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Energy Efficient Routing in Wireless Mesh Networks using Multi-Objective Dwarf Mongoose Optimization Algorithm

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ABSTRACT- Wireless Mesh Networks (WMNs) are part of wireless technologies that are known for their flexibility and extended coverage. Wireless applications have reached their peak in applications related to various fields such as healthcare, image processing, and so on. However, delay and energy efficiency are considered the two aspects that diminish the performance of WMNs. To overcome the aforementioned issues, this research introduces an effective routing method using Multi-Objective Dwarf Mongoose Optimization Algorithm (MO-DMOA). The MO-DMOA performs routing by considering the multiple paths using an enriched population resource. The nomadic behavior of MO-DMOA helps in detecting the optimal routing path with minimized over-exploitation. The proposed MO-DMOA is evaluated with different routing schemes such as Load Balance and Interference Avoid-Partially Overlapped Channels Assignment (LBIA-POCA) framework, and Multi-Objective Dyna Q-based Routing (MODQR). The outcomes obtained through the experimental analysis show that the proposed approach acquires a better throughput of 13.5×10^5 kbps for 22 flows, whereas the existing LBIA-POCA achieves a throughput 60×10^3 kbps.

Keywords: Energy efficiency; load balance; multi-objective dwarf mongoose optimization algorithm; routing; wireless mesh networks

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1. INTRODUCTION

Wireless Mesh Networks (WMNs) are decentralized network systems that are known for their self-configurable property which requires a less cost for installation when compared with other wireless networks [1,2]. Moreover, WMNs find their place in various applications related to automation, smart buildings, telehealth care and so on. The WMNs are comprised of three kinds of nodes: Mesh Gateways (MG), Mesh Clients (MC), and Mesh Routers (MR) [3]. The MRs are considered as backbones due to their efficiency in enabling multi-hop communication. The mesh clients help the end user to perform communication with others through access points [4]. The mesh routers have wireless interface cards in their architecture which provide flexibility and better coverage during the time of communication [5,6]. A common channel must be selected for smooth communication among MC and MR. The data traffic in WMNs is based on gateways and clients, where the traffic based on the gateway is convergent and the traffic based on the client is based on multiple hops [7].

The network performance of WMN is probably increased by an effective routing among the nodes. However, when inappropriate routes are selected, it leads to congestion among the nodes and increases delay while transmitting the data packets [8,9]. The end-to-end node in WMNs is present beyond the radio transmission range, so an effective routing algorithm plays an important role in creating a route path from the node at the source, to the node at the destination [10,11]. The routing determines a sequential node pattern with data packets transmitted by each node [12]. But, routing in a low broadband range of WMNs is a complex process due to the increased workload at each node. This increased workload leads to the consumption of more power and affects the overall process of routing [13,14]. So, the usage of heuristic optimization in routing probably improves the routing performance among nodes of a wireless mesh network with minimum energy consumption and better throughput [15]. This research considers the drawbacks related to energy consumption and increased delay as the motivation, and proposes an optimization based on a routing protocol to minimize the energy consumption and delay.

The major contributions of this research are listed as follows:

(1) This research introduces a multi-objective routing protocol using Dwarf Mongoose Optimization algorithm which performs a nomadic search strategy to detect the optimal route for transmitting data packets.

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(2) To focus on minimalizing the consumption of energy by the nodes, and the delay that occurs during the time of transmission, the proposed MO-DMOA detects an optimal path using its enriched population strength which minimizes the time of searching for an optimal route.

The remaining manuscript is structured as follows: the related works of this research are presented in *Section 2*, while *Section 3* describes the proposed methodology. *Section 4* presents the results obtained by the proposed model and its analysis. Finally, the conclusion of this overall research is presented in *section 5*.

2. RELATED WORKS

This section describes some of the existing routing techniques that use different algorithms to perform optimal routing over wireless mesh networks.

Yuan and Chen [16] introduced a Secured Routing Protocol based on Dynamic Reputation and Load Balancing (SRP-DRLB) in Wireless Mesh Networks (WMNs). The SRP-DRLB effectively predicted traffic reputation among the nodes of WMNs and utilized edge weight methodology to access more data packets. The transmission routes were dynamically adjusted using SRP-DRLB which minimized the reputation of nodes and traffic. Moreover, the suggested approach helped in balancing the load in the network with minimum energy consumption. However, the time taken to transmit the data was high in this model.

Lahsen-Cheriff et al. [17] introduced an effective routing scheme using two algorithms namely, Directional Neighbors Discovery algorithm (DND) and Ant –Q for Energy Efficient Routing over Beams (AQ-EERoB). The DND helped in setting up the network for varying power levels and directions of the beam. The AQ-EERoB algorithm was utilized in effective routing which transmit the data packets with better throughput and minimal energy consumption. However, the suggested approach did not consider the quality of the channel in a cross layer of the network.

