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JOURNAL OF AL-QADISIYAH FOR COMPUTER SCIENCE AND MATHEMATICS

ISSN:2521-3504(online) ISSN:2074-0204(print)



# Energy Optimization Approach in Wireless Sensor Network

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## ARTICLE INFO

### Article history:

Received: 10 /07/2024

Revised form: 11 /08/2024

Accepted : 20 /08/2024

Available online: 30 /09/2024

### Keywords:

Internet of Things - Wireless  
Sensor Network - Routing  
Algorithm - Energy Consumption.

## ABSTRACT

In recent years, the importance of routing protocols in wireless sensor networks and the Internet of Things has been demonstrated by the numerous studies that have been presented in this area. because it is crucial to the network's functionality and effectiveness. Among routing's main goals are lowering latency, enhancing reliability, and averting network collisions. Additionally, it can be claimed that the type of network routing affects service quality, network longevity, and network traffic load control. Thus, in order to lower routing error and boost network performance and efficiency, the firefly is employed in this study to identify the best information transmission path within the network. It is also employed to reduce energy consumption. Taking into account the ability of evolutionary algorithms to optimize specified objective functions, we attempted to lower the network's energy consumption. The network can enhance the number of sending packets with the beginning energy of 3 joules from 1480 rounds to 1798 rounds, based on the proposed algorithm's results. Additionally, by contrasting the approaches described in the same article, it was discovered that the suggested approach can send roughly 40.11% more packets than the RM-LB algorithm and 1.9573% more than the OMS-LB technique. Additionally, it was discovered that by raising the starting energy to 150 joules, the suggested technique outperformed the other two algorithms by 51.23% and 45.17%, respectively, and was able to lengthen the longevity. This was in comparison to the RM-LB method and the OMS-LB method.

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<https://doi.org/10.29304/jqcm.2024.16.31647>

## 1. Introduction

In the past years, among the emergence of new technologies, the Internet of Things has had a special effect, and its emergence has led to the emergence of many sensors and communications in all aspects of life. With the use of the Internet, the Internet of Things (IoT) has linked numerous sensors for purposes including tracking, monitoring and complete communication between objects and humans in many fields, and information is available to the user every second with the help of sensors [1]. A sensor that can listen to and sense its surroundings, a stimulus that can plan actions based on inductive inference, the dispatching of rules, and a decision-making module that can make intelligent decisions by deftly implementing rules are all effective ways to build a smart device. The performance of the Internet of Things is influenced by a wide range of issues, such as scalability, energy consumption in data

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centers, design, configuration, linguistic communication, data flow, and building an overarching framework [2]. Energy-optimal intelligent routing is a crucial factor to take into account in this scenario while transmitting data from the sensors to the sink node. Only wireless sensor networks in the Internet of Things can bring about a fundamental shift in data communication. Consequently, the Internet of Things is useless without the sensor network's assistance.

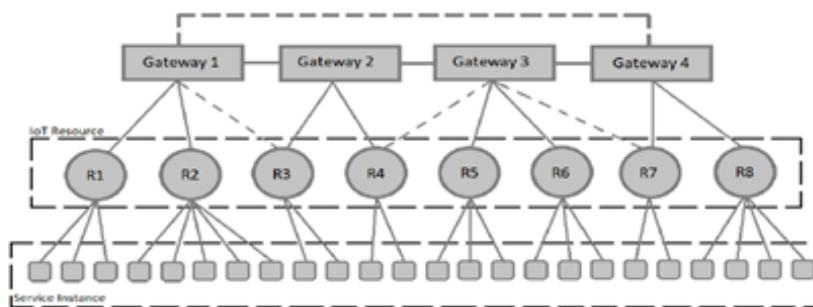
In the IoT environment, the wireless sensor network [3]. is a key element that has impacted the networking and Internet of Things communities as a whole, particularly with the advancement of microelectromechanical systems that facilitate the use of changing smart sensors. These sensor nodes, which are part of sensor networks, have the ability to listen to their surroundings and gather environmental data. This data is then transmitted to the user via a central station. In a situation like this, battery life is a crucial factor that nodes' designs should take into account [4]. The power resources of a sensor node are finite and cannot be replaced. For this reason, energy-efficient sensor network node design is required, freeing up the appropriate protocols to concentrate on enhancing the network's overall quality. One effective topology design and control strategy for improving network efficiency in sensor network nodes is clustering of nodes. Network conditions are improved by clustering and clustering-based routing. The two main steps in cluster-based routing are cluster head selection and cluster head routing [5-7]. By using cluster heads to collect data from other nodes and resending this information from cluster heads to central stations, energy consumption can be saved [8]. Therefore, choosing the right cluster head among the nodes can improve the energy efficiency and increase the lifetime of the sensor network. In addition, most researchers have focused on cluster head selection in clustering and cluster-based routing.

## 2. Methodology of Proposed Method

There are many challenges in the field of WSN & IoT networks, such as network efficiency, scalability, security, interoperability, routing, reliability, and load balancing in the network are among the most important challenges in this field. In the context of wireless information dissemination, many algorithms have been proposed; However, given that this is among the most crucial problems with wireless networks, new initiatives are still being proposed in this field. The challenges and effective parameters in the Internet of Things and their calculation methods are examined, and then the method of using the firefly method is explained in order to provide a reliable information dissemination solution in the WSN & IoT network. In order to select the cluster head node, various criteria are used, such as the energy level of the node, the accessibility of the node, reliability of the node, as well as the distance of the node from the message center. In the following, each of the service parameters used in this research is briefly explained, and in the following, the method of using parameters affecting Internet of Things routing is fully described.

