International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Ingénierie des Systèmes d'Information
Vol. 29, No. 6, December, 2024, pp. 2391-2398
Journal homepage: http://iieta.org/journals/isi

Adaptive Rendezvous Based Congestion Control Using Optimized Bio-Inspired Algorithm for Clustered WSN

R. Anto Pravin[1*], X. S. Asha Shiny[2], V. Baby Vennila[3], S. Ramasamy[4], R. Uma Mageswari[1], S. Satish Kumar[5]

[1] Department of Computer Science and Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai 600062, India
[2] Department of Information Technology, CMR Engineering College, Hyderabad 501401, India
[3] Department of Information Technology, SSM College of Engineering, Namakkal 637209, India
[4] Department of Computer Science and Engineering, Hindusthan Institute of Technology, Coimbatore 641032, India
[5] Department of Electrical and Electronics Engineering, AMET University, Chennai 603112, India

Corresponding Author Email: antovpravin@gmail.com

https://doi.org/10.18280/isi.290626

Received: 29 December 2022
Revised: 9 February 2023
Accepted: 30 May 2024
Available online: 25 December 2024

Keywords:
ant colony optimization, clustering, congestion control, rendezvous, reinforcement learning

ABSTRACT

In Wireless Sensor Networks (WSNs), congestion control is essential for ensuring effective data transfer and extending the network's lifetime. When combining Reinforcement learning with Ant Colony Optimization (ACO) for congestion control in clustered WSNs, the strategy usually makes use of both methods' advantages to improve data routing and control traffic load. This research presents a novel approach named Adaptive Rendezvous based Congestion Control (ARCC) for congestion control by selecting the rendezvous nodes as Cluster Head (CH) using ACO integrated with Reinforcement learning model. By optimizing energy consumption, lowering congestion, and enhancing data transmission dependability overall, the proposed strategy aims to improve network performance.

1. INTRODUCTION

Wireless sensor networks are self-managed infrastructure which is comprised with multi-distributed sensor nodes that autonomously monitor environmental parameters like temperature and humidity or it also helps in identifying the motion of movable targets alike wildlife or the expansion of wild fire [1, 2]. Nodes in these networks are defined by their intrinsic constraints with respect to energy availability, processing capacity, and communication capabilities. Consequently, as energy efficiency has a direct impact on communication performance and the network's total lifespan, it is an essential component of routing algorithms in WSNs. The optimization of these algorithms remains a focus of active research in order to guarantee reliable and sustainable network operation in various applications.

Inspired by swarm intelligence, the Ant Colony Optimizer (ACO) [3] simulates the efficient, self-organized, and decentralized path-finding behavior of ant colonies. Using these features to find the best routes from source to destination nodes is the fundamental idea behind the ACO routing protocol [4]. ACO is especially useful for complicated routing problems in distributed environments because it allows dynamic adaptation to changing network conditions by emulating the pheromone trails that ants naturally use to communicate. This method improves route optimization while also improving the network's resilience and scalability [5].

Based on historical and real-time data, machine learning models can be integrated into the ACO framework to forecast network circumstances, such as traffic congestion, node failures, or energy depletion. Because of these forecasts, ACO can more quickly adapt its routing strategies to changing network conditions.

Objectives: To implement a congestion control strategy that focuses on the strategic selection of rendezvous nodes as CHs using ACO, enhanced by machine learning for better decision-making. The rendezvous nodes, selected based on their potential to balance traffic load and energy efficiency, play a crucial role in reducing congestion and improving network performance.

2. RELATED WORKS

Recent years have brought about the implementation of a number of bio-inspired based routing optimization algorithms to address the main issues with energy supply, computational capacity, and wireless connectivity that plague WSNs. Below is a discussion of a few of them for reference purposes. This method uses an optimized routing algorithm on ant colonies with neighborhood queries to find the optimal paths. The ACO technique was introduced for data aggregation-based optimal route discovery [6]. Here once the network topology was defined, the sink nodes utilize ACO to determine the optimal path, which the sensors then use to communicate with one another. However, this approach requires one to have a prior awareness of the entire network topology. ACO was used to build a multicast data routing system to generate transmission channels for nodes located in different places. Using a load dispersal technique, many paths sub-trees were initially established in order to stop growing load intensity. Subsequently, the appropriate pheromone update technique was employed to preserve the previously effective paths, and eventually, the heuristic factor was employed to transfer traffic load to paths with reduced traffic loads in order to remove the unsuccessful paths.

An additional heuristic function which provides optimal solution for the problem was taken into consideration for the improved ACO routing algorithm [7]. The range of communication and the leftover energy are considered for identifying the optimal data transmission mode [8]. A technique for WSN routing was implemented that can be more efficient based on the needs of path length, latency, and remaining node energy. Based on the mobile sink model, a Robust Reinforcement Q-Learning Approach (RRQLA) was proposed as a dynamic routing strategy for effective data collecting. Here, the Q-Learning technique was used to create an autonomous learning process for relay node selection based on shortest path. The learning algorithms effectively maintain the network system's stability while simultaneously enhancing its performance and producing optimal benefits [9].

