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Reducing Energy Consumption in Sensor-Based Internet of Things Networks Based on Multi-Objective Optimization Algorithms

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Abstract

Energy is an important parameter in establishing various communications types in the sensor-based IoT. Sensors usually possess low-energy and non-rechargeable batteries since these sensors are often applied in places and applications that cannot be recharged. The most important objective of the present study is to minimize the energy consumption of sensors and increase the IoT network's lifetime by applying multi-objective optimization algorithms when selecting cluster heads and routing between cluster heads for transferring data to the base station. In the present article, after distributing the sensor nodes in the network, the type-2 fuzzy algorithm has been employed to select the cluster heads and also the genetic algorithm has been used to create a tree between the cluster heads and base station. After selecting the cluster heads, the normal nodes become cluster members and send their data to the cluster head. After collecting and aggregating the data by the cluster heads, the data is transferred to the base station from the path specified by the genetic algorithm. The proposed algorithm was implemented with MATLAB simulator and compared with LEACH, MB-CBCCP, and DCABGA protocols, the simulation results indicate the better performance of the proposed algorithm in different environments compared to the mentioned protocols. Due to the limited energy in the sensor-based IoT and the fact that they cannot be recharged in most applications, the use of multi-objective optimization algorithms in the design and implementation of routing and clustering algorithms has a significant impact on the increase in the lifetime of these networks.

Keywords: Internet of Things (IoT) Based on Wireless Sensor; Clustering; and Routing; Type-2 Fuzzy and Genetic Algorithms; Multi-Objective Optimization Algorithms.

1- Introduction

IoT is one of the new technologies in the present era. The IoT is defined as the communication and integration of intelligent objects. Different objects include cell phones, sensors, radio-frequency identification (RFID) tags are part of the IoT that connect to the Internet through wired and wireless sensor networks. Smart objects can sense, collect, and transfer data to meet users' different needs [1] [2].
The IoT is referred to as the precise connection between the digital and physical worlds [3]. Different IoT researchers have described objects in different ways [4] [5]:

- "A dynamic global network infrastructure with the capability of automatically adjusting based on interactive communication standards and protocols which are physical and virtual "objects" with physical properties, virtual characters, and identities, applies intelligent interfaces and is aggregated with the data network in an integrated manner."
- "A global infrastructure for the data society that provides advanced services by connecting (physical and virtual) objects based on available and evolving data and communication technologies."

In sensor-based IoT networks, the battery is the main power supply for sensor nodes, and in most applications, due to the abundance and unavailability of sensors, replacing their energy resource is impossible or extremely challenging. The energy resource in a sensor is limited, and as a result of energy discharge, the sensor node makes the sensory and covering area smaller. Hence, energy conservation in wireless sensor-based IoT networks is one of the issues that should be considered [6] [7].
There are many approaches to minimize the energy consumption in the sensor-based IoT network, one of the most extensively used and effective of which is the enhancement of clustering and routing algorithms in these

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networks, which has recently been considered by many researchers. Due to the lack of energy resources in sensor-based IoT networks, designing energy- efficient algorithms to reduce sensors' energy consumption is considered significantly important [8].

The network can be divided into small parts where the sensors are partitioned into clusters; a cluster head exists in each of which with the role of collecting data from member nodes and send them to the base station. The advantages of clustering include scalability of the network, localization of route settings, preservation of communication bandwidth through decreasing the relayed packets, minimizing energy consumption rate, and stability of network topology [9].

Clustering supports scalability and is capable of being expanded to any level. There are local communications between the sensor nodes inside the clusters. Moreover, clustering can stabilize the network topology at sensor level and reduce the maintenance overload of the topology. Sensors are not only involved in communication with their cluster heads and are not affected by changes in the surface between the cluster heads [10] [11].

In most of the existing approaches in selecting the cluster heads, two-step processes are applied; in the first stage, the cluster head is randomly selected and then in the second stage, a cluster head that has more energy is selected from among the member nodes to balance energy consumption.

In these approaches, only the nodes' energy is considered, and the location and sensors' density are not taken into account. The network may face the hotspot problem and cause cluster heads in critical paths or near the base station to be discharged and get out of the network [12] [13]. Some solutions to this problem emerged, include unequal clustering, in which clusters of different sizes were formed based on the distance from the cluster head to the base station. In these solutions, the clusters' size closer to the base station is smaller than the farther clusters.

The routing problem is as important as the clustering issue. In general, routing provides a response to the following question: How does an entity get from source to destination? In the IoT network, the entity is a data packet, and a couple of computing devices are the destination and source of the data packet. A computing device can be an internet device (e.g., a personal computer or server) or an IoT device (e.g., sensor node, smartphone, or an RFID tag). The computing device is also called the routing node. Packets must pass through intermediate nodes before entering the destination because there is not always a direct physical path between the destination and source of the data packet. Multi-step routing is another name for this approach. The set of steps, namely the routing of intermediate nodes present in the data packet transfer, is called the routing path [13], [14].

