Received: June 28, 2023. Revised: August 6, 2023.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Effective Routing Using Multi-Objective Levy flight- Artificial Rabbit Optimization Algorithm for Wireless Mesh Networks

Kamadenahalli Narayanaswamy Prema[1]* **Mandalur Basavarajappa Ushadevi[2]**

[1]*Electronics and Communication Engineering, JNN College of Engineering, Shivamogga, India*
[2]*Electronics and Telecommunication Engineering, JNN College of Engineering, Shivamogga, India*
* Corresponding author's Email: premakn@jnnce.ac.in

Abstract: Wireless mesh networks (WMNs) are familiar due to their unique characteristics such as adaptability, flexibility and less time for transmitting data packets. The routing technique acts a significant role in transmitting data among the nodes. Moreover, the routing technique is mainly responsible to improve the performance of WMNs with various applications. With the rapid development of various applications, energy, and distance are fundamental aspects which aid in next-level communication. But, recent research has not provided a clear idea of improving the transmission quality by offering an optimal route. These challenges are overwhelmed using the proposed multi-objective levy flight artificial rabbit optimization algorithm (ML-AROA) for energy and distance aware (EDA) route discovery. The proposed ML-AROA is an improvisation of the ARO algorithm where the Levy flight technique is implemented to create a random number in a regular manner which is characterized by the generation of arbitrary numbers and helps to jump out the local solutions. Moreover, the convergence accuracy gets enhanced by offering flexibility to detect an optimal route for the transmission of data packets. The results obtained from the experiment shows that the suggested ML-AROA attained better network throughput of 12×10^5 Kbps which is comparatively higher than load balance and interference avoid-partially overlapped channels assignment (LBIA-POCA) framework and multi-objective dyna Q based routing (MODQR) technique.

Keywords: Energy, Multi-objective levy flight artificial rabbit optimization, Routing, Transmission distance, Wireless mesh networks.

1. Introduction

WMNs have become an extensively used multi-hop wireless structure which is known for its less cost computation and high vulnerability [1,2]. Moreover, WMNs are self-configured and self-organized where the nodes generate a mesh connection among each other by an ad hoc network. WMNs are broadly utilized in various applications like transportation systems, broadband networks, and automation [3]. WMN is comprised of multi-radio routers and single-radio clients [4]. The mesh routers are generally static with multi-radio interfaces and the mesh clients consist of a single radio interface [5]. The WMN can create connectivity with both wired and wireless customers. The wired connections integrate the access points to mesh routers and the mesh router has the permission to reach every part of the nodes. Moreover, the router is responsible to handle the Inbound and outbound packets. Every individual packet of the router is stored in the input buffer and queued for the output buffer through queueing process [6, 7]. WMNs are employed with more routing protocols where each protocol is designated with its routing strategy and the protocols are classified into proactive, reactive and hybrid techniques [8].

The flexibility feature of WMN helps to construct a multi-hop route for wireless communication among smart appliances [9]. The multi-hop route is based on mesh topology which needs energy efficiency and reliability for routing. But, traffic from mobile clients to the gateway causes overload and leads to the degradation of smart appliances. So, introducing an improved routing technique is essential while routing over WMNs [10, 11]. Besides, the network necessitates effective routing to provide a quality guarantee for traffic flow. Moreover, the energy consumption for transmitting data is a major problem that is to be solved to improvise lifetime of the network. The placement of WMN leads to NP-hard problem which occurs due to the intractability of real-size instances. When the computational time grows exponentially, it leads to an increase in complex optimization problems [12, 13]. In recent years, more researchers have been developed to minimize the transmission distance and energy consumption. However, there is a need aroused for an optimization-based routing protocol to improve the throughput rate [14, 15]. By knowing the challenges in existing works, this research introduced an optimization based routing technique to attain energy efficiency with a minimum transmission path.

The major contributions of this research are listed as follows:

1. This research focused on building a multi-objective routing model using an optimization algorithm. The improvement is made in the artificial rabbit optimization technique by introducing the Levy flight strategy in a random hidden phase to enhance the convergence accuracy of the routing model.
2. The proposed research mainly focused on energy and transmission distance which is attained using ML-AROA. The detection of the optimal route with the shortest distance helps to achieve energy efficiency.

The rest of the manuscript is arranged as follows: Section 2 provides the related works and section 3 describes the proposed methodology. Section 4 presents the results obtained from the proposed technique and finally, section 5 presents the overall conclusion of this research.

2. Related works

Yang [16] have introduced a load balance and interference avoid-partially overlapped channels assignment (LBIA-POCA) framework in wireless mesh networks (WMN) to enhance the throughput of the network by managing the channels and interfaces. Initially, the interface of the neighboring nodes was assigned by Huffman tree based centralization algorithm. Then, the links were distributed into non-interface links in the scheduled time slot. The introduced LBIA-POCA can minimize the end-to-end delay and packet loss rate. However, LBIA-POCA was not suitable for multicast routing and channel assignment.

Singh [17] have developed an adaptive routing algorithm based on reinforcement learning in WMN which can minimize the delivery time and prohibit the congestion of the network. The adaptive routing algorithm was a combination of various derivatives of Q-routing and the reinforcement-based routing was utilized to reserve the Q-values using control messages. The adaptive algorithm updates the Q-value by using the decay constant variable and attains high mobility state. However, the Q-table consumes time to implement and reflect the network status.