An RL-based routing technique for WSNs was introduced. This algorithm builds routes dynamically by considering the network's real-time status. Through the careful selection of reward functions, this approach facilitates the development of optimal routes with the goal of minimizing transmission delay and improving dependability [10]. Recognizing the essential function of reward functions, this research proposes three consistent reward functions to efficiently calculate the Q-value.

In WSNs, mobility was introduced for mobile information gathering [11] and it can be called as tour management technique. Here, the data collection tour is periodically launched by the M-collector from the dynamic data sink. It then queries each sensor, gathering data automatically and sending it to the static sink. The mobile sink traverses the networks' divided, size-regular segments to collect data in an energy-balanced way [12]. In order to minimize the time required for both sink shifting and sensor data uploading, the Multi-hop Weighted Revenue (MWR) approach [13] was proposed. On the other hand, MWR has a large computational complexity of O (n4).

Division and Rule agreeing ACO (DRACO) as a rendezvous fortitude method was proposed for the collection of information for dispersed WSNs with dynamic edge nodes. The goals of this protocol are to minimize the path length and achieve a full communication system [14]. It is specifically designed for partitioned networks, which are significantly more complex than standard circumstances. Path generation technologies are used for streamlining the data transfer procedure.

The Energy efficient load Balancing Ant-based Routing method (EBAR) was developed for WSNs. EBAR incorporates a pseudo-random route discovery process and an enhanced pheromone trail update mechanism to distribute energy consumption more evenly across sensor nodes. It improves the efficiency of heuristic update approach that optimizes route creation using a greedy expected energy cost metric. Additionally, to minimize the energy expenditure due to control overhead, EBAR implements an energy-based opportunistic broadcast strategy [15].

The Transmission with Multiple Load Balancing Scheme (TMLBS) uses ant colony optimization to build transmission paths for nodes in various locations. It features three key load balancing strategies such as load decentralization, which creates multiple sub-trees to distribute traffic and prevent overload; load maintenance, which retains optimal paths through pheromone updates; and load diversion, which redirects traffic to less congested paths using heuristic factors for improved performance [16].

Multiple sink Load Balancing Mechanism (MLBM) for WSN was proposed which adaptively distributes network traffic across multiple sinks based on their real-time load. By preventing any sink from becoming overloaded, this mechanism reduces the risk of early battery depletion and unexpected network shutdowns [17]. Energy Efficient Secured CH Clustered Routing (E^2SCR) was proposed for WSN based Smart Dust tactic. A smart dust node is selected as the cluster head when it has excess energy, a superior communication range, and low mobility. The Energy Responsive (ER) selection method and the Maximal Nodal Superfluous Energy assessment method are integrated with this approach to optimize energy efficiency during routing. [18]. Power consumption and network longevity are two issues that Underwater Wireless Sensor Networks (UWSNs) must deal with. Cooperative protocols named Co-operative Energy Efficient Routing (CEER) and co-UWSN have been offered as solutions to this method [19].

Cluster Energy Hop-based Dynamic Route Selection (CEH-DRS), a dynamic route selection protocol for mobile wireless sensor networks was introduced. CEH-DRS optimize route selection based on production zones, improving cluster selection and overall network performance. Soft computing approaches are found to be more effective in accurately detecting and selecting optimal paths [20]. Connection Quality based Energy Efficient Routing (CQE2R) protocol enhances connection reliability by estimating link quality and utilizes energy and link data for route planning and node selection. This approach effectively reduces packet loss, improves packet delivery ratio, and minimizes delay in packet transmission [21].

Most of the previously mentioned algorithms primarily emphasize path length and residual energy, often overlooking other critical aspects of energy management, such as average energy, minimum energy thresholds, network lifetime, and task scheduling overheads. This neglect can lead to an imbalance in the network's overall energy depletion.

The relevance of this study is rooted in the identified limitation of existing research, where energy efficiency has been a primary concern, potentially neglecting other vital aspects of wireless sensor networks. The proposed Adaptive Rendezvous based Congestion Control (ARCC) mechanism explicitly addresses this gap by prioritizing network structural design elements such as rendezvous locations and route segmentation. This emphasis on congestion awareness becomes crucial for applications demanding not only energy efficiency but also reduced delays and effective congestion control.

3. CONGESTION AWARE CLUSTERING MODEL

In this proposed work, Adaptive Rendezvous based Congestion Control method is proposed based on ACO which is integrated with machine learning model. This mechanism includes the selection of Cluster Leads (Ls) using rendezvous points within each cluster, with a strong emphasis on reducing congestion during data transmission. It also involves identifying the optimal route by utilizing an ACO integrated with a Reinforcement Learning (RL) model, followed by efficient data transmission. ACO algorithm integrated with machine learning is proposed to predict potential congestion points and energy depletion.

