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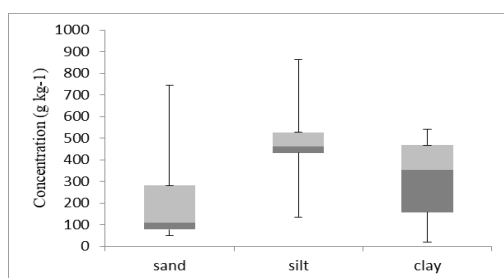
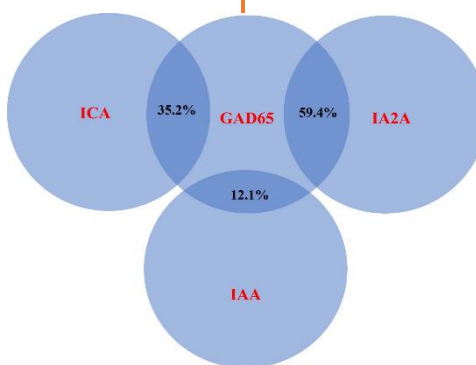
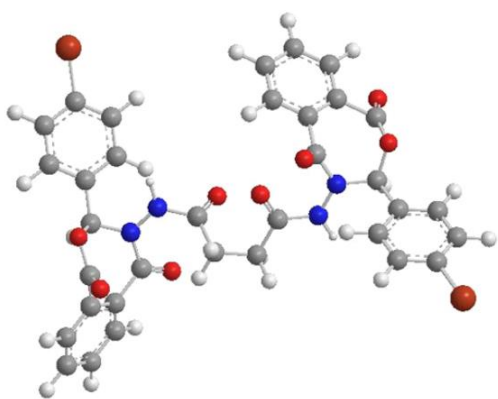
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Reducing Energy Consumption and Clustering in Wireless Sensor Networks using an Improved Discrete Gorilla Troops Optimization Algorithm with Fuzzy Rules

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Abstract

Among the most common and extensively operated methods in wireless sensor networks (WSN) to increase the efficiency and performance of WSN is network clustering because, through this solution, data is transmitted through the closest possible path. In the clustering method, a portion of the nodes in the network become cluster heads, then a cluster is formed by joining the nodes close to the cluster head. However, the main and important problem in this issue is preventing the creation of unbalanced clusters since the spreading of cluster heads in the network can be unequal. In this paper, we have presented an algorithm based on the discrete Gorilla Troops Optimizer (DGTOA) algorithm and K-Means with a fuzzy clustering approach. In this model, first, several cluster heads are chosen by applying the discrete DGTOA algorithm, and then the output of the DGTOA algorithm is given as initial points and coordinates in K-means. Finally, the cluster head is utilized to wield the fuzzy system. Also, different criteria and graphs were used to compare the proposed model, and the obtained results were measured with other methods, and the obtained outcomes indicate the high performance of the proposed model.

Introduction

Significant progress is being made in the field of infrastructure in various sectors, such as smart transportation, smart networks, and smart homes, which makes sensors a key element. Because they are directly related to communication and information technologies since sensors are embedded inside devices to transmit useful data for analysis [1]. WSN is one of the most generally utilized networks that are applied in numerous fields including military, medicine, and agriculture [3 ,2]. However, one of this kind of network's primary flaws is damaged nodes or recharging the nodes as it can be costly in harsh environments. In WSN, the network works until the nodes run out of power. Therefore, designing an efficient and capable model for routing with efficient energy increases the existence of nodes is a vital issue in WSN. To increase the lifetime of WSN and dwindle energy utilization, hierarchical routing protocols based on clustering are used, which result in a decline in using energy up and ultimately an increase in lifetime since the data transmission distance is reduced to the minimum possible distance [3] . This issue emphasizes the use of an effective protocol in WSN. In this model, the operational area is divided into clusters using protocols. The cluster head in charge of each cluster is tasked with connecting the members of the cluster. The cluster head also receives the data from the nodes and then delivers it to the sink nodes. However, in protocols based on clustering, the cluster heads should be correctly

selected and the cluster structure should be correctly separated. Among all the issues in these networks, choosing the right cluster head is of much greater importance [4].