Yang et al. [18] introduced a Load Balance and Interference Avoid-Partially Overlapped Channels Assignment (LBIA-POCA) approach in WMNs to increase the throughput of the channel interfaces. At the initial stage, the neighbor node's interface was allocated using Huffman's algorithm, and then the non-interface links were distributed within the scheduled time. The suggested approach probably diminished the loss rate of data packets during transmission but was not suitable for the multicast assignment of channels.

Chai and Zeng [19] developed a Multi-Objective Dyna Q-based Routing (MODQR) approach to minimize the delay and improve energy efficiency during data transmission. The suggested MODQR utilized Dyna Q algorithm which effectively enhanced the speed of convergence, and helped in the detection of an optimal path for data transmission. The MODOR prohibited asymmetrical characters, therefore improving the probability of transmission failure. However, the architectural structure of MODQR was in a stationary stage that was not modifiable based on the nature of the WMN.

Bordier et al. [20] introduced Buffer Occupancy and link state Opportunistic Routing (OBOR) which utilized router buffer occupancy in selecting the optimal path using the queuing information theory. The proposed approach adjusted the selected route of the whole WMN and improved the network throughput with available channel information. Moreover, OBOR is applied to the multi-hop WMNs with enhanced cell coverage. Nonetheless, in this model, network traffic occurs when the average values are not provided.

Overall, the existing methodologies described in the related works faced issues while transmitting data packets from the node at source to the node at destination in a shorter time. Moreover, the existing techniques do not suit multi-objective fitness functions. The poor routing path generated by the existing approaches also increase the delay time and packet loss. Thus, the suggested approach in this study effectively minimizes energy consumption while transmitting data packets from the source node to the destination node.

3. ENERGY EFFICIENT ROUTING USING MO-DMOA

This research introduces a Multi-Objective Dwarf Mongoose Optimization Algorithm (MO-DMOA) which provides energy efficient routing over wireless mesh networks. The proposed MO-DMOA involves an efficient searching process and provides an optimistic route for the transmission of data packets. The diagrammatic representation of the overall process involved in routing using the proposed MO-DMOA is depicted in *figure 1* as follows:

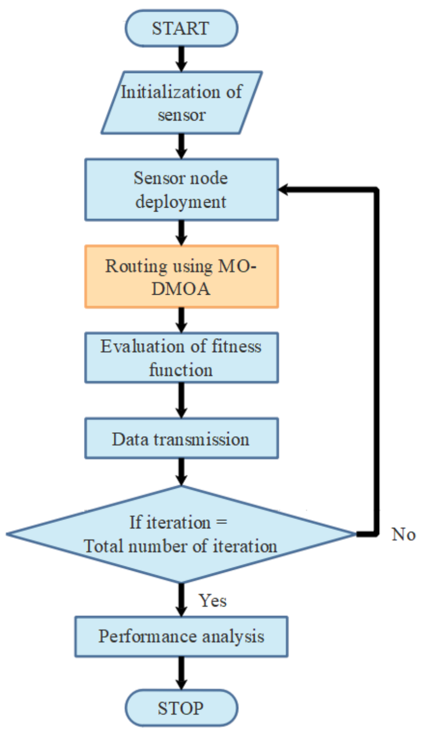

Figure 1: Overall process involved in routing using MO-DMOA

3.1 Network Model

The structure of the wireless mesh network is exhibited as a connectivity graph which is denoted in *equation (1)* as follows:

$$G = (V, L) \tag{1}$$

Where, the set of mesh nodes is denoted as V and the set of wireless links is denoted as L. The WMNs utilize two ray ground reflection models with small scale fading models to detect the loss of path. The power received from node i to the node j is represented as P_{ij} which is presented in equation (2) as follows:

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

Where, P_{Ti} denotes the power that is transmitted from node i, G_t and G_r respectively denote the gain of the transmitting and receiving antenna. The height of the transmitting and receiving antenna are respectively denoted as h_t and h_r. The distance between the source and the destination node is denoted as d_{ij} and the parameter of small-scale fading is denoted as δ_{ij}. Whenever the maximum count of re-transmission occurs, the packet gets dropped.

3.2 Overview of Multi-Objective Dwarf Mongoose Optimization Algorithm (MO-DMOA)

The dwarf mongoose has distinct territorial actions to prevent themselves from predator attacks. The mongoose's deadly bite is known as skull-crush bite which helps them to prevent them from attacks. The size of their prey is limited by this killing strategy, and no coordinated killing of huge animals are reported. The restricted form of prey collection has a considerable impact on the social behavior and environmental adaptations of mongooses to make up for efficient family nourishment. The mongoose's two primary compensating behavioral adjustments are as follows:

3.2.1 Size of the prey, Usage of Space, and Size of Group

The dwarf mongoose experiences a seminomadic lifestyle which allows the family to travel quite extensive distances for foraging before returning to the mound. Moreover, it ensures that no area of the territory is over-hunted, thus decreasing prey depletion and ensuring equitable predation across the entire territory. The group forages as a unit, with the alpha female maintaining cohesion by vocalization or a brief nasal "peep" at 2 kHz. The distance traveled on each day is determined by the group size, the young one's existence, and the foraging disruption induced by predator hiding. The alpha female begins foraging and decides on the foraging path, distance traveled, and sleeping mounds.