There is a classification in distributed sensor-based IoT network routing compared to the centralized one: This classification has been provided based on the location of the routing decision-making, namely the location that specifies which path the data packets to be transferred. Two options are available: distributed centralized. In a distributed method, a node or set of adjacent nodes makes the routing decision and do not possess the entire network's data but only have information around their local status (and probably, their neighbors' status). Therefore, routing decisions are made only based on this limited knowledge. Flexibility is the advantage of distributed routing because decisions are distributed and can be made by each node. The disadvantages of this method are that the routes may not be optimal, and there is a possibility that the load distribution is not adjusted because only local data is applied. In the centralized method, there is a super-node with resources and complete knowledge of the network's status. This super-node controls all nodes, calculates the optimal path for each data packet, determines unused nodes and bottlenecks, and adapts the paths. Complete control over all network dimensions is the advantage of centralized routing; thus, optimal routes must be calculated. The disadvantage of this method is the high maintenance cost of the super-node [15][16].

In this article, a new reducing energy consumption method is proposed that considers the importance of the parameters of the distance between the cluster heads, the density of the sensors, the residual energy of the nodes, the centrality, and the distance between the cluster head to the base station.

The contributions of the proposed method as follows.

- Applying the parameters of residual energy, density and centrality to select the appropriate cluster heads.
- Applying the shortest route between the cluster heads to the base station.
- Evaluating the effectiveness of the proposed method using a simulation tool in comparison to the counterpart approaches.

The following sections of the present articles are organized as the following. In Section 2, previous works are addressed; the proposed algorithm is discussed in detail in Section 3, in Section 4, the results obtained from the simulations are analyzed by the authors, and a conclusion is presented in the final section.

2- Previous Works

Clustering the network's nodes is a successful topology control and design technique that can be applied to increase network efficiency. Clustering-based routing leads to the enhancement of network conditions. The two main steps in clustering-based routing include selecting cluster heads and routing by cluster heads [16]. Energy conservation is possible by utilizing cluster heads to collect data from other nodes and resend it from cluster heads to central stations [17]. Therefore, selecting the appropriate cluster head from the nodes can enhance energy efficiency and increase the sensor network's lifetime.

In this section, the authors will discuss some routing and clustering protocols that have been considered in recent years.

Low-energy adaptive clustering hierarchy (LEACH) is a distributed algorithm in which the selection of the cluster head is performed locally [18] [19]. In this approach, the cluster head are randomly selected in the first step, and all data processing, including data integration and collection, are performed locally inside the cluster. In LEACH, the shape of clusters has been distributed using an algorithm in which the nodes make decisions independently without any centralized control. First, a node randomly decides to become a cluster head with the probability of p and broadcast its decision. Any node but the cluster head can be a desired member of the cluster head according to the minimum energy required to communicate with the cluster head. The cluster head rotates alternately between cluster nodes for maintaining the balance of the rotation load [21]. This rotation is done through taking each node i for selecting a random number T(i) in the interval [0,1]. If the number T(i) is lower than the threshold given in equation(1), each node i becomes a cluster head for the current rotation:

$$T(i) = \frac{p}{1-(r.mod\frac{1}{p})}, i \in G \tag{1}$$

Where p denotes the desired percentage of nodes in the sensor population, r implies the number of rounds, and G denotes the set of nodes that did not exist in the previous 1/p round. LEACH leads to the development of the topology of the cluster of a hob in which every single node can be transferred directly to the cluster head and then to the base station.

The limitations of LEACH: in spite of the fact that the LEACH leads to the energy conservation of nodes and increases the network's lifetime, it still includes some limitations [22] [23]:

- LEACH is appropriate only for small size networks.
- At the start point of every single round, the selection of the cluster heads from these nodes is performed randomly and regardless of the remaining energy via LEACH.
- Direct communication of each cluster head with the base station is made using LEACH, regardless of whether the distance is small or not.
- Cluster heads can be centralized in one place; thus, nodes will be separated (without cluster head).
- There is no mechanism in LEACH to ensure that selected cluster heads are uniformly distributed on the network.

The MECBCCP protocol was introduced by Rhoni et al. [1] for the WSN-based IoT network. In this method, the network environment is layered for clustering operations. Afterward, gateway nodes, cluster head, and coordinators are specified respectively, and then the normal nodes become the nearest node to the getaway, and gateway nodes are connected to head clusters. The cluster heads are then connected to the coordinators, and also the coordinator nodes are connected to the nearest coordinator node of the upper cluster. In the next step, the coordinators of the last layer are connected directly to the sink, and finally, the cluster head of the last layer is directly connected to the base station.

In this technique, relay nodes (RNs) are picked randomly, and no distance parameter is taken into account for the next RN selection. Consequently, some RNs may overlap, which leads to additional system costs (due to selecting the node as RN) and the use of inefficient resources. The number of selected RNs can vary from cluster to cluster and depends on the cluster nodes' density.

Dynamic clustering with relay nodes (DCRN): In this article [24], a dynamic clustering algorithm using genetics has been presented. In this algorithm, the nodes are first placed in an environment in a random manner, and the sink is placed in a static state outside the environment. Then, the cluster heads are picked by a genetic algorithm, the fitness function of which includes: 1) set of distances of all head clusters from the base station, 2) cluster distance: set of distances of all nodes from their cluster heads, 3) standard deviation of cluster distance, and 4) Transmitted energy. After the cluster heads are determined, the normal nodes become the member of the nearest cluster head.

After this step, the data is collected by normal nodes and sent to the cluster head, and then the cluster heads send the data to the base station in a single-step manner, which leads to an increase in the energy consumption of the cluster heads farther from the base station.

