Original Research

Optimization of Mobile Base Station Placement to Reduce Energy Consumption in Multi-hop Wireless Sensor Network

Gholamreza Farahani[1*]. Ameneh Farahani[2]

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* Corresponding Author, farahani.gh@irost.org

1- Department of Electrical Engineering and Information Technology, Iranian Research Organization for Science and Technology (IROST), Tehran, Iran
2- Department of Industrial Engineering, Ooj Institute of Higher Education, Qazvin, Iran

Abstract
Nowadays, wireless sensor networks (WSNs) use in different sectors. The problem in these networks is the non-rechargeable batteries of these sensors, which limit the use of the network. Therefore, the optimal energy consumption of sensors is an open research topic. In this paper, a new algorithm with the Development of Genetic Algorithm with the Floyd Warshall (DGAFW) has been proposed. Using the proposed DGAFW algorithm, the clusters and nodes of each cluster are first determined with the Floyd Warshall algorithm**.** Then the Cluster Head (CH) is specified by fuzzy logic**.** Finally, the optimal placement of the base station is specified by the combination of the Genetic Algorithm and the Floyd Warshall. The DGAFW algorithm is based on minimizing the distance of sending multi-hop messages. The simulation is done in MATLAB 2023a online software. The simulation results obtained from the DGAFW algorithm have been compared by the distance, the energy in each round, and the rounds of activity in the case where the placement of the base station is fixed or randomly determined in each round. The results show that the DGAFW algorithm compared to the case of random base station and fixed station respectively, has 12.7% and 14.3% shorter average message-sending distance in each round, 14.7% and 19.1% more residual energy and also 36% and 48% more rounds of network activity.

Keywords- Floyd Warshall algorithm; Fuzzy logic; Genetic algorithm; Mobile base station; Wireless Sensor Network

INTRODUCTION

Today, with the use of Wireless sensor networks (WSN) many problems solve. A new understanding of future life is created. In the case of WSNs, topics such as network security, signal processing, data management, topics related to radio communications, and most importantly energy consumption management are of researcher's interest. Energy management is the basis of other topics because it is not possible to recharge or replace dead nodes (disabled due to the end of the energy source). These nodes are usually located in difficult and inaccessible environments and are often randomly scattered in the specified area. Therefore, two parameters of lifetime and network coverage are of particular importance in the efficiency of sensor networks. Since monitoring applications are time-consuming tasks, it is expected that the networks are long enough to be able to obtain the necessary information. However, the most important goal of the WSN is the rational management of energy resources.

In total, the energy consumption of nodes in WSN takes place in three parts. Sensing, data processing and communication. Among these three parts, communication, that is, receiving and sending data, consumes the most energy. Therefore, research on reducing energy consumption in this part continues. Many methods have been used for routing that include collecting, sending and processing data. The clustering is one of the most important of them. In this method, nodes are grouped into clusters and one node selects as the head. The Cluster Head (CH) node reduces energy consumption due to the reduction of bandwidth, the scheduling of node activity, and the aggregation and combination of data in the CH node. Various clustering algorithms have been introduced in WSNs, and main issues such as the following have caused the inefficiency of these algorithms:

- The amount of energy and the location of the nodes are not known.
- High energy consumption in CHs.
- Shortness the lifespan.
- The long distance of some CHs.
- The base station is fixed.

Various researches have been conducted in this field. Li et al. [1] have used support vector machine for energy distribution system in WSN. In another research, a routing protocol using K-means clustering is presented, which first selects a CH with the lowest energy consumption, and then the routing process is performed with the help of this CH for other nodes [2]. Loh and Penn [3] have proposed a hierarchical routing protocol. A secure routing protocol aimed at clustering large-scale WSNs, which has reduced energy consumption in all dimensions has been proposed by Zahariadis et al. [4]. It greatly increased security in routing compared to other methods. Karthikeyan et al. [5] have worked on finding neighboring nodes in a WSN. The authors have proposed a new method for neighbor discovery in a WSN to reduce delay, and network power consumption and increase service quality using routing with Ad-hoc On-demand Multipath Distance Vector (AOMDV) protocol. The usefulness of multi-hop routing in WSN to improve lifetime by load balancing with the help of clustering has been investigated by Hurni and Braun [6].

