Received signal strength indication based clustering and aggregating data using Q-learning in mobile Ad Hoc network

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ABSTRACT

Clustering is a significant idea for extending the scalability and enhancing the energy in the mobile ad-hoc network (MANET). In addition, the clustering concept is used to diminishes the cost of communication. The re-clustering procedure makes expensive, and frequent re-clustering procedure makes extra routing overhead and extra energy utilization. To solve these issues, received signal strength indication (RSSI) based clustering and aggregating data (RCAD) using Q-learning in MANET is proposed. In this approach, we build the clusters by node RSSI. The fuzzy logic system (FLS) is used to select the cluster head (CH) by the node mobility and node utilization energy. Q-learning-based data-aggregation for improving mobile node routing efficiency in MANET. Here, we can find an optimum next-hop node utilizing their Q-values established on the rewards (RD). Since the RD rule is used to decide the best solution for the Q-learning technique. This RD is computed by present bandwidth (PB), present energy (PE), present packet delivery (PDD), and hop count (HC) parameter for selecting the data aggregator from sender to receiver. The experimental outcomes illustrate that the RCAD approach increases 155 CH round and raises 24% cluster lifetime in the MANET.

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1. INTRODUCTION

MANETs are self-organized networks without any fixed infrastructure. The topology changes are very frequent in MANETs due to nodes' mobility. The topology maintenance creates an extra overhead, as the mobility information of a single node is shared with all nodes in the network. To address the topology maintenance overhead problem in MANETs, the researchers proposed different cluster-based algorithms to reduce the size of a routing table [1]. The clusters are formed to adjust the topology changes within the cluster locally. If a node wants to communicate with a node outside the cluster, it only communicates with its CH. The CH communicates with other CHs to transmit data toward the destination. To efficiently utilize the clustering mechanism, stable and balanced clusters are required. Some metrics, such as relative mobility (node speed and direction), node degree, residual energy, communication workload, and neighbor's behavior, are required to form good quality and optimized clusters [2].

In MANET, every node acts as an autonomous, and it transmits the data packet efficiently. The sender sends the data to the destination via intermediate nodes. Conversely, while functional to a MANET, many issues happen generally because of the nonexistence of centralized management and the movement of the nodes [3]. MANETs applications are raised rapidly, and nowadays, MANETs are able to offer several services. MANET's major conducive components are the accessibility of radios that can adjust to the situation of the channel and communicate at multiple data rates. However, it creates additional loads [4].While the MANET size is huge and nodes are randomly moving, and the clustering attains scalability. On the other hand, the clustering method has its limitations because of the cluster structure as well as management [5]. The fundamental dispute to accomplish the scalability and the cost of clustering represents the efficiency of clustering [6]. The exchange of information is associated while local actions, for example, energy drain or node mobility. Several clustering approaches modification the clusters entirely as well as the CHs are re-elected [7]. In this approach, the genetic algorithm (GA) is used to discover the fitness function for receiving the optimized route. It offers an optimization procedure to choose the efficient routes which present the greatest fitness values based on the highest remaining energy and minimum data traffic. However, this approach increases the hop count [8].

The load-balanced clustering infrastructure (LBCI) approach is adjusted to enhance the capacity. Here, the integer linear programming finds out the feasible solution, and it offers data distribution timely. This approach measures the delay based on the evaluated value and the real past value concurrently to improve the inaccurate difficulty of the measured value. Then distributed data scheduling algorithm that employs the limited bandwidth. However, the correction of delays received may be involved through definite environmental components, and it increases the energy utilization [9]. Reinforcement learning and heuristic algorithm is used to choose the neighbors to transmit the packet to the destination. This approach is for forecasting the node behavior via reinforcement learning [10]. The Q-learning algorithm computes the action value. The bi-objective intelligent routing approach is used to minimize a long-run cost function that contains pathway energy cost as well as delay. The multi-agent reinforcement learning technique evaluates the optimal routing in the absence of information about the system's statistics [11]. Data gathering and data aggregation are key issues in the network. Data aggregation approaches maintain proficient dynamic updates, and aggregation methods permit updating the data structure resourcefully when managing the routing function [12]. This article is structured as follows: section 2 describes the received signal strength indication (RSSI) based clustering and aggregating data using Q-learning in MANET. Section 3 contains simulation results. Finally, section 4 present the conclusion.