Multi-objective fuzzy clustering algorithm (MOFCA) [25] [26]. MOFCA algorithm is proposed for solving sudden energy loss in homogeneous wireless sensor networks. In MOFCA, in each round, a number between 0 and 1 is picked by each node; if the chosen number is smaller compared to the threshold (a percentage of the number of cluster heads), one can consider this node as a temporary cluster head. Then, temporary cluster heads can calculate their competitive radius using fuzzy inputs and fuzzy logic, fuzzy inputs include node density, distance to the base station, and remaining energy. Every temporary cluster head sends a message based on its maximum competitive radius and predetermined radius. A temporary cluster head withdraws from the competition if it receives this message from another temporary cluster head with a higher energy level. In the case that the two nodes' energy levels are equal, the density parameter is applied to compare them. Higher-density temporary nodes of cluster head are selected as final nodes of cluster head. The non-cluster head nodes join the nearest cluster head After determining the final nodes of the cluster head.

Energy conserved unequal clustering with fuzzy logic (ECUCF) [27]. In this method, a number between 0 and 1 is picked randomly by each node; in the case that this number is smaller compared to the predetermined threshold, one can consider it as the initial cluster head. Then, on the basis of the proximity of the node, the remaining energy, and the distance to the base station, using fuzzy logic, the whole network is divided into three parts. In each section, the comparison of the energy of the node with the energy threshold is performed. In the case that the node's energy is lower than the threshold, the node goes to sleep; otherwise, the node remains active. Each primary node of cluster head calculates its competitive radius with respect to the inputs, including information of node section, distance to the base station, and remaining energy, and then publishes a message within its competitive radius. In the case that the message receiver has lower remaining energy compared to the sender node, it withdraws from the competition for being a cluster head. In the case that a normal node observes this message, selects the cluster head according to the fuzzy inputs (distance, remaining energy, and proximity of the node) and joins the corresponding cluster [26].

3- System Model

Before describing the proposed algorithm, it is noteworthy to discuss the hypotheses taken into account in this method as the following:

- Simulation is performed in several scenarios; depending on the scenario, the sensors' energy is either homogeneous or heterogeneous. In the state of being homogeneous, the energy of all nodes equals 1 J, and when the environment is heterogeneous, the energy of half of the sensors is equal to 2 J.
- Nodes have been randomly and uniformly distributed in the environment.
- The base station (sink) can be anywhere in the network environment; however, it has been considered outside the environment in the present paper.
- It is not essential for all nodes to be fixed after distribution. However, here, mobility does not involve many alterations of initial location through remote control but only involves ground displacements, including displacements or erosion resulting from external objects that cause in place alterations.
- Energy consumption in the nodes is not a result of mobility because it has been assumed to be performed by external resources.

3-1- Energy Consumption Model

The consumption model of energy in sensor networks is directly related to the way of designing of access control sub layer to media in these networks. However if we want to use a common model which is independent of the design parameters defined in the access control sublayer to the media, we use the following relations for modeling the energy consumption amount in the networks. The energy consumption model is considered just the same as the Leach's one, in the proposed algorithm, which both models use the open space channel (energy dissipation d^2) and the multi-path channel (energy dissipation d^4) depending on the distance between transmitter and receiver. Thereupon, the energy used to send a 1-bit packet at the distance of d is obtained using equation (2) [28] [18]:

$$E_{Tx}(l,d) = E_{Tx}-elec(l) + E_{Tx-amp}(l,d) = \begin{cases} lE_{elec} + l_{\varepsilon fs} d^2 & d < d_0 \\ lE_{elec} + l_{\varepsilon fs} d^4 & d \geq d_0 \end{cases} \tag{2}$$

In this Equation, E_{elec} is the energy required to activate the electronic circuits, ε_{fs} and ε_{amp} are the energies required to amplify the signals sent to transmit a bit in the open space model and the multi-path model, respectively. d is the distance among nodes, also d_0 is the threshold value of distance obtained from equation(3) [29] [18]:

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{amp}}} \tag{3}$$

The energy used to receive a 1-bit packet is obtained from equation (4) too.

$$E_{Rx}(l) = E_{Rx-elec}(l) = lE_{elec} \tag{4}$$

3-2- Proposed Method

The main objective of the present study is the reduction of the energy consumption of IoT-based sensor networks. Thus, an approach based on multi-objective algorithms has been introduced to minimize energy consumption in the network. Multi-objective optimization methods are used to find the best possible answer (near-optimal) in an acceptable time. In this section, the proposed algorithm will be described in detail.

Proposed Algorithm

```
Select nodes in sensing area for clustering
For k=1: number of nodes
        Calculate remain energy, density and centerality of nodes;
        Calculate fuzzy a mount of nodes with Relay Fuzzy Logic 2 ();
        Sort nodes according to fuzzy amount;
        Select 10 percent of node with maximum fuzzy amount
    as cluster heads;
End_For
        For i=1: number of nodes
          If node_i is normal node
            Node_i joins to nearest clusterhead_k;
               End_IF
End_For
Routing to send cluster head information
Route= Route Genetic Algorithm ();
For i= clusterhead
        Clusterhead _i joins to route;
End_For
Last node of route, connects to sink;
```

Fuzzy logic can make precise decisions in real-time and is simple in terms of resiliency. Moreover, the type-2 fuzzy logic model can accurately manage the measurement level of uncertainty compared to the type-1 fuzzy logic model because its membership functions are fuzzy sets. Figure (4) indicates the type-2 fuzzy block diagram [30].

