1 when $M \geq \frac{E[H]}{2}$, (ii). Narrow HRT (NHRT) or Group-2 when $M < \frac{E[H]}{2}$, (iii). Extended HNRT (EHNRT) or Group-3 when $M \geq \frac{E[H]}{2}$ and (iv). Narrow HNRT (NHNRT) or Group-4 when $M < \frac{E[H]}{2}$.

A. Buffer Partitioning using Reliability Thresholds

Once the data is categorized, this protocol allocates each group into its Virtual Segment (VS), where Q_g is the VS range of $group\_n$. The range of all segments is adaptively adjusted regarding the traffic load of all groups. This is the major operation of the Queue Controller (QC). The QC handles the VS of the buffer using lend and move-away policies. The lending policy shifts free space from specific VS with the Highest Free Space (HFS) to the other. It is performed if there is available or unutilized space in the buffer. The move-away policy discards data when there is no more residual space in each VS. For this purpose, two thresholds such as T_1 and T_2 are represented to be the protection for the VSs of EHRT and NHRT, correspondingly. Additionally, the threshold T is represented to be the protection for the EHNRT and NHNRT. According to the threshold ranges, this protocol moves data from a VS and the creating space emerges to the other VS. As a result, these threshold ranges should be properly selected by the RL algorithm.

Figure 1 depicts the decision task of the QC when the arriving data packet belongs to Group-1, Group-2, Group-3 or Group-4 packets.

B. Reinforcement Learning Algorithm for Threshold Selection

The standard learning structure of RL involves a mediator, a surrounding, a limited state space S, a collection of offered tasks$A$ for the mediator and a bonus value: $S \times A \to R$. The main idea of RL is to learn the mediator for offering good solutions by trial-and-error practices with the surrounding. During all interval t, the mediator accounts for a task $a_t$based on the search of the current state s_t in the surrounding. Once the task is performed, the state of the surrounding will change to a fresh state s_{t+1}.

Concurrently, the mediator will accept a bonus r_t that reflects the range of state changes. This kind of mediator-surrounding practice is a periodic task. The RL mediator is a long-sighted decision-maker, therefore its intention is to maximize its projected joint bonus over an interval: $\mathbb{E}[\sum_{t=0}^{\infty} \gamma^t r_t]$, where $\gamma \in (0,1]$ is a variable concession on forthcoming bonus. Its plan is achieved by learning a policy that guides the mediator on how to choose proper tasks at multiple states. Q-learning is a popular RL model that does not need modeling. It does not require any prior knowledge about the network, such as the possibility of state transition. It can try to make sensible predictions based on experiences.

The mediator holds a Q-factor $\left(Q(s,a)\right)$ for all state-task sets, which portrays the projected long-term bonus whilst taking $a$at s. According to this value, the mediator can recognize the projected Q-factor for each task at the ongoing state. Besides, the mediator decides which tasks have to be taken for collecting the greatest joint bonus in the long run. Each interval when practice occurs, the Q-factor is adjusted iteratively as:

$$Q(s_t,a_t) \leftarrow Q(s_t,a_t) + \alpha * \left[r(s_t,a_t) + \gamma * \max_a Q(s_{t+1},a) - Q(s_t,a_t)\right] \quad (1)$$

In Eq. (1), $\alpha \in (0,1]$ is the learning ratio, $r(s_t,a_t)$ is the bonus collected by taking a_t in s_t and γ is the discount %. The Q-learning approach typically defines the Q-factor in tabular form. However, it is unsuitable for dealing with complex control concerns involving several states and actions. This RL utilizes the Deep Neural Network (DNN) to create the correlation between all state-activity pairings and their associated Q-factor to address this challenge. In addition, a deep Q-learning model based on the core DNN is being built to decide on optional activities for the mediator. Figure 2 illustrates the RL processes in the mediator-surrounding interface network.