In addition, the machine learning part supports in dynamically modifying the exploration-exploitation balance and pheromone evaporation rates of the ACO, maintaining the algorithm's efficacy in a range of network settings. The system model for the proposed ARCC mechanism is shown in Figure 1. The WSN is divided into clusters, with each cluster containing multiple sensor nodes and one CL. The selection of CLs is crucial since CL handles most of the data aggregation and transmission tasks.

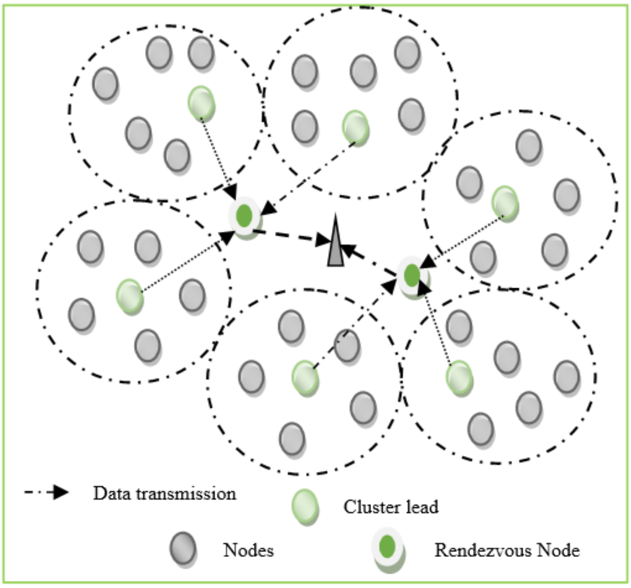

Figure 1. ARCC system model

The ACO algorithm is typically used to identify the shortest path between the sender (source node) and the sink (destination node). The source node (nest) broadcasts route request (RRq) control packets, representing pheromone intensity, to find the most efficient available path towards the destination node (food). The pheromones left by the ants (indicating signal strength) evaporate over time based on their intensity level, which correlates with the path availability time. Each node maintains a routing table, and when a node requires data, it sends RRq packets containing node IDs, relay node count, energy levels, and link availability time. This information is crucial for selecting the best and most optimal route for future transmission requests toward the receiving node. The intermediate nodes or count of intermediate hops is used to determine path length in a WSN. Suppose ‘x’ is the source node within a cluster, and ‘y’ is the receiving node, specifically the Rendezvous Mobile Node (R_{MN}). In that case, the probability of finding an optimal path is calculated based on the factors like Received signal strength (R_{SS}), intermediate relay count and leftover energy levels of the node.

Through the mechanism of RL integrated ACO algorithm the path is constructed between source and destination points, which generate ‘n’ possible solutions through an iterative process. Among these, the most efficient solution is selected as the optimal route. Further, reinforcement learning is integrated with ACO.

The RL model evaluates the routes discovered by the ACO based on criteria like energy consumption, latency, and data packet delivery success. Successful paths are reinforced with positive rewards, encouraging their selection in the future, while less efficient paths are neglected. Therefore, the combined approach allows the network to dynamically adjust routing strategies in response to real-time changes, such as node failures or fluctuating energy levels. The connectivity between the nodes is determined for successful communication. The nodes initiate the communication by using Route Request (RRq) and Route Reply (RRp) messages. Eq. (1) is used for calculating the maximum available link duration of the discarded RRq.

The channel link quality (L_A) that exists between source (S_i) and destination (D_i) points is determined through the Eq. (1),

$$(L_A) = \sum\{\varphi_{Si,Di} + (2\pi r_q . I_o^2)\} \tag{1}$$

Here the term ‘$2\pi r_q(I_o)$’ indicates the received power signal. Eq. (2) is therefore used to calculate the communication quality probability for accessible linkage with the optimal route length.

$$P_{Si,Di} = \frac{\phi_{SiDi}{}^{\alpha i} \cdot \mu_{SiDi}{}^{\beta i}}{\sum CQ(L_A)} \tag{2}$$

where, μ_{ij}→ successive RRq; $\varphi_{Si,Di}$→(1/route length(S_i, D_i))→ route length(S_i, D_i) denotes the path length among source and destination nodes S_i and D_i; αi and βi → analytical aspects to determine the time period of link availability.

3.1 Determining rendezvous cluster points

To reduce the consumption of energy through the network, data transfer is carried out using the most effective cluster lead node among the clustered nodes. Cluster lead nodes are those that have greater residual energy and a stronger R_{SS} compared to the rendezvous node. As a result, determining each group node's energy level and selecting the one with the highest R_{SS} comprises the CL selection procedure. To make sure the best CL node is chosen, the cluster's nodes' current energy levels are frequently evaluated.