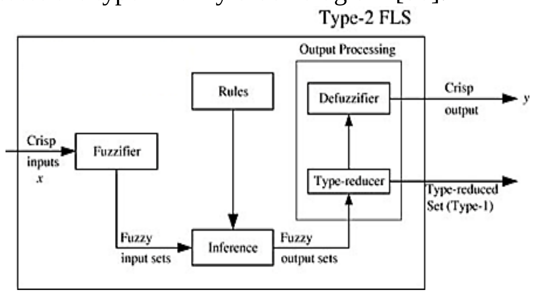

Fig.4. type-2 fuzzy diagram [30]

IT2 FLCs [1] control uncertainties better than IT1 FLCs [2]; therefore, they are used more widely. The two essential differences between IT2 and IT1 FLCs include: 1) Adaptiveness, that is, using embedded T1 fuzzy sets to calculate the type-reduced interval change bounds as input changes, and 2) Novelty, that is using the upper and lower membership functions simultaneously in computing each bound. The T1 FLCs lack the features and cannot implement the complex IT2 FLC control level based on the same rule base [31]. Here are some differences between IT1 and IT2 FLCs:

- IT2 FS [3] membership grade is interval rather than a crisp number in T1 FS, so T2 models intrapersonal and interpersonal uncertainties as an intrinsic feature of natural language better than T1.
- Using IT2 FS to represent FLC inputs and outputs makes rule base reduction better than IT1 FS [32], [33]. FOU [4] ability to express more uncertainties leads to covering input/ output domains with fewer FSs. Thus, the rule base is constructed using expert knowledge and enhanced robustness [34] [35].
- IT2 FLC leads to a smoother control surface than IT1 FLC, especially in the steady state area.
- IT2 FLCs are more adaptive and more capable than IT1 FLCs in realizing the complex input-output relationships. According to Karnik and Mendel [36], the IT2 fuzzy logic system is considered various embedded T1 fuzzy logic system collections.
- According to Wu [37], various membership function degree of IT2 FS is used in the different rule base, while in IT1 FS the same membership function degree is used in the diverse rule base. So IT2 FLC is more complex than IT1 FLC, and T1 FLC cannot implement using the same rule base.

In the proposed method routing and clustering energy aware using multi-objective optimization techniques (RCEMO), the algorithm starts working after the sensors are distributed in the environment. In the proposed method, the cluster heads are specified by the type-2 fuzzy algorithm in the base station, and also, the path between the base station and cluster heads is specified by the genetic algorithm. The proposed algorithm works based on the round, and every single round includes two phases: 1) setup, 2) steady state.

In every round, the cluster heads are specified by the type-2 fuzzy algorithm, and the path between the base station and cluster heads is specified by the genetic algorithm. Then, the base station sends a message to the cluster heads so that the cluster heads to be aware of their role and the specified tree (path) from the cluster heads to the base station. After this step, the sensors that received the message of "becoming cluster heads" inform the other network sensors of their role by sending an broadcast message within the network. Afterward, the normal nodes receive the cluster heads' messages and try to join them and become members of cluster heads so that to use less energy for communicating with them and also their distance to the cluster heads to be short. Then, after the final decision of each normal node to join the selected cluster head, it notifies the desired cluster head of its decision by sending a Join-REQ message.

After all the sensors are joint to the cluster heads, the time-division multiple access (TDMA), scheduling operation is carried out by the cluster head to prevent the data collision during the transfer. Moreover, with the identification of the cluster heads, the operation of routing from the cluster heads to the base station is performed by the genetic algorithm, and the cluster heads are notified to be aware of the considered route for transferring data to the base station in the same round. Then, the steady state phase begins. At this phase, all sensors transmit their data in specific slots by applying unique distribution code. In the proposed algorithm, all sensors start the setup phase according to the coordination of the base station with each other. Cluster heads also use the same distribution code for sending their data and also listen to the channel before sending the data. If the channel is empty, they send the data; otherwise, they wait for a random period of time.

Cluster heads are specified by the type-2 fuzzy algorithm and according to the parameters of remaining energy: density (the ratio of neighboring nodes to all nodes, the higher it is, the node is more suitable for becoming cluster head) and centrality (meaning that the node is central to its neighboring nodes and is equal to the sum of the total distance between the node and its neighbors). The lower value indicates that the node needs less energy and is suitable for becoming a cluster head. Following the selection of the cluster head, other sensors can be members of one of the clusters through communicating with a cluster head and based on the required distance and energy for communication.

The equation of the remaining energy is as follows:

$$E = E_R \tag{4}$$

Where, E_R is the nodes' remaining energy.

The density of the nodes is equal to:

[1] Interval type-2 fuzzy logic controllers
[2] Interval type-1 fuzzy logic controllers
[3] Fuzzy set
[4] Footprint of uncertainty

$$D = \frac{N_n}{N_T} \tag{5}$$

Where, N_n denote the neighboring nodes, and N_T implies the total nodes.

Centrality is also defined as follows:

$$C = \sum d_i \tag{6}$$

Where, d_i is the distance to the neighboring node.

Due to the different ranges of input variables in each cluster and to make them applicable for any size of the network, we adjust the range of values of the input variables between 0 and 1 using equation (7):

$$N_i(x) = \frac{x_i}{\max(x)} \tag{7}$$

x_i is the crisp value of node i, max(x) is the maximum value of the variable in the corresponding clusters of node i, and N(x) is the normalized value which is a value between 0 and 1.

