REDUCING ENERGY CONSUMPTION IN IOT BY A ROUTING WHALE OPTIMIZATION ALGORITHM

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ABSTRACT

The Internet of Things is a new concept in the world of information and communication technology, in which for each being (whether it be a human, an animal or an object), the possibility of sending and receiving data through communication networks such as the Internet or Intranet is provided. Wireless sensors have limited energy resources due to their use of batteries in supplying energy, and since battery replacement in these sensors is not usually feasible, the longevity of wireless sensor networks is limited. Therefore, reducing the energy consumption of the used sensors in IoT networks to increase the network lifetime is one of the crucial challenges and parameters in such networks. In this paper, a routing protocol has been proposed and stimulated which is based on the function of the whale optimization algorithm. Clustering is performed through a routing method which is based on energy level, collision reduction, distance between cluster head node and destination, and neighbor energy. Furthermore, the selection of the cluster head node is performed based on the maximum remaining energy, the least distance with other clusters, and energy consumption, where energy consumption for reaching the base station is minimized. By de-creasing the level of cluster head energy from the specified threshold value from among the nodes in the same cluster, a node with an energy level above the threshold would be selected as the new cluster head. Moreover, four conditions (i.e. the shortest route, the leading route, the least distance to the source node, and destination node) are applied for routing. The proposed method was compared to LEACH, EEUC, EECRP, BEAR and CCR algorithms, and the results indicated the superiority of the proposed method to other methods in terms of the number of dead nodes.

Keywords*: *Internet of Things, Clustering, Routing, Energy Consumption, Whale Optimization Algorithm

1.0 INTRODUCTION

The Internet is a global network that connects many users to each other; however, the structure of this network has been varying, whereby a new member is being added to this collection of users. This new member is not a user and is referred to as Things, which has been extracted from the term “of the Things”. A thing may refer to any device having a sensor for the exchange of information. In general, it can be said that the Internet of Things (IoT) is a network of embedded physical objects with electronic components, software, sensors, and connections to make them provide more services through exchanging in-formation (at an unprecedented rate and scale) with the manufacturer, operator, or other devices [1-2].

The IoT can improve the quality of life in various aspects, including medical services, smart homes, smart cities, industries, environment and water conservation, energy management and consumption, and so on. Data transfer is of paramount importance for communication, and time plays a critical role in the interaction among humans, as well as between humans and machines/devices while transferring data, so that a message can reach its destination within a determined time period. To this end, data should use the minimum or the shortest route to reach the destination. Routing is the process of creating and maintaining routes among nodes in wireless networks, and is of primary importance in IoT issues. Since the routes in IoT networks are constantly changing due to the dynamic and mobile nature of the nodes in these net-works, which per se causes frequent changes in network connectivity and division, there is a need for the discovery of new paths to send data. As a result, the development of routing algorithms in IoT networks has become a major challenge for researchers. There are two types of routing protocols, one based on topology and the other on clustering benchmarks [3-4]. Topology refers to the order of the nodes and objects in the network (based on the

maintenance of routing information), and the nodes in the clustering technique are grouped into a cluster. In each cluster, a cluster head is selected, and the cluster head communicates with other cluster heads to transmit the packet, which, ultimately, saves the node energy by communicating through the cluster heads. Several studies have been conducted on energy-saving issues in wireless sensor networks [5-6].

The IoT system requires a powerful network infrastructure and an appropriate routing structure. Energy consumption issues should be considered in order to increase the longevity of the node in network systems. Saving energy and increasing the lifetime of wireless networks is an important feature of the nodes. A node consumes most of its energy to transmit and receive packets. In the IoT, the battery is the main source of power to the node. However, it is difficult in most cases for users to reach the nodes. Regarding the large number of nodes, the battery replacement is often impossible; however, the battery power of a node is also limited. Thus, energy conservation has become a major concern in wireless networks. In order to reduce energy consumption and extend network lifetime, new and effective energy-saving methods should be developed. The present study aims to provide a routing method based on machine learning algorithms to reduce energy consumption and increase the network lifetime in IoT systems. In these networks, the best route to the optimum point (destination) can be determined by using machine learning algorithms [7-9]. In this paper, the main objective is to perform IoT routing using an optimized, innovative, and nature-inspired algorithm called Whale Optimization Algorithm (WOA) in order to optimize energy consumption and network lifetime. This method imitates the behavior of humpback whales and has been inspired by the bubble-net hunting strategy.

The main contribution of this work is to reduce the energy consumption using a novel routing method. It inherently considers the two method: First, a WOA is used for clustering and selecting the optimal cluster heads, and then a WOA is applied to send data from the cluster heads to the BS. The proposed method consists of two phases. In each phase, the parameters of service quality, such as energy consumption is investigated separately. To improve scalability, the sensor nodes are clustered in the first phase using the WOA, and then, the best cluster heads are selected. The results of the network performance analysis show that the proposed method can improve network performance in terms of energy consumption and network life.

This paper encompasses five sections. In Section 2, a review of previous studies is presented. In the third section, the optimization algorithm is described. Section 4 addresses the simulation results, while a general comparison is performed between the proposed model and several studies published in recent years. In Section 5, a summary of the proposed method and its results are presented.

2.0 RELATED STUDIES

Xia et al. [4] proposed an energy-efficient routing algorithm based on unequal clustering theory and connected graph theory for wireless sensor network. They focused on the beam selection from the vertex-based measurement and the transmission power of the sensor nodes. In their algorithm, nodes were subdivided into different unequal clusters.