Ant colony optimization (ACO) based fuzzy logic (F-ANT) approach is used to discover an efficient route based on the node bandwidth, node congestion rate, and RSS. To find the most efficient this approach increases the packet delivery and minimizes the routing overhead. However, this approach creates additional routing overhead and lacking scalability [13]. An intelligent naïve Bayesian probabilistic estimation is used for building a stable clustering. This scheme is used to enhance the routing through the awareness of the traffic. The CH is preferred from the path having the highest traffic to enhance the stability as well as lifespan [14]. The self-organization-based clustering approach is used to enhance network stability and scalability. This approach applies the Bio-inspired behavior of birds flocking for the cluster arrangement as well as management. It is used to minimize congestion as well as enhance the function. Also, it minimizes the additional energy utilization [15]. An adaptive geographic routing approach is used to improve transmission quality. However, using the greedy forward method to counter local maximizations raises the network delay [16].

Structure-free approach for replica insensitive data aggregation. This approach explains a token that executing a self-repelling random walk and aggregates data from nodesIt also minimizes the overhead of messages [17]. A peer-to-peer data dissemination approach is implemented to enhance the capacity of the network. It gives the data a timely manner among nodes [18]. This approach increases the packet delivery rate and minimizes the delay. However, it does not consider the length of the packet [19]. A hybrid distributed monitoring is a hierarchical-based technique for the dissemination of query and aggregating data. The gossip-based method is used to assist hierarchical topography to be whole the data aggregation and provide robustness and stability in MANET [20]. BlockTree is a monitoring approach, and it describes the idea of location-aware delivery and aggregates information. However, this approach offers precise results in the communication medium [21]. The census approach is used for aggregating the data. This approach evades a great overhead during node mobility [22]. Adaptive fuzzy multiple attribute decision routing determines the fuzzy score based on direction, distance, and location, and density. Here, transmit the data packets by the fuzzy score. It selects the stable route during the highest convergence rate and speed. It minimized the network delay. However, this approach can't be able to select the better node during the highest traffic load [23]. The volunteer nodes of ant colony optimization (VNACO) approach is used to minimize the delay. In MANET, the node moving out of transmission range while the volunteer node hears the loss data packet next distributes the information to the transmitter node. In this approach, node connectivity, energy, time of transmission processing, as well as available bandwidth metrics are used to select the volunteer nodes. The ant colony optimization technique is used to provide the optimal route and minimize the routing overhead. However, this approach increases energy consumption [24]. This approach using an auto-encoder that assists the fuzzy clustering technique to defeat the deficiency that the function is simple to be affected through the amount of clusters [25]. An Efficient Self-Reconfiguration and Route Selection approach is used to alleviate failures of link. This approach repeatedlyobserves the energy efficiency and enhance the network function [26]. High-speed mobility methodis a severedistress for mobile nodes in the MANET [27].Improved uplink throughput and energy efficiency approach effort optimize the throughput energy in the clustering [28].

2. RSSI BASED CLUSTERING AND AGGREGATING DATA USING Q-LEARNING

A MANET contains the number of mobile nodes, and these nodes are deployed in a specific region, and mobile nodes are moving freely in any way. The mobile nodes are allocated with distinctive IDs, and each mobile node can be aware of its neighboring nodes inside its communication range via HELLO and handling a table of neighbor details. In MANET, node mobility is a significant factor since the movement can't predict easily. Energy utilization is also a significant component because the node energy is dried completely; as a result, the node is dead.

2.1. Clustering

Clustering is a significant idea for extending the scalability and enhancing the energy in the MANET. In addition, the clustering concept is used to diminishes the cost of communication. In a clustering rule, initially, the clusters are assembled to perform their tasks on one round next do the re-clustering process. This re-clustering procedure makes expensive also network database completely renewed. Furthermore, the frequent re-clustering procedure makes extra routing overhead and extra energy utilization. To solve these issues, fuzzy logic system FLS is used to enhance the MANET lifetime. In this approach, the clusters contain several mobile nodes and CH. We build the clusters by node RSSI. Figure 1 illustrates the block diagram of clustering and aggregating data (RCAD).