Chai and Zeng [18] introduced a multi-objective dyna Q based routing (MODQR) technique to minimize the delay and energy performance. The MODQR minimize the delay, interference, asymmetrical conditions and the probable conditions for the transmission failure. This research utilized Dyna Q reinforcement algorithm which can effectively improvise the convergence speed and can overcome the problems related to route discovery in uncertain conditions. However, the least hop count node selected by using MODQR experienced maximum delay and heavy load.

Mahajan [19] have introduced a QL-feed forward routing (QFFR) algorithm that integrates reinforcement based on a Q-learning algorithm with feed-forward neural network. The QFFR can adapt to the network atmosphere and perform routing decisions. The introduced QFFR can perform effective routing and enhance the spanning size of the nodes. However, the architecture of the proposed QFFR was a stagnant structure that cannot be customized based on the requirements.

Lahsen-Cherif [20] have introduced a joint optimization scheme for energy consumption and throughput in wireless mesh networks (WMNs). At the initial stage, the joint optimization problem was formulated as a mixed integer linear problem (MILP) by utilizing weighted objective function. After, this Ant-Q learning approach was utilized to minimize the complexity and enhance the convergence. The routing scheme based on ant-Q algorithm was used to find an optimal path for transmitting power. However, the introduced optimization scheme doesn't consider channel quality.

Anita and Sasikumar [21] have introduced a multiple disjoint path determination (MDPD) scheme which was based on demand routing in WMN to articulate route discovery and latency at the time of transmitting data. The MDPD utilized queue dynamics while queuing delay that offers adaptability to the network and provides efficiency to optimize the network traffic. Moreover, the MDPD method

Received: June 28, 2023. Revised: August 6, 2023.

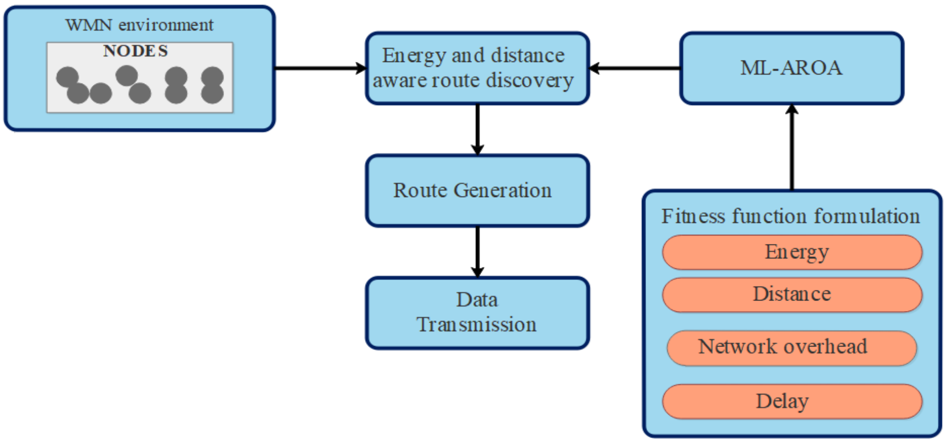

Figure. 1 Block diagram for ML-AROA based routing

effectively minimized the delay and overhead while providing broadband internet access, However, the MDPD consumed more time to discover multiple joint paths.

Pan Lu [22] have introduced a reliable routing algorithm which integrates breadth first search and graph neural network which was known as GraphSAGE. The suggested approach creates network labels which helps to evaluate the shortest routing path. The GraphSAGE-based optimization was effective for real time network and outsource better throughput. However, the suggested approach consumed more resource when the topology of the network becomes complex.

Overall, the existing methodologies faced problems related to time complexities which consume more time to detect the optimal path for routing. The poor routing path created by the existing approach affects the quality of the transmission channel which increase the delay time for transmitting the data packets from source to destination. The higher delay rate consumes energy to transmit the data and affects the overall performance. The proposed method was built by focusing on usage minimum distance and energy to transmit the data from the source node to the destination node. Generally, when the transmission distance becomes low then the energy consumption of nodes will also be minimized.

3. Ml-Aroa for eda routing

In this research, the energy and distance aware routing method is introduced by using multi-objective levy flight-artificial rabbits optimization algorithm (ML-AROA). The ML-AROA attained a better balance between the phases of exploration and exploitation to enhance the process of searching. The introduced ML-AROA minimized energy consumption by reducing the transmission path and reducing the time delay. Thus, the proposed ML-AROA achieved better efficiency while routing over the WMNs and the block diagram of the proposed ML-AROA for EDA routing is represented in Fig. 1

3.1 Network model

The WMNs are modeled as an undirected graph of $G(N_s, L_s)$ where, the node set which is comprised of routers, clients, and gateways is represented as N_s and the link of the wireless set among the mesh routers is denoted as L_s . The mesh routers are comprised of wireless interfaces to perform effective routing. To evaluate the route loss, a two-ray reflection model is utilized which considered small scale fading and receives the power at j^{th}node from i^{th}node which is represented in Eq. (1) as follows:

$$P_{ij} = P_{Ti} \times \frac{G_t G_r h_t^2 h_r^2 \delta_{ij}}{(d_{ij})^4} \tag{1}$$

Where the transmitted power of node i is represented as P_{Ti}, the gain that occurred at the time of transmitting and receiving is denoted as G_t and G_r respectively. The height of the transmitting and receiver antenna is denoted as h_t and h_r respectively. The small-scale fading and the distance among the node is denoted as δ_{ij} and d_{ij} respectively. When the transmission gets failed, the packets are retransmitted. Likewise, when more retransmission is extended, the data packet gets dropped. Energy and distance-aware routing is employed to achieve reliable communication among WMNs.