High leftover energy (LE) nodes are chosen by considering how much energy they used in earlier transmissions. Selection of higher LE nodes is essential to maintaining dependable network connectivity. Low-energy nodes are essentially kept out of the routing process by setting and upholding a threshold that gives priority to higher-energy nodes throughout the network. As stated in Eq. (3), the energy spent rate (E_{Spent}), which determines nodes with high residual energy, is determined by taking the difference between the previous energy level (E_P) and the current energy level (Ec) at the current time. Hence this strategy not only improves the network's overall efficiency but also its stability and performance.

$$E_{Spent} = \left(\frac{E_P - \mathrm{E}_C}{\mathrm{C}_{\mathrm{time}}}\right) \tag{3}$$

The average of the total energy that comprises each node "n" at any given moment is used to determine the threshold energy level, or "E_T." Consequently, Eq. (4) is used to calculate the average energy present rate in order to estimate E_T.

$$E_T = Avg\left(E_{Spent}\right) \forall n \tag{4}$$

The term R_{SS} refers to the range of frequencies at which the signal can propagate between nodes. An effective communication range, also known as a propagation range, is the range at which nodes may interact with one another. Communication quality is determined using this R_{SS}.

The transmission power of a node is determined by its distance from another node and by using R_{SS}. By calculating the R_{SS}, the nodes' communication quality can be evaluated. In order to choose the highest R_{SS} (n), the average R_{SS} (Avg_R_{SS}) is determined. As a result, high energy leftover and high R_{SS} (n) are selected as CL_{node}. Eq. (5) is used to calculate the average R_{SS} (Avg_(R_{SS})) for each node in the cluster.

$$Avg\_R_{SS} = \pi r^2 S = \frac{\sum_{i=1}^{n} R_{SS}}{n}(RRq(n)) \tag{5}$$

The average Th_{RSS} is used to calculate the R_{SS} threshold point. The distance between the nodes determines the variation in transmission power between them. The "Si" node transmits RRq up to its determined range of communication, and the calculated point of threshold is used to measure the R_{SS} of the RRq that are received. The received RRq is processed if the RRq from 'Si' is superior to the Avg_R_{SS}; else, the received RRq is dropped. In order to choose the rendezvous CL node which moves towards the BS, the maximum range of RS2 is computed. The proposed ARCC scheme's flow diagram is displayed in Figure 2.

3.2 Data routing

To prevent congestion during data transmission in a WSN, the transmission path is divided into two segments: from the CL node to the rendezvous node, and from the rendezvous node to the BS. CL nodes are selected based on those with the maximum Receiving Signal Strength (max_R_{SS}), ensuring that the transmission power of overall network is minimized for each communication request. The routing process involves selecting the path with the minimum number of hop-counts by sequencing CL nodes until the nearest rendezvous node is identified and connected to the BS. The average of the maximum R_{SS} values is evaluated for locating the nearest rendezvous node relative to the cluster holding the data for transmission to the BS, as described in Eq. (6).

The average of the maximum R_{SS} is considered to identify the nearest rendezvous node within the cluster that holds the data to be transmitted to the BS.

$$Avg\{Max(R_{SS})\} = \frac{\sum_{i=1}^{Mx(n)} Mx\,(Ag\_RS2_i)}{n} \tag{6}$$

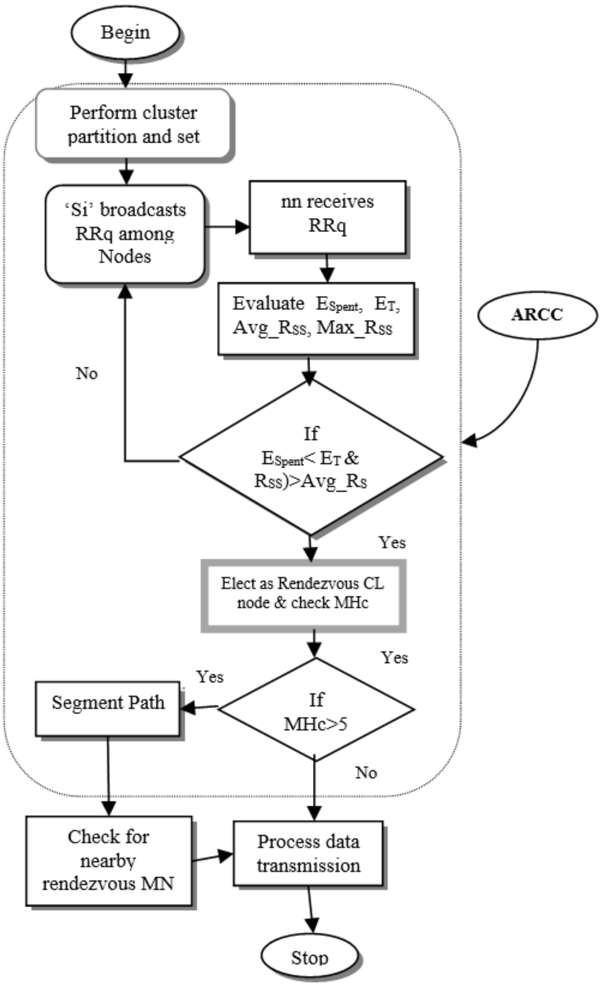

Figure 2. Flow diagram of ARCC

The pheromone concentration along the travelled route is updated in relation to the minimal hop count (M_{HC}) once the ant completes its journey from the Source node (S_i), to destination point (D_i) the data transmission process is done through rendezvous cluster lead node, as described in Eq. (7).