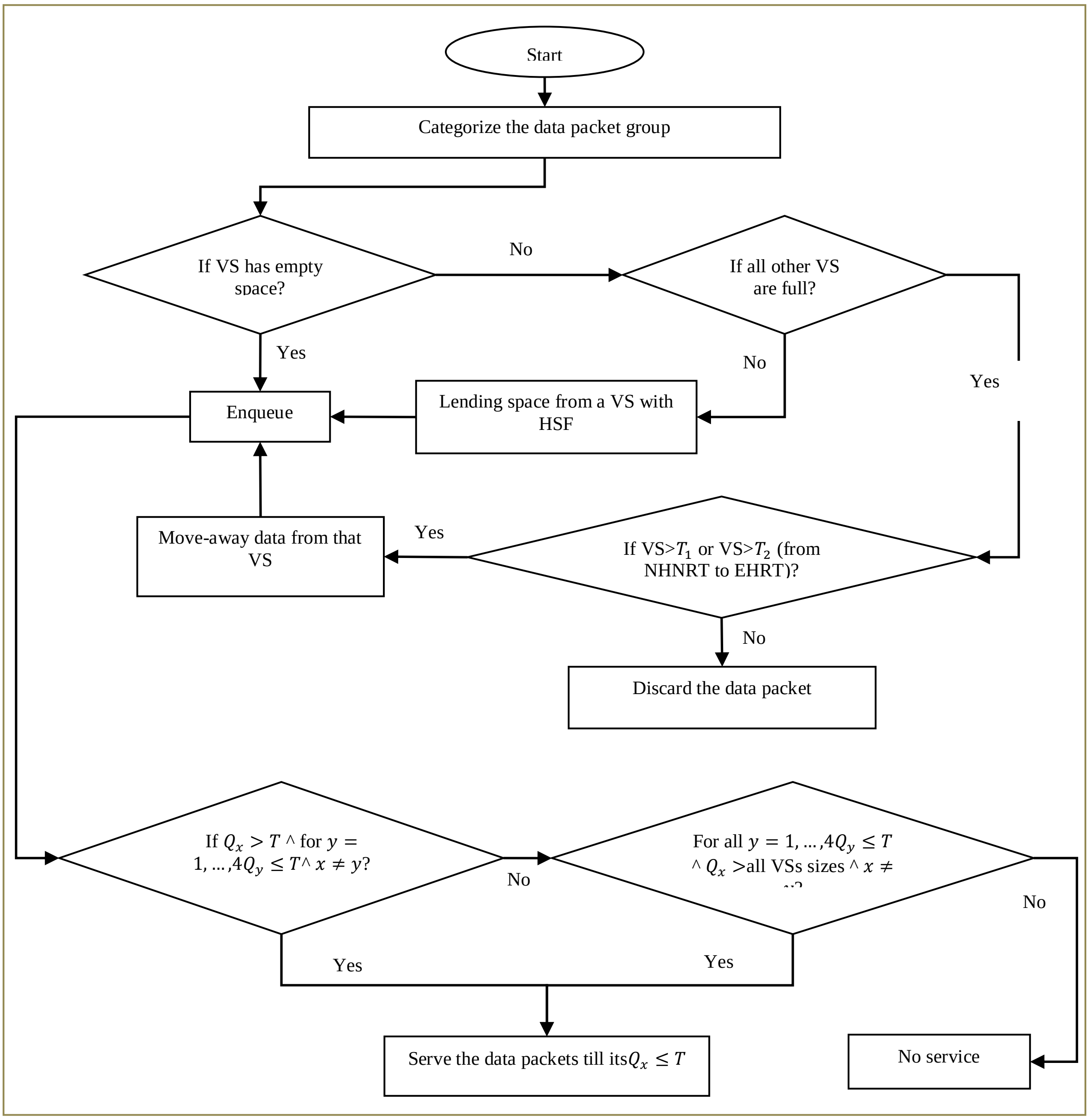

Fig 1. Decision Task of the Queue Controller for ELEQSSM-ML Protocol

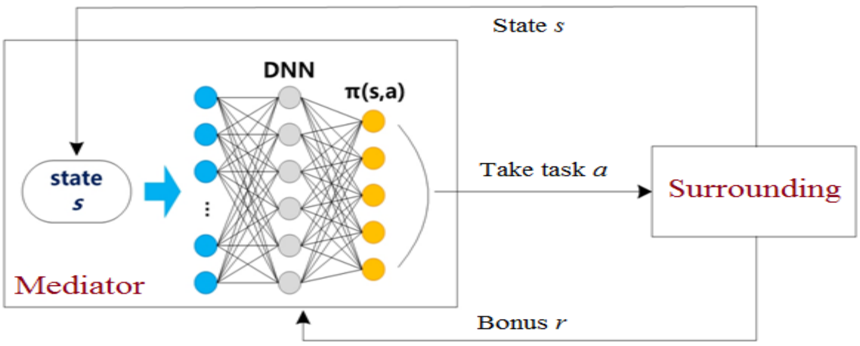

Fig 2. Schematic Overview of RL with DNN Framework

➢ *Training Stage*

For all solution intervals t_j for j^{th}data, the DRL mediator executes a task $a_j$based on the ongoing state s_j. After obtaining the direct bonusr_j and the successive state s_{j+1}, the transfer summary$\left(s_j, a_j, r_j, s_{j+1}\right)$ is added into replay memory Δ with facility N_Δ. All intervals during fine-tuning the Q-learning, weight and bias variables (w, θ) of the DNN are updated by the mini-batch which has a predetermined number of random samples $S_\Delta$from Δ. To reduce the time complexity, such an updating could exist every Usolution interval$(U \geq 1)$. Because the interface replay policy allows the mediator to train from random shift samples rather than series interfaces, the link between learning data is lost, resulting in a reduction in the difference of fine-tuned variables. Further, the utilization of learning data is substantial since each sample is potentially picked more than once to fine-tune variables.

To avoid additional divergence and volatility in DNN variables during learning phases, two DNNs: target and analysis networks are used concurrently. These two networks have a similar design but different variables. While fine-tuning Q-learning, the target network is used to create desirable Q-factors. One distinguishing feature of a target network is that it is briefly frozen. Its variables are copied from the analysis network on a regular basis. In contrast, the analysis network keeps the new variables and is used to forecast Q-factors.