### 2.1. Objective Function

In computing related to the Internet of Things, It is considered necessary for all resource nodes to speak with one another. Consequently, the entire cost of network communication needs to be computed for the routing and resource allocation problems. It is believed that every source communicates with other sources. In Fig. 1. the general schematic of the network is shown



**Fig. 1- Graphical schematic of communication between gateways and resources (nodes) of WSN&IoT network**

The objective function is determined by calculating the overall cost of these messages. The total cost function is defined as  $T_c$ . Therefore, the goal of the method in question is to reduce this objective function, which is in the form of equation (1) [11]:

$$T_c = \frac{\sum_{j=1}^{|V_g|} (d_j^r \times d^g)}{p} \tag{1}$$

that  $|V_g|$  equivalent to the quantity of data transmission network gateways,  $d_j^r$  is the same as the total cost of packet transmission between the  $j$ -th node and all of its associated resources, and  $d^g$  is equivalent to the overall cost, computed using the equation, of communication between nodes (2). Stated differently, the overall communication expense for every node resource is due to the multiplication of  $d_j^r$  and  $d^g$ . We shall have a portion of the proportion  $T_c$  if we compute this value for each node.

$$d^g = \sum_{i=1}^{|V_g|} \sum_{j=1}^{(d_j^r \times d^g)} l_{ij} \tag{2}$$

where  $l_{ij}$  is the same as the communication expense incurred by gates  $i$  and  $j$ .  $d_j^r$  is also calculated using the equation (3):

$$d_j^r = \sum_{k=1}^{|V_g^j|} \varepsilon_{jk} \tag{3}$$

where  $\varepsilon_{jk}$  is equivalent to the  $j$ -th gateway's and all associated nodes' communication cost.  $|V_g^j|$  is the same as the quantity of nodes corresponding to gateway  $j$ . Another point that is paid attention to in this research is the penalty function related to load balance in the network. Based on this, the proposed method should reduce  $T_c$ , where  $P$  indicates that if it becomes equal to zero, it means that a penalty is considered for the objective function, and if it becomes equal to 1, it means that there are normal conditions for the nodes. Every node's value of  $p$  is computed, which is obtained through the equation (4):

$$P = 1 + \sum_{i=1}^{|V_g|} P_i \tag{4}$$

that  $|V_g|$  is equal to the total number of gates and  $p_i$  is equal to the penalty function of each node, which is calculated using the equation (5):

$$P_i = \{1 \text{ if } g_i^t \leq \varepsilon \frac{|V_r|}{|V_g|} \quad 0 \text{ if } g_i^t > \varepsilon \frac{|V_r|}{|V_g|} \tag{5}$$

where  $g_i^t$  is equal to the number of nodes assigned to gateway  $i$ ,  $|V_r|$  is equal to the number of nodes and  $\varepsilon$  is equal to a fixed number. Based on this, the symbols used in this model can be expressed as follows:

- $T_c$  general objective function
- $|V_g|$  The number of gateways

- $|V_r|$  The number of IoT network nodes  
 $|v_g^j|$  The number of nodes assigned to gateway j  
 $d_j^r$  total expense for the data transmission between gateways and nodes  
 $d^g$  Total communication cost between gateways  
 $g_i^t$  Number of resources allocated to node i  
 $\varepsilon_{jk}$  communication cost between gateway j and nodes assigned to it  
 $P$  total amount of the fine  
 $p_i$  Penalty value for the node i  
 $\varepsilon$  constant value

## 2.2. Firefly Algorithm

This method has been used since it was introduced in 2008 and was inspired by the behavior and flashing patterns of real fireflies. Since NP-Hard is a member of the random algorithm family, it can be applied to optimization, engineering, and other problems involving a kind of random search to find a set of solutions. The firefly algorithm, at its most basic, selects the optimal solution for survival by producing solutions inside a search space. By using random search, one can escape the local optimality trap. In the context of metaheuristic algorithms, exploitation refers to a population-based algorithm's primary focus, whereas discovery refers to the process of identifying many solutions inside the search space. The search procedure is among the top local options [12]. There are two important issues in the firefly algorithm: Changes in light intensity ( $I$ ), and formulating the level of attractiveness ( $\beta$ ). Since fireflies only need local information in their neighborhood to navigate, the number of detectable peaks is expected to be a function of the radial sensing range. Essentially, when every firefly's sensing range encompasses the whole search space, all worms will gravitate towards the global optimum, disregarding the local optimum. It is simply not possible to examine an appropriate fixed neighborhood range for all objective functions, since the pre-known information about the objective function (e.g., the number of peaks or the distance between peaks) is not assumed for the problem. For instance, it is more appropriate to select the neighborhood range  $r_d$  for the objective function whose distance between peaks is less than  $r_d$  than it is for functions whose distance is more than  $r_d$ . Thus, in order to detect the existence of numerous peaks in multimode function optimization problems, Glowworm swarm optimization GSO employs an adaptive neighborhood board [13].

As seen in the flowchart above, each firefly is selected as an initial value of the objective function and by forming the initial population, it determines the value of the objective function and updates the objective function based on the optimal values of the worms. This algorithm outperforms others, including the particle swarm algorithm and the genetic algorithm, and it is a comprehensive mode of these two algorithms, which results in the particle swarm algorithm by setting  $\gamma$  towards infinity and by setting  $\gamma$  towards zero. On the one hand, this algorithm, like the genetic algorithm, is not involved in actions such as mutation and selection, and on the other hand, like the particle swarm algorithm, the comparison with two global and local particles is not done, and each particle in the search space is compared with one particle [14-15].

## 2.3. Proposed Algorithm

In short, the steps of the proposed firefly-based algorithm for information dissemination in WSN&IoT networks are as follows. The proposed algorithm is repeated for each round of information dissemination by updating the values of the quality-of-service parameters. The flowchart of the proposed method can be shown using Fig. 2. which displays all the steps of the proposed algorithm from the starting point to the final part.