$$P_{Si,Di}(t+1) = \{(1-\rho)P_{Si,Di}(t+1)\} + \Delta P_{Si,Di}(t) \quad (7)$$

The value of pheromone intensity is eventually updated after each and every data transmission from the S_i to the BS. The transmission path is divided into segments: from the source node within a cluster to a nearby rendezvous cluster lead node, and from rendezvous cluster lead node to the BS. This segmentation helps in managing the routing process more efficiently.

Table 1. Algorithm for SRCC

```
Begin
Create the network
Form clusters by grouping the nodes;
For each nn (current_ node) do {
      Broadcast RRq to its nn
      Estimate CL metrics E_Spent & R_SS
If
E_Spent<E_T; R_SS>Avg_R_SS(n)
        Elect CL node
Then
Pick Min_Hop_count
Process data transmission
If
BS is far from CL then do
      Segment the Path
Compute Mx (Avg_R_SS) CL
Choose nearest rendezvous CL node moves towards BS
Identify the best path & proceed data transmission (S_i, D_i)
End
```

As the pheromone values are updated, RL models dynamically adjust the parameters based on real-time network conditions and past experiences. This allows the system to adaptively select the best Cluster Lead (CL) nodes and the nearest rendezvous nodes that provide the lowest MHc (minimum hop count) towards the BS, ensuring energy-efficient and reliable data transmission. Table 1 gives the algorithm of proposed ARCC model.

Finally, from the 'n' number of received RRp, the path with the highest pheromone concentration and the most favourable RL-predicted performance metrics is chosen. This combined approach of ACO with reinforcement learning not only ensures the selection of the optimal path but also continuously improves the decision-making process, enhancing the network's overall performance and adaptability to changing conditions.

4. RESULT ANALYSIS

The effectiveness of the proposed mechanism ARCC and the considered existing schemes MLBM, DRACO, and CQE2R are evaluated using the simulation tool called Network Simulator-2 (NS-2). NS-2 is an open-source simulation tool that uses Object oriented tool command Interface (OTcl) along with C++ for coding and simulation, making it highly versatile for network performance evaluation. The network consisting of 200 nodes distributed within a 1200m×1500m area was simulated to assess both the proposed ARCC and the existing techniques. The simulation analysis was conducted using the metrics such as, data delivery rate, transmission delay, control overhead, energy consumption rate and network lifetime. These metrics provide a comprehensive view of the network's performance, highlighting the strengths and weaknesses of each technique. The simulation results are used to determine how well the ARCC method improves network efficiency, reduces energy consumption, and enhances overall data transmission reliability compared to the other methods. Table 2 gives simulation parameters.

Table 2. Simulation parameters

Parameter	Value
Type of channel	Wireless medium
Simulation period	600 ms
Node count	200
Nodes placement	Random
MAC layer	IEEE 802.11
Traffic model	Constant Bit Rate
Transmission range	250m
Interface type	WirelessPhy
Radio propagation model	TwoRayGround

4.1 Packet Delivery Rate

The Data or Packet Delivery Rate (PDR) is a metric that measures the rate at which data packets are successfully delivered to their intended destination, as determined by the Constant Bit Rate (CBR) sources. This metric is crucial in evaluating the efficiency of a network, and reflects the efficiency of system's data transmission.

In order to calculate the PDR, the total number of correctly transmitted data packets is measured over a given period (T), and this value is analyzed in relation to the number of network nodes (n). The PDR is typically expressed as a percentage, where a higher PDR indicates better network performance and reliability. The formula used to compute the PDR is provided in Eq. (8), which takes into account the time and the number of nodes in the network.

$$PDR = \frac{\sum_0^n Pkts\_Delivered}{T} \quad (8)$$

The data packets that are successfully delivered to the receiver for both the proposed ARCC and the conventional schemes such as MLBM, DRACO and CQE2R are illustrated in Figure 3.