3.2 Overview of multi-objective levy-flight artificial rabbit optimization algorithm (ML-AROA)

The ARO algorithm is based on the survival strategy of the rabbits based on detour foraging and random hiding. Between the two strategies, detour foraging is an exploration phase where the rabbits safeguard themselves to prevent detection by their predators while eating the grass near their burrows. Random hiding is another technique of rabbits to hide in random burrows while invasion of predators. In every search algorithm, the initialization is considered as the foremost process, similarly in the ARO algorithm, the initialization is considered as the beginning stage. The process of initialization is performed based on the Eq. (2) as follows:

$$p_{i,k} = r.(ub_k - lb_k) + lb_{k,} k = 1,2,\ldots,d \tag{2}$$

Where the position of i th rabbit is represented as $p_{i,k}$ and the random number is denoted as r.

3.2.1. Exploration phase

During the exploration phase (i.e. detour foraging), every individual rabbit will move around in search of food and explore the location of another rabbit to get enough food. The process of detour foraging is mathematically represented in Eq. (3) as follows:

$$v_i(t+1) = p_j(t) + R.\left(p_i(t) - p_j(t)\right) + round\left(0.5 \times (0.05 + r_1)\right).n_1 \tag{3}$$

Where $R = l.c$ and the value of l are mathematically denoted in Eq. (4) as follows:

$$l = \left(e - e^{\left(\frac{t-1}{T_{max}}\right)^2}.\ sin\,(2\pi r_2)\right) \tag{4}$$

Where the updated position of the rabbit is denoted as $v_i(t+1)$ and the position of ith rabbit is denoted as p_i and the position of the rabbit in a randomized state is denoted as p_j. The maximum number of iterations is denoted as T_{max}, the ceiling function is represented as $[.]$ and the standardized normal function is represented as n_1.

3.2.2. Exploitation phase

Similarly, during the exploitation stage (i.e. Random hiding), the rabbit dug many burrow and randomly select the nest to safeguard themselves from their predators. The burrow j produced by the ith rabbit is mathematically represented in Eq. (5).

$$b_{i,j}(t) = p_i(t) + H.g.p_i(t) \tag{5}$$

Where $H = \frac{T_{max}-t+1}{T_{max}}.n_2$ and the value of n_2 lies among the range of (0,1). The hidden parameter which varies in a linear range is denoted as H and the standardized normal distribution is denoted as n_2.

The improved formula of the random hiding method is represented in Eq. (6) as follows:

$$v_i(t+1) = p_i(t) + R.\left(r_4.p_i(t) - p_i(t)\right) \tag{6}$$

Eqs. (7) and (8) mentioned below shows the mathematical representation of a randomly produced burrow by the rabbit to safeguard them from predators.

$$g_r(k) = \begin{cases} 1\ if\ k=[r_5.d], k=1,\ldots,d \\ 0 \quad\quad\quad\quad\quad\quad\quad\quad else \end{cases} \tag{7}$$

$$b_{i,r}(t) = p_i(t) + H.gr.p_i(t) \tag{8}$$

Where the updated position of the rabbit is represented as $v_i(t+1)$ and the randomly selected burrow is denoted as $b_{i,r}(t)$. The random numbers produced among the interval 0 to 1 is denoted as r_4 and r_5.

After these two enhancements, the position of the ith rabbit is renewed which is presented in Eq. (9) as follows:

$$p_i(t+1) = \begin{cases} p_i(t) if\ f(p_i(t)) \le f(v_i(t+1)) \\ v_i(t+1)\ else\ f((p_i(t)) > f(v_i(t+1)) \end{cases} \tag{9}$$

Eq. (9) presented above shows an adaptive update and the rabbit decides to change its position or stay in its current position based on the evaluated adaptive value. The energy of the rabbit is based on the time taken in the phase of exploration and exploitation. The energy factor of the rabbit is represented in Eq. (10) as follows:

$$A(t) = 4.(1 - \frac{t}{T_{max}}).ln\frac{1}{r} \tag{10}$$

Where the random number is denoted as r which lies among the range of (0,1).

However, the issues occur in the existing artificial rabbit optimization algorithm and lead to poor accuracy rate which affects the routing performance among WMNs. So, this research focused on the hybridization technique where the enhancement is made by the hybrid technique. To overcome the issues related to poor accuracy rate, this research proposed an enhanced Levy-flight Artificial Rabbit Optimization (ML-AROA) which can alleviate poor accuracy value. The levy flight used in this research can boost the accuracy of the optimization algorithms.