Another energy-efficient routing protocol was proposed in [6] to improve network performance in IoT using WSN. It consists of three main parts. The first part includes a new distributed cluster formation technique that enables a local node to organize itself. In the second part, a new set of algorithms are used for cluster adaptation and cluster head rotation (CH). A new mechanism is used in the third part to reduce energy consumption for telecommunications. In particular, the residual energy of the nodes is considered to calculate the center position. This protocol is also suitable for networks that require a long lifetime.

In [8], a routing protocol called Adaptive Balanced Energy Routing (BEAR) was proposed. It worked in three stages including preparation, tree construction, and data transfer stage. At preparation stage, all nodes shared information about their energy levels and their residual location, and at tree construction stage, the algorithm utilized location information. Particularly, BEAR selects nodes with residual energy relatively higher than the average residual energy of the network. This can balance the energy consumption between surrogate and facilitator nodes.

Razaque et al. [9] proposed an optimized cluster chain protocol which was a hybrid method of LEACH and PEGASIS. It was an improvement on PEGASIS and LEACH and used an energy-efficient routing algorithm to transfer data to the WSN.

In [10], a routing method was proposed and simulated using a public algorithm in order to reduce delivery delay. This algorithm, which was proposed for coordinating duplicate databases, ensures a sufficient number of random data exchanges in the network, so that all nodes can eventually receive all messages; thus, the delivery rate is 100%. Public routing is similar to flooding transmission in the network since it is to send each message to all the nodes in the network.

In each stage, such as in flooding transmission, the message is not sent to all neighbor nodes, though, a series of specific measures (such as using GPS) are used to navigate the receiver location, thereby reducing the consumption of network resources (such as memory). There is, however, an intense need for bandwidth and buffers.

In [11], a simple routing method called direct transmission was proposed. In this method, when a source node generates a message, it stores it into its buffer and carries it until there is a collision with a destination node so that it can deliver the message to this node. In this method, only one version of the message is generated, which results in the lowest data transmission in message delivery, and, thereby, a minimum overload on the network. The message delivery may be delayed a lot since there is no limitation on delivery delays.

In 2016, researchers used content-centric routing technology to solve the traffic congestion problem in the central network [12]. By routing the data connected to intermediate relay nodes for processing, data collection can be achieved at a higher rate; hence, the network traffic is effectively reduced. As a result, a significant decrease in latency can be achieved. In addition, the transfer of duplicate data after data collection can be eliminated, which largely reduces energy consumption on wireless communications and, consequently, saves the battery lifetime. In this paper, two methods have been proposed and simulated to implement this technology. The first method is content-centric routing (CCR), and the second integrates the first method with the IETF RPL protocol, both of which are implemented on the Contiki platform using the TelosB. The simulation results show the superiority of the first method in terms of low network latency, high energy efficiency, and reliability.

In 2015, following a thorough review of various methods for IoT routing, researchers proposed and simulated a technique called EECBR (Energy-Efficient Content-Based Routing) to optimize energy use [13]. The proposed algorithm uses a centrally-constructed virtual topology, in which routing is distributed in such a way that the routes of events are directed towards optimal subscribers or sensors. The technique was implemented and simulated using the Omnet ++ software, and the simulation results were superior to the other compared cases in terms of energy variance.

In [14], a new method was proposed to remove the deficiencies and limitations of memory resources, computational power, and node power energy of the wireless sensor terminal in the IoT, which was carried out using IoT routing based on energy-aware clustering. This method was called RA-AODVjr and developed by integrating the RA cluster and the AODVjr routing protocol. In this protocol, the best neighbor in the terminal node is selected, and the network traffic is balanced when the source of the terminal node is restricted and the wireless routing network is used. The simulation results indicate that the conditions to reach the load balancing are restricted to limited energy nodes. Compared to the AODVjr protocol, the method proposed in this study reached load balancing in a better way. This is due to the technology of access to neighbor nodes. In the local network, the traffic is better balanced and average delay time decreases as a result of better routing.

In 2014, researchers provided two IoT routing methods based on the ant colony algorithm [15]. The energy-efficient probabilistic routing (EEPR) method, which is related to routing for the lost packets, is based on probability. The EEPR algorithm controls the request packets to reduce missing packets and network traffic in the core of the AODV protocol. A source node forwards the route request (RREQ) packets to the neighbor nodes to transmit a data packet. In one variety of AODV protocols, each node transmitting a RREQ packet forwards the same packet to neighbor nodes. In other words, each node not forwarding the RREQ packets interrupts the entire connection. The energy distance function is used to implement the EEPR method. In the study, two different routing methods were developed. One was the ETX method that created a suitable bond between the nodes. Each node periodically received the packets of a small band and forwarded them to the neighbor nodes. In the second method, the probability of links between the two nodes was achieved through using the energy variance of the adjacent nodes. The simulation results in a large network with high lifetime using a colony algorithm have yielded better results than the AODV algorithm.

Spyropoulos et al. presented a spray and focus method to restrict the delivery overhead of a message [16]. In this method, first there is a spraying phase where a source node generates L forwarding tokens for its message. Each send token indicates that its node can generate and send another copy of a particular message. When a relay node has just one token, there is then a focus phase, where the message is sent to an-other relay node according to certain criteria. These forwarding criteria are based on a set of timers re-cording the time spent since the two nodes met each other.

In 2018, Yousif et al. proposed a clustering method to increase the lifetime of nodes in an IoT network [17]. One of the most critical challenges in the IoT is to reduce energy consumption to extend the lifetime of the sensors in the network. The clustering technique is one of the techniques used to reduce consume energy. A majority of clustering techniques select cluster heads either randomly without considering significant parameters, or based on a centralized approach using

the base station, which can affect the network scalability. Furthermore, single-hop connections are used by nodes to send their measured data to the cluster head, which leads to an increase in the energy consumption of cluster headings in large-scale networks. In [17], a clustering method has been proposed based on the distributed approach. Different parameters were considered for cluster head selection and multi-hop connections. The results showed that the pro-posed method revealed better efficiency in terms of energy consumption and the number of live nodes.