3.2.2 Provision of the Food

The prey is not provided to the younger ones and the lactating females, thus the social organization among the group of mongooses is affected. A specified population of mongooses serve as babysitters who remain with the younger ones, until the rest of the population comes back to their habitat. The dwarf mongooses do not have the tendency to construct the new nest so they get shifted from one mound to another in search of food. Whenever the younger ones combine with the population, they are incapable of moving for longer distances. Consequently, the prohibition of younger ones helps to enhance the movement of the group. The nomadic behavior inhibits the over-exploitation phase and confirms the exploration of the entire population.

3.3 Initialization of Population

The optimization of DMO starts by initiating the mongoose population which is presented in *equation (3)*, where the population is created based on the limit of upper bound and lower bound values.

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,d-1} & x_{1,d} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,d-1} & x_{2,d} \\ \vdots & \vdots & x_{i,j} & \vdots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,d-1} & x_{n,d} \end{bmatrix} \tag{3}$$

Where, the candidate population is denoted as X which is created in a randomized manner based on *equation (4)* as follows:

$$x_{i,j} = U_{rn}(var\ min, var\ max, var\ size) \tag{4}$$

Where, the uniformly distributed random number is denoted as U_{rn}, the variation in the lower and upper bounds are denoted as $varmin$ and $varmax$.

3.4 MO-DMOA

The DMOA is based on a behavioral adaptation of the dwarf mongoose which is comprised of three phases: alpha group, scouts and babysitters. These three phases of the DMO are described in the following section.

3.4.1 Alpha Phase

The fitness of every individual population is evaluated during the time of population initialization. The probable value of every individual population is evaluated using the *equation (5).*

$$\alpha = \frac{fit_i}{\sum_{i=1}^{n} fit_i} \tag{5}$$

Where, α denotes the alpha female, where the total count of mongooses in the population responds to the total number of babysitters. The alpha female produces a *peep* sound to maintain the family in the path. The sleeping mound at the initial stage is denoted as $\emptyset$, and the position of the mongoose at the time of searching for food is denoted in *equation (6).*

$$X_{i+1} = X_i + U_{rn} \times peep \tag{6}$$

Where, the uniformly distributed randomized number is denoted as U_{rn} . After completion of every iteration, the mongoose tends to vary its sleeping mound which is mathematically expressed in *equation (7).*

$$sm_i = \frac{fit_{i+1} - fit_1}{max\{|fit_{i+1}, fit_1|\}} \tag{7}$$

The average of the sleeping mound is evaluated using the *equation (8).*

$$\varphi = \frac{\sum_{i=1}^{n} sm_i}{n} \tag{8}$$

Where, the iteration of the sleeping mound is denoted as sm_i and the average value of the population in the sleeping mound is denoted as φ. After this stage, the scouting phase occurs where the next source of food is calculated when the babysitter is varied.

3.4.2 Scout Phase

Since the scout mongoose does not remain in the same sleeping mound, it varies to another mound to improve the stage of exploration. The process of discovering the new sleeping mound is numerically represented in *equation (9).*

$$X_{i+1} = \begin{cases} X_i - CF \times U_{rn} \times rand \times [X_i - \vec{M}] & if\ \varphi_{i+1} > \varphi_i \\ X_i + CF \times U_{rn} \times rand \times [X_i - \vec{M}] & else \end{cases} \tag{9}$$

Where, the random number which relies upon between the range of 0 and 1 is represented by $rand$, and the value of $CF = \left(1 - \frac{iter}{Max_{iter}}\right)^{\left(2\frac{iter}{Max_{iter}}\right)}$ which represents the movements of the population. The vector $\vec{M} = \sum_{i=1}^{n} \frac{X_i \times sm_j}{X_i}$ signifies the movement of the population to a new mound.

3.4.3 Babysitters

The babysitters are submissive to the group members and stay with the younger ones to take care of them daily. The total count of babysitters is based on the size of the entire population, and this affects the algorithm by minimizing the size of the total population. The babysitters interchange the parameter based on previous information of the scout and the food source. The fitness value of the babysitter is assigned as zero by verifying the average weight of the alpha group and emphasizing the stage of exploitation. In DMO, the number of babysitters is considered as the parameter that needs to be fine-tuned to obtain superior features. Moreover, the iterations vary based on the population size.