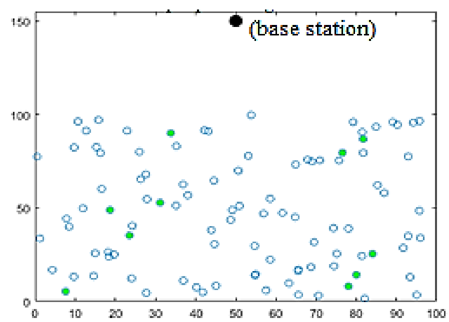

Fig.5. Selection of cluster heads using type-2 fuzzy logic

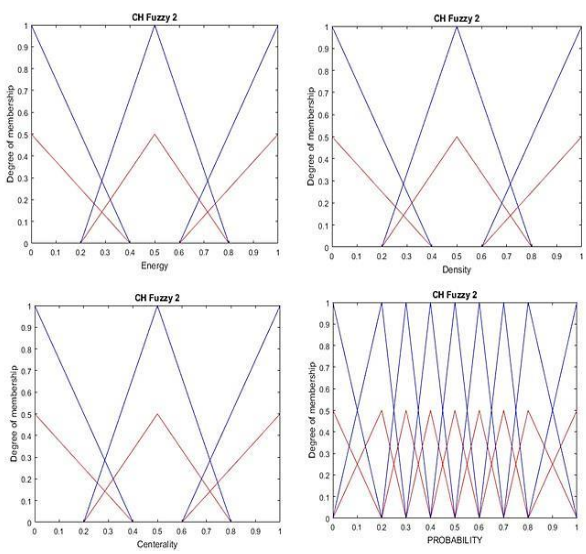

Fig.6. membership function, remaining energy, density, centrality, and output membership function

After the membership functions of all three parameters, as well as the output membership function, are created, the fuzzy rules are formed according to Table (1) and then defined to the fuzzy network.

Table 1. fuzzy rules

Row	Energy	Density	Centerality	Probability
1	Low	Low	Low	3
2	Low	Low	Medium	2
3	Low	Low	High	1
4	Low	Medium	Low	4
5	Low	Medium	Medium	3
6	Low	Medium	High	2
7	Low	High	Low	5
8	Low	High	Medium	4
9	Low	High	High	3
10	Medium	Low	Low	4
11	Medium	Low	Medium	3
12	Medium	Low	High	2
13	Medium	Medium	Low	6
14	Medium	Medium	Medium	5
15	Medium	Medium	High	4
16	Medium	High	Low	7
17	Medium	High	Medium	6
18	Medium	High	High	5
19	High	Low	Low	7
20	High	Low	Medium	6
21	High	Low	High	5
22	High	Medium	Low	9
23	High	Medium	Medium	8
24	High	Medium	High	7
25	High	High	Low	9
26	High	High	Medium	9
27	High	High	High	8

Then the fuzzy value of each node is obtained, and the 10% of the nodes with best values are determined as cluster heads, and the base station informs the cluster heads of their role. Afterward, the cluster heads send a message of “becoming cluster heads” within the network, and each normal node that receives this message becomes the member of the considered cluster head based on its energy and distance to the cluster head node and announces its membership to the cluster head. As mentioned earlier, routing is performed by applying a genetic algorithm, explained in the following. In a population-based genetic algorithm, a population possesses a set of chromosomes, each of which includes a set of genes. In the present article, there is an initial population that includes several chromosomes. The number of chromosomes’ genes equals the quantity of cluster heads minus one, the value field of which is initialized with random numbers between 0 and 1. Also, its cost equals the network's energy consumption when creating the path between the base station and cluster heads using the Prüfer algorithm [38] of the desired tree. The cost value is calculated as follows:

$$\mathrm{Cos}\,t = \sum_{i=1}^{i=k} E_{Consumed} \quad (8)$$

$E_{Consumed}$ is the energy used by the cluster heads on the path to the base station for sending data to the base station.

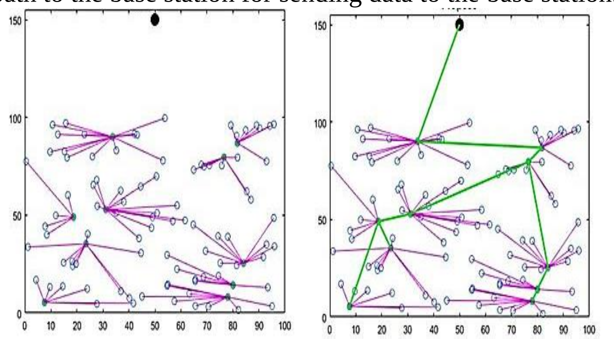

Fig.7. Taking members by cluster heads and identifying the path between cluster heads by the genetic algorithm

In the problem stated in this article, each chromosome can be a solution to the problem. A flow chart of evolutionary algorithms and the structure of the genetic algorithm is presented as the following [39]:

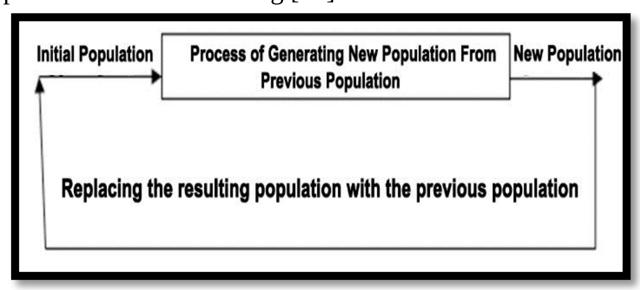

Fig.8. The generation process continues until the desired solution is obtained (normally, the initial population is generated randomly) [23]