In the above-reviewed articles, one of the main problems was the non-simultaneous implementation of some benchmarks such as energy level, collision reduction, distance between cluster head node and destination, and neighbor energy in clustering. In the present study however, there has been an attempt to simultaneously apply these benchmarks in clustering and to use the whale optimization model for routing and transmitting information.

3.0 WHALE OPTIMIZATION ALGORITHM(WOA)

Since WOA is theoretically a metaheuristic algorithm, it can be used for optimization issues from a theoretical perspective. This is because it has both extraction and exploration capabilities. It helps the other agents take advantage of the best records in the domain. By adaptive variation of the search vector A, the WOA clustering algorithm can gently move among exploration and exploitation. More specifically, reducing A can lead to exploration for certain iterations (| A |> = 1) while others are assigned to exploitation (| A | <1) [18-19]. It is worthy to mention that the WOA only encompasses two adaptive internal parameters (A \& C).

3.1 Encircling Prey

Whales can detect the place of their preys and catch them. The optimal position in the search area is not recognized by analogy. The WOA method therefore presumes the best candidate solution is the target prey or a nearly optimum condition. This phenomenon is presented in Eq. (1) and (2):

$$\vec{D} = |\vec{C}.\overrightarrow{X^*}(t) - \vec{X}(t)| \quad (1)$$

$$\vec{X}(t-1) = \overrightarrow{X^*}(t) - \vec{A}.\vec{D} \quad (2)$$

Where t shows the current iteration, $\vec{A}$ and $\vec{C}$ denote the coefficient vectors, and $\vec{X}$ stands for the position vector. The position vector of the best solution is indicated by $\vec{X}^*$. It should be noted that $\vec{X}^*$ must be updated if there is a better solution. The coefficient vectors $\vec{A}$ and $\vec{C}$ can be computed as follows:

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \quad (3)$$

$$\vec{C} = 2.\vec{r} \quad (4)$$

Where $\vec{a}$ linearly decreases from 2 to 0 over the course of iterations (in both exploration and extraction phases), and $\vec{r}$ is a random vector with values ranging from 0 to 1.

3.2 Bubble-Net Attacking Method (Extraction Phase)

The bubble-net behavior of humpback whales can be mathematically modeled by:

The shrinking encircling mechanism: This action is achieved by reducing the value of $\vec{a}$ in Eq. (3). It must be noted that the variation range of A decreases by a. More specifically, A is a random number in [-a, +a], and $\vec{a}$ ranges from 2 to 0 over the course of iterations. By selecting random numbers for A in [-1,1], the new position of a search agent can be determined everywhere among the original positions of the agent and the positions of the best current agent.

Note that the humpback whales swim along a spiral-shaped path and within a shrinking circle at the same time. A probability of 50% was assumed for the whale to select either the shrinking encircling mechanism or the spiral model in order to update the whale position over the course of optimization. The mathematical model is as follows:

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X^*}(t) - \vec{A}.\vec{D} & if \;\; p < 0.5 \\ \vec{D}'.e^{bl}.\cos(2\pi l) + \overrightarrow{X^*}(t) & if \;\; p \geq 0.5 \end{cases} \quad (5)$$

In this equation, P is a random number in [0, 1], $\vec{D}$ indicates the distance between the ith whale and the prey (the best solution so far), b is a constant to define the spiral logarithmic form, and l is a random number in [1, 1].

4.0 THE PROPOSED METHOD

The proposed IoT routing method is performed to reduce energy consumption in two phases, where the first is related to clustering, and the second concerns a steady state for routing. Since the clustering method is one of the effective ways to optimize the energy consumption of the sensors used in the IoT, reduce the energy consumption of sensors and increase their lifetime, and, consequently, to increase the overall lifetime of the network, clustering was used in the proposed method to reduce network energy consumption. Moreover, dynamic courses were also used to prevent re-clustering.

To cluster the network, a number of nodes with higher energy are first selected as the cluster head based on the amount of energy remaining in the sensor nodes. The other sensor nodes are connected to each selected cluster based on their distance from the selected clusters, and they then become cluster members. Finally, some clusters are generated in the network. Accordingly, the nodes feel the data from the environment and forward them to their cluster head. Then, based on generated routing and their distance from the central station, the cluster heads forward the aggregated data received from the node members of their cluster and forward them either to another cluster head as the next step in the routing or directly to the base station.

Hierarchical clustering in the IoT can significantly affect the system's overall scalability, life span, energy efficiency, and latency. Hierarchical routing is an efficient method contributing to lower energy consumption in a cluster, and helps aggregate and combine data to reduce the number of messages sent to the base station. A single-level network may cause overheads in clusters when increasing the density of sensors.

Such overheads may result in unsuccessful follow-ups of the event. In addition, a single-level architecture is not scalable for a large set of nodes that covers a wide area because the sensors usually fail to communicate on a long route. Hierarchical clustering is efficient, especially in applications requiring scalability. In this regard, scalability is necessary for gaining load balancing and appropriate utilization of resources as well as applications requiring effective data aggregation. Clustering is a part of the routing protocols.