Shin et al. [7] have used the A^2OMDV protocol. A special routing protocol with minimum energy consumption in a reliable transmission environment has been developed by Vidhyapriya and Vanathi [8]. It involves both node and quality to identify the best possible path to the destination with minimum energy consumption. Farahani [9] has used a fuzzy clustering and Particle Swarm Optimization (PSO) algorithm in WSNs to reduce energy consumption for multiple routing. Kumar et al. [10] have proposed a CH selection scheme from nodes in a WSN to increase the network life with the help of load balancing and use fuzzy logic to select the CH and AOMDV protocol to discover the route in a WSN. Farahani [11] with use of clustering has been reduced the energy consumption in WSNs. Samundiswary and Anandkumar [12] have analyzed the performance of two protocols Ad-hoc On-demand Distance Vector (AODV) and Energy efficient AODV (EAODV) with different packet sizes in Constant Bit Rate (CBR) traffic. Also, Farahani [13] has improved the network performance with optimization of sensor placement in WSN. Makyandi et al. [14] have investigated intrusion in WSNs with the help of a Genetic algorithm. Malicious or maladaptive nodes throughout the network provide additional observations of network behaviour by analyzing sensor events in their neighborhoods. The intrusion detection operation has been carried out in an environment of 100x100 and 200 initial nodes, which have 1000 joules of energy at the initial time of execution. The results of using multi-objective Genetic algorithm method and then the fuzzy algorithm with the combination of the multi-objective Genetics has been discussed. The obtained results show that the use of the multi-objective Genetic fuzzy method has better results than the single mode of the multi-objective Genetic algorithm. Farahani [15] has introduced a new Cross Correlation based Feature Selection (CCFS) method to improve performance of the intrusion detections in the networks. Also, he has proposed a black hole attack detection using K-Nearest Neighbor (KNN) algorithm and reputation calculation in the mobile networks [16]. Singh and Verma [17] have presented a protocol based on the cross-layer routing protocol of optimal distributed energy consumption in sensitive adaptive thresholds for heterogeneous networks. In the method, a probabilistic weight has been assigned to the CHs of each cluster of the network. In another research, the Novel Energy Aware Hierarchical Cluster-based (NEACH) routing protocol presented by Ke et al. [18]. Yigit et al. [19] have proposed an energy-aware routing considering the priority of multi-channel scheduling for routing so that the channel could be selected during routing with minimum energy consumption. Another research has used the

On-Hole Children Reconnection (OHCR) protocol in WSNs [20]. The central base is considered as the target area. Ramanan and Raj [21] have introduced the Derived Genetic Algorithm Optimization scheme for Energy Efficient Routing (DGAO-EER).

Mansi and Patel [22] have optimized the routing energy in WSNs based on the optimal number of CHs, dynamic cluster size, multi-hop approach, and CH replacement cost, and use simulation to validate the optimization. Raghavendra and Mahadevaswamy [23] have modelled energy consumption and expressed them as a fuzzy membership function. Their proposed solution is more efficient and hence extends the network lifetime. Sahu and Patil [24] have introduced dual CHs. With the presence of the Internet of Things and the necessity of customer relationship management [25] and the design of an organizational structure based on customer relationship [26], as well as in places where information sharing systems are needed [27], the role of wireless sensor networks becomes very colorful. Yaghoobi and Khairabadi [28] have presented an energy-conscious approach in the Internet of Things.

According to the literature review and the conducted research, the contributions of this paper are as follows:

- Introducing the new proposed DGAFW algorithm by developing the Floyd Warshall algorithm and the Genetic algorithm to optimize energy consumption by using the shortest path and mobile base station for multi-hop routing.
- Determining the clusters and nodes of each cluster using the developed Floyd Warshall algorithm.
- Selection of the CH for each cluster based on distance and energy using fuzzy inference.
- Finding the optimal location of the mobile base station based on the developed Genetic algorithm with the Floyd Warshall algorithm.

The assumptions of this paper are as follows:

- Distribute several homogeneous nodes randomly.
- Each sensor node is fed with a limited energy source in which the energy level is the same for all sensors at the beginning.
- There is only one mobile base station, which is unlimited in terms of energy compared to other nodes.
- The clusters and nodes of each cluster are not known and are determined dynamically in each round.
- The heads of the clusters are not clear at the beginning and are considered according to the clusters in each round.
- The base station is mobile and it is optimally determined in each round.
- The minimum amount of energy to be allocated to each node is known.

PROPOSED ALGORITHM

The nodes in the WSN are presented in two dimensions. All the sensor nodes are fixed in the potential points and are assumed to be stationary. If they are dynamic and moving, the calculations will be a little more complicated, which is not the subject of this paper. In each round, the energy of each node is obtained from equation (1).

$$EN_{ip} = Energy - \sum_{p=1}^{p-1} E_{ip} \qquad \forall i \in I, p \in P \tag{1}$$

In (1), $Energy$ is the initial energy, E_{ip} is the energy available in period p, and EN_{ip} is the energy consumed in cycle p. The distance between two sensors is calculated as the Euclidean distance, which is obtained from (2). The location of the i and j sensors is two-dimensional space. In the coordinate axis, x_i and y_i are the coordinate of the sensor i and x_j and y_j are the coordinate of the sensor j.

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

A node in each round, if its energy is higher than a threshold level, consumes energy in three ways, one based on being an intermediate node in each round, the second based on receiving information, and the third based on sending information. The energy of each node in each round is calculated as (3).

$$E_{ip} = z_{jikp}\left(Er_{jip} + Et_{ikp}\right) + Es_{ilp} + Ech_{lip} \tag{3}$$

In (3), z_{jikp} is a zero or one; its value is one if node i is located in cycle p, the interface between nodes j and k, and otherwise it is equal to zero. If node i is the middle node between j and k, Er_{jip} is the energy consumed in node i when receiving information in round p. Et_{ikp} is the energy consumed in i to transmit information to the node k in the circle p. Es_{ilp} is the energy consumed in round p if node i only sends information to node l and Ech_{lip} is the energy consumed in round p if node i only receives information from node l.