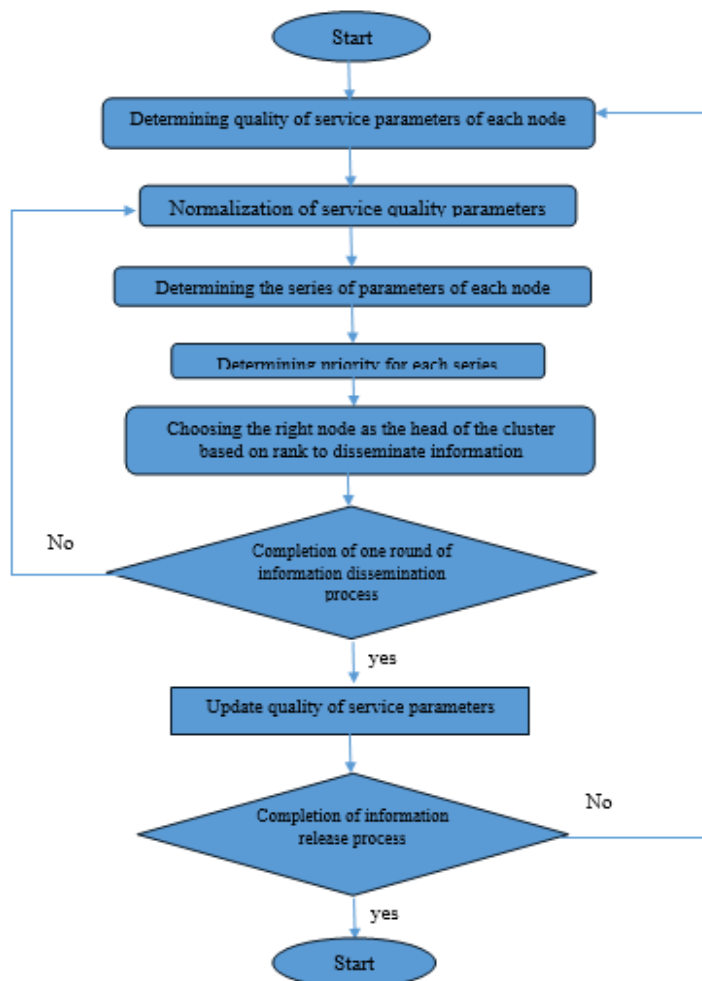


Fig. 2- Flowchart of the proposed method

### 3. Evaluation of the Proposed Method

As the title of this article suggests, our goal is to choose the best path in terms of energy consumption, therefore, in order to investigate this issue more precisely, by using the Enyder tree and clustering nodes and implementing the proposed algorithm in order to achieve the optimal energy consumption according to the model We will discuss it below. In this research, the proposed network is modeled as a graph  $G(V, E)$ , where E is the edges connecting the nodes in V and V is the collection of nodes. If node  $i$  sends b data bit to node  $j$ , the amount of energy it uses is:

$$E_{TX}(i, j) = b(\alpha_1 + \alpha_2 \times d_{i,j}^\gamma) \tag{6}$$

where  $d_{i,j}$  is the actual separation between nodes  $i$  and  $j$  and  $\alpha_1$  is the amount of energy consumption per bit created by the transmission circuit. Also,  $\alpha_2 d_{i,j}^\gamma$  shows how much energy the amplifier uses for each bit, where  $\alpha_2$  is the

amplifier circuit's total energy usage. In addition, the energy consumption of node  $i$  to receive  $b$  bits from node  $j$  is equal to:

$$E_{RX}(i, j) = b \times \beta \quad (7)$$

where  $\beta$  represents the energy consumption per bit for the receiver circuit.

In this research, in terms of the number of steps, the closest RP node to node  $i$  is found using a function named  $H(i, M)$ . and  $M$  is the set of RP nodes:

$$H(i, M) = \{h_{i, m_j} | \forall m_k \in M, h_{i, m_j} \leq h_{i, m_k} \quad (8)$$

where  $h_{i, j}$  is the step distance between nodes  $i$  and  $j$ .

For each RP ( $m_i$ ), this algorithm creates a data transmission tree called  $T_{m_i}$ , which consists of the closest nodes to this RP node. The number of  $NFD(i)$  packets of data that node  $i$  sends to the nearest RP (i.e.,  $m_i$ )  $D$  is equal to the total number of packets produced by the system plus the total number of packets produced by its offspring for each time interval. in the data transmission tree  $T_{m_i}$ :

$$NFD(i) = C(i, T_{m_j}) + 1 \quad (9)$$

where  $C(i, T_{m_j})$ , is a function that, in the sent data tree, returns the number of children of each node  $i$ . The root of this tree is the RP node corresponding to this node  $i$

### 3.1. Energy-efficient and delay-aware movement path

The aim of this method is to find a path  $M = m_0, m_1, m_2, \dots, m_n, m_0$  such that  $m_i \in V$  so that:

- 1) The  $M$  path's length shouldn't exceed  $l_{max}$
- 2) The amount of energy used to transmit the sensed data to path  $M$ , which is defined as  $(E_{TX} + E_{RX}) \sum_{i \in V} H(i, M)$ , is at its lowest throughout the period of time  $D$  to be

Note that when all nodes are set to RP, the least amount of energy is used. This is due to in this case nodes do not send packets to other nodes. But in this case, it is difficult to find a path whose length is less than  $l_{max}$ .

Because they are in charge of sending data to the nodes that are far from the sink, the nodes near the sink experience congestion in multi-hop communication. Therefore, the closer the node is to the sink, the higher its energy consumption will be. While the energy of nodes far from the sink usually remains at 90%. Therefore, this problem causes that the energy consumption in the network is not uniform and the network suffers from leakage. As a result, this problem causes disconnection between the sink and some nodes.

The proposed algorithm receives the graph  $G(V, E)$  which is randomly formed depending on the number of nodes and network dimensions, as input and returns RPs as output. If the path length is less than  $l_{max}$ , the selected node remains as RP. Otherwise, this node will be removed from the path. The routing method eliminates RP nodes that stop receiving data packets from other nodes after designating a node as RP. Each RP node has a defined "removed" variable, which is set to true in the event that an RP is deleted, for this reason. A deleted RP won't be eliminated from the path again if it is inserted again because its removed variable is true. In the proposed method, we start the survey from the master stations and step by step send a message based on the sink location to the other nodes. In

this case, other nodes turn on their smart antennas in a very short time. With this message, by recognizing the strength and direction of the source signal, they can determine their location relative to that station; Then, after receiving the location message of the network nodes and determining its optimal physical location, the sink sends the message of its movement path to the others. This will continue until the end.