3.2.3. Levy flight technique

The Levy flight method is one of the significant techniques utilized in providing vitality to enhance the efficiency of the optimization algorithms. The Levy flight algorithm creates a random number in a regular manner which is characterized by the generation of arbitrary numbers and helps to jump out the local solutions. Eq. (11) denotes the Levy distribution function which is mentioned as follows:

$$Levy(t) \sim u = t^{-1-\gamma}, 0 < \gamma \leq 2 \quad (11)$$

Where the length of the step is denoted as t which is evaluated using the Eq. (12). Eqs. (13-16) presents the formulae to obtain a solution for step size.

$$t = \frac{u}{|v|^{1/\gamma}} \quad (12)$$

$$u \sim N(0, \sigma_u^2), v \sim N(0, \sigma_v^2) \quad (13)$$

$$\sigma_u = \left(\frac{\Gamma(1+\beta).sin\,(\pi.^{\beta}/_{2})}{\Gamma(1+\beta/2).\beta.2^{(\beta-1)/2)}} \right)^{1/\beta} \quad (14)$$

$$\sigma_v = 1 \quad (15)$$

Where u and v follow the Gaussian distribution function and the variance is denoted as σ_v^2, σ_u^2. The Gamma function is denoted as Γ and the parameter of the correlation is denoted as β.

The random numbers r_4 present in the random hiding phases are replaced using Levy flight strategy. The random hiding stage is the exploitation stage where the Levy flight technique was used to prohibit ARO fell in the local solution Moreover, the Levy flight technique helps to enhance the accuracy of convergence and offers flexibility at the phase of random hiding. The Eq. (16) presented below is the random hidden phase which is based on Levy flight strategy.

$$v_i(t+1) = p_i(t+1) \\ +R.\left(\alpha.levy(\beta).b_{i,r}(t) - p_i(t)\right), i = 1, \dots, N \quad (16)$$

3.3 Energy and distance-aware route discovery using ML-AROA

In this section, the process involved in routing using ML-AROA is described in detail. The energy-efficient and the shortest route is discovered to transmit the packets from the transmitter to the receiver using the ML-AROA. Moreover, the efficiency of ML-AROA in finding an optimal path in WMN is discussed.

3.3.1. Initialization

This is the foremost stage which is based on deploying the sensor nodes in WMN environment. The ML-AROA starts with initiating the individuals by making use of the probable route from transmitter to receiver. The dimension of every individual equals the total count of relay nodes that exists in the path of transmission. The individual is assigned i whose location $x_i = (x_{i,1}(t), x_{i,2}(t) \dots, x_{i,dim}(t))$ where the location of each individual (i.e. $x_{i,loc}, 1 \leq loc \leq dim$) denotes the successive node which is responsible for effective route discovery.

3.3.2. Multi-objective fitness function formulation

The optimal route using the proposed ML-AROA is selected by considering the fitness functions such as delay, residual energy, transmission distance and network overhead. The Eq. (17) is utilized in formulating the fitness function.

$$Fitness\ function = \beta_1 \times Delay + \beta_2 \times Energy \\ +\beta_3 \times Distance + \beta_4 \times Network\ overhead \quad (17)$$

Where $\beta_1, \beta_2, \beta_3$ and β_4 are the weighted parameters of fitness functions such as delay, energy, distance and network overhead respectively.

(i) Delay is one of the significant fitness parameters which is used to compute the transmission path of packets. When the delay is minimum, the routing will be effective and enhance the route discovery process. In WMNs, the delay is evaluated based on the transmitting the packets from transmitter to receiver and it is computed using the Eq. (18) as follows:

$$D = \sum_{\substack{ld=1 \\ i=1}}^{m^{id}} \frac{l^{id}}{AS_i^{ld}} \quad (18)$$

Where the average length of the path is denoted as l^{id}, the time duration is denoted as i and the total count of packets is denoted as AS_i^{ld}.

(ii) Energy is one of the challenging problems while discovering the optimal route for packet transmission. Based on the proposed methodology, the most essential factor in selecting the rote is energy. For nominating the effective route, the proposed method utilized the initial energy and residual energy of nodes. The energy ratio makes the process of detecting path energy-dependent. The node which has high residual energy has a great probability to conquest the process of discovering the route. The energy ratio is evaluated using the Eq. (19) as follows:

$$E = \sum_{i=1}^{N} \frac{E_0}{E_0 - s(i).E} \tag{19}$$

Where total nodes are represented as N, energy at the initial stage is denoted as E_o and the node's energy in its present state is represented as $s(i)$. When the energy ratio of the nodes gets minimized, it leads to a diminution of cost. The overall performance of the network gets reduced when the node with less energy is selected to find the optimal route.

(iii) Distance is utilized to compute the route with minimum transmission distance. When the transmission distance gets higher, the energy consumption of the nodes also gets increased. The distance among the node is denoted as minimum number of edges which is present in the route from one node to another. The distance is evaluated using the Eq. (20) as follows:

$$Distance = \frac{d(i,j)}{R} \tag{20}$$

Where distance among source i and destination j is denoted as $d(i,j)$, the distance between the radius of the neighborhood is denoted as R. The distance $d(i,j)$ is evaluated using the Eq. (21) as follows:

$$d(i,j) = \sqrt{\left(x_i - x_j\right)^2 - \left(y_i - y_j\right)^2} \tag{21}$$

Where the coordinate point of the nodes i and j are denoted as x_i, y_i and x_j, y_j correspondingly.

(iv) Network overhead is known as the total number of resources utilized by every individual node in WMNs. In other words, it is defined as the data utilized to send the payload inside the data packets and it is evaluated using the Eq. (22) as follows:

Table 1. Simulation parameters

Parameters	Values
Network topology	Random topology
Transmission range	250 m
Size of the data packet	512 Bytes
Physical transmission	2Mbps
Simulation time	1000 s

$$Network\ overhead = (header \times 100)/(payload - header) \tag{22}$$

The fore mentioned fitness parameters such as delay, residual energy, transmission distance and network overhead are utilized for detecting the optimal route with minimum energy consumption and shortest transmission distance in WMNs.