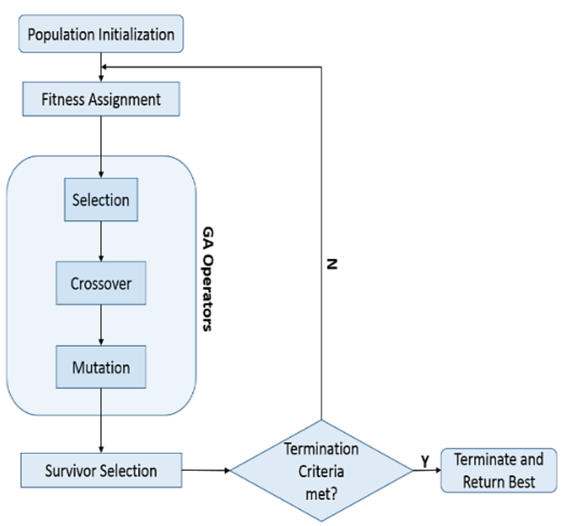

Fig.9. General structure of the genetic algorithm [23]

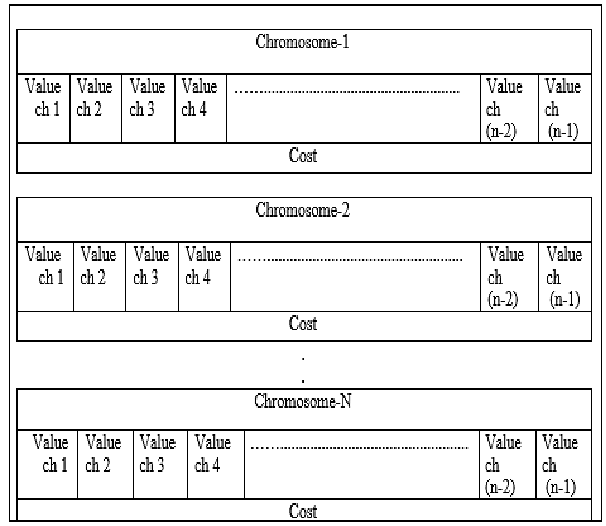

Fig.10. The view of the population in the proposed method

The population is initialized randomly. The number of iterations of the genetic algorithm is set to be 100 for finding the most suitable tree. In the proposed algorithm, 10% and 20% of the population are considered to mutation and selection, respectively.

After random initializing the genes in each chromosome, the paths are determined, and the amount of energy consumed by the network is calculated by the Prüfer algorithm. The next step is selecting parents based on the roulette wheel selection algorithm; 20% of the chromosomes with lower costs (lower network energy consumption) are selected as parents. The single point cross over operation is performed on these parents, and the new chromosomes are known as the children of the next generation. After this operation, a mutation occurs, which is done randomly on the genes of the chromosomes. Then, the new population replaces the previous population, and this operation is performed up to 100 iterations so that the best chromosome to be selected as the path from the clusters to the base station.

Finally, the chromosome with lower cost is picked as the solution to the problem, and a path between the base station and the cluster heads is formed by the Prüfer code, which is announced by the base station to the cluster heads in the setup phase.

The pseudo-code of the proposed method is presented as follows:

Clustering Fuzzy Type2 Algorithm

/ for every round */*

1. Select CH based on *Fuzzy Logic Type-2 if*-then rules from the sensor nodes with Membership Function (Remaining energy, Density and Centrality)
2. In each round, select 10 precent node for CHs

/ for CHs */*

3. All CHs collect and aggregate data

/ end of for */*

/ end of rounds */*

Routing Genetic Algorithm

```
1.  Ititialize random chromosomes;
2.  Evaluate chromosomes;
3.  While (stopping condition is not met)
4.      For i=all chromosomes
5.          Select two parents in the population;
6.          Generate two offsprings by crossover operation with probability Pc;
7.          Add offsprings to population;
8.          Mutate some offsprings with probability Pm;
9.      End For
10.         For i=all chromosomes
11.             Fitness(i)=consumed energy for forwarding data according to selected route;
12.         End For
13.         Sort Population according to fitness;
14.         Select best part of population as next population;
15.     End While
16.     Select best chromosome;
```

4- Findings

The proposed method has been simulated with MATLAB software in several different scenarios and compared with LEACH, ME-CBCCP, and DCABGA protocols.

Table 2. General parameters for simulations (Transmit Amplifier if destination to BS<=d0 ε_{fs} =10 pJ/bit/m^2 ,Transmit Amplifier if destination to BS >=d0 ε_{amp} = 0.0013 pJ/bit/m^4)

Parameter	Value	Parameter	Value
E_0	1J,2 J	ε_{fs}	10 pJ/bit/m^2
E_{elect}	5 nJ/bit	ε_{amp}	0.0013 pJ/bit/m^4
E_{DA}	5 nJ/bit/message	L_D	4000 bits
d_{break}	87.7 m	L_c	16 bits

In the first test, 200 sensor nodes were randomly distributed in an area of 300*300 square meters, in which the initial energy of all sensors is identical and equal to 1 J (homogeneous environment), and the base station is fixed and in the position 150*400. The sensors are in an environment where the movement of all is through external factors. This movement does not reduce their energy, but their position changes in each round.