In addition to supporting network scalability and reducing energy consumption (through data aggregation), clustering includes various benefits consistent with different purposes. In this paper, using the WOA, we also address the advantages of collision reduction, which are referred to as recent challenges in wireless networks. On the other hand, clustering can stabilize the network topology at the sensor's level and decrease the overhead and overall maintenance costs of the topology, implying that the sensors are used only when connected to their cluster heads, and that the cluster heads are not affected when there are variations in the levels of cluster heads. Additionally, the cluster can implement some optimized management strategies to enhance network performance and increase the nodes' battery life, which in turn results in enhanced network lifetime.

Cluster-based routing protocols are among the most remarkable approaches to energy consumption reduction in wireless sensor networks. This new clustering protocol, called the WOA-based clustering protocol, clusters the network nodes based on energy level, collision reduction, distance between cluster head node and destination, and neighbor energy, and it better balances the energy in clusters, enhances the network lifetime, and maintains the network coverage. The present study aimed to improve the traditional clustering (location-based clustering) approach in order to achieve the main goal of wireless sensor networks, i.e., increasing the network lifetime while maintaining network coverage, and thus to provide an integrated approach for location-energy-based clustering. The researchers in the present study believed that energy-based clustering can create clusters with the same energy level and distribute the energy efficiently across the network nodes. Fig. 1 shows the main steps of the proposed method for routing in the Internet of Things.

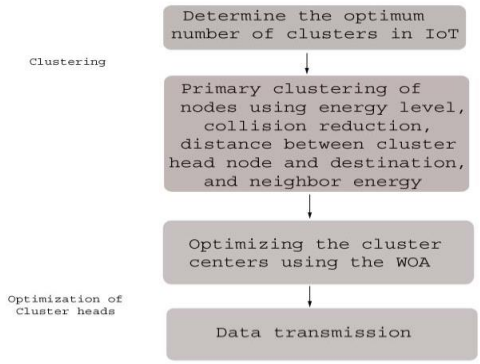

Fig. 1: Routing in IoT

As it can be observed, routing in the proposed method consists of three steps:
• Clustering
• Optimization of cluster heads
• Data transmission
In the following sections, the three steps will be explained in details.

4.1 Clustering

The main purpose of this stage in the proposed method is to divide sensor network nodes into a number of clusters. The sensor node clustering step involves two phases. In the first phase, the optimum number of clusters is determined based on the validation indices. The clustering algorithm depends on several factors, such as the number of clusters and the distance between them. One of the major issues in clustering is to select the appropriate number of clusters. In general, it can be claimed that the number of clusters is appropriate if:

• The samples in a cluster are similar to the greatest extent possible: the common criterion to determine the data density is data variance.
• Samples belonging to different clusters are kept separated as much as possible.

In other words, the clusters should have the maximum density and be separated as much as possible. Clustering can be defined as follows: An uncontrolled categorization approach in which no prior knowledge of the categories is available. In all of the existing methods, the specified number of clusters is taken as a default to provide the right clustering solution. This contradicts with the initial assumption of uncontrolled classification set forth in the clustering definition. Traditional clustering algorithms are considered to be among the appropriate clustering methods, and require the number of clusters to be specified at the beginning of the algorithm. The goal of cluster validation is to find clusters having the best fit with the concerned data. In general, three approaches are used to measure and calculate the degree of separation in clusters:

• The distance between the closest data and two clusters;
• The distance between the farthest data and two clusters; and
• The distance of the cluster heads.

The main objective of sensor clustering is to divide the sensors into a number of different clusters based on their similarity. Thus, the sensors in each cluster are more similar to each other, and the features in different clusters are less similar. Most of the methods proposed for sensor clustering have shortcomings as follows:

• In the majority of clustering methods, the number of clusters must be specified before the clustering algorithm is performed. In other words, the parameter k, which specifies the number of clusters, in most of these methods must be specified by the user. Generally, the number of clusters for the basic task features is difficult to be specified, and the optimum number of cluster errors can only be determined by using trial and error techniques.
• Distribution of data in a cluster is one of the significant criteria in clustering, which had been ignored in most of the previous methods presented for clustering sensors. The feature scattering in a cluster can greatly enhance the performance of the clustering algorithm.
• In a majority of the current sensor clustering methods, all features are considered in the same way in the clustering process and have an equal impact on clustering, while the features with more similarity should be considered of greater impact in the clustering process.

We use binary encoding to encrypt the problem. We show the nodes of the cluster head (CH) with one and the members of the clusters (normal nodes) with zero. We assume that 100 nodes are randomly distributed in an environment of 100 x 100 m. Initially, a number of nodes are randomly selected as cluster head.In this paper, the WOA was used to deal with these problems and cluster sensor nodes.

4.2 Optimization of Cluster Heads

Initially, a number of nodes are randomly selected as cluster heads. In the next rounds , a number of nodes are selected as the cluster head using WOA. Here, the cluster heads are represented by one and the regular nodes by zero. Each regular node calculates its distance from the cluster heads and eventually becomes a member of the cluster that has the shortest distance to the cluster head of the cluster. As can be seen, at the end of each round, each node is either a cluster head or a member of a cluster.

In a cluster-based routing for IoT, CHs consume more energy. This is due to the additional burden of receiving, collecting, and aggregating data from sensor nodes and transmitting the aggregated data to the BS. Therefore, proper

selection of CHs plays an important role in saving energy consumption of sensor nodes to increase the network lifetime. In this paper, we use a method similar to the one proposed in the article [20] with a new and more efficient fitness function for clustering and selecting the CHs. The WOA uses a BS to perform the clustering operation, and as a result, the WOA determines the appropriate clusters for the network. The BS sends the full network details to all sensor nodes through public broadcast. The message sent by the BS includes the number of CHs, the members associated with each CH, and the number of transfers for this configuration. All nodes receive packets sent by the BS, and so do the clusters. Therefore, the cluster formation stage is completed, followed by the data transfer phase by the next phase of the proposed method.