Thus, the threshold values are optimized for each group of data to allocate them into the appropriate VS. Moreover, the allocator computes which data will be served depending on the significance of the data and $Q_g$of $group\_n, n = 1, \ldots, 4$.

Algorithm:
Input: Overall buffer size (B) and effective arrival rate (λ) of group n at any node
Output: Optimal threshold ranges T_1, T_2 and T
Begin

Initialize α, γ, learning rate β, initial training period τ, mini-batch S_Δ, replay time η;

Initialize $\Delta$with N_Δ;

Initialize analysis and desired activity-Q with random variables, $w$and θ;
$\boldsymbol{for}(B \ and\ \lambda\ at\ each\ node)$

Randomly select an activity; or else, $a_j = \operatorname*{argmax}_a Q(s_j, a; w, \theta)$;

Train j according to a_j, receive incentive r_j and observe state shift at consecutive decision period t_{j+1} with a new state s_{j+1};
Accumulate shift $\left(s_j, a_j, r_j, s_{j+1}\right)$in Δ;
$\boldsymbol{if}(j \geq \tau\ and\ j \equiv 0 \bmod \beta)$
$\boldsymbol{if}(j \equiv 0 \bmod \eta)$
Set $\hat{Q} = Q$;
$\boldsymbol{end\ if}$
Randomly choose samples $S_\Delta$from Δ;
$\boldsymbol{for}(each\ shift(s_k, a_k, r_k, s_{k+1})\ in\ S_\Delta)$
$target_k = r_k + \gamma * \max_{a'} \hat{Q}(s_{k+1}, a'; w', \theta')$;
Fine-tune DNN variables w, θ with a loss value of $target_k - Q(s_k, a_k; w, \theta)^2$;
$\boldsymbol{end\ for}$
$\boldsymbol{end\ if}$
$\boldsymbol{end\ for}$
Return Optimal values of thresholds;