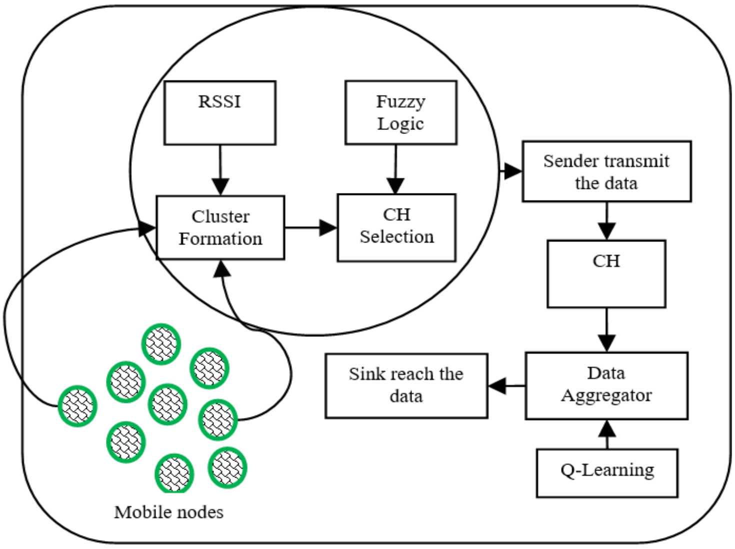

Figure 1. Block diagram of RCAD

RSSI is a valuable parameter to recognize the distance between CH and its neighbour. The lesser value of RSSI represents that node is positioned distant from the CH, and the great value of RSSI illustrates that the distance between the sender and its neighbour is not extremely distant. The RSSI value is separated into 3 stages: the lower stage, middle stage, and the higher level. If the RSSI value is low, that represents the node cannot join this cluster, and it should maintain as a member of non-cluster. If the RSSI value is medium, that denotes the node feel right to a region of a cluster member. If the RSSI value is high, that represents a node that goes to a region chosen as Cluster members. Algorithm 1 shows the categorization of the MANET.

Algorithm 1: Categorize the MANET node
```
For each node
M= Minimum RSSI value;
A= Average RSSI value;
G=Greater RSSI value;
If (Obtain an request message);
Do (recognize RSSI value);
if ( RSSI = M) then
Not select a cluster members;
return node status
if ( RSSI = A) then
Chances for select a cluster members;
return node status
if ( RSSI = G) then
Confirms the nodes are selected as cluster members;
return node status
```

2.2. CH election

The CH is elected by the factors of mobility of node and energy utilization of node. These factors are explained clearly. The minimum node mobility (NM) and minimum node utilization energy (NUE) are used to discover the round's maximum length. Figure 2 illustrates the FLS of the RCAD. From this figure, node mobility and node energy utilization values are given as the input, generating the output, i.e., length of the round (LR). The length of the round value computation is given.

$$LR = Max(round[LR_{max} * FIS(NM, NUE)], 1) \tag{1}$$

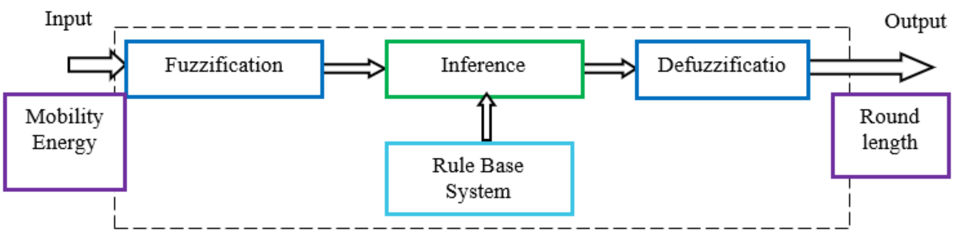

Figure 2. FLS of RCAD

Each and every node is updated of $LR_{max,}$ and the maximum LR value node is chosen as a CH.The fuzzy set reports the NUE input variables are very low, low, middle, enough, and high. Additionally, the fuzzy set mobility input variables are near, enough, and far away. The fuzzy set input is NM and NUE, and LR is the output factor variables are very high, high, middle, small, and very small.

Table 1. Fuzzy mapping rules

Node mobility	Node utilized energy	Length of round
near	Very low	Very high
near	low	high
near	middle	middle
near	high	small
enough	Very low	Very high
enough	low	high
enough	middle	middle
enough	high	small
far away	Very low	small
far away	low	small
far away	enough	Very small
far away	high	Very small

In this approach, heuristic data are functional for the dissemination of predefined fuzzy rules along with the below rules: a mobile node with the smallest node and minimum energy utilization node makes a higher LR. Table 1 illustrates the fuzzy mapping rules. The defuzzification process provides a single crisp number. The defuzzification of FIS has been attained through the center of area (CoA) method.