Therefore, the proposed routing method based on the firefly method presented in this research can be proposed based on the following three patterns:

### ***3.2. Average with total residual energy in the network when using a node as an intermediate node***

In this case, in the routing of each candidate node that was still alive, it is selected as an intermediate node and each time based on the nodes closer to the intermediate node and closer to the sink, the power consumption of the set is calculated and finally the average with the total remaining power in the network with the assumption that node  $i$  is an intermediate node is calculated. Finally, a node is selected as an intermediary node, the average remaining power of the network in the intermediary state of that node is maximum compared to other states.

### ***3.2. Residual power variance in nodes***

Variance is a statistical parameter that refers to the dispersion of information. If the cost function is designed to minimize the variance, we can be sure that the power consumption will be adjusted so that the set of nodes consume the same power and the power of the network set tends to zero relatively homogeneously.

This cost function is very appropriate in that it will lead to the maximum sharpening of the ninety-dead curve. But its problem is that it does not pay attention to the network lifetime as a key parameter and it will not create the maximum possible mode in terms of lifetime.

### ***3.4 Coefficient of changes***

One of the statistical parameters that can be very helpful in such applications, despite being simple, is the coefficient of variation criterion. This measure, which is the result of dividing the root of the variance or the standard deviation by the average of the information, shows us the amount of information compared to the middle point or the average, and it can be very fruitful and practical in terms of application in the Internet of Things network. Because if this value is minimized, it means that the numerator has a minimum value and the denominator has a maximum value. The minimization of the face means the greatest proximity in the power consumption of the nodes when choosing the interface node and the maximization of the deviation with the average means the longest network life time as possible. Therefore, based on the explanations given, among the proposed cost functions, average, variance, and coefficient of variation, the coefficient of variation was selected as the most suitable cost function, although the results of other possible functions were also given in the simulations to show the correctness of the reasoning. In terms of the amount of calculations, the coefficient of variation will not impose a different computational burden on the system compared to the calculation of the cost function, and from this point of view, the proposed cost function is the same as the desired cost function, and no more computational load will be applied in this part.

### ***3.5 Analysis of execution time***

Although the Internet of Things sends information in relatively long intervals and is considered a very active and low-traffic network, however, the execution and calculation time of the interface is very important. This is mostly

because if the execution time of the method is high, it means that the amount of power consumed in the sink node, which has the task of selecting the interface, is high, and despite the conventional design of the sink battery being stronger than other nodes, this node is exposed to all Being able is placed.

In addition, in all simulations and cost functions, the lightness of the computational load is important when selecting a candidate node as an interface and is considered a strong point for the algorithm. The calculation of the coefficient of variation as a proposed relationship is not much different from the calculation load formula, and the only difference is the small amount of calculation load, more standard deviation compared to the distance, which can also be neglected, but a very important and overlooked point is the amount of affection. It is necessary to obtain the numbers of the standard deviation and the average of the remaining energy in the network every time.

In the proposed method, it was assumed that we select each node as an interface, and in this case, based on the nodes that will be connected to it and the nodes that are directly connected to the sink, the power consumption of each node is calculated and finally, after this Pre-simulation, the value of the standard deviation and the average residual energy in the network will be calculated and this formula will be evaluated.

#### 4. Simulation and presentation of results

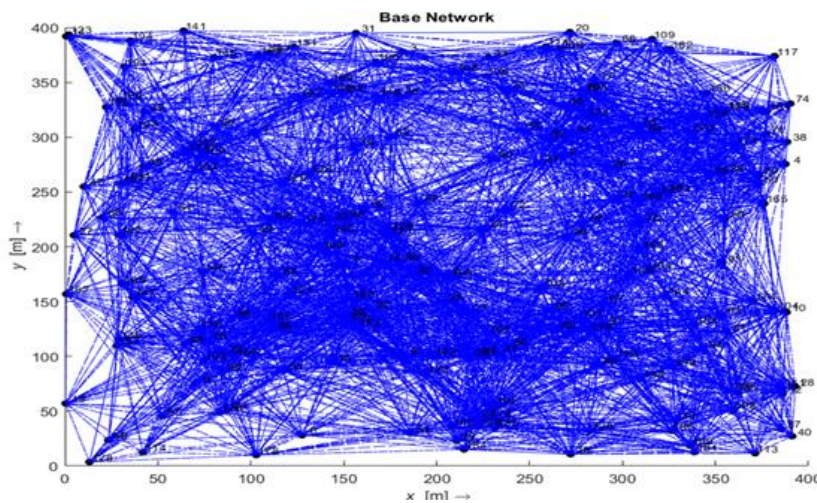
The information exchange between the nodes of the proposed integrated network will be considered based on the specifications of the following table based on the article [10]. Therefore, the investigated network and its information are given in Table 1.