During implementation, all nodes transmit their data to the BS, whereby the BS compares the average energy of the nodes and states that the nodes whose energy value is higher than the average energy can be selected as CHs. To implement the whale optimization algorithm in clustering, after calculating the average energy at the BS, the nodes with medium-to-high energy are selected. Also, some CHs with minimum cost function will be selected using the whale optimization algorithm.

Now, n cluster-head nodes are considered as the search whales:

$$CH = CH1, CH2, \ldots, \quad CHn \tag{6}$$

Considering that the nodes in the network are fixed, the desired whale position (CH) is denoted by CHi in a two-dimensional space in order to mimic the position of whales in WOA. In other words:

$$Posi\ (t) = xi(t), yi(t) \tag{7}$$

So the best position of the search whale is used to determine the best solution, which is used to select the most optimal CH. Also, for implementation, the position of the search whale on the screen is randomly selected first and then replaced with the nearest node. Next, the value of proportion with the corresponding cost function is calculated for all search whales, and the best search whale is selected. They are then updated based on the position of other search whales considering the superior search whale of the WOA parameters. The following are the steps of the proposed method and its pseudo-code to select the best CH based on the whale optimization algorithm.

The CH selection will be based on the fitness function. We also know that in the whale optimization algorithm, the fitness function plays a vital role in identifying and detecting the prey (target node). In this section, we first introduce the parameters of the fitness function and then introduce an efficient fitness function.

The main parameters in this step is to select a cluster head from each cluster based on a set of predefined criteria. To select cluster heads, the following four criteria were considered:

- $f1$: Total energy of the selected cluster heads;
- $f2$: Total distance of the nodes in a concerned cluster from the cluster head;
- $f3$: No central node collision within its cluster; and
- $f4$: Total distance of the selected cluster heads from each other.

As it can be noticed, the higher the first and third criteria, the lower the other two criteria will be which represents better cluster heads. Thus, the proposed method is a multi-objective algorithm that needs to be optimized. Given the multi-objective nature of the problem, the fitness function for the selection of the cluster heads in the proposed method is defined as Equation (6):

$$Fitness = \alpha f_1 + \beta \frac{1}{f_2} + \gamma f_3 + \lambda \frac{1}{f_4} \tag{8}$$

where β, λ, γ, and α are four constant parameters determining the effect of these four different criteria and their value is between [0,1]. As it can be noticed, the optimization is to maximize the target function. Since the second and fourth criteria must be minimized, they are inversely represented in the fitness function.

The aim is for the WOA to select a cluster head node in each cluster with regard to various parameters described. In the proposed method, a specific form of WOA was used in a binary way for discrete environments. In this algorithm, each whale had coordinates in a two-dimensional environment, with each coordinate taking a binary value of one or zero. In

fact, the value *one* showed the whale's inclusion and the value *zero* represented the whale's exclusion in that dimension. To form appropriate clusters in this paper, the distance between the whale located at (X, Y) and prey located at (X*, Y*) was first calculated, and the neighbor function, which encompassed n × n matrix, was used for clustering. It should be noted that *n* is the total number of clusters, and the distance between the whales is calculated according to Equation (7):

$$d_{i,j} = \sqrt{\sum_{i,j=1}^{n} (p_{(i,:)} - p_{(j,:)})^2} \quad (9)$$

In Equation (7), *p* indicates the position of the whales and $p_{(i,:)}$ expresses the coordinate of whale *i* in comparison to other whales. After clustering, the distance among all the nodes is measured, and the node with the shortest distance from the others is selected as the cluster head node.

The best solution is to obtain the highest value of the fitness function and have enough residual energy. In this case, we can say that there are enough neighboring nodes to convert to a cluster-head node. The above definitions are summarized in Figure 3.

```
Algorithm 1          Select best CHs with WOA
Input: A graph represents the nodes and Base Station
Output: A Set of Optimal Cluster heades
for each round do
    Initialize Whale Population (search agents)
    Initialize Random Position for each whale
    Evaluate Fitness Function Using Eq.8 at Position p
            if Fitness(p) > Fitness(X*) then
                X*=p
                set X* as best solution
            end if
        while r<rmax do
                while i<imax do
                        Update  the values of a, A, C, I, p
                                if p<0.5 then
                                        Use Shrinking encircling Mechanism Using Eq.2
                                    else if p≥0.5 then
                                            Use Spiral Updating Mechanism Using Eq.5
                                    end if
                            Update the positions of all search agents
                end while
            Calculate the fitness function for all whales
            Update X* with with the position of best solution
        end while
    Send the set of Cluster Heads to Base station for next phase
end for
```

Fig. 2: The pseudo-code of the WOA clustering algorithm

Clusters are formed once the optimal CHs have been selected. To determine which cluster a node belongs to, first the Euclidean distance of that node to all the CHs is calculated. The distance between node i and CHs is d, calculated as follows:

$$d = \sqrt{(node - C)^2 + 2} \quad (10)$$

In this equation, Node represents the desired node, C represents the cluster head, and d is the distance from this node to the cluster head. The pseudo-code of this operation is given in Figure 3.

```
function [G, D, clusters]=GetClusters(x,params)
   N=params.N;
   Nodes=params.Nodes;
   C=Nodes(logical(x),:);
   nc=size(C,1);
   clusters.Center=[];
   clusters.Members=[|];
   clusters=repmat(clusters,nc,1);
     for k=1:nc
       clusters(k).Center=C(k,:);
     end
   G=zeros(N,1);
   D=zeros(N,1);
      for i=1:N
          node=Nodes(i,:);
          node=repmat(node,nc,1);
          d=sqrt(sum((node-C).^2,2));
          [min_d ,cc]=min(d);
          G(i)=cc;
          D(i)=min_d;
          clusters(cc).Members=[clusters(cc).Members i];
        end
end
```

Fig. 3: Pseudo-Code for cluster formation

Finally, the node is placed in the cluster that shows the shortest distance from its cluster head. At the end of clustering stage, each survived node is either a cluster head or a regular node which belongs to a cluster. Once the most optimal arrangement of the CHs and the nodes related to each cluster has been determined, the BS transmits the data containing identification information to each node on the network to determine their location.