2.2. Data gathering

After selecting CH, then execute the aggregation function based on the QL procedure. QL is a type of machine learning that handles the issue of node mobility and decides optimal performance to attain its goals by the learning of QoS parameters and its communications. The QL goal is to enhance the reward of an agent through actions in reply to a MANET. Here, every mobile node acts as an agent, and it can formulate definite results and discover a possible path for arriving at any association. The agent selection of route result is applied to reward or penalize the related routing decision of the routing approach. So that better decisions are chosen through rewards (RDs) and worst decisions are rejected through the penalty.

QL can solve the static routing issues since it can capture the movement situation proficiently. The action at every mobile node is the chosen of the forwarder node for transmitting the information to the receiver node. QL is utilized to receive the optimal action-selection procedure applying a Q value (QV). The QV denotes the action of future reward. We monitored the routing approach's decisions, in which better results are chosen through RD, and worst decisions are rejected through the penalty. While we require to initiate a route and the receiver is not the sender node's vicinity, the node will discover for its route table as well as QoS state tables initially. Here S represents the States, and A represents the action. With executing agent transmission from one to another to learn the environment. The decision to choose one of the given state's actions is to enhance the RDs of weight that comprise present and future RDs.

In traditional routing approaches, managing and observing the network by the centralized controller acts as an agent as a result, which increases both the cost expensive and the routing overhead and can create complexity to identify the status of MANET. But the proposed approach does not have a present central agent; every mobile node acts as an agent, and they cooperatively share the information among neighbor nodes to make sure that every mobile node identifies the behavior of state transmission. The proposed approach element as follows {S, A, RD, P}. Here, S denotes the state, A denotes the Action, R denotes the reward, and P represents the possibility of communication. Let present state represents the s_l, next state denotes the s_m, and the action of present state represents the neighbor node list. We assume t denotes the waiting time for aggregated information is forward to choose the next neighbor node. Let N represents the mobile nodes count, and NL represents the list of neighbor nodes. The states and actions are defined as follows.

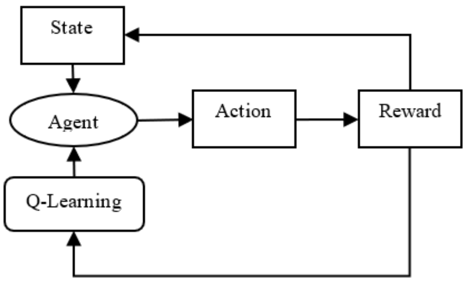

Figure 3. State diagram of RCAD

In QL, the value of the QV-table assists in discovering the greatest action for every state, in that the function of action value Q(s, a) gives the RDs of present and upcoming while action a is executed at state s. We believe that the agent chooses an action an in s, finds RD and goes into new state s'. Next, the QV, Q(s, a) is reorganized as follows:

$$QV(s,a) - (1-\lambda)QV(s,a) + \lambda\{RD + \beta . QV(s',a)\} \quad (2)$$

here, λ denotes the rate of learning and β describes the future RD discount factor.Figure 3, illustrates the states and actions of the RCAD approach. Assume the action denotes the aggregated information is forward to the present state to next state, the RD is specified to the present state *s*; the action of QV-table for state *s*is adapted. However, the present state *s*does not have the QV-table of the next state to update its Q-table. It denotes the efficiency of data aggregation and improves QoS energy at the following node selection; moreover, it is calculated at the next state. Hence, while the next node replies acknowledge the aggregated information to the sender, it also admits its maximum Q-values and calculated reward RD. Since the RD rule is used to decide a QL best solution. Here, we compute the RD by present bandwidth (PB), present energy (PE), present packet delivery (PDD), and hop count (HC) from sender to receiver. We compute the RD value is given:

$$RD = \beta^{HC} \times (PB + PE + PDD) \tag{3}$$

here, the additional discount factor is applied to the nodes reward that is required to avoid back warding. When the next state node's present energy is moderately large, and the distance between the present and the next state nodes is small, it minimizes the energy utilization in the network. Discount factors range between 0 to 1.