3.3.3. Iterative process in discovering the optimal route using ML-AROA

The transmission routes are initialized as individuals using ML-AROA which is upgraded based on two strategies such as detour foraging (exploration phase) and random hiding (exploitation phase) which is mentioned in Eqs. (3) and (6). After these two enhancements, the position of the i th node is renewed which is presented in Eq. (9) and the position of every individual node gets upgraded based on the Levy flight technique which is denoted in Eq. (16). The cost function presented in Eq. (17) is used to identify the optimal individual results for energy and distance-aware routing over WMNs.

4. Results and analysis

This section provides a detailed discussion of the results obtained from the proposed ML-AROA for EDA routing.

The design and implementation for the reliable transmission using the proposed ML-AROA are employed using MATLAB R2020a and the system gets operation with specifications such as 16GB RAM and i7 processor in Windows 11 operating system. Table 1 presents the simulation parameter utilized while implementing ML-AROA to detect the optimal route for data transmission in WMNs.

4.1 Performance analysis

The performance of the proposed ML-AROA is evaluated by means of network throughput, average packet loss rate and average end-to-end delay. In this research, the efficiency of the proposed ML-AROA is evaluated with conventional protocols such as low energy adaptive clustering hierarchy (LEACH) and

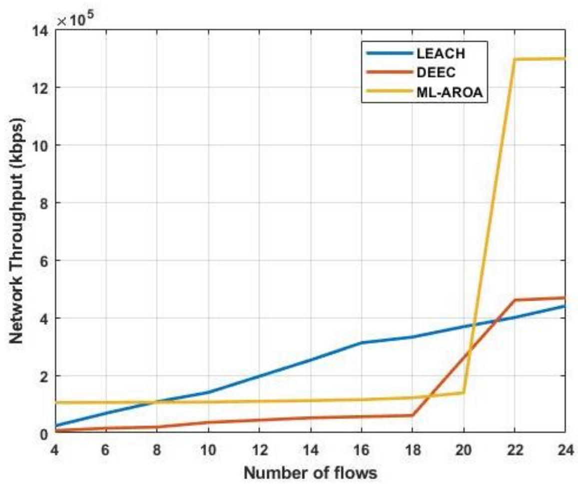

Figure. 2 Graphical representations for evaluation of network throughput

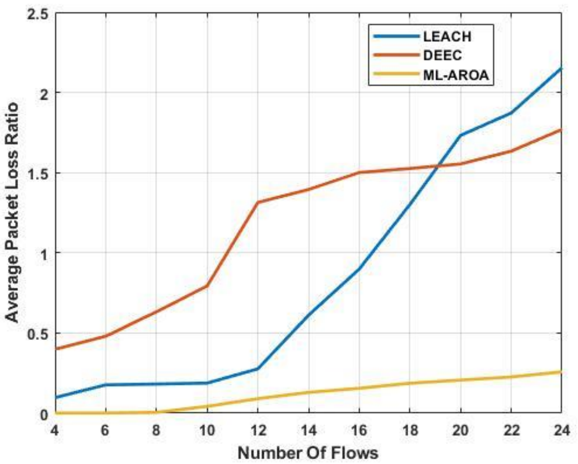

Figure. 3 Graphical representations for evaluation of average packet loss

distributed energy efficient clustering (DEEC). The LEACH protocol is the type of hierarchical routing protocol that is comprised of similar characteristics to the proposed method and the DEEC is a distributed protocol based on the clustering technique which is mainly utilized in multi-hop environments. The following subsections evaluate the efficiency of ML-AROA with LEACH and DEEC based on network throughput, average packet loss and average end-to-end delay.

4.1.1. Network throughput

The network throughput is defined as the amount of data transferred successfully from the node at the source to the node at the destination in a specified period. In random topology, the viability of the route gets varied frequently, so the throughput acts as an excellent indicator to access the quality of the route. The graphical representation for evaluating the performance of the proposed method with LEACH and DEEC is shown in Fig. 2 as follows:

The results from Fig. 2 show that the proposed ML-AROA has achieved better network throughput when compared with LEACH and DEEC. For instance, when the performance is evaluated for 22 flows, the proposed ML-AROA has achieved a throughput of 13×10^5 Kbps whereas LEACH and DEEC have obtained a throughput of 4×10^5 Kbps and 4.25×10^5 Kbps respectively. The proposed ML-AROA provide a random number in a regular manner which is characterized by the generation of arbitrary number and helps to jump out the local solution. This better result is due to the capability of the proposed ML-AROA in providing a random number in a regular manner which is characterized by the generation of arbitrary numbers and helps to jump out the local solution. This strategy used in the proposed approach enhances the accuracy of convergence and offers flexibility to find an effective route for data transmission.

4.1.2. Average packet loss

It is defined as the ratio of the total count of transmitted data packets which does not reach the destination side. The graphical representation for average packet loss is represented in Fig. 3.