**Table 1 - System simulation information.**

Amounts	Parameters
200	Number of nodes
3J	Primary energy $E_0$
5 nJ / bit / signal	Energy for data accumulation $E_{DA}$
50nj / bit	Energy from receiving data $E_{elec}$
10 Pj / bit / m <sup>2</sup>	Boosting energy for short distances $E_{fs}$
0.0013 Pj / bit / m <sup>4</sup>	Reinforcement energy for multi-path distances $\epsilon_{TR}$
$\sqrt{\frac{\epsilon_{FS}}{\epsilon_{TR}}}$	Communication range of nodes $d_0$
3 meters per second	Device movement speed (nodes)

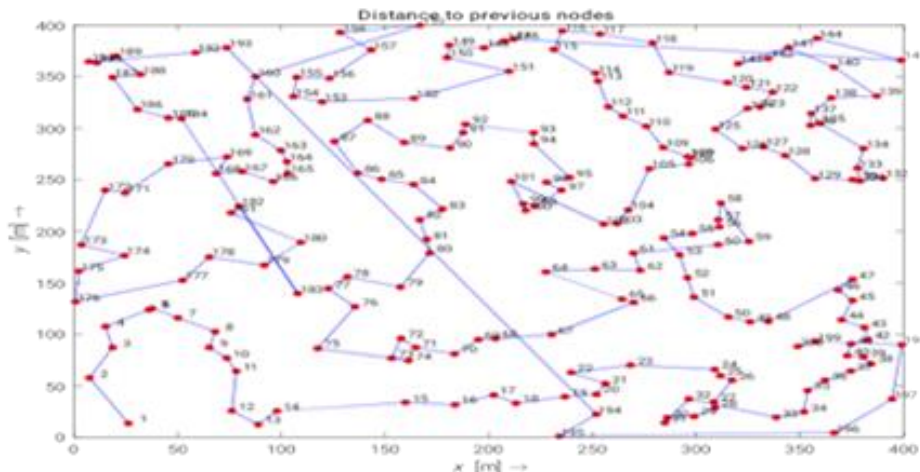


The probability of storing information in nodes should be chosen appropriately so that nodes with higher energy levels and shorter distances are prioritized in sync with other nodes with a very high probability. Because these nodes have a higher level of security and a higher value than other nodes in the network. Therefore, first the sink calculates the total distance of the surrounding nodes, then according to the number of tasks it has to perform and what proportion of the total energy level each node allocates, based on the nodes' positions and locations, a priority is determined. Another criterion is defined as energy density, which for a node is equal to the amount of energy that can be provided to the cluster head according to the spatial distance. That is, the node with the largest spatial distance is considered as  $L$ , and the rest of the nodes, which have a distance of  $l < L$ , normalize the energy level according to the ratio of the distance from the origin as the energy coefficient. These factors cause the sink to place itself in a place at any moment where it can receive packet information from virtual cluster heads with the least amount of energy consumed by these cluster heads. According to the movement of the sink in the network, and the investigation of the prevailing conditions, the sink seeks to be placed in any place with the aim of reducing the consumption of resources and reducing costs.



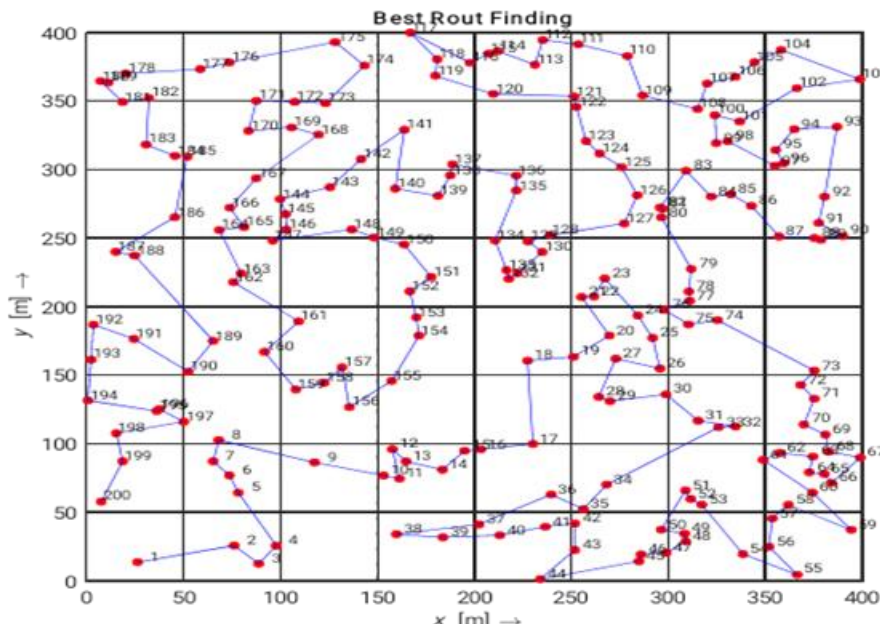
**Fig. 3- Basic network graph formation**

As shown in Fig. 3, Every node first compiles a list of its neighbors and keeps a database with each one's identification number, approximate energy level, distance, and task amount allocated to it. Every node in the system sends out a first message to the nodes nearby, letting them know where it is and how much energy it has left. The message is stored by each node in its actions vector according to energy level. Then, every node will transmit data via potential routing by taking this data into account and figuring out the priority function, as seen in Fig. 4.



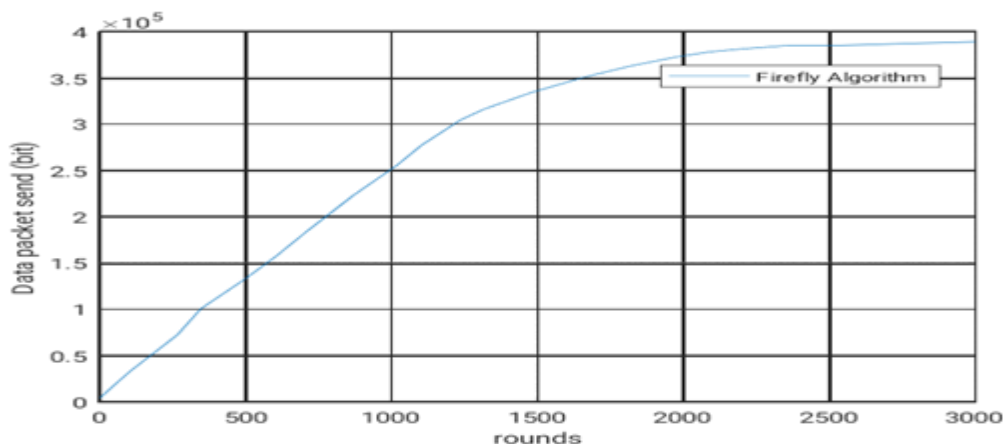
**Fig. 4- Calculation of the placement distance of nodes relative to each other.**