The main goals of hierarchical routing algorithms are to reduce the energy. Therefore, these algorithms are the most suitable method for routing in these networks. In these algorithms, network nodes are clustered and, in each cluster, a cluster head is specified. Many clustering algorithms have been designed, these algorithms are dependent on the arrangement of nodes in the network, network architecture, and characteristics of CHs. CHs can be one of the sensors in the cluster or pre-selected by the network designer, it is also possible that the CHs are a normal node similar to other nodes or a sensor with richer resources. Cluster members can be fixed or variable.

I. The developed Floyd Warshall algorithm

In this paper, the clusters and nodes of each cluster varies in each round, and the membership of nodes to clusters changes over time. Because of the transmission distance is directly related to energy; therefore, determining the clusters and assigning nodes to the clusters is based on the shortest path of information transmission. Information transmission in WSNs is a non-directional network, and due to the possibility of information transmission in the form of multiple hops to the CH, therefore, in each round, the shortest path between both nodes is obtained by the Floyd Warshall algorithm. The reason for using this algorithm and finding the shortest path between two nodes is that each node has the possibility of being assigned to any cluster in each round, and also each node has the possibility of becoming a CH based on other sensors belonging to each cluster. Floyd Warshall algorithm determines the shortest path between any two nodes. Three nodes *i*, *j* and *k* and their communication properties are as follows. If $d_{ij} + d_{jk} < d_{ik}$ then the shortest path from *i* to node *k* is possible by passing through node *j*. Therefore, the path *i* to *j* and to *k* is the shortest path from node *i* to node *k*. In the design of this algorithm, the matrix of distances *D* and the matrix of sequence of nodes *S* are used. So, the matrix *D*:

$$d_{ij} = \begin{cases} d_{ij} & If\ there\ is\ an\ arc\ between\ the\ i\ and\ j \\ \infty & If\ there\ is\ no\ arc\ between\ node\ i\ and\ j \\ 0 & If\ i\ =\ j \end{cases}$$

and in the matrix *S*:

$$S_{ij} = \begin{cases} k & If\ there\ is\ an\ intermediate\ node\ between\ i\ and\ j \\ j & If\ there\ is\ no\ intermediate\ node\ between\ i\ and\ j \end{cases}$$

The steps of the algorithm:
Step-0: Set $D_0 = D$ and $S = S_0$ and *k=1*.
General step *k*: Consider row and column *k* as the axial row and column.
For each non-axial member $d_{ij}^{(k-1)}$.

$$\text{If } d_{ik}^{(k-1)} + d_{kj}^{(k-1)} < d_{ij}^{(k-1)}$$

Then set

$$d_{ij}^{(k)} = d_{ik}^{(k-1)} + d_{kj}^{(k-1)}$$

$$s_{ij}^{(k)} = k$$

Otherwise set

$$d_{ij}^{(k)} = d_{ij}^{(k-1)}$$

$$s_{ij}^{(k)} = s_{ij}^{(k-1)}$$

If *k=n* then stop otherwise put *k+1* and repeat this step.

In Floyd's algorithm, the new matrices *D* and *S* are obtained from the previous corresponding matrices as below:

$$D_0 = D \rightarrow D_1 \rightarrow D_2 \rightarrow \cdots \rightarrow D_n$$
$$S_0 = S \rightarrow S_1 \rightarrow S_2 \rightarrow \cdots \rightarrow S_n$$

After determining the shortest path, the following steps in the algorithm are used:

Step-1: Set i=1 and check until j=n, if $d_{ij} \leq d_0$, node j is placed in cluster i and j is placed instead of d_{ij}, and if $d_{ij} > d_0$, set zero instead of d_{ij}.
Step-2: Then i=i+1 is set and step one is repeated until i=n.
Step-3: Set i=1 again and check until j=n, whenever the algorithm reaches the number j, the nodes assigned to node j in the previous round of the algorithm are added to node i.
Step-4: Set i=i+1 and step-3 is repeated until i=n.
Step-5: Determine the clusters and nodes.
Step-6: End of the algorithm.

II. Fuzzy inference to determine CHs

After determining the number of clusters and assigning nodes to each cluster, the CH must be determined in each round. In this paper, two fuzzy criteria are used to determine the CH, i.e., the energy and the distance of the nodes from the candidate node. The CH is selected based on fuzzy logic. Many parameters can be used to select the CH, but it should be known that when the number of parameters increases, the rules table increases, therefore calculations and of course time and energy consumption increase. In each round, each node obtains its chance parameter with fuzzy logic based on two basic descriptors of energy and the distance of nodes from the candidate node. The distance matrix of nodes in multi-hop transmission is obtained in the previous step when determining the nodes assigned to each cluster and determining the number of clusters. A fuzzy inference system consists of the following four main parts:

1) Fuzzifier, which is a deterministic converter of input to fuzzy.
2) Knowledge base, which contains the information of fuzzy rules.
3) Inference engine, which explains the reasoning mechanism of the system.
4) Defuzzifier, which converts the output of the system into a definite and real number.