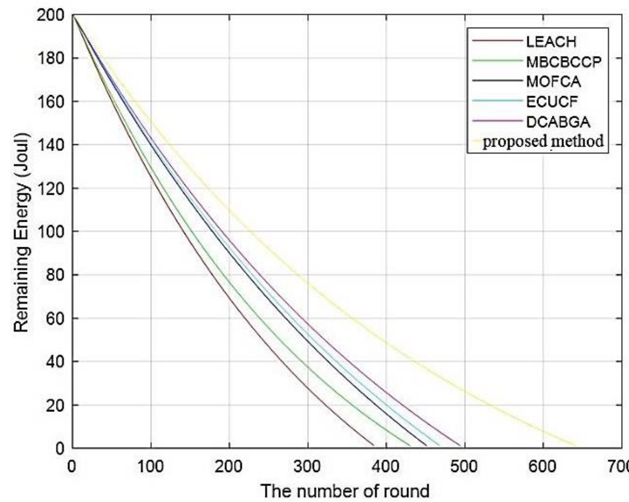

Fig.11. Comparison of remaining energy and energy consumption in the network

It is clear from figure (11) that the proposed method has enhanced the energy consumption of the network compared to previous algorithms. The proposed algorithm has increased the network's lifetime by approximately 30%, 33%,40%, 46%, and 58% compared to the DCABGA, ECUCF, MOFCA, MBCBCCP, and LEACH algorithms, respectively.

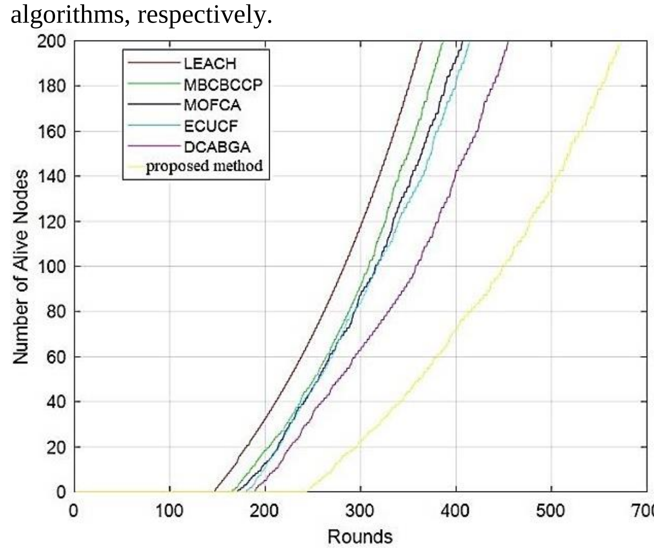

Fig.12. Comparison of the number of dead nodes in the network

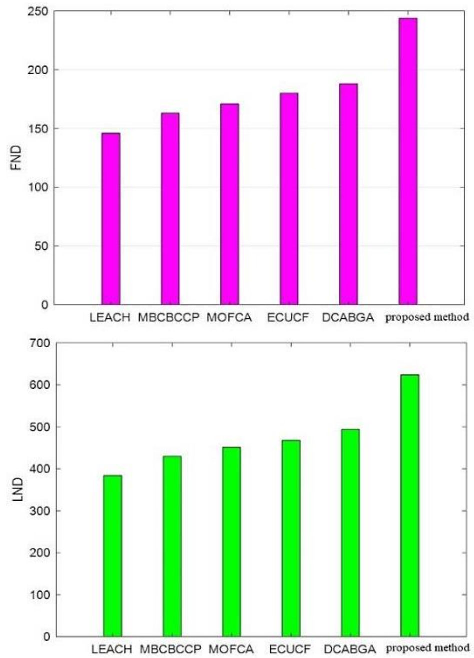

Fig.13. Comparison of the first node dead and last node dead

According to figures (12) and (13), it can be deduced that the proposed algorithm is better compared to other methods in both the first node dead (FND) and the last node dead (LND), and the sensors remain alive for a longer period of time. In the proposed method, FND and LND occur in rounds 244 and 642, respectively. In the DCABGA algorithm, FND and LND occur in rounds 188 and 494, respectively. In the ECUCF algorithm, FND and LND occur in rounds 180 and 488, respectively, In the MOFCA algorithm, FND and LND occur in rounds 171 and 469, respectively, In the MBCBCCP algorithm, FND and LND occur in rounds 163 and 430, respectively. In the LEACH FND algorithm, FND and LND occur in rounds 146 and 384, respectively. These values indicate that the efficiency of the proposed method is more appropriate and acceptable than other algorithms.