Until today, various types of clustering techniques have been developed, each of which has its advantages and disadvantages[5]. Meta-heuristic algorithms are one of the conventional methods in clustering because these algorithms have a critical performance in solving problems in unknown and complex spaces and can be easily integrated with different operators, because problems in different optimization spaces, including discrete and continuous, can be experimentally evaluated [6]. Machine learning methods are also a suitable option for solving clustering problems. A comprehensive and efficient model can be achieved by combining machine learning methods and clustering algorithms because by combining these types of methods, the disadvantages of the two methods are overlapped with each other's advantages and a valuable model is obtained [7 ,6]. As might be expected, the selection of cluster heads in different protocols can become one of the most challenging issues in this correct clustering [8-12], as many methods have been presented for cluster building until now, and each of these methods has potential disadvantages. One of these disadvantages can be the imposition of additional computational load on the network, which can increase energy usage. One of the appropriate and efficient methods is the use of fuzzy systems, because using this system, the heads of clusters are selected more accurately and intelligently [13].

This paper's main contributions are as follows:

- Using the proposed model in solving the clustering problem in Bayesian sensor networks.
- Analysis and review of the proposed model with different scenarios and comparison with different models.
- Reduction in energy consumption in both large and small dimensions of the network, and the lifespan of the network has also increased substantially.

Related Works

Up to now, various clustering methods have been presented for WSNs, and each of these methods uses a specific technique and method for network clustering, the most common methods are the use of clustering methods based on meta-heuristics algorithms and machine learning. The main reason for the widespread use of these methods can be easy implementation and quality results. As was anticipated, considering that the number of meta-heuristic algorithms can be large, various meta-heuristic algorithms have been used to solve this problem.

To link sensors in the network, the fuzzy system was utilized for clustering, and Particle Swarm Optimization (PSO) was employed to anticipate the first values of cluster heads[14]. Then the authors evaluated and tested their model using NS2. In this article, the authors compared their proposed model with various methods including E-OEEPR, and evaluated that they were able to achieve quality results. In another research [15], the authors utilized the PSO algorithm and the fuzzy system to decrease energy utilization in WNS, which finally achieved good results compared to the methods. In [16], improved PSO and fuzzy system were implemented to improve energy efficiency in WSN, and this model can also achieve good results.

Swarm-based meta-heuristic algorithms have been usually utilized in sensor network clustering. In [17], a linked algorithm based on the Whale Optimizer Algorithm(WOA) and PSO algorithms is utilized for clustering in WSN. In this model, the fuzzy system is also implemented to choose the cluster head. In another research [18], the WOA algorithm was used to alleviate energy utilization and clustering in WSN, and in this model, genetic mutation operators were utilized to increase performance. Genetic operators can greatly help in increasing the performance of meta-engineering algorithms in solving the issue of clustering in WSNs. They presented a hybrid algorithm of Moth flame optimization (MFO) and genetics for clustering WSNs to alleviate energy usage, and finally, they evaluated the efficiency of their designed model with other methods such as

LEACH, HEED, and ABC. In [19], the authors tried to scrutinize the performance of swarm-based algorithms. In this article, the application of 60 meta-heuristic algorithms in WSN clustering was implemented and compared with each other.

Machine learning methods are used for clustering WSN networks because these methods are easy to implement and can reduce energy consumption. Energy-Efficient Clustering Algorithm (EECA)[20] is one of the new methods that authors utilized machine learning methods for clustering and reducing energy usage. In this technique, the target area is separated into smaller parts, and then the Artificial Neural Network (ANN) method is implemented to choose the cluster head in each area, and the nodes with the predefined minimum energy level have the highest priority. The authors used four factors to pick each node as a cluster leader via ANN: distance to the base station, number of neighbors, residual energy, and number of events identified. This model is compared with several existing protocols. In another study [6], ANN was utilized for clustering and data aggregation in WSN networks. In [21], an affinity propagation-based self-adaptive clustering strategy blends the consanguinity propagation (AP) technique with the K-medoids method. In this system, first, the cluster centers and primary clusters are selected using K-medoids, then the altered K-medoids to design the network using repetition action start the optimization operation. The results shown in this article indicate better performance in comparison with the EDDUCA, the LEACH-AP, heterogeneous multi-level WSN, and UCR-H performed better. In another investigation, the combination of machine learning methods and meta-heuristic algorithms was utilized for the clustering of WSN networks, which they named a hybrid system based on Machine Learning and Metaheuristics. The results shown indicate a rise in the existence of the network using this model.