3. SIMULATION ANALYSIS

The simulations are utilized to compare RCAD with VNACO, and LBCI approaches. Our simulation tool is established on network simulator-2.35. We used the NS2 simulator to perform the simulation of the presented clustering technique. We also used random waypoint mobility to create the RCAD scenario and the traffic flow. Here, using 5 m/s to 25 m/s mobility.

It illustrates the number of packets successfully delivered by the destination node. The ratio of packets delivery is greater in the RCAD approach equated to the LBCI and VNACOapproaches, as explained in Figure 4. Owing to Q-learning-based data aggregation is minimized, the highest losses of packet hence raise the packet delivery.

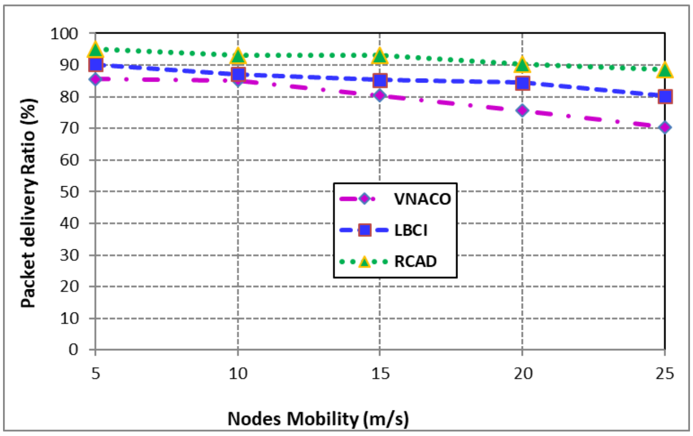

Figure 4. Packet delivery ratio of VNACO, LBCI, and RCAD based on node mobility

In the RCAD approach, the packet losses ratio is lower than the LBCI, and VNACO approaches are illustrated in Figure 5. LBCI and VNACO approaches have the greatest packet losses in the MANET since these approaches are increasing energy consumption. However, RCAD forms the clusters by node RSS and data forwarder by Q-learning method, thus minimizing the MANET packet losses.

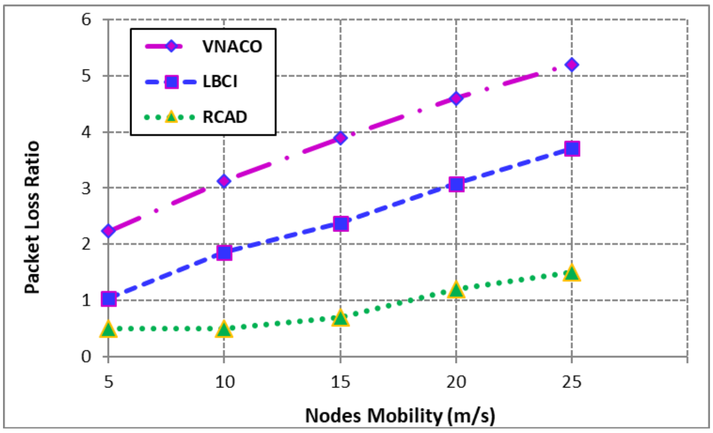

Figure 5. Packet loss ratio of VNACO, LBCI, and RCAD based on node mobility

Figure 6 demonstrates the comparison of CH lifetime for VNACO, LBCI, and RCAD in various mobile velocities. As node mobility raises, the CH lifetime of VNACO, LBCI, and RCAD will drop down. This represents that the necessary QoS is not the definite owing breaking of the route; otherwise, nodes move to other locations. Although, RCAD approach CH present the lifetime is 700 to 650 seconds. But, VNACO and LBCI approach lifetime is below 500 to 425 seconds.