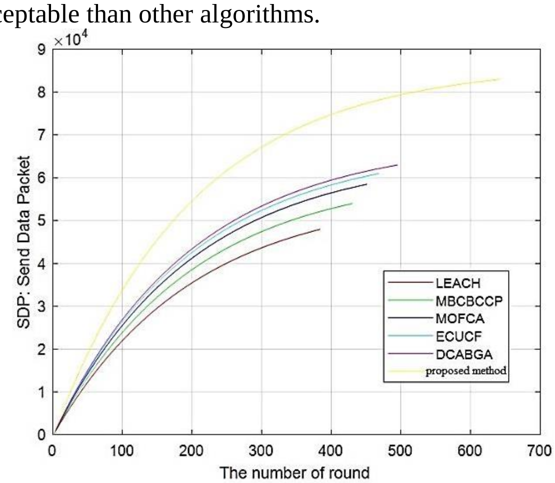

Fig.14. Number of packets sent to the base station

As indicated in figure (14), the number of packets sent to the base station in the proposed method is approximately equal to $8.3*10^4$. While, the numbers of packets sent to the base station in DCABGA, ECUCF, MOFCA, MBCBCCP, and LEACH, are approximately equal to $6.3*10^4$, $6.1*10^4$, $5.8*10^4$, $5.4*10^4$, and $4.8*10^4$, respectively, which indicates that the number of packets sent to the base station in the proposed method is about 33%, 38%, 43%, 48%, and 63% higher than DCABGA, ECUCF, MOFCA, MBCBCCP, and LEACH algorithms, respectively.

Then the mentioned test is performed with the same number of sensors in 400*400 m^2 and base station (200*550) environments as well as 500*500 m^2 and base station (250*750) environments in a state that the environment is heterogeneous (also half of the nodes have the energy twice of other nodes).

Table 3. Comparison of various methods in different environments

Death of the 100% Nodes	Death of the first node	Lifetime / method	
248	98	LEACH	400*400 m^2
280	110	MBCBCCP	
296	116	MOFCA	
310	121	ECUCF	
325	128	DCABGA	
438	173	RCEMO	
86	46	LEACH	500*500 m^2
103	51	MBCBCCP	
110	54	MOFCA	
115	57	ECUCF	
120	60	DCABGA	
162	81	RCEMO	

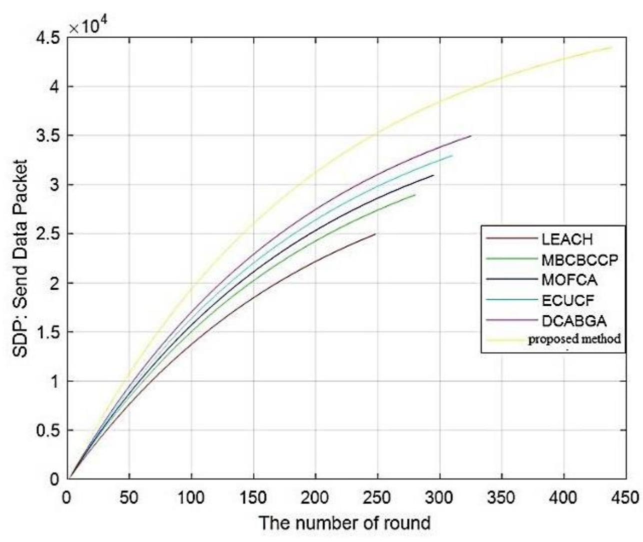

Fig.15. Number of packages sent to the base station in the 400*400 environment

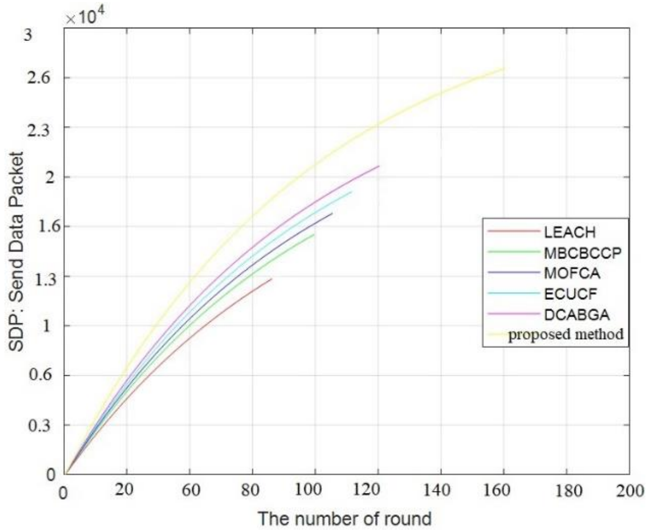

Fig.16. Number of packets sent to the base station in the 500*500 environment

As shown in the above figures, the proposed method improves the network's lifetime by about 35%, 38%, 43%, 47%, and 63% compared to DCABGA, ECUCF, MOFCA, MBCBCCP, and LEACH, respectively. The number of packets sent to the base station is increased by approximately 32%, 37%, 42%, 46%, and 58% compared to DCABGA, ECUCF, MOFCA, MBCBCCP, and LEACH, respectively.

5- Conclusion

In the present article, a clustering-based routing approach based on multi-objective optimization algorithms was proposed for optimizing the lifetime of the sensor-based IoT network and improving energy consumption. The proposed algorithm, called RCEMO, has applied the type-2 fuzzy algorithm for clustering and has used a genetic algorithm for routing from the cluster heat to the base station. According to the conducted tests, it was concluded that the proposed algorithm had improved the energy consumption, and therefore the wireless sensor-based IoT network's lifetime has been increased. Moreover, the number of data sent by the proposed method to the base station has been increased significantly compared to previous methods. In future work, other multi-objective optimization and machine learning algorithms can be applied to develop the proposed protocol. In this way, a model can be created to vote on the selection of the cluster head and routing so that the node for becoming cluster head as well as the path chosen by voting as the cluster head node and the path from the cluster head to the base station to be selected.

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