3.5 MO-DMOA for Energy-Efficient Routing in WMNs

This section describes the process involved in routing using the proposed MO-DMOA. The nomadic behavior of DMOA helps to prohibit the over exploitation which is resonated with the need for exploration in multi-objective optimization to avoid convergence to local optima. Additionally, only a specified parameter is needed to be fine-tuned (*i.e.* number of babysitters). This minimal complexity in tuning the parameter is helpful in multi-objective optimization. These advantageous characteristics of the proposed approach makes MO-DMOA effective for multi-objective optimization, rather than other optimization techniques. The proposed approach considers the energy efficiency and the shortest path to transmit data from the source node to the destination node, thereby using minimal energy and delay. The suggested approach considers energy efficiency as the major factor while selecting the optimal routing path for transmitting the data packets.

3.5.1 Initialization

Initialization is considered the primary stage where the sensor nodes get deployed in the mesh network. The proposed MO-DMOA initiates the population of individuals by finding an effective route to transmit data packets from the node at the source to the node at destination. The dimensional value of an individual node is equal to the total number of relay nodes that exist in the transmission path. The individuals in the entire population are allocated as i, as represented mathematically in equation (10).

$$x_i = (x_{i,1}(t), x_{i,2}(t) \dots, x_{i,n}(t)) \tag{10}$$

Where, $x_i(.)$ is the dimension of the individuals in the entire population.

3.5.2 Derivation of Fitness Function by considering the Multi-Objective Parameters

The proposed MO-DMOA selects the optimistic route for the transmission of data packets by considering the fitness functions such as delay, energy, distance, and network overhead. This section presents their description along with the iterative process involved in finding the optimal route using MO-DMOA.

- Delay is defined as the time taken to transmit the data packets from the node at source to the node at destination in the environment of WMN. The minimized delay makes the routing process effective by discovering the optimal route in a short period. The delay is evaluated using *equation (11).*

$$Delay = \sum_{\substack{ld=1 \\ i=1}}^{m^{id}} \frac{l^{id}}{AS_i^{ld}} \tag{11}$$

Here, the length of the route taken to transmit the data packets is denoted as l^{id}, the total data packets subjected to the destination node from the source node are signified as AS_i^{ld}, and the time period is represented as i.

- Energy is one of the most important parameters to be considered while selecting the optimal route for data transmission. For selecting the ideal route, the proposed MO-DMOA considers the energy at the initial stage, as well as the energy at the residual stage. The node with a higher ratio residual energy is considered the ideal node for transmitting the data packets, and it is represented in *equation (12).*

$$Energy = \sum_{i=1}^{N} \frac{E_0}{E_0 - s(i).E} \tag{12}$$

Here, N is the total count of nodes and the energy at the initial stage is denoted as E_0. The energy of the node at its initial phase is represented as $s(i)$.

- The distance referred to is the transmission distance which is defined as the path where the data packets travel from the source node to the destination node. When the transmission path of data packets becomes higher, it leads to higher energy consumption, and is evaluated using the *equation (13).*

$$Transmission\ distance = \frac{d(i,j)}{R} \quad (13)$$

Here, $d(i,j)$ denotes the distance between the source node and the destination node, the distance of the neighborhood radius is denoted as R. The value of $d(i,j)$ is evaluated using the equation (14).

$$d(i,j) = \sqrt{(x_i - x_j)^2 - (y_i - y_j)^2} \quad (14)$$

Where, x_i, y_i and x_j, y_j represents the coordinate point of i^{th} node and j^{th} node, respectively.

- Network overhead is defined as the additional processing of data that takes place while transmitting and receiving the data over the WMNs. The network overhead is evaluated using the *equation (15).*

$$Network\ overhead = \frac{(header \times 100)}{payload - header} \quad (15)$$

The aforementioned fitness metrics which are, delay, energy, distance, and overhead are used in identifying the optimal route for the transmission of data packets with a minimized consumption of energy at a short distance.

The combination and prioritization of the objective functions are achieved by assigning weights to each objective in the fitness function. The weighted sum of objectives is multiplied with the respective weights that represent the overall fitness value. Moreover, the fore mentioned fitness functions are non-conflicting in nature, so instead of minimizing them separately, the objectives are converted to a single objective function using the weighted sum approach. So, the normalization function is deployed in individual fitness functions, as represented in *equation (16)*. Here, the weighted parameters of fitness function: delay, energy, distance, and the network overhead are represented as β_1, β_2, β_3 and β_4, correspondingly.

$$F(x) = \frac{f_i - f_{min}}{f_{max} - f_{min}} \quad (16)$$

Where, the functional value is represented as f_i, minimum and the maximum values are represented as f_{min} and f_{max}, correspondingly. Here, the normalized value lies between the range of 0 and 1.