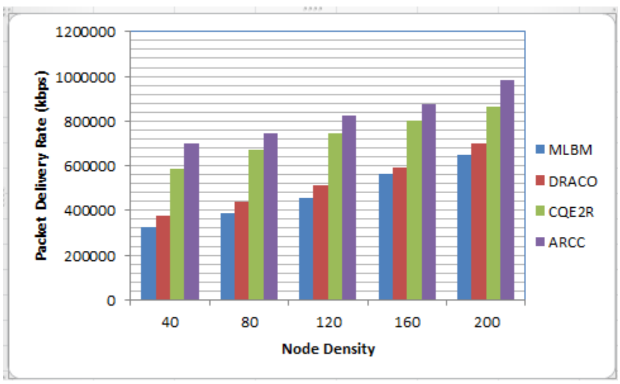

Figure 3. Packet Delivery Rate

From the analysis it is proved that the proposed ARCC achieves higher delivery rates of packets when compared to conventional schemas MLBM, DRACO, and CQE2R which can also lead to improve the performance of the network.

4.2 Data transmission delay

Transmission delay refers to the total time it takes for a data packet to travel from one node to another in a network, including any queuing delay that occurs at intermediate nodes. This metric is crucial for assessing the efficiency and effectiveness of the proposed system's routing strategy, as it directly impacts the speed and reliability of data transmission within the network.

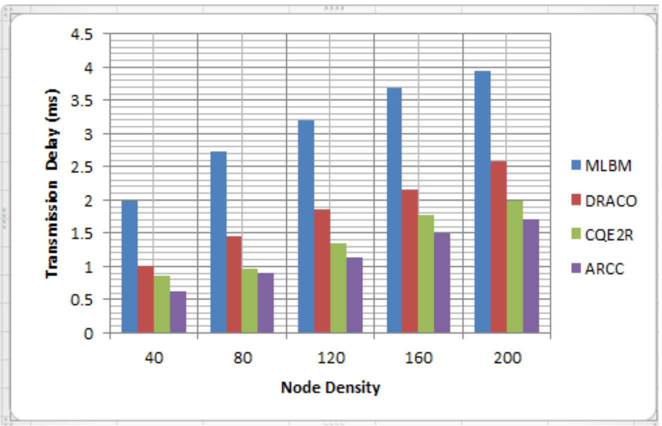

Figure 4. Average transmission delay

A lower transmission delay indicates a more efficient routing process, as data packets are delivered more quickly and with fewer interruptions. Eq. (9) is used to describe the delays during data transmission, with "n" representing the number of nodes in the network. This equation helps quantify the delay, providing a clear measure of the system's ability to handle data packets promptly.

$$Delay = \frac{\sum_0^n Pkt\ recvd\ time - Pkt\ send\ time}{n} \quad (9)$$

The average data transfer time for the proposed ARCC and conventional schemes are shown in Figure 4 according to the node density (number of nodes). When the proposed technique is compared to traditional methods like MLBM, DRACO, and CQE2R, it results in a decreased transmission delay for data transit time.

4.3 Control overhead

Minimizing the transmission of unnecessary control messages can significantly reduce data congestion and energy consumption within the network. By implementing a route segmentation strategy combined with rendezvous CL mobile nodes, cluster heads can transmit data more efficiently, effectively reducing congestion during the transmission of control packets. Consequently, the proposed method lowers route scheduling costs when an increasing number of active nodes participate in the routing process.

The control overheads during transmission are illustrated in Figure 5 for the proposed ARCC method in comparison with existing schemes such as MLBM, DRACO, and CQE2R. The proposed ARCC scheme demonstrates lower control packet overheads compared to these existing methods. This reduction in overhead is largely due to the ARCC's ability to effectively minimize the congestion rate within the network.

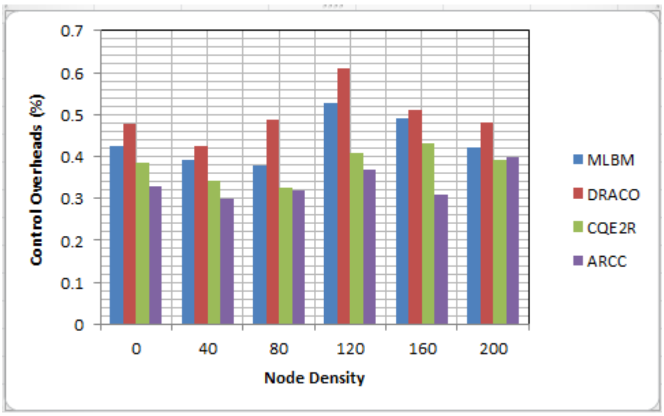

Figure 5. Control packet overheads

4.4 Network lifespan

The network lifespan can be defined from various perspectives, such as the number of nodes that remain operational, the percentage of active nodes, the time until the network can no longer maintain a functional backbone, or the percentage of nodes which is connected to the rendezvous cluster, among others. However, the most commonly used definition refers to the time until the first node in the network depletes its energy. This measure is often represented by the optimal number of network communication rounds completed before any node runs out of energy.