The information is expressed based on the following two important parameters:

- Energy: Energy variable that represents the energy level of a node in each round.
- Paired distance of nodes to each other: This variable shows the distance of nodes from each other to transmit information. Energy consumption to send a message is directly related to the distance between two nodes, i.e., *d*, therefore, the lower calculated distance value causes the higher chance of a node to become a CH.

Linguistic variables have been used for fuzzy inputs of energy and distance of cluster nodes from each other. Three levels are defined for energy: low, medium, and high. Also, for distance, there are three levels: short, medium, and high. The output states the chance to become a CH, is eight levels: very high, high, relatively high, medium, relatively medium, very low, low and relatively low. Because the inputs are two variables and each variable can have three different levels, then the table of rules has $3^2 = 9$ rules. The membership function of both variables is triangular. The CH is dynamically selected according to energy and distance in each round. The default clustering protocol is the developed Floyd Warshall algorithm, and CH selection is done by fuzzy inference. After the clustering and selection of the CH, it is necessary to specify the optimal placement of the base station for sending messages, which is also based on the distance and using the Genetic algorithm developed with Floyd Warshall algorithm.

III. The developed Genetic Algorithm with Floyd Warshall (DGAFW) algorithm to specify the optimal placement of the base station

In this algorithm, the shortest path between the CH nodes and the location of the mobile base station is determined. Information transmission from the CHs to the base station can be carried out in single-hop or multi-hop. The Genetic algorithm works well in the general search, but it converges to an optimal solution slowly, and the possibility of the algorithm falling into the local optimum is high. Setting the parameters of meta-heuristic algorithms, including the Genetic algorithm, is one of the main factors affecting the efficiency of the algorithm, in such a way that the incorrect selection of the parameters of an algorithm leads to its poor performance. The Taguchi method was used to specify the optimal parameters of the Genetic algorithm. Taguchi's orthogonal arrays make it possible to examine a large number of factors with a small number of tests. In this method, to find the optimal levels of the factors, the efficiency criterion of the signal-to-noise ratio (SNR) is maximized. The SNR refers to the mean of the squared deviations of the objective function, which minimizes the mean and variance of the qualitative characteristics to bring them closer to the expected values.

The parameters affecting the efficiency of the Genetic algorithm are the initial population, the type of selection, the type of crossover, the transfer rate of the mother population to the next generation, the crossover rate, and the mutation rate. The stopping condition is the number of repetitions without improvement, which is considered equal to 20. Factors and levels considered for the Genetic algorithm are according to Table I. The operation of selection means the choosing of elites from the current population as parents to produce offspring. There are several ways to select the best, including random selection, roulette wheel, rank selection, tournament selection, and uniform selection. In the random method, parents are randomly selected from the initial population. In the roulette wheel method, chromosomes are selected based on fitness. The greater the fitness of the chromosomes, the more chance they have to be selected. In this method, the fitness of each chromosome is added to the fitness of other chromosomes and a distance from zero to the sum of all fitnesses is produced. This distance is usually considered as a circle. Then, a number is randomly selected from this interval, the chromosome corresponding to that number is selected as the parent [29]. In the rank selection, the population is first sorted according to fitness, and if there are N chromosomes, the worst chromosome is ranked 1, and so on until the best chromosome is ranked "N". In this method, the probability of selecting a chromosome is arranged according to its rank in this list instead of its fitness. In the tournament method, several members are randomly separated from the population and the member who has the best fitness among them is selected to participate in the next generation [29]. In uniform selection, the chance of choosing all parents for the next generation is the same.

Using the crossover operator, it produces two new children by copying selected bits from each parent. There are several types of crossover operators, including single-point, two-point, Precedence Preservative Crossover (ppx crossover), multi-point and uniform. In the single-point method, a random point is considered on both chromosomes that are selected as parents. The bits on one side of the selected point are transferred between the two chromosomes, thus creating two children, each of which has a portion of the Genetic information of each of its two parents. In the two-point crossing method, two points are randomly selected from the parent chromosomes. The bits between the two points in the two parents are transferred between them and the children are produced [29]. In multi-point mode, multiple points are considered as cut points and bits are transferred between these points between parents. In the Precedence Preservative Crossover (ppx crossover) method, first a vector is randomly created as long as the parent chromosomes with numbers 1 and 2. Then the child's chromosome is formed according to the created random vector in such a way that wherever the number 1 is placed in this vector, the gene from parent 1 and wherever the number 2 is placed, the gene from parent 2 must be transferred to the child's chromosome. After the transfer of a gene from one parent, that gene is removed from the other parent's chromosome [30]. In the uniform crossover, each gene in the offspring chromosome is created by copying the corresponding gene from one or the other parent based on a randomly generated crossover mask. Each bit is chosen with equal probability from one of the parents. This probability may not be equal. Minitab 18.1 software was used to obtain the orthogonal array corresponding to the number of 6 factors in 5 levels, and the output the software is L_{25} which is the orthogonal array that is considered for this purpose by Minitab 18.1 software. The Genetic algorithm program was executed with different levels considered for the factors, and then using Minitab 18.1, the most optimal level of each factor for the value of the objective function as the response variable was obtained. Also, using Minitab 18.1, the most optimal level of each factor was obtained for the duration of the time as the response variable. Therefore, the best levels of factors according to Table 2 were obtained for the Genetic algorithm, which was used for the performed simulation.