3.5.3 Generation of Routing Path using MO-DMOA

The proposed MO-DMOA is employed for finding the optimal path for transmission of data packets. During the time of route generation, the node that is detected nearer to the destination node is considered the final node. Additionally, the multi-objective fitness parameters, energy, distance, delay, and throughput, are considered while generating the transmission path. By employing the process defined in the following steps, an effective routing is performed.

(1) Initially, the population of mongoose is initialized with the probable paths from the source node to the destination node. Every individual dimension of the mongoose equals the total count of intermediate nodes that exist in the path of transmission.

(2) After this, the fitness of each path is updated based on the stage of exploration and exploitation, whose information are discussed in the previous section.

(3) The fitness parameters namely, distance, energy, delay and throughput are considered during the generation of route using the proposed MO-DMOA. The fitness function is formulated by using the *equation (17)* as shown below:

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

Here, the weighted parameters of the fitness functions delay, energy, distance, and network overhead are simultaneously represented as β_1, β_2, β_3 and β_4. The value of β_1 is 0.25, β_2 is 0.25, β_3 is 0.3 and β_4 is 0.2. The sum of the weighted parameter values equals to 1, where the prioritization is provided to the transmission distance, because the minimal distance helps to reduce the energy consumption while transmitting the data packets. The fitness function presented in *equation (16)* helps to identify the optimistic route with high energy efficiency at the shortest distance. Thus, the energy consumption at the node during data packet transmission is possible to be minimized using the proposed MO-DMOA, alongside improving the lifespan of the network. The pseudocode for routing process using the proposed MO-DMOA is given below:

Pseudocode for routing using MO-DMOA

1. Initialize pheromone and heuristic exponential weight
2. Create an initial population mongoose and baby sitters
3. Set baby sitter exchange parameter L.
4. For iter=1: max-iter
5. Selection of best individual based on the *equation (5)*
6. The process of discovering new sleeping mound based on *equation (9)*
7. Update the multi-objective fitness function for routing using *equation (16)*
8. end for
9. output the optimal routing path from source to destination

4. RESULTS AND ANALYSIS

This section provides a brief discussion of the results evaluated using the proposed MO-DMOA for energy-efficient routing. For a reliable transmission, the proposed approach is implemented in MATLAB R2020a software on a system with the specifications of 16GB Random Access Memory, Intel core i7 processor and Windows 11 operating system. *Table 1* below presents the simulation parameters utilized at the time of implementation of the proposed approach to find the optimistic route for data transmission.

Table 1: Simulation Parameters

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

4.1 Performance Evaluation

In this research, the effectiveness of the suggested approach is computed based on three metrics: throughput of the network, average packet loss and average end-to-end delay. The proposed MO-DMOA is compared with the conventional protocols like Low Energy Adaptive Clustering Hierarchy (LEACH) and Distributed Energy Efficient Clustering (DEEC). LEACH is a kind of hierarchical routing method that is similar to the proposed MO-DMOA, whereas the DEEC is a kind of distributed protocol that is used in a multi-hop environment. The aforementioned metrics are used to calculate the efficacy of the existing LEACH and DEEC in comparison with the proposed ML-AROA.

4.1.1 Network Throughput

The throughput is stated as the quantity of \ data packets transmitted successfully from the source node to the destination node. In the random topology environment, the feasibility of the route differs. Hence, the throughput acts as an excellent metric to evaluate the quality of transmission route. *Figure 2* presented below shows the graphical representation of evaluating the network throughput of the routing techniques.

The throughput of the proposed MO-DMOA is comparatively higher than the throughput obtained by existing DEEC and LEACH. For 24 flows, the proposed MO-DMOA achieves a throughput of 13.8×10^5 kbps, whereas the existing DEEC and LEACH obtain a throughput of 4.8×10^5 kbps and 4.5×10^5 kbps, respectively. When the number of flows gets increased, the transmission of data packets also increases. Besides, the network throughput gets increased due to minimization of node failure in the proposed MO-DWOA. Nonetheless, the superior results accomplished are due to the nomadic behavior of MO-DMOA in finding the optimal path by expanding the size of their population, thereby minimizing the overexploitation.

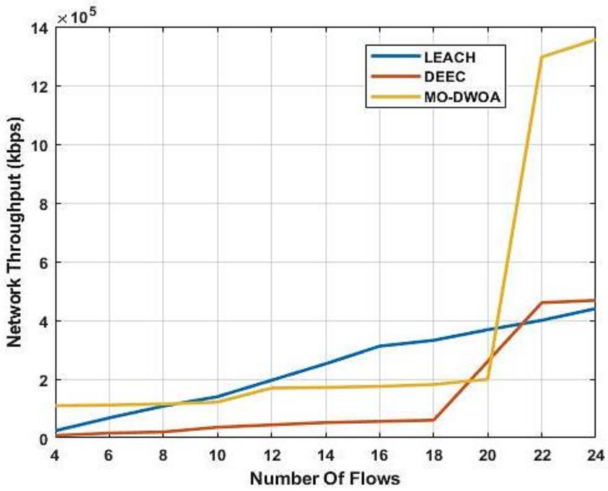

Figure 2: Graphical representation for evaluation of network throughput

4.1.2 Average Packet Loss

The average packet loss is defined as the number of transmitted packets which does not reach the node at the destination side from the source. *Figure 3* depicted below illustrates a graphical representation of average packet loss in different routing techniques, including the proposed one.