The network lifespan analysis for the proposed ARCC method in comparison to conventional schemes such as MLBM, DRACO, and CQE2R is shown in Figure 6. The proposed ARCC scheme demonstrates a significantly improved overall system lifetime compared to the existing methods. This enhancement is attributed to ARCC's efficient energy management and optimized routing strategies, which help to prolong the operational duration of the network by delaying the exhaustion of node energy.

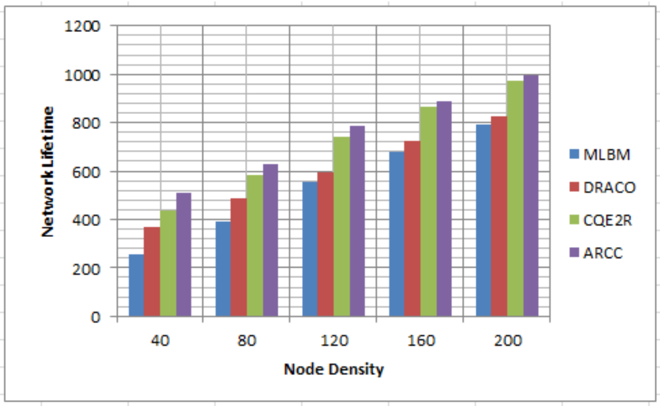

Figure 6. Lifespan of network

4.5 Energy consumption

Residual energy refers to the remaining energy in a node at a given time. The energy consumption of a node is computed by comparing the energy it has used to the total energy it originally had. This calculation helps in assessing the efficiency and longevity of the node within the network. Essentially, residual energy represents the difference between the initial energy level of the node and the energy expended during network operations. This metric is crucial for assessing the node's remaining operational capacity and for making decisions about routing and energy management within the network.

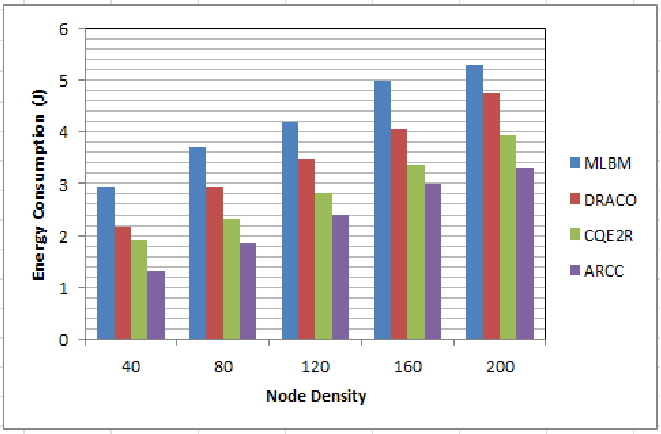

Figure 7. Consumption of energy

Figure 7 compares the average energy consumption of the proposed ARCC method with traditional methods such as MLBM, DRACO, and CQE2R. The results indicate that the proposed ARCC scheme consumes significantly less energy throughout the entire process compared to the existing schemes. This reduction in energy consumption is a key advantage of the ARCC method, as it enhances overall network efficiency and prolongs the network's operational lifetime.

5. CONCLUSIONS

The proposed ARCC mechanism is designed with a strong focus on optimizing the network's structural design by strategically locating the active rendezvous cluster lead nodes. It also implements route segmentation to control congestion and reduce unnecessary delays. The ARCC mechanism mainly operates in two key steps like it identifies the optimal route by leveraging an ACO integrated with a RL algorithm, ensuring effective data transmission through the rendezvous points within each cluster. This approach is particularly effective in minimizing congestion during data transmission. When comparing the efficiency of the ARCC scheme with the existing CQE2R approach, simulation results demonstrate a significant improvement, with the ARCC method achieving 28.4% increase in terms of PDR. This notable enhancement underscores the effectiveness of the ARCC mechanism in providing more reliable and efficient data transmission within complex network environments.

REFERENCES

[1] Deif, D.S., Gadallah, Y. (2017). An ant colony optimization approach for the deployment of reliable wireless sensor networks. IEEE Access, 5: 10744-10756. https://doi.org/10.1109/ACCESS.2017.2711484

[2] Kiruba, D.G., Benitha, J. (2022). Fuzzy based energy proficient secure clustered routing (FEPSRC) for IOT-MWSN. Journal of Intelligent & Fuzzy Systems, 43(6): 7633-7645. https://doi.org/10.3233/JIFS-212014

[3] Kar, A.K. (2016). Bio inspired computing—A review of algorithms and scope of applications. Expert Systems with Applications, 59: 20-32. https://doi.org/10.1016/j.eswa.2016.04.018

[4] Liu, X. (2017). Routing protocols based on ant colony optimization in wireless sensor networks: A survey. IEEE Access, 5: 26303-26317. https://doi.org/10.1109/ACCESS.2017.2769663