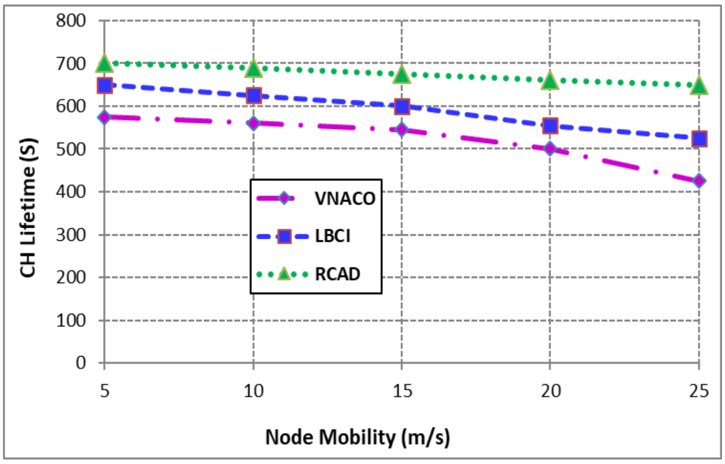

Figure 6. CH lifetime of VNACO, LBCI, and RCAD based on node mobility

Figure 7 demonstrates that the Cluster Rounds of VNACO, LBCI, and RCAD are based on node count. From this figure, the count raises the cluster round also raised. From this figure, the RCAD raises the cluster rounds compared to the LBCI and VNACO approaches since the RCAD approach chooses the CH by the round length. This round length is computed by the node mobility with minimum utilized energy. As a result, increases the CH rounds in the MANET.

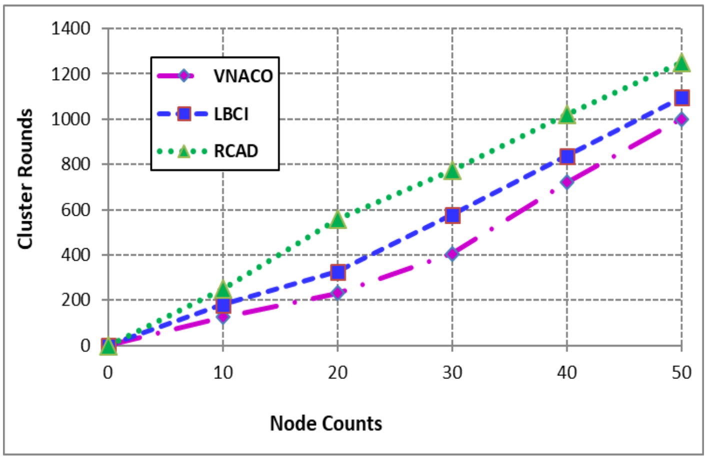

Figure 7. Cluster rounds of VNACO, LBCI, and RCAD based on node count

Figure 8 indicates the remaining energy of VNACO, LBCI, and RCAD based on node mobility. The figure illustrates that the remaining energy of the VNACO approach is very low compared to the RCAD and LBCI approaches. The RCAD approach is to select the CH based on node utilized energy. As a result, minimizing the CH dead issues in the network. LBCI approach also increases the energy consumption than the RCAD approach.

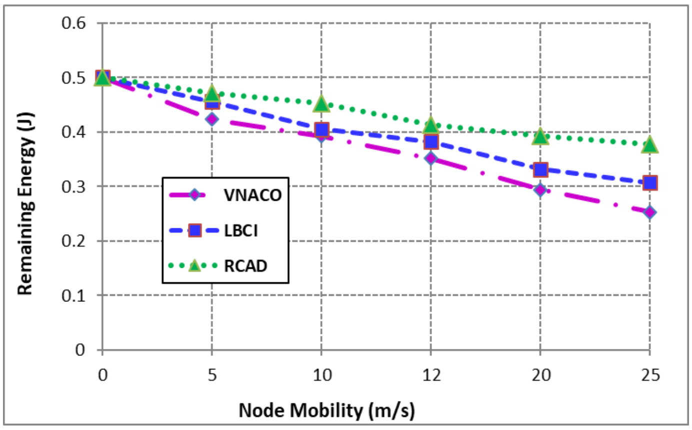

Figure 8. Remaining energy of VNACO, LBCI, and RCAD based on node mobility

4. CONCLUSION

This paper presents the RSSI-based clustering and aggregating data using Q-learning. In this approach, network nodes are categorized as the RSSI to form the clusters. Node utilized energy and node mobility parameters to measure the length of the round. This length of the round is evaluated by the fuzzy fitness function. The Q-learning method is used for aggregating data from sender to receiver. Q-learning's goal is to improve the reward of an agent through actions in reply to a MANET. In this approach, the mobile nodes can find an optimum next-hop node utilizing their QV established on the RDs. This RD is computed by bandwidth, energy, packet delivery, and hop count to select the efficient data aggregator. Experimental results illustrate that the RCAD approach increases the network remaining energy and ratio of packet delivery. Furthermore, it enhances both the lifetime and the CH round in the MANET.

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