The results from *figure 3* show the efficiency of the suggested MO-DMOA in providing minimum packet loss when compared with the previous techniques, LEACH and DEEC. For 24 flows, the proposed approach loses the data packets in the 0.1 ratio whereas the existing LEACH and DEEC lose the data packets in the ratio of 2.1 and 1.75, respectively. The superior outcome of minimalized packet loss is due to the efficiency of MO-DMOA in providing multi-hop routing that helps to transfer data with a minimal loss.

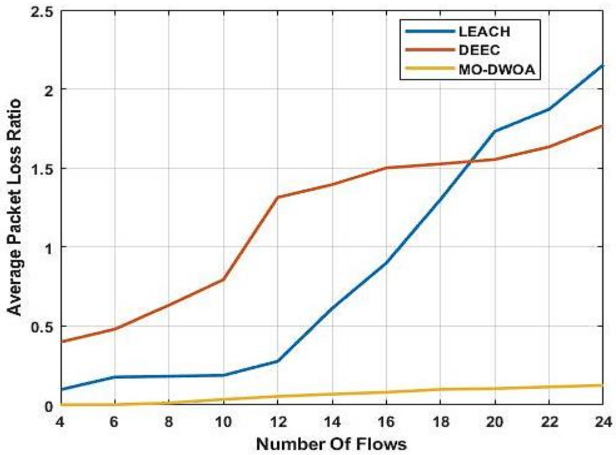

Figure 3: Graphical representation for evaluation of average packet loss

4.1.3 Average end-to-end Delay

Average end-to-end Delay is defined as the time duration taken to transmit the data packets from the source node to the destination node. *Figure 4* depicted below demonstrates the graph of the average end-to-end delay among different routing techniques, inclusive of the proposed MO-DMOA.

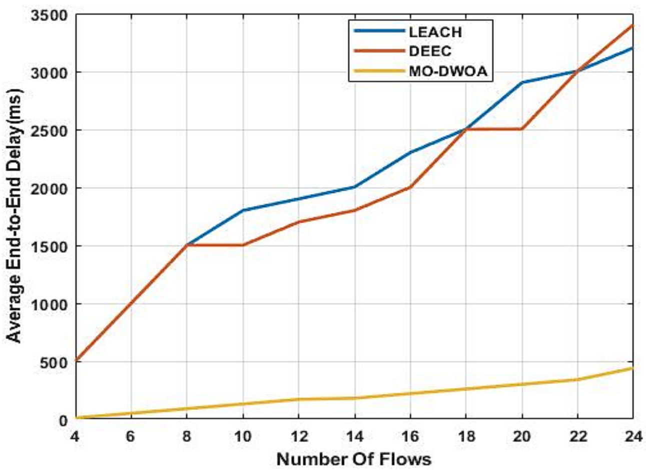

Figure 4: Graphical representation for evaluation of average end to end delay

The results from *figure 4* show that the proposed MO-DMOA achieves minimum delay while transmitting the data packets when compared with DEEC and LEACH. For instance, the

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proposed approach attains a delay of 400ms which is relatively lower than that of the existing LEACH (3200ms) and DEEC (3400ms). This outcome is a resultant of the efficacy of the suggested approach in finding the shortest path by using its enriched resource of population.

4.1.4 Time Complexity and Computational Complexity

The proposed MO-DMOA achieves a time complexity of 3.72 seconds for 100 iterations while selecting the optimal routing path for transmitting the data packets. The time complexity of detecting the optimal routing path using the proposed MO-DMOA varies in accordance with the factors of number of iterations, fitness function evaluation and the exploration phase. The MO-DMOA takes place in multiple number of iterations to search for an optimal solution which impacts the time complexity. The computational complexity of MO-DMOA is represented as $O(n)$ which is comprised with exploration of the best position, choosing alpha female and assessing the sleeping mounds. The total computational complexity of the proposed MO-DMOA is based on the following function, as represented in *equation (18).*

$$O(iter \times d \times \alpha \times sm \times \vec{M} \times n + CFE \times n) \qquad (18)$$

Where, the total number of iterations is represented as $iter$, cost of function is represented as CFE, and the dimensional size is represented as d.