Allocate and serve the data packets by comparing the VSs size with threshold values;

End

IV. SIMULATION RESULTS

In this section, the effectiveness of ELEQSSM-ML routing protocol is assessed by modeling it in Network Simulator version 2.35 (NS2.35) and discussed with the conventional protocols: EBMP [10], BAMF [16] and ELQSSM-ML [8] regarding different network metrics. Table I provides the model specifications.

TABLE I. SPECIFICATIONS OF NETWORK MODEL

Variables		**Value**
Simulation area		$1000 \times 1000 m^2$
No. of nodes		100
MAC category		IEEE 802.11
Channel category		Wireless channel
Antenna		Omni-directional
Propagation category		Two ray ground
Required bandwidth		500 kbps
Packet's header length		10 bytes
Packet's payload length		512 bytes
Batch size for randomized network coding		32
Multiplying variable		1.2
Queue size		64 packets
Traffic category		Constant Bit Rate (CBR)
Q_{fix} to generate multicast trees		0.3
Timeframe between 2 successive tree refreshes		4
Data rate		11 Mbps
Transmit energy		0.0316 W
Simulation interval		200 sec
Control packet length	$hello$	160 bytes
	$table\_query$	10 bytes
	$table\_reply$	1500 bytes
	$route\_query$	10 bytes
	$route\_found$	20 bytes

A. l-Hop Latency

It is the time required to disseminate a data from every node to the other.

$$l_n = MAC\_l_n \times Exp\_data_n \tag{2}$$

Where $MAC\_l_n = \left(Exp\_bf\_slot_n \times \left(1 + \frac{b}{n}_{\_rate_n}\right) + Exp\_slot_n\right) \times Exp\_effort_n$ (3)

$$\left(\frac{b}{n}\right)^f_{\_rate_n} = \frac{b\_slot_n + b\_slot\_occp_f}{n\_slot_n - b\_slot\_occp_f} \quad (4)$$

In Eq. (2), l_n is the 1-hop latency of n^{th} node, MAC_l_n is the MAC access latency of a data disseminated from n and Exp_data_n is the expected amount of data in the MAC queue of n at a stable period. In Eq. (3), $Exp\_bf\_slot_n$ is the expected amount of backoff duration slots of n at a stable period, $\frac{b}{n}_{\_rate_n}$ is the busy/free channel ratio obtained by n at a specified period, Exp_slot_n is the expected amount of period slots essential for n to disseminate the data at a specified period and Exp_effort_n is the expected amount of broadcast attempts by n at a specified period. In Eq. (4), $\left(\frac{b}{n}\right)^f_{\_rate_n}$ is the busy/free channel ratio obtained by n in a specified period with a required traffic/packet (f) agreed, b_slot_n is the amount of busy period slots noticed by n in a specified period, n_slot_n is the amount of free period slots noticed by n and $b\_slot\_occp_f$ is the amount of busy period slots occupied by f.