In order to provide priority to nodes with higher energy levels and shorter distances from other nodes in the sink, it is important to choose the likelihood of storing information in the nodes suitably. Because these nodes have a higher level of security and a higher value than other nodes in the network. Therefore, first the sink calculates the total distance of the surrounding nodes, then according to the number of tasks it has to perform and what proportion of the total energy level each node takes, a priority is calculated based on the position and location of the nodes. Another criterion is defined as energy density, which for a node is equal to the amount of energy that can be provided to the cluster head according to the spatial distance. That is, the node with the largest spatial distance is considered as  $L$ , and the rest of the nodes, which have a distance of  $l < L$ , normalize the energy level according to the ratio of the distance from the origin as the energy coefficient. These factors cause the sink to place itself in a place where it can receive the packet information from the cluster heads with the least amount of energy consumed by these cluster heads. According to the movement of the sink in the network, and the examination of the prevailing conditions, the sink seeks to be placed in any place with the aim of reducing the consumption of resources and reducing costs. As shown in Fig.5. the sink continues to search for the best location at each moment.



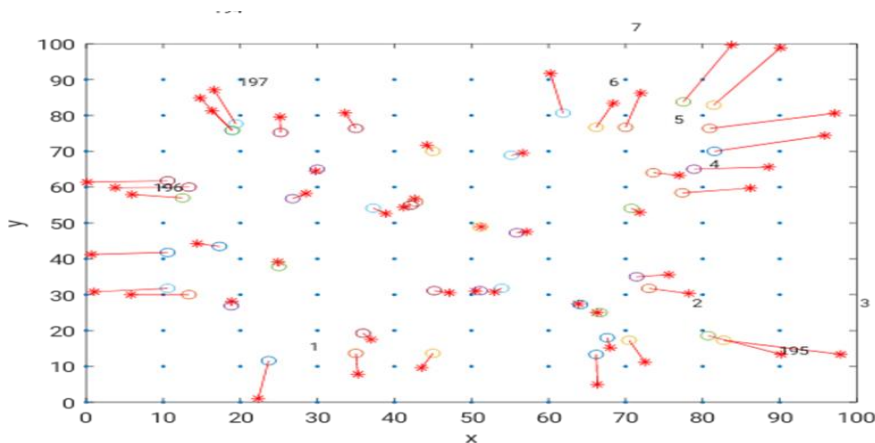
**Fig. 5- Finding the best data transmission path for each node.**

Based on determining the distance of the nodes from the sink and the activity level of the nodes in the network, the information about the packets is stored in the network. The storage level has a direct relationship with the energy level and the lifetime of the nodes in the network. Therefore, the way to transfer stored information is very important. As shown in Figure 5. with the increase in the amount of data transmission, as sink as the amount of energy consumed by the nodes, considering the optimal location of the sink in order to receive information by the nodes, the data transmission rate decreases, but still maintains their quality. becomes as can be seen in Fig. 6. as the number of data transmission rounds increases, due to the energy consumption between nodes to send and receive data, the network experiences a blackout as its energy drops, however because of the transmission The data transmission slope is still rising when using intermediary nodes and the proper path between nodes in the network. This indicates that the network is operational and has not been shut off.



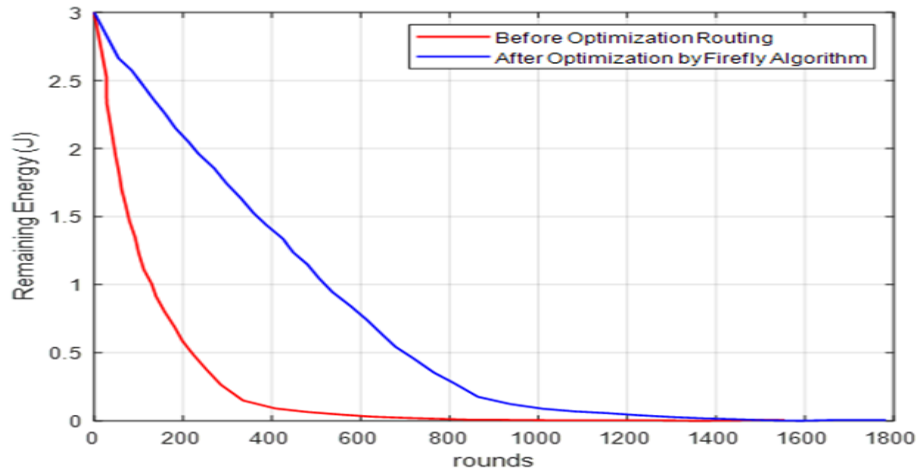
**Fig. 6- Data transmission rate.**

Finally, by applying the firefly method in order to create new cluster heads, the path of data transmission is improved and by using the final routing, the amount of storage is reduced, which leads to the reduction of unnecessary use of resources and the reduction of related costs. It reduces Fig. 7. shows the final routing probabilities of the node at different times using the firefly-based clustering and routing algorithm for the desired