TABLE 1
FACTORS AND LEVELS DEFINED FOR TAGUCHI METHOD OF GENETIC ALGORITHM

Levels	Factors					
	Primary population	Selection type	Type of crossover	Rate of mother population transmission to the next generation	Crossover rate	Mutation rate
1	20	Random	Single-point	0.5	0.8	0.01
2	40	Roulette wheel	Two-point	0.4	0.85	0.08
3	60	Ranking	Precedence Preservative Crossover (ppx crossover)	0.6	0.9	0.1
4	80	Tournament	Multi-point	0.7	0.95	0.15
5	100	Uniform	Uniform	0.8	0.99	0.2

TABLE 2
BEST LEVELS OF FACTORS FOR GENETIC ALGORITHM AS RESPONSE VARIABLE IN TAGUCHI METHOD

Levels	Factors					
	Primary population	Selection type	Type of crossover	Rate of mother population transmission to the next generation	Crossover rate	Mutation rate
The best level	80	Random	Two-point	0.7	0.95	0.08

IV. Parameters

The nodes are considered to be 100, the initial energy of the network is 1 joule and the dimensions of the network are 1000x1000 square meters. The network parameters and also the parameters used in fuzzy inference and the DGAFW algorithm used in the simulations are listed in Tables III to VI. According to Table V, the sending radius is 250 meters and the energy for sending 1000 bits data packet size is 2.2×10^{-5}. The distribution of the nodes is random and a node will die if its energy is less than 0.0055.

TABLE 3
FUZZY DEFINITIONS FOR ENERGY

Energy range	Fuzzy definition
(0.2,0.4,0.5)	Low
(0.4,0.6,0.8)	Medium
(0.7,0.8,1)	High

TABLE 4
FUZZY DEFINITIONS FOR DISTANCE

Energy range	Fuzzy definition
(0,150,250)	Short
(200,400,650)	Medium
(600,800,1000)	Much

TABLE 5
MODEL PARAMETERS OF WSN

Network parameters	Amounts
Sending radius	250 meters
Diffusion model	Free space
Er_{jip}	2.2×10^{-5} joules per meter for 1000 bits
Et_{ikp}	2.2×10^{-5} joules per meter for 1000 bits
Es_{ilp}	2.2×10^{-5} joules per meter for 1000 bits
Ech_{lip}	2.2×10^{-5} joules per meter for 1000 bits
Data packet size	1000 bits
Distribution of nodes	Random
Media Access Control (MAC) protocol	IEEE 802.11
Network stop condition	Death of 30% of nodes
Amount of energy for node death	Less than 0.0055

TABLE 6
FUZZY RULES

Rule number	Energy	Optima distance between nodes	Selection chance
1	Low	Short	Relatively medium
2	Low	Short	Much
3	Low	Short	Very much
4	Medium	Medium	Medium
5	Medium	Medium	Relatively much
6	Medium	Medium	Much
7	High	Much	Very small
8	High	Much	Small
9	High	Much	Relatively small

SIMULATION AND RESULTS

The simulation has been done in the MATLAB. To implement the proposed DGAFW algorithm, a program was written in MATLAB version 2023a online and it was executed on an Intel Core i9 processor computer with 8 GB of RAM. At the beginning of the algorithm, the nodes are randomly located as shown in Figure 1.