The results from Fig. 3 show that the proposed ML-AROA has dropped minimum packets at the time of transmitting information from the transmitter to the receiver. For instance, the average packet loss rate is evaluated for 22 flows and the proposed method dropped packets at the minimum average of 0.25 while the LEACH and DEEC dropped packets at the average value of 1.7 and 1.9 respectively. The better result is due to the efficiency of ML-AROA in improvising the convergence accuracy and providing flexibility during the exploitation stage. This act helps to select the optimal transmission route which safely delivers the packets to the receiver with minimum loss.

4.1.3. Average end to end delay

The average end to end delay is stated as the delay which occurs during the time period of transmitting the data packets and receiving the data packets at the receiver side. Fig. 3 shows the graphical representation of outcome obtained while evaluating the end-to-end delay.

The results from Fig. 4 show that the proposed ML-AROA has achieved minimum delay when related to LEACH and DEEC. For example, when the delay is evaluated for 22 flows, the proposed ML-

Table 2. Comparison of existing methods with the proposed technique for a number of flows

Performance measures	Methods	No. of Flows		
		10	16	22
Network throughput (Kbps)	LBIA-POCA [16]	20×10^3	38×10^3	60×10^3
	ML-AROA	10.6×10^4	11.6×10^4	12×10^5
Average packet loss ratio	LBIA-POCA [16]	0.24	0.47	0.51
	ML-AROA	0.04	0.15	0.22
Average end to end delay (ms)	LBIA-POCA [16]	250	1200	1500
	ML-AROA	160.16	280.2	400.4

Table 3. Comparison of existing methods with the proposed technique for transmission rate

Performance measures	Methods	Transmission rate (packets/second)		
		80	90	100
Network throughput (Kbps)	MODQR [18]	690	720	740
	ML-AROA	2.16×10^4	2.19×10^4	2.2×10^4
Average packet loss ratio (%)	MODQR [18]	-	5.72	15.23
	ML-AROA	0.1	2.12	3.23
Average end to end delay (ms)	MODQR [18]	40	320	390
	ML-AROA	15	124	178

Table 4. Comparison of packet loss and end-to-end delay for different node counts

Performance measures	Methods	No.of.nodes			
		4	12	20	28
Average packet loss ratio (%)	GraphSAGE-based optimization [22]	2.25	0.8	0.6	0.75
	ML-AROA	0.045	0.097	0.174	0. 21
Average end-to-end delay (ms)	GraphSAGE-based optimization [22]	122	77	70	72
	ML-AROA	45.098	49.432	56.745	67.321

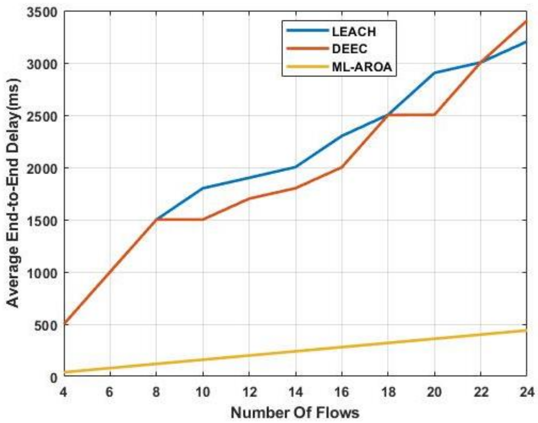

Figure. 4 Graphical representations for evaluation of average end-to-end delay

AROA has achieved a minimum delay of 400 ms whereas LEACH and DEEC have achieved a delay of 3000 ms. The better result is due to the levy flight technique in a proposed method which optimizes the randomization in networks and is employed in choosing an optimal route.

4.2 Comparative analysis

This section provides a comparative result of the proposed ML-AROA with the existing LBIA-POCA [16], MODQR [18] and GraphSAGE-based optimization [22] based on performance metrics such as network throughput, average end-to-end delay and average packet loss. Table 2 shows the experimental results obtained for ML-AROA with the existing techniques.

The results from Table 2 show that the proposed ML-AROA has achieved better results in throughput with minimized packet drop and delay. When the delay is evaluated for 22 flows, the proposed method the Levy flight strategy which enhances the convergence accuracy and provides flexibility to the WMN to detect an optimal route. Fig. 5. Shows the graphical representation for comparison of

(a) network throughput
(b) average packet loss ratio and
(c) average end-to-end delay among the proposed approach and LBIA-POCA.