**Fig. 7- Final routing of nodes using the proposed method**

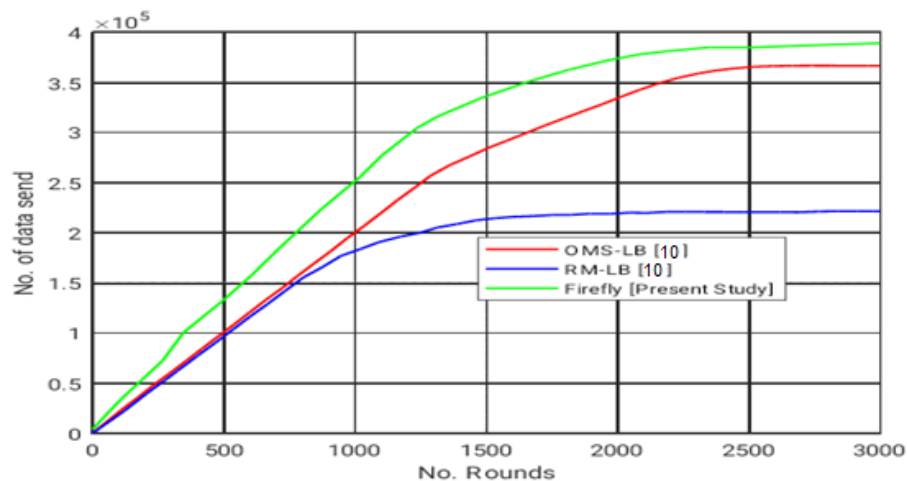
In Fig. 7, the drawn lines between red stars and blue circles indicate the allowed movement range of nodes based on the final position of the virtual cluster heads. As can be seen, the considered network is dynamic and the colored circles and red stars represent the initial location and the allowed movement range of the same nodes, so that optimal routing between nodes can be established based on it. Also, in this routing, due to the data broadcast based on which the nodes are able to communicate with more nodes, less energy is spent due to the reduction of the packet transmission path, which ultimately leads to an increase in the network's lifespan. Finally, the amount of energy consumption by network nodes can be determined before and after optimal routing it is shown in Fig. 8.



**Fig. 8 Comparison of energy consumption in network nodes.**

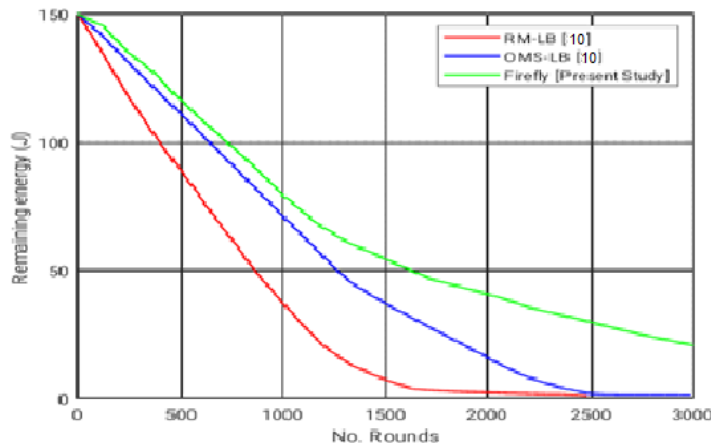
As can be seen, after applying the proposed method, the number of rounds of the network lifetime has increased from 1480 rounds to 1798 rounds in order to save energy in the network, which shows that the load balance in the network and the reduction of energy consumption between nodes be This problem can be justified because in the whole network, using the firefly optimization algorithm, the movement space of the nodes has been determined and according to it, the optimal path between the communication links of the nodes has been selected so that based on the positioning of the nodes, the nodes Determine whether or not to use them so that packets are transmitted with less speed and energy.

In the following, we will compare the results obtained in terms of energy consumption and packet sending delay in the proposed network using the article [10]. In this article, two approaches, OMS-LB and RM-LB, are used in order to determine the path of packet transmission, in which the number of sent packets (vertical axis) is selected as a criterion for comparison with the current research.



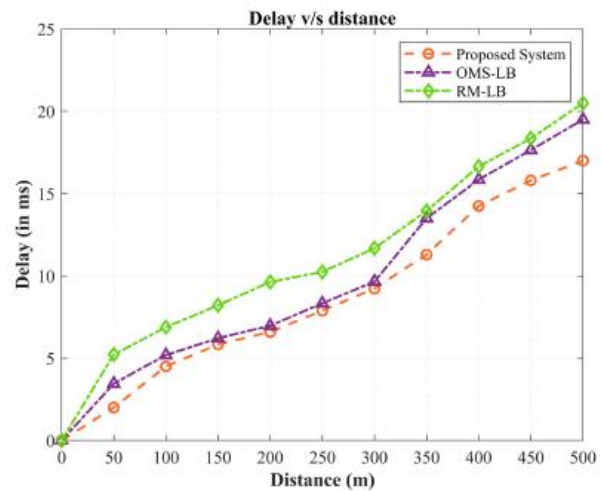
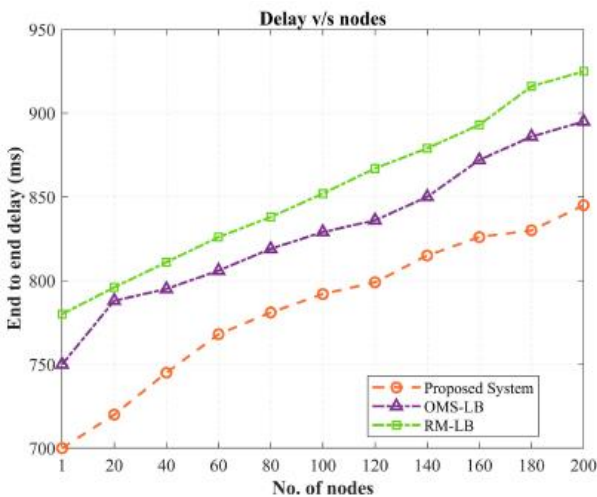
**Fig. 9- Comparison of the number of packets sent in the network.**

In Fig. 9, a comparison is presented regarding the amount of packet transmission in equal number of rounds. As can be seen, the method based on the proposed algorithm of this research has performed better than the OMS-LB algorithm by about 1.9573 percent and compared to the RM-LB algorithm by about 40.11 percent. increases, the trend of sending rate will be upward. In this figure, the horizontal axis indicates the number of rounds of data exchange and the vertical axis indicates the number of packets sent in each round. Also, in order to establish a proper comparison scale between the results of this research and the article [10]. the initial energy of the nodes was increased by 150 joules so that the remaining energy in the network can be compared using the OMS-LB and RM-LB methods. This comparison is presented in Fig. 10.