4.2 Comparative Analysis

This section provides the comparative results of the proposed MO-DMOA in contrast with that of the existing routing techniques: LBIA-POCA [18] and MODQR [19] by considering the performance metrics namely, network throughput, average packet loss and average end-to-end delay. The results obtained while evaluating the proposed method against the existing methodologies are presented in *table 2*, as follows:

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

Performance measures	Methods	No. of. Flows		
		10	**16**	**22**
Network throughput (Kbps)	LBIA-POCA [18]	20×10^3	38×10^3	60×10^3
	MO-DMOA	17.5×10^4	12.9×10^5	13.5×10^5
Average packet loss ratio	LBIA-POCA [18]	0.24	0.47	0.51
	MO-DMOA	0.03	0.08	0.11
Average end to end delay (ms)	LBIA-POCA [18]	250	1200	1500
	MO-DMOA	130.20	220.12	340.25

The outcomes acquired from the comparative *table 2* proves the effectiveness of the proposed MO-DMOA which achieves better throughput with minimal packet loss and delay. The delay for 22 flows is evaluated for both LBIA-POCA and MO-DMOA, where the proposed method obtains a delay of 340.25ms which is lesser than that of the existing LBIA-POCA with 1500ms. This superior result of MO-DMOA results from the usage of multiple populations that perform a robust search to find an optimistic route. The *figure 5* presents a graphical description for the network throughput based on different number of flows, while there is a graphical description given for the evaluation of average packet loss in *figure 6*. Finally, a graphical description for end-to-end delay is displayed in *figure 7.*

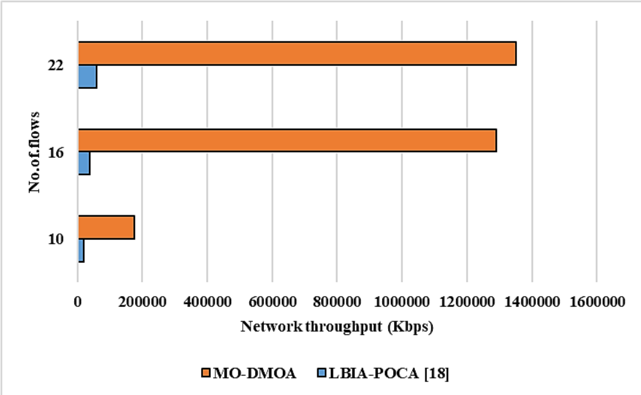

Figure 5: Graphical representation for evaluation of network throughput

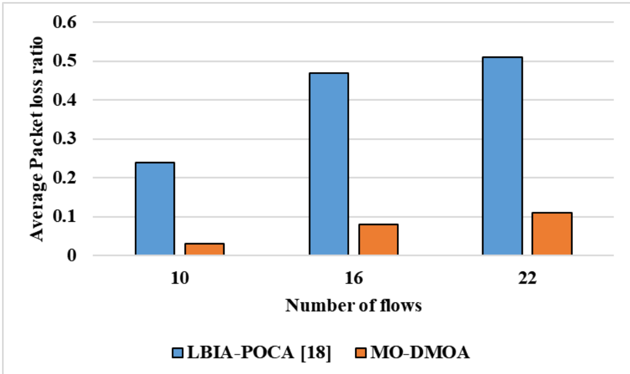

Figure 6: Graphical representation for evaluation of average packet loss

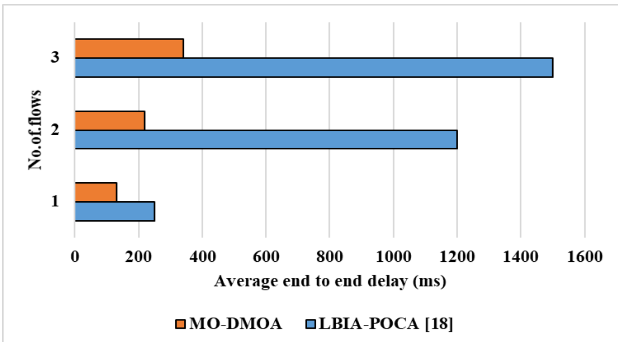

Figure 7: Graphical representation for evaluation of average end to end delay

Secondly, the performance of the proposed MO-DMOA is evaluated based on the transmission rate. The comparison is performed among the existing MODOR and the proposed MO-DMOA for different transmission rates of 80, 90, and 100, as presented in *table 3*. *Figure 8* depicts a graph for the average end-to-end delay of the proposed method against that of the existing MODOR for various transmission rates of 80, 90 and 100.

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 [19]	690	720	740
	MO-DMOA	2.25×10^4	2.9×10^4	3.2×10^4
Average packet loss ratio (%)	MODQR [19]	-	5.72	15.23
	MO-DMOA	0.09	1.52	2.93
Average end to end delay (ms)	MODQR [19]	40	320	390
	MO-DMOA	12	120	165

The obtained results show that the proposed approach obtains an average delay of 165ms, whereas the existing MODQR obtains a delay of 390ms. These results show that the proposed method acquires a minimum delay, and is sturdy due to its nomadic behavior which performs a random search to find the optimal route with the shortest distance.