4.3 Data Transmission using WOA

At this stage, the data of each cluster head are sent in a few hops to the base station using the WOA. All nodes are clustered by the previous phase. After each clustering phase, the location and specifications of the cluster heads are sent as input for the next step to select the optimal path. In the second phase, the routing operation is performed by these cluster heads by using WOA in five rounds. Then, the clustering phase is performed again by the WOA, and the new cluster heads are delivered to the second phase. In each of these five rounds, the cluster member nodes first send their data as a single hop to the cluster head. The cluster head then aggregates the received data and sends the aggregated data to the base station by multi-hop sending using the WOA.

In Section 4-2, we used the WOA algorithm to select the best CHs. There, the input of the algorithm was all the nodes of the network and the output of the algorithm were the optimal cluster heads. Now we want to select the appropriate CHs to transfer data to the base station. For this purpose, we use an algorithm similar to the algorithm 1. Here the input of the algorithm is all CHs and its output is CHs to transfer data to the base station. To calculate the algorithm, we use the equations of Section 4-2, including: 6,7,8 and 9. In this step, the parameters of the fittness function are as follows:

- D: The distance between cluster head and base station.
- E: The cluster head residual energy: due to the higher energy consumption of the CH, a CH with more residual energy should be selected.

Finally, we use the following fittness function to select the best path:

$$Fitness = \alpha E_i + \beta \frac{1}{D_{CH_i,BS}} \quad (11)$$

Alpha and Beta are randomly selected from zero to 1. The CH energy, E, is the residual energy of the i-th CH and

$D_{CH_i,BS}$ is the distance between CH and BS. The best solution is obtained when a function with the highest value is achieved. After the CH has transmitted its data to BS, the previous steps will be repeated for transmitting the next data. The above definitions are summarized in Figure 4.

```
Algorithm 2          Routing to the BS with WOA
1: Input: A Set of Optimal Cluster Heads and BS
2: Output: An Optimal Route Between the Cluster Heads And The Base Station
3:   for each round do
4:       Initialize Whale Population (search agents)
5:       Initialize Random Position for each whale
6:       Evaluate Fitness Function Using 11 at Position p
7:               if Fitness(p) > Fitness(X*) then
8:                   X*=p
9:                   set X* as best solution
10:              end if
11:         while r<rmax do
12:                  while i<imax do
13:                          Update   the values of a, A, C, I, p
14:                                  if p<0.5 then
15:                                          Use Shrinking encircling Mechanism Using Eq.2
16:                                      else if p≥0.5 then
17:                                              Use Spiral Updating Mechanism Using Eq.5
18:                                      end if
19:                          Update the positions of all search agents
20:                  end while
21:              Calculate the fitness function for all whales
22:              Update X* with with the position of best solution
23:         end while
24:      Send the set of Cluster Heads to Base station for next phase
25: end for
```

Fig. 4: The pseudo-code of the WOA routing algorithm

Clustering is done ten times. After each selection of cluster heads by Section 4-2, five routing operations are performed using Section 3-4. This is shown in Figure 5.

Fig. 5: Number of clustering and routing round

4.4 Energy Model

The energy consumed for transmitting *k* data bits to the distance *d* is calculated by Equations (8) and (9):

$$E_{Tx}(k,d) = E_{Tx}(k) + E_{Tx_amp}(k,d) \quad (8)$$

$$E_{Tx}(k,d) = \begin{cases} kE_{elec}(k,d) + k\,\varepsilon_{friss}d^2 & if \quad d<d_{crossover} \\ kE_{elec}(k,d) + k\,\varepsilon_{two-ray-amp}d^4 & else \end{cases} \quad (9)$$

The energy consumed for receiving *k* data bits is calculated by Equation (10):

$$E_{Rx}(k,d) = E_{Rx_elec}(k) = kE_{elec} \quad (10)$$

In the above equation, we have *Eelec* as the transmit/receive energy, *k* as the message size in bits, *d* as the distance between the receiver and the transmitter, E_{tx_amp} as amplification energy, ε_{friss} as the amplification factor and $d_{crossover}$ as the threshold distance, in which the transmit factor varies[21].

5.0 SIMULATION AND PERFORMANCE EVALUATION

In this section, we simulate and present the results and compare the proposed method with different methods.

5.1 Simulation Parameters

It is worth mentioning that the environment assumed for simulation is intended to be a 200x200 square environment, and the number of simulation iterations was assumed to be 50. The proposed method has been implemented via the Contiki OS and validated through the Cooja simulator [22-23]. The detailed parameters that were used in our simulation are listed in Table 1[15].