**Fig. 10- Comparison of the amount of remaining energy in the network considering the initial energy equal to 150 joules.**

As can be seen, by increasing the initial energy of the network up to 150 joules, the proposed method has been able to have a high capability compared to the article [10] and maintain the network actively up to the number of rounds of 4500. In particular, it can be acknowledged that the proposed method has been able to perform better than the RM-LB method by 51.2336% and by 45.1739% compared to the OMS-LB method up to the number of rounds of 3000.



End-to-end delay: With reference to the delay constraints, Figs. 11 and 12 examine the suggested system as well as OMS-LB and RM-LB. The system delay is then decreased by the network length by preventing packet retransmission. The results demonstrate that the system's mobile sink MS delay has been reduced to the OMS-LB, RM-LB approach. This drop is the result of OMS-LB's effective usage of AI. RM-LB selects the coordinates of the CHs as an aggregate point and transfers priority to data collecting.

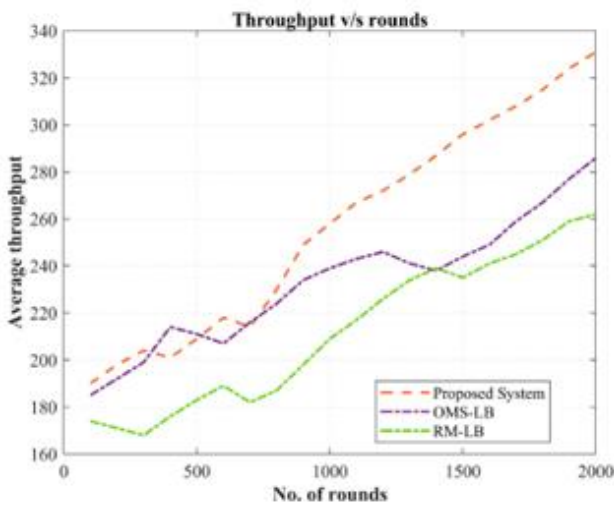


Fig. 13- System average throughput.

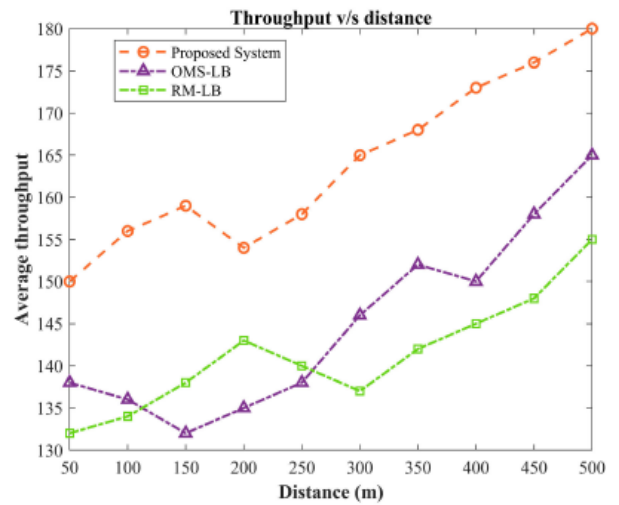


Fig. 14- System average throughput with respect to distance.

Average throughput: The total throughput of all suggested methods for I-IoT nodes is displayed in Figs. 13 and 14, together with the distance traveled and network performance. Through the use of sinks to collect high-quality data that flows to CHs in the network, network performance increases with high throughput. By reducing CH congestion and facilitating efficient MS movement within the network, Artificial Bee Colony ABC allows for the achievement of the maximum throughput, which is compared to OMS-LB, RM-LB, and the proposed method of the system by 74%, 79%, and 86% in the main case and by 70%, 75%, and 81% in the distance. In order to further compare with previous researches, we present Table 2.

Table 2 - performance comparison of algorithms.

Algorithm execution time(seconds)	Network lifetime (rounds)	Error rate (percentage)	Method	Research
37.421	4352	11.45	DV-Hop	[6]
39.928	4108	8.32	Using Mamdani fuzzy logic	[7]

29.665	4691	7.47	Use the whale algorithm	[8]
34.15	4728	1.26	OMS-LB	[9]
30.635	4859	0.0255	The Firefly algorithm	current study

Based on the comparison presented in the above table, it is concluded that the whale algorithm has a higher speed than other algorithms, especially the combined algorithm presented in this research, while the proposed method in this research is faster than all the algorithms. The error rate is lower and has a higher effect on increasing the network lifetime.

## 5. Conclusion

In this research, we proposed an optimal routing algorithm based on the firefly algorithm. This algorithm is not only energy efficient but also depends on distribution in the network. Our proposed algorithm considers parameters such as residual energy levels, distance to indentation, and density parameters in the calculations of competitive radius of clustering vertices. In this research, using the concept of Internet of Things in which the energy consumed to send and receive information is of great importance, the firefly algorithm that improves clustering and packet transmission path by nodes in the Internet of Things network in order to Determining the optimal route of information transmission in the network was used with the aim of reducing routing errors and reducing energy consumption and swarm (reducing delay) in order to increase the efficiency and performance of the network. The method's quantity of mistake was reported at the conclusion. In this study, we attempted to minimize the energy usage of the Internet of Things by utilizing evolutionary algorithms' abilities to optimize specified objective functions. According to the results of the proposed algorithm, it was observed that by using the firefly algorithm, the network is able to increase the number of sending packets with the initial energy of 3 joules from 1480 rounds to 1798 rounds. Additionally, by contrasting the approaches described in the paper [10], it was discovered that the suggested approach may send roughly 40.11% more packets than the RM-LB algorithm and 1.9573% more than the OMS-LB technique. Additionally, by raising the beginning energy to 150 joules, it was discovered that the suggested technique outperformed these two algorithms, outperforming the RM-LB method by 51.23% and the OMS-LB method by 45.17%, thus extending its longevity.

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