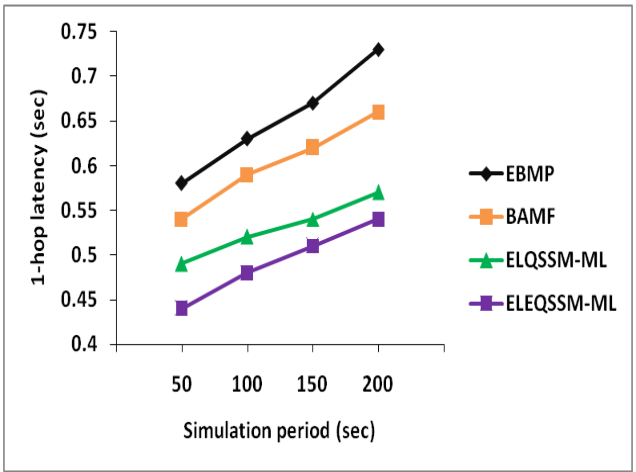

Fig 3. 1-hop Latency vs. Simulation Period

Fig 3 shows 1-hop latency (in sec) of EBMP, BAMF, ELQSSM-ML, and ELEQSSM-ML protocols under different simulation periods (in sec). It signifies that when increasing the simulation period, the ELEQSSM-ML-based routing protocol can decrease 1-hop latency compared to other protocols, i.e., 1-hop latency of ELEQSSM-ML for simulating 100sec is 23.81% less than the EBMP, 18.64% less than the BAMF and 7.69% less than the ELQSSM-ML protocols.

B. End-to-end Latency

It is the time needed to disseminate the data between an origin to the multiple targets.

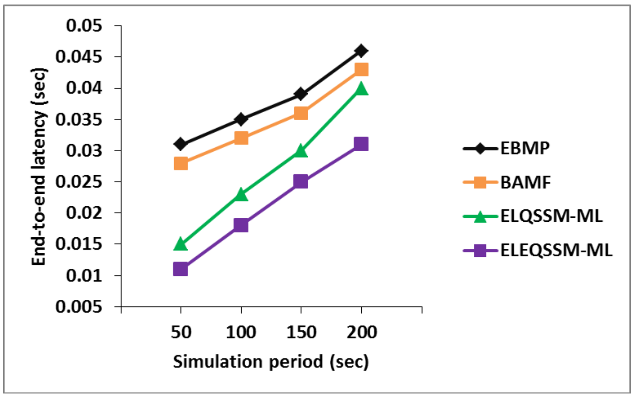

Fig 4. End-to-end Latency vs. Simulation Period

Fig 4 depicts the end-to-end latency (in sec) of EBMP, BAMF, ELQSSM-ML, and ELEQSSM-ML protocols under varied simulation period (in sec). It indicates that when increasing the simulation period, the ELEQSSM-ML can decrease the end-to-end latency compared to the other protocols, i.e., the end-to-end latency of ELEQSSM-ML for simulating 100sec is 48.57% lower than the EBMP, 43.75% lower than the BAMF and 21.74% lower than the ELQSSM-ML protocols.

C. Success Rate

It is the proportion of amount of data delivered effectively at the target to the amount of data disseminated from an origin.Fig 5 displays the success rate of EBMP, BAMF, ELQSSM-ML, and ELEQSSM-ML protocols using different amount of nodes. It addresses that the ELEQSSM-ML can increase the success rate than all other protocols, i.e., the success rate of ELEQSSM-ML for 100 nodes is 21.54% greater than the EBMP, 16.18% greater than the BAMF and 5.33% greater than ELQSSM-ML algorithms.

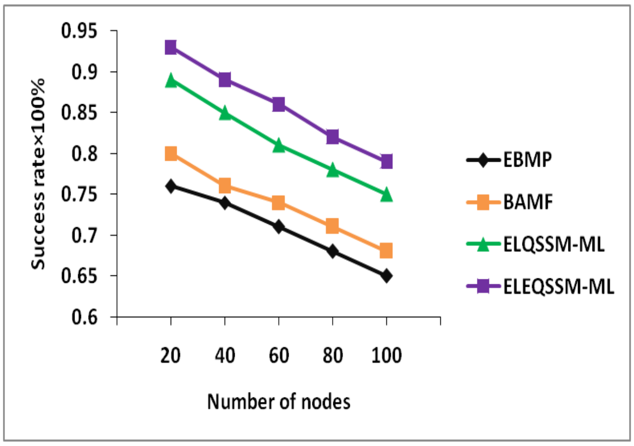

Fig 5. Success Rate vs. Number of Nodes

D. Admittance Rate

It is the ratio of the amount of accepted multicast traffic to the amount of preferred multicast traffic.