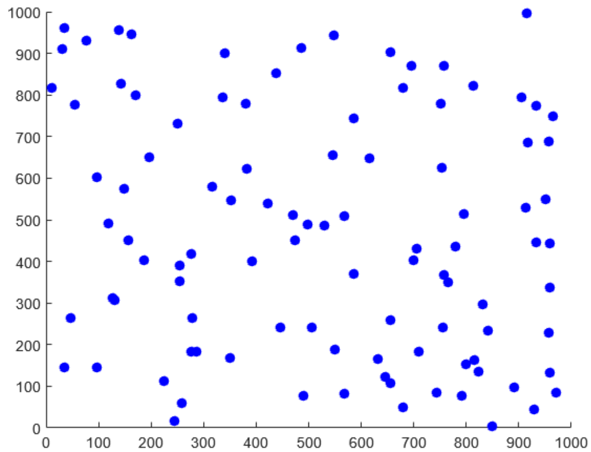

FIGURE 1
RANDOM LOCATION OF SENSOR NODES

Then, the Euclidean distance is calculated, and then using the developed Floyd Warshall algorithm, the shortest path between each pair of nodes and intermediate nodes in multi-hop transmission is determined, and by determining the maximum allowed distance between the clusters of each node, the clusters and nodes of each cluster is determined. According to the clusters and nodes of each cluster, the CHs should be determined in a fuzzy manner. As explained earlier, two fuzzy input variables, the amount of energy and the distance, according to the multi-hop path of information transmission, are defined. Nine rules according to the three levels defined for these variables. The Mamdani fuzzy system is used (in Figure 2). In Figures 3 and 4, the membership functions and linguistic variables of the inputs i.e., energy and distance are shown. The fuzzy laws are 9 laws in total. Figure 5 shows the fuzzy. In Figure 6, a level of fuzzy sets is displayed.