[5] Gui, T., Ma, C., Wang, F., Wilkins, D.E. (2016). Survey on swarm intelligence based routing protocols for wireless sensor networks: An extensive study. In IEEE International Conference on Industrial Technology (ICIT), Taipei, Taiwan, pp. 1944-1949. https://doi.org/10.1109/ICIT.2016.7475064

[6] Kiruba, D.G., Benita, J. (2021). Energy capable clustering method for extend the duration of IoT based mobile wireless sensor network with remote nodes. Energy Harvesting and Systems, 8(1): 55-61. https://doi.org/10.1515/ehs-2021-0006

[7] Sun, Y., Dong, W., Chen, Y. (2017). An improved routing algorithm based on ant colony optimization in wireless sensor networks. IEEE Communications Letters, 21(6): 1317-1320. https://doi.org/10.1109/LCOMM.2017.2672959

[8] Rajesh, D., Rajanna, G.S. (2022). CSCRT protocol with energy efficient secured CH clustering for smart dust network using quantum key distribution. International Journal of Safety and Security Engineering, 12(4): 441-448.

[9] Krishnan, M., Lim, Y., (2021). Reinforcement learning-based dynamic routing using mobile sink for data collection in WSNs and IoT applications. Journal of Network and Computer Applications, 194: 103223. https://doi.org/10.1016/j.jnca.2021.103223

[10] Prabhu, D., Alageswaran, R., Miruna Joe Amali, S., (2023). Multiple agent based reinforcement learning for energy efficient routing in WSN. Wireless Networks, 29(4): 1787-1797. https://doi.org/10.1007/s11276-022-03198-0

[11] Rajesh D. (2022). Energy-resourceful routing by fuzzy based secured CH clustering for smart dust. International Journal of Electrical and Electronics Research (IJEER), 10(3): 659-663. https://ijeer.forexjournal.co.in/archive/volume-10/ijeer-100340.html.

[12] Gharaei, N., Bakar, K.A., Hashim, S.Z.M., Pourasl, A.H. (2019). Inter-and intra-cluster movement of mobile sink algorithms for cluster-based networks to enhance the network lifetime. Ad Hoc Networks, 85: 60-70. https://doi.org/10.1016/j.adhoc.2018.10.020

[13] Rajesh, D., Jaya, T. (2021). ECIGC-MWSN: Energy capable information gathering in clustered secured CH based routing in MWSN. Materials Today: Proceedings, 43: 3457-3462. https://doi.org/10.1016/j.matpr.2020.09.100

[14] Liu, X.X., Qiu, T., Dai, B., Yang, L., Liu, A.F., Wang, J.T. (2020). Swarm intelligence-based rendezvous selection via edge computing for mobile sensor networks. IEEE Internet of Things Journal, 7(10): 9471-9480. https://doi.org/10.1109/JIOT.2020.2973401

[15] Li, X., Keegan, B., Mtenzi, F., Weise, T., Tan, M. (2019).

Energy-efficient load balancing ant based routing algorithm for wireless sensor networks. IEEE Access, 7: 113182-113196. https://doi.org/10.1109/ACCESS.2019.2934889

[16] Liu, X.X., Qiu, T., Wang, T. (2019). Load-balanced data dissemination for wireless sensor networks: A nature-inspired approach. IEEE Internet of Things Journal, 6(6): 9256-9265. https://doi.org/10.1109/JIOT.2019.2900763

[17] Onwuegbuzie, I.U., Abd-Razak, S., Al-Dhaqm, A. (2021). Multi-sink load-balancing mechanism for wireless sensor networks. In 2021 IEEE International Conference on Computing, Kuala Lumpur, Malaysia, pp. 140-145. https://doi.org/10.1109/ICOCO53166.2021.9673578

[18] Rajesh, D., Kiruba, D.G. (2022). Energy efficient secured CH clustered routing (E^2SCR) in smart dust network. Journal of Intelligent & Fuzzy Systems, 43(6): 8349-8357. https://doi.org/10.3233/JIFS-212012

[19] Shah, S.M., Sun, Z., Zaman, K., Hussain, A., Ullah, I., Ghadi, Y.Y., Khan, M.A., Nasimov, R. (2023). Advancements in neighboring-based energy-efficient routing protocol (NBEER) for underwater wireless sensor networks. Sensors, 23(13): 6025. https://doi.org/10.3390/s23136025

[20] Almuzaini, K.K., Joshi, S., Ojo, S., Aggarwal, M., Suman, P., Pareek, P.K., Shukla, P.K. (2023). Optimization of the operational state's routing for mobile wireless sensor networks. Wireless Networks, 30: 5247-5261. https://doi.org/10.1007/s11276-023-03246-3

[21] Shahid, M., Tariq, M., Iqbal, Z., Albarakati, H.M., Fatima, N., Khan, M.A., Shabaz, M. (2024). Link-quality based energy-efficient routing protocol for WSN in IoT. IEEE Transactions on Consumer Electronics, 70(1): 4645-4653. https://doi.org/10.1109/TCE.2024.3356195