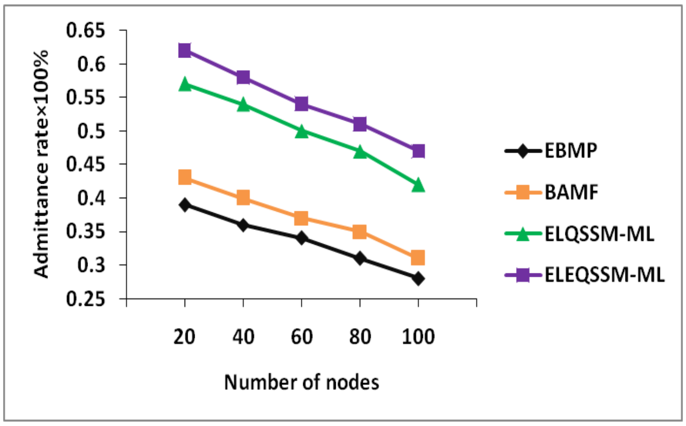

Fig 6. Admission Rate vs. Number of Nodes

Fig 6 depicts the admission rate of EBMP, BAMF, ELQSSM-ML, and ELEQSSM-ML protocols for varying number of nodes. It indicates that when increasing the number of nodes in the MANET, the ELEQSSM-ML can maximize the admission rate compared to the other protocols, i.e., the admission rate of ELQSSM-ML for 100 nodes is 67.86% greater than the EBMP, 51.61% greater than the BAMF and 11.9% greater than the ELQSSM-ML protocols.

E. Control Byte Overhead

It is the amount of control bytes transmitted per data.

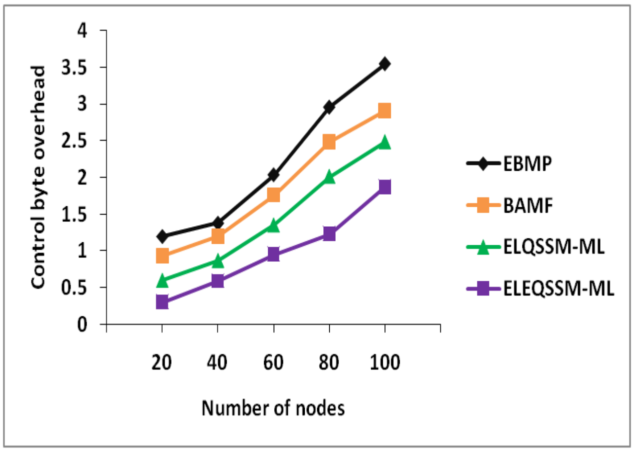

Fig 7. Control Byte Overhead vs. Number of Nodes

Fig 7 portrays the number of control bytes of EBMP, BAMF, ELQSSM-ML, and ELEQSSM-ML protocols with different number of nodes. It observes that the ELEQSSM-ML can decrease the number of control bytes considerably than all other protocols, i.e., the amount of control bytes for ELEQSSM-ML using 100 nodes is 47.32% less than the EBMP, 35.74% less than the BAMF and 24.6% less than the ELQSSM-ML protocols.

V. CONCLUSION

In this paper, the ELEQSSM-ML-based routing protocol was developed for applying the adaptive hop-aware buffer handling method into the ELQSSM-ML protocol. Initially, each node's buffer size was split into multiple segments depending on the hop count and QoS for various categories of data packets. After that, every segment's size was adaptively adjusted according to the traffic load and reliability thresholds for different categories of data packets. Such thresholds were decided by the RL strategy which helps to avoid the packet dropping. At last, the simulation results concluded that the ELEQSSM-ML-based protocol has the maximum success and admittance ratio, the minimum 1-hop and end-to-end latencies than the other classic protocols for multicast routing in multi-rate MANETs.

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