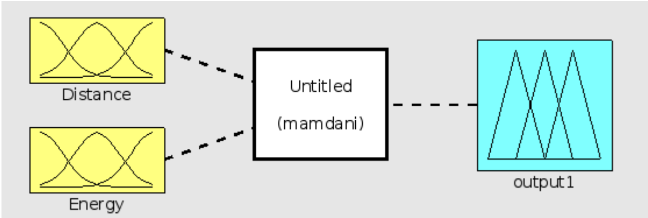

FIGURE 2
PARAMETERS OF FUZZY INFERENCE SYSTEM

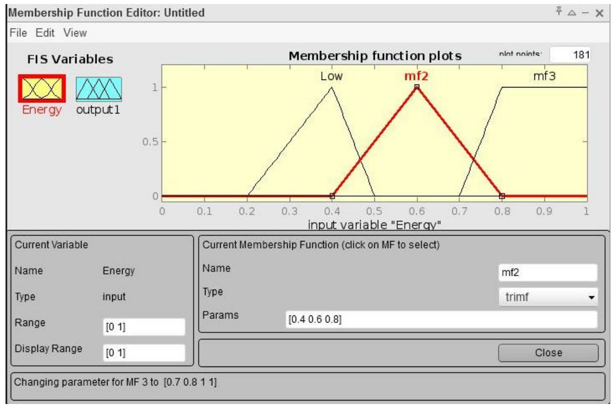

FIGURE 3
MEMBERSHIP FUNCTIONS OF THE LINGUISTIC VARIABLE OF ENERGY INPUT

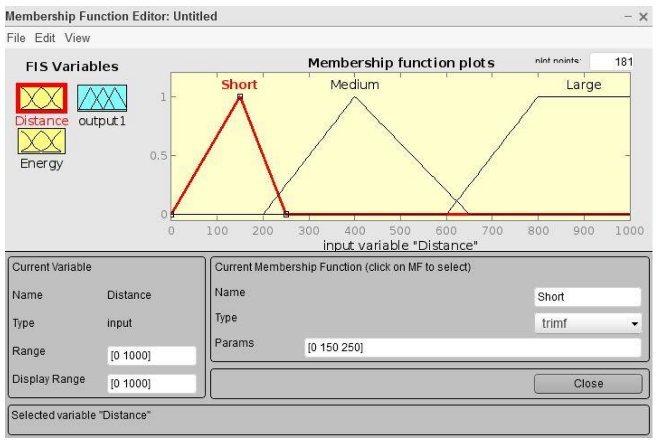

FIGURE 4
MEMBERSHIP FUNCTIONS OF DISTANCE INPUT LINGUISTIC VARIABLE

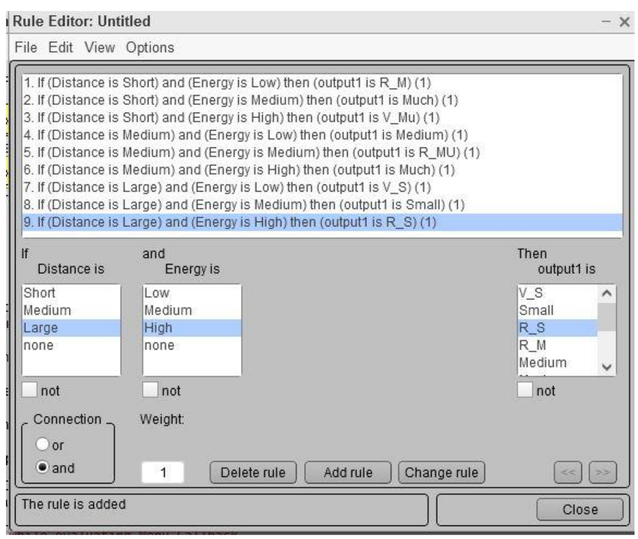

FIGURE 5
FUZZY RULE SET

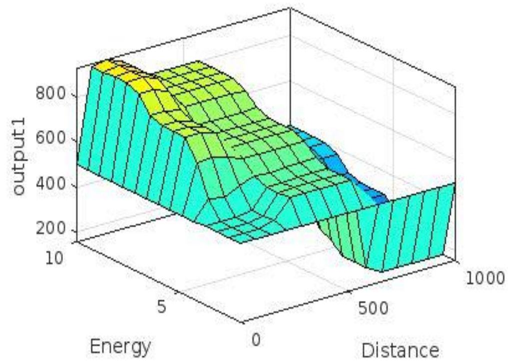

FIGURE 6
A LEVEL OF FUZZY SETS

According to Figure 6, the blue parts have the lowest probability of being selected as the CH; because in this part the energy is low and the distance is high. Moving from the blue part to the green part and then to the yellow part increases the chance of choosing the CH. To obtain the place of the base station, the Genetic algorithm has been used. The reason for using Meta-heuristic algorithms is that space is a continuous environment and therefore there is an infinite search space, but Meta-heuristic algorithms obtain an acceptable answer in an acceptable time. The objective function is to minimize the distance between the CHs and the mobile base station candidate point. To calculate the distance, the Euclidean distance is used, which is the objective function as (4).

$$Min\ d(i,X) = \sum_{i=1}^{I'}((x_i - x_b)^2 + (y_i - y_b)^2) \quad (4)$$

where (x_b, y_b) is the candidate point for the moving base station, (x_i, y_i) is the location of the CH points, and I' is the set of CH nodes. The constraints of this algorithm are $0 \le x_b \le 1000$ and $0 \le y_b \le 1000$.

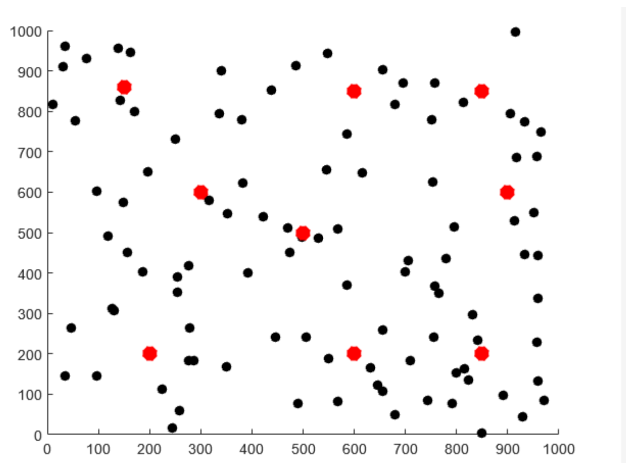

FIGURE 7
THE DEPLOYMENT OF NODES IN THE FIRST ROUND WITH NINE CHS IN RED

The considered parameters for the Genetic algorithm are according to Table II. The stopping condition of the algorithm is 20 iterations without improvement at the point defined as the base station. The optimal objective function value is 3190.7489 meters and the optimal location is (550,540) which is shown in Figure 8 with green color.

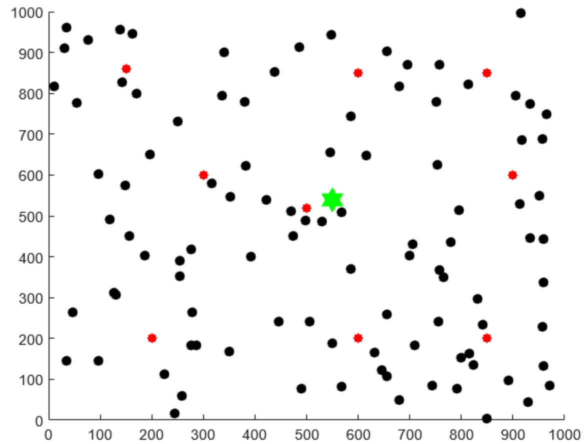

FIGURE 8
THE LOCATION OF THE OPTIMAL BASE STATION IN THE FIRST ROUND

The termination criterion is the death of 30% of the nodes. To evaluate the proposed DGAFW method, the distance and the number of rounds obtained by the algorithm have been compared with the distance and the number of rounds obtained in the case where the location is random and also the case where the location is fixed. In the fixed mode, the location is (500, 500). In the case of random, the location is considered randomly in each round. As shown in Figure 9, the distance in the optimal case is no worse than the fixed base location and the random base location at any distance. Also, the rounds in the DGAFW that find the optimal location is 113 rounds, in the case where the location is random, it is 73 rounds, and in the case that the location is fixed, it is 58 rounds. Therefore, the rounds in the DGAFW algorithm are higher than the rounds in the other two modes. Figure 10 also indicates the amount of remaining energy in each round in three modes of optimal, random and fixed location of the base station. The results show that the DGAFW algorithm compared to the case of random base station and fixed station respectively, has 12.7% and 14.3% shorter average message-sending distance in each round, 14.7% and 19.1% more residual energy and also 36% and 48% more rounds of network activity. Therefore, the proposed DGAFW algorithm has balanced the energy by optimizing the routing of the messages sent between the network nodes, and for this reason, the rounds compared to the fixed location and also the random location of the base station has increased significantly.