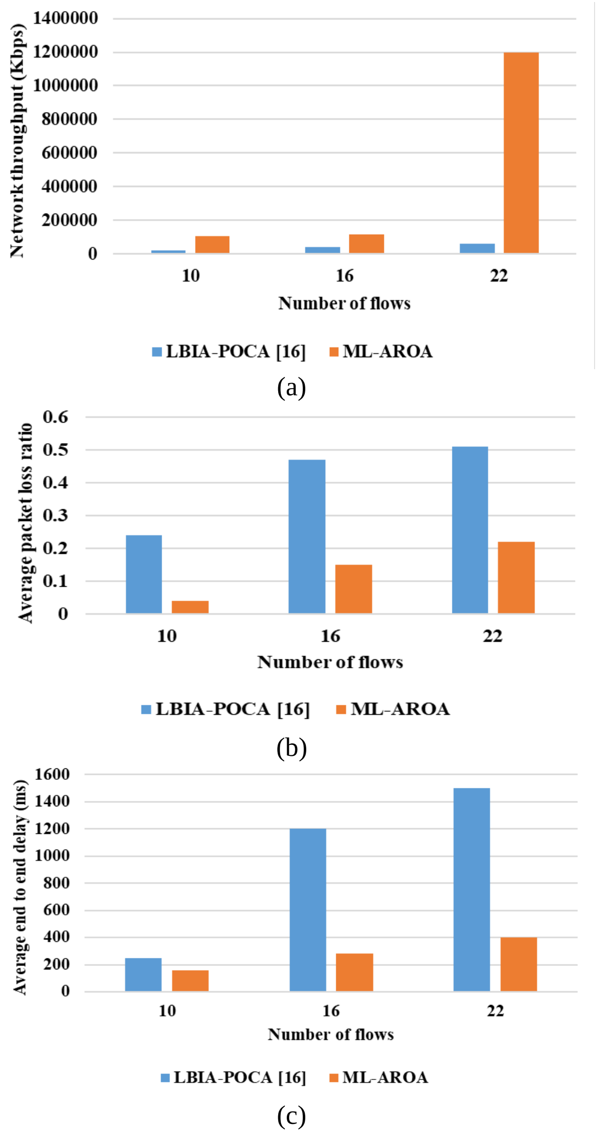

Figure. 5 The graphical representation for comparison of: (a) Network throughput of LBIA-POCA and ML-AROA, (b) Average packet loss ratio of LBIA-POCA and ML-AROA, and (c) Average end-to-end delay among the proposed approach and LBIA-POCA

In Table 3, the results are evaluated based on the transmission rate for performance metrics such as network throughput, average end-to-end delay and average packet loss.

The results from Table 3 show the outcome obtained from the proposed method based on the transmission rate. The proposed ML-AROA has achieved better results in overall metrics such as network throughput, average packet loss ratio and end to end delay. For instance, the delay of ML-AROA is 178 ms for 100 transmissions whereas the existing MODQR has taken about 390 ms for transmitting the same 100 packets. This result shows that the proposed ML-AROA has achieved efficiency in finding the optimal route for data transmission.

In Table 4, the performance of the proposed approach is evaluated for different number of nodes ranges from 4 to 28. The comparison is performed with state of art GraphSAGE-based optimization approach based on delay and packet loss ratio. The obtained results show that the proposed approach outperforms well in both the metrics. For example, the average end to end delay of the proposed approach is 67.32 ms for 28 nodes whereas the delay of existing GraphSAGE optimization is 72 ms. The minimal delay of the proposed approach is due to the effectiveness of ML-AROA which detects the shortest path to transmit the data packets.

5. Conclusion

An effective routing technique has a great ability in improving the performance of the network. The ML-AROA proposed in this manuscript focuses on solving multi-objective routing problems related to energy and transmission distance. The proposed ML-AROA is an enhancement of the artificial rabbit optimization algorithm by including the Levy Flight strategy which maximizes the convergence accuracy and offers flexibility to detect the optimal route. The optimal route detected by the proposed ML-AROA is greatly responsible to transmit the data packets from the source to the destination with minimum time delay by using the shortest path. The Levy-flight strategy combined with the exploitation stage of AROA helps to identify the shortest transmission distance. The outcome from the experiment indicates that the proposed ML-AROA has achieved a minimum delay time of 400.4 ms for 22 flows, but the existing LBIA-POCA has achieved a delay of 1500 ms for the same 22 flows. In the future, this research will be further extended by using the hybridization of metaheuristic algorithms to enhance the routing efficiency in WMNs.

Notation list

Parameter	Description
N_s	Node set
L_s	Link among mesh network
P_{Ti}	Transmitted power of the node i
G_t	Gain obtained while transmitting data packets
G_r	Gain obtained while receiving data packets
h_t	Height of the transmitting antenna
h_r	Height of the receiving antenna
δ_{ij}	Small scale fading
d_{ij}	Distance among the node
p_i	Position of the rabbit

p_j	Position of the rabbit in randomized state
r	Random number ranges among (0,1)
$v_i(t+1)$	Updated position of the rabbit in ith iteration
T_{max}	Maximum number of iterations
n_1	Standardized normal function
$b_{i,r}(t)$	Random burrow selected by rabbit
u and v	Gaussian distribution function
σ_v^2 and σ_u^2	Variance values
Γ	Gamma function
β	Correlation parameter
l^{id}	Average length of the path
AS_i^{ld}	Total count of packets
N	Total Number of nodes
E_o	Energy at the initial stage
$s(i)$	Energy of the node in present state
$d(i,j)$	Distance among the source i and destination j
R	Radius of the neighbourhood
x_i, y_i	Coordinate point of node i
x_j, y_j	Coordinate point of node j

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

For this research work all authors' have equally contributed in Conceptualization, methodology, validation, resources, writing—original draft preparation, writing—review and editing.

References

[1] X. Yuan and Y. Chen, "Secure routing protocol based on dynamic reputation and load balancing in wireless mesh networks", *Journal of Cloud Computing*, Vol. 11, p. 77, 2022.

[2] Y. Chai and X. J. Zeng, "Delay-and interference-aware routing for wireless mesh network", *IEEE Systems Journal*, Vol. 14, No. 3, pp. 4119-4130, 2020.

[3] S. K. Narayana and N. T. Hosur, "Priority based trust efficient routing using ant colony optimization for IoT-based mobile wireless mesh networks", *International Journal of Intelligent Engineering and Systems*, Vol. 15, No. 2, pp. 99-106, 2022, doi: 10.22266/ijies2022.0430.10.