Table 1: parameters used in simulation

Parameter	Value
Network size	200x200
Number of sensor nodes	100
Initial energy (J)	2
Transmitting/Reception energy	50 nJ/bit
Mac	802.11
Bandwidth	200 Kbps
Beam forming energy (nJ/bit)	5
l (length of data)	500 bit
BS's locations	inside
OS	Coniki 2.6
Number of Sinks	1

5.2 Simulation Result

Fig. 2 represents the various routes traversed to transmit information after 50 rounds, which are obtained by repeating different courses of the algorithm iterations. In the iterations, sequential changes in cluster heads and multiple routings for cluster changes were also considered.

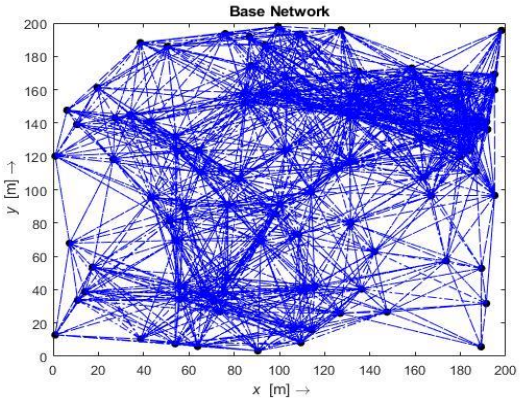

Fig. 6: Traversed routes per 50 simulation rounds

As it can be observed, routing is performed for all the nodes within different courses so that the energy consumption is distributed throughout the network. According to Fig. 3, after about 25 rounds out of 50 rounds considered for simulation, about 28% of the initial energy of the network nodes was consumed.

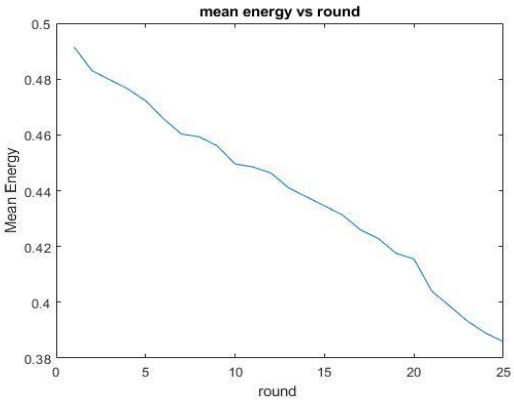

Fig7: Remaining energy after 25 round

This reflected the high energy consumption of the sensor network in the early rounds. Fig. 4 also shows the mean energy remained in the nodes after 50 rounds of the algorithm execution. About 49% of the energy was consumed in these 50 rounds, indicating that the proposed method can achieve promising results in comparison to EEUC[4], EECRP[6], BEAR[8], LEACH[9] and CCR[12]. The comparative details are then discussed.

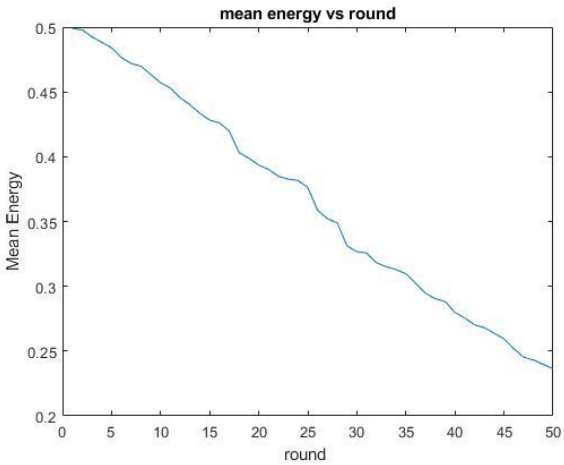

Fig.8: Remaining energy after 50 round

In Fig. 5, the mean energy variance of 50 simulation iterations is shown. This figure indicates that the energy variance is surprisingly low. It is due to the close relationship between node energies in the network. This is because the goal is to use all the nodes in the routing.

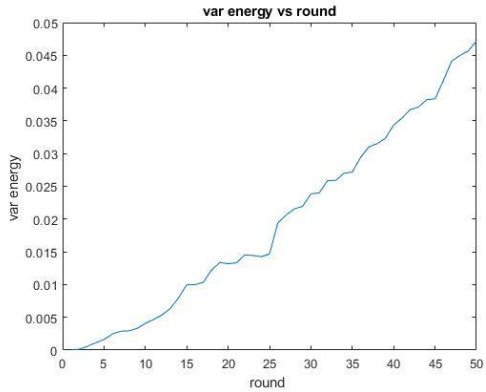

Fig. 9: Mean energy variance in 50 simulation round

In Figure 6, the WOA is depicted. It is used to reduce the fitness function. This algorithm encompasses four routing conditions indicated in section (4.2). As it can be observed in the figure, the optimal route selection method shows the excessive reduction of the fitness function. It considers all four conditions in 100 rounds of the algorithm iterations. This means that the function F (x1, x2) increases almost linearly in different directions, suggesting that the fitness function is optimized under different conditions.

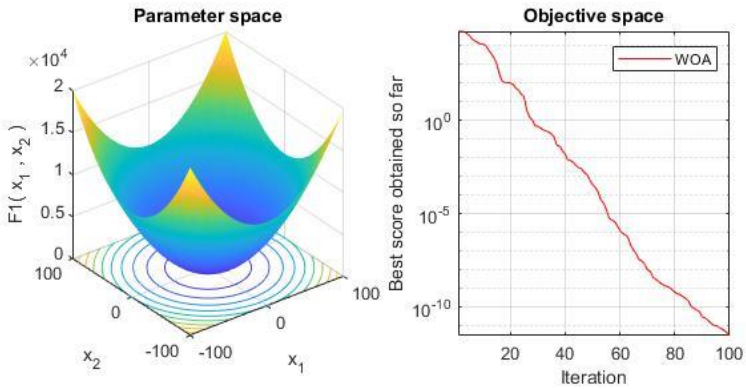

Fig. 10: Optimizing the routing function cost

5.3 Comparison Results

To have a fair comparison, the proposed method was compared to 5 different algorithms in the same simulation designs. In Fig. 7, the remaining energy for each algorithm is shown. It is noted that these results were obtained from the simulation of their original methods.