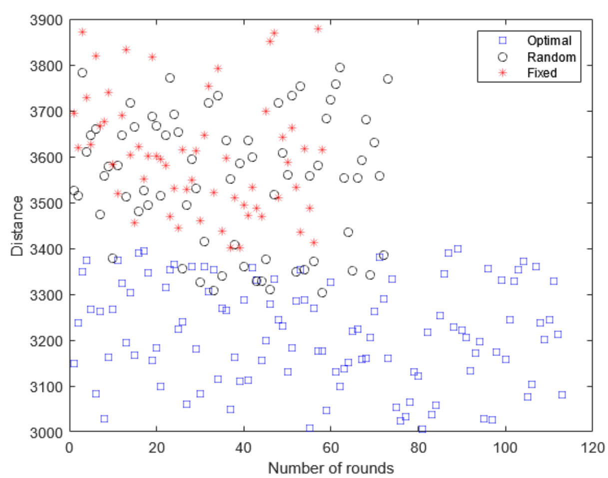

FIGURE 9
THE AMOUNT OF DISTANCE IN EACH ROUND IN THE STATE OF FIXED, RANDOM AND OPTIMAL BASE LOCATION

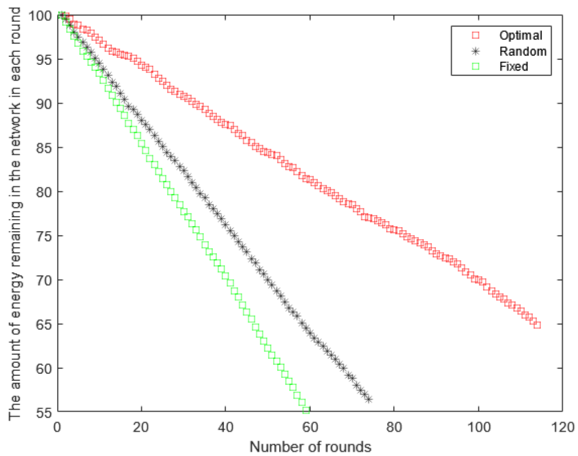

FIGURE 10

AMOUNT OF REMAINING ENERGY IN EACH ROUND IN FIXED, RANDOM AND OPTIMAL BASE LOCATION

CONCLUSION

Generally, the efficiency of WSNs will be evaluated with a set of parameters. The lifetime is one of the most important of them because the nodes have little battery in this network. Another important parameter in networks is routing, which consumes energy depending on the length of the path and intermediate nodes to send messages, so routing optimization increases network efficiency and longevity. According to this issue, in this paper, the new proposed DGAFW algorithm is introduced, which first determines the clusters and nodes assigned to each cluster using the developed Floyd Warshall algorithm, and then, using fuzzy inference, the CHs are determined based on the distance and amount of energy consumed in each round. Then, taking into consideration the mobile base station, its optimal placement location is obtained using the developed Genetic algorithm with the Floyd Warshall algorithm to minimize the transmission distance of the messages sent from the nodes to the base in the form of multiple hops.

According to obtaining the optimal transmission path using the developed Floyd Warshall algorithm in determining the number of clusters, determining the CHs and transferring from the CHs to the base station, it can be claimed that the presented algorithm reduces the energy consumption during message reception and transmission. To evaluate the presented method, the distance and the number of rounds obtained by the DGAFW algorithm have been compared with the distance and the number of rounds obtained in the case where the location is random and also the case where the location is fixed. The results show that the DGAFW algorithm compared to the case of random base station and fixed station respectively, has 12.7% and 14.3% shorter average message-sending distance in each round, 14.7% and 19.1% more residual energy and also 36% and 48% more rounds of network activity. Therefore, the distance in the optimal state in each round is shorter than the fixed base location and random base location. Also, the number of rounds in the DGAFW algorithm is significantly higher than the other two methods. Also, the amount of residual energy in the network in each round was evaluated in three modes optimal, random and fixed location.

The residual energy in the DGAFW algorithm is higher than the other two methods. This is because the proposed algorithm balances the energy by optimizing the routing of the messages sent between the network nodes. Therefore, the rounds compared to the state of the fixed location and also the random location of the base station can be significantly increased. As suggestions for developing methods to reduce energy in WSNs, the new approaches based on artificial intelligence and other meta-heuristic algorithms can be used in a combined manner to cover the weaknesses of each algorithm. Other optimization methods can be used to determine the clusters and nodes assigned to each cluster. In this paper, only the location of the mobile base station has been discussed, and finding an optimal path to change the location, from the previous place to the new optimal location, is one of the other things that can be carried out in the future. The network in the proposed method is assumed to be homogeneous, while networks with different conditions, for example; non-homogeneous networks can be considered. In non-homogeneous networks, all sensors are not the same in terms of energy sources, so the selection of CHs can be made from nodes with more energy and priority. Also, the simultaneity of clustering optimization and finding the location of the base station can be another future research.

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