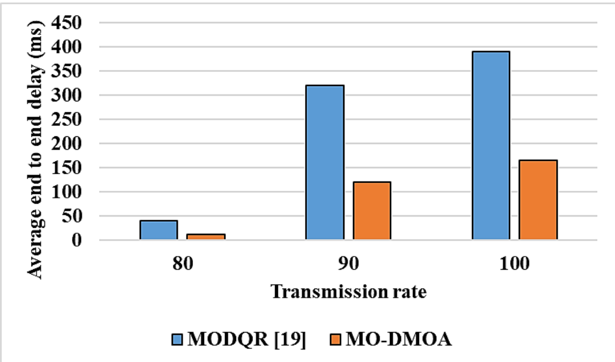

Figure 8: Graphical representation for evaluation of average end to end delay for various transmission rate

Table 4 exhibits the experimental results obtained while contrasting the proposed MO-DMOA with the existing MODQR, based on average energy consumption for varying transmission rates.

Table 4: Comparison of energy efficiency for different transmission rate

Performance measures	Methods	Transmission rate (Packets/second)						
		40	50	60	70	80	90	100
Average energy consumption (J/p)	MODQR [19]	0.43	0.36	0.32	0.28	0.26	0.25	0.26
	MO-DMOA	0.48	0.42	0.39	0.35	0.32	0.30	0.28

The results from the *table 4* prove that the proposed approach achieves superior results when contrasted against the existing MO-DMOA. The residual energy of the proposed MO-DMOA for 40 packets/second is 0.48 J/p, whereas the residual energy of existing MODQR is 0.43 J/p. Therefore, the preferable outcome of the proposed approach is owing to the selection of optimal routing path using the proposed MO-DMOA which selects the shortest effective path to transmit data packets.

4.3 Discussion

In this section, the results achieved by the proposed approach along with the comparative methods' results and their limitations are discussed. The efficiency of the proposed approach is assessed in terms of network throughput, packet loss, average end to end delay and average energy consumption. The efficiency of MO-DMOA is assessed with two existing approaches, LBIA-POCA [18] and MODQR [19]. Based on the number of flows of 10, 16 and 22, the efficiency of MO-DMOA is evaluated in comparison with LBIA-POCA. Similarly, based on the transmission rate, the performance of the proposed MO-DMOA is analyzed with the existing MODQR. The delay for 22 flows is evaluated for both LBIA-POCA and MO-DMOA, wherein the proposed method obtains a delay of 340.25ms which is lesser than the existing LBIA-POCA with 1500ms. This surpassing result of the MO-DMOA is a resultant of the usage of multiple populations that perform a robust search to find an optimistic route. Besides, the proposed approach obtained an average delay of 165ms, whereas the existing MODQR obtained a delay of 390ms. This superior result of MO-DMOA is due to the nomadic behavior of DMOA that helps to prohibit over-exploitation which is resonated with the need for exploration in multi-objective optimization for avoiding convergence to local optima.

5. CONCLUSION

The development of an effective routing technique probably enhances the quality of the routing process with minimal delay and energy efficiency. This research introduces MO-DMOA to perform effective routing over WMNs with minimized energy consumption and end-to-end delay. The optimistic route identified with the help of the proposed approach helps to transmit the data packets from the source node to the destination node, with minimized loss and delay. Moreover, the proposed approach performs nomadic search which helps in finding the optimal path for data transmission. The experimental results evidence that the proposed MO-DMOA achieves a better throughput of 13.5×10^5 kbps for 22 flows, whereas the existing LBIA-POCA exhibits a throughput of 60×10^3 kbps for the same 22 flows. Similarly, when assessing the proposed approach with MODQR based on a 100-transmission rate, the proposed approach acquires 3.2×10^4 kbps whereas the existing approach achieves 740 kbps. These acquired results prove the effectiveness of the proposed approach when compared with the existing methods. In the future, the channel quality can be increased by using a cross-layered approach with hybridized routing techniques.

Author Contributions

Conceptualization, K.N.P. and M.B.U.; methodology, K.N.P.; software, K.N.P.; validation, K.N.P., S.M.S. and M.B.U.; formal analysis, K.N.P.; investigation, K.N.P.; resources, K.N.P.; data curation, K.N.P.; writing—original draft preparation, K.N.P.; writing—review and editing, S.M.S.; visualization, M.B.U..; supervision, M.B.U.; project administration, S.M.S.; funding acquisition, S.M.S. All authors have read and agreed to the published version of the manuscript".

Conflicts of Interest

The authors declare no conflict of interest.

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