[4] M. K. Sastry, A. A. K. Mohammad, and M. A. Arif, "Optimized Energy-efficient Load Balance Routing Protocol for Wireless Mesh Networks", *International Journal of Advanced Computer Science and Applications*, Vol. 12, No. 8, pp. 605-610, 2021.

[5] L. H. Binh and T. V. T. Duong, "Load balancing routing under constraints of quality of transmission in mesh wireless network based on software defined networking", *Journal of Communications and Networks*, Vol. 23, No. 1, pp. 12-22, 2021.

[6] S. M. Taleb, Y. Meraihi, S. Mirjalili, D. Acheli, A. R. Cherif, and A. B. Gabis, "Mesh Router Nodes Placement for Wireless Mesh Networks Based on an Enhanced Moth-Flame Optimization Algorithm", *Mobile Networks and Applications*, 2023.

[7] V. Jyothi, and M. V. Subramanyam, "An enhanced routing technique to improve the network lifetime of cognitive sensor network", *Wireless Personal Communications*, Vol. 127, No. 2, pp. 1241-1264, 2022.

[8] D. S. Keerthi, A. S. Rani, and T. G. Basavaraju, "Buffer based Routing Mechanism for Load Balancing in Wireless Mesh Networks", *International Journal of Computer Engineering and Technology*, Vol. 10, No. 1, pp. 1-10, 2019.

[9] M. Bano, A. Qayyum, R. N. B. Rais, and S. S. A. Gilani, "Soft-Mesh: A Robust Routing Architecture for Hybrid SDN and Wireless Mesh Networks", *IEEE Access*, Vol. 9, pp. 87715-87730, 2021.

[10] L. H. Binh and T. K. Truong, "An Efficient Method for Solving Router Placement Problem in Wireless Mesh Networks Using Multi-Verse Optimizer Algorithm", *Sensors*, Vol. 22, No. 15, p. 5494, 2022.

[11] S. M. Taleb, Y. Meraihi, A. B. Gabis, S. Mirjalili, A. Zaguia, and A. R. Cherif, "Solving the Mesh Router Nodes Placement in Wireless Mesh Networks Using Coyote Optimization Algorithm", *IEEE Access*, Vol. 10, pp. 52744-52759, 2022.

[12] S. M. Taleb, Y. Meraihi, A. B. Gabis, S. Mirjalili, and A. R. Cherif, "Nodes placement in wireless mesh networks using optimization approaches: A survey", *Neural Computing and Applications*, Vol. 34, No. 7, pp. 5283-5319, 2022.

[13] A. Samuylov, D. Moltchanov, R. Kovalchukov, A. Gaydamaka, A. Pyattaev, and Y. Koucheryavy, "GAR: Gradient assisted routing for topology self-organization in dynamic mesh networks", *Computer Communications*, Vol. 190, pp. 10-23, 2022.

[14] G. P. Raja, and S. Mangai, "Firefly load balancing based energy optimized routing for multimedia data delivery in wireless mesh

Received: June 28, 2023. Revised: August 6, 2023.

network", *Cluster Computing*, Vol. 22, No. 5, pp. 12077-12090, 2019.

[15] A. Barolli, S. Sakamoto, K. Bylykbashi, and L. Barolli, "A Hybrid Intelligent Simulation System for Building IoT Networks: Performance Comparison of Different Router Replacement Methods for WMNs Considering Stadium Distribution of IoT Devices", *Sensors*, Vol. 22, No. 20, p. 7727, 2022.

[16] L. Yang, Y. Li, S. Wang, and H. Xiao, "Interference-Avoid Channel Assignment for Multi-Radio Multi-Channel Wireless Mesh Networks With Hybrid Traffic", *IEEE Access*, Vol. 7, pp. 67167-67177, 2019.

[17] A. Singh, S. Prakash, and S. Singh, "Optimization of reinforcement routing for wireless mesh network using machine learning and high-performance computing", *Concurrency and Computation: Practice and Experience,* Vol. 34, No. 15, p. e6960, 2022.

[18] Y. Chai and X. J. Zeng, "A multi-objective Dyna-Q based routing in wireless mesh network", *Applied Soft Computing*, Vol. 108, p. 107486, 2021.

[19] S. Mahajan, R. Harikrishnan, and K. Kotecha, "Adaptive Routing in Wireless Mesh Networks Using Hybrid Reinforcement Learning Algorithm", *IEEE Access*, Vol. 10, pp. 107961-107979, 2022.

[20] I. L. Cherif, L. Zitoune, and V. Vèque, "Energy efficient routing for wireless mesh networks with directional antennas: When Q-learning meets ant systems", *Ad Hoc Networks*, Vol. 121, p. 102589, 2021.

[21] C. S. Anita and R. Sasikumar, "Neighbor Coverage and Bandwidth Aware Multiple Disjoint Path Discovery in Wireless Mesh Networks", *Wireless Personal Communications*, Vol. 126, No. 4, pp. 2949-2968, 2022.

[22] P. Lu, C. Jing, and X. Zhu, "GraphSAGE-Based Multi-Path Reliable Routing Algorithm for Wireless Mesh Networks", *Processes*, Vol. 11, No. 4, p.1255, 2023.