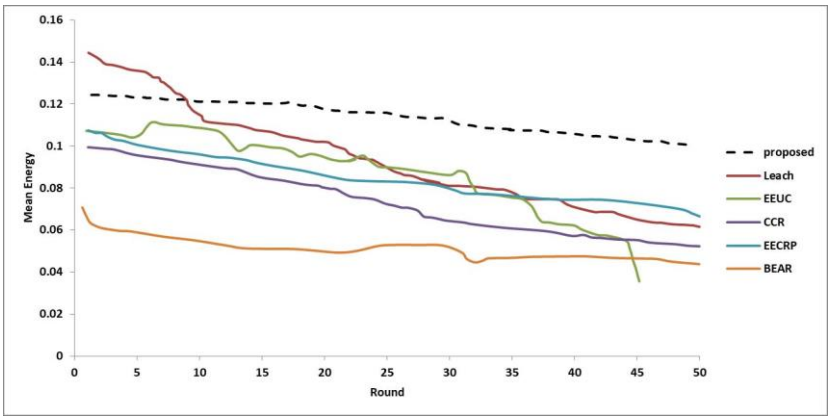

Fig. 11: Comparing the remaining energy of various algorithms with the proposed method

To have a better comparison, each of the methods was simulated in 50 iterations. In Fig. 8, the comparison results of these algorithms are provided. To do so, the six algorithms with specified energy values in 50 rounds are simulated, and the percentages of primary energy and remaining energy are presented. According to this figure, the proposed method, using

the WOA, shows a higher optimization percentage than the other five algorithms.

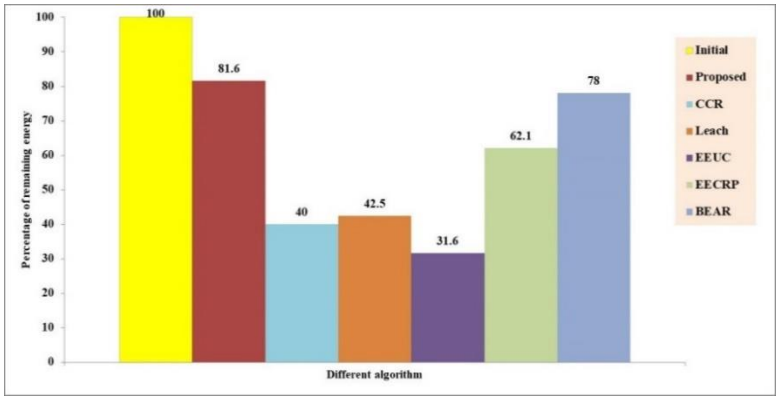

Fig. 12: Comparing the percentage of remaining energy in 50 rounds of iterations for different algorithms

For further comparison, the frequencies of dead nodes in 50 rounds of simulation were compared for 100 nodes. Fig. (9) shows the comparison of dead nodes. According to the obtained results, the proposed method, with the WOA, generally revealed a better performance than the other methods. The percentage of improvement was slightly lower in the early iterations than the subsequent ones due to the nature of the WOA.

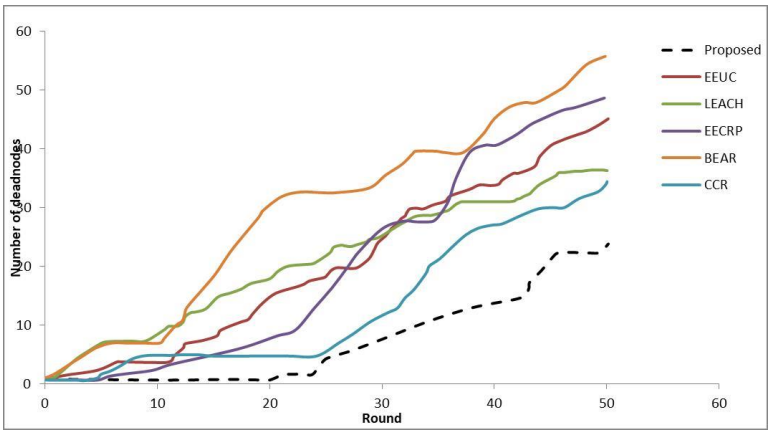

Fig. 13: Comparing the number of dead nodes in the proposed method with other methods

6.0 CONCLUSION

This study aimed to reduce the energy consumption of the IoT according to the potentials of evolutionary algorithms in optimizing cost functions. For this purpose, the clustering method was used to increase the network lifetime and control the energy consumption of sensor nodes in the IoT. To optimize the clustering and routing methods, the WOA was used for simulation, where more acceptable results were obtained for this method compared to other algorithms. One of the shortcomings of this method is the lack of using an optimization algorithm in the clustering phase. In future studies, we, firstly, can optimize the clustering criteria by WOA, then, we can use them in clustering. Using this method, the energy consumption for 25 iterations was about 28% of the primary energy, and the mean energy variance indicates the energy level of using all nodes in clustering. According to comparisons with other algorithms, the proposed method was better in terms of energy efficiency and saved more energy. Moreover, there were some improvements regarding the number of dead nodes. Future work may include the use of newly developed meta-heuristic algorithms in IoT clustering and routing.

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