Each of the models discussed in this section has a series of weaknesses and strengths, some of which can be implementation complexity or computational complexity. In this paper, we try to introduce a powerful model based on machine methods and meta-heuristic algorithms and then use the fuzzy system to achieve a powerful algorithm with reduced energy in WSN networks.

Proposed Solution

In this research, we describe a hybrid approach for clustering WSNs that is based on the GTO, K-MEANS, and fuzzy systems. Each of the methods used in this model is explained in the relevant sections.

Network Model

The network model is the one employed in this research. Also, the area of the network is considered to be rectangular $X*Y$. In addition, S Sink = $\{s_1, s_2, \dots, s_n\}$ is considered in the network, and the portion of sink nodes is less than the entire number of nodes. On the other hand, each sink node has a limited capacity which is shown using Equation (1).

$$Capacity < C \forall i < S \quad (1)$$

The limitation of the capacity in the sink node C can be the limitation of the buffer or the processing capability, the total capacity can be calculated with Equation (2). Also, according to the i request at the input, the total required capacity should not exceed the total number of sink nodes, which is shown in Equation 3.

$$TC = \sum_{i=1}^s C \quad (2)$$

$$\sum_{j=1}^t Req_j < TC \quad (3)$$

In this model, nodes are placed in j cluster $C = \{c_1, c_2, \dots, c_n\}$, and the number of clusters must be lower than the entire number of nodes. Furthermore, in every cluster, a node chooses the cluster head $CN = \{cn_1, cn_2, \dots, cn_n\}$, and the number of cluster heads must be lower than the total number of nodes. Finally, Equation 4 is used to determine the number of sink nodes H needed to mask all cluster heads.

$$|H| \geq \left\lceil \frac{|CN|}{e(C)} \right\rceil \quad (4)$$

The available AS sink node for is the sink node in the transfer area $j(Q_s)$ which is calculated using Equation 6.

$$AS \subseteq S \quad (5)$$

$$AS_i = \{S_j | dis(CN_i, S_j) \leq Q_s\} \quad (6)$$

$$S = \bigcup_{i=1}^c AS_i \quad (7)$$

Discrete Gorilla Troops Optimization Algorithm

The DGTOA algorithm hinges on the civic and group behavior of gorillas in nature presented by Abdollahzadeh et.al [22]. In this algorithm, 5 different mechanisms are used for optimization operations. These mechanisms are included in the two phases of discovery and exploitation, each of which gives a different capability to the DGTOA algorithm. 3 operators were utilized in the exploration phase of the gorilla troop's algorithm, and 2 operators were implemented in the exploitation phase.

Exploration Phase

Entire gorillas are presumed as search agents in the DGTOA algorithm, and the best solution in terms of cost is considered a silverback gorilla in this algorithm. In the exploration phase, as mentioned, three different mechanisms were used, namely a movement to other gorillas, migration to an unidentified place, and migration in the direction of an identified location. Each of these mechanisms produces solutions with different patterns during the optimization operation, which leads to an increase in the search capabilities of this algorithm. Finally, these three strategies are shown in Equation 8.

$$GX(t + 1) = \begin{cases} (BU - BL) * r_1 + BL, rand < P, \\ (r_2 - C) * Xr(t) + L * H, rand \geq 0.5, \\ X(i) - L(L * (X(t) - GXr)) + r_3 * (X(t) - GXr(t)), rand < 0.5 \end{cases} \quad (8)$$

In Equation 8, GX represents the current vector of the solution position and r_1, r_2, r_3 , and $rand$ represents a randomly produced number in the range of 1 and 0. BL and BU represent the lower and upper bound of the problem, respectively. p is a fixed parameter that must be set before starting the optimization operation, and this parameter determines the probability of selecting the first operator during the optimization operation. GX_r ,

And X_r is a randomly selected solution in the whole population. The values related to H, L, and C parameters are also calculated using equations 9-13.

$$C = F \times (1 - It/Max It) \quad (9)$$

$$F = \cos(2 \times r4) + 1 \quad (10)$$

$$L = C \times l \quad (11)$$

$$H = Z \times X(t) \quad (12)$$

$$Z = [-C, C] \quad (13)$$

Where $r4$ is randomly generated in the range of 1 and 0. l is also a random number between -1 and 1, and $Max It$ and It signify all the number of iterations and the current iteration number, respectively. \cos represents the cosine function, Finally, at the end of the exploration stage, the cost of all new production solutions is calculated. The new solution will be substituted for the old solution if its cost is less than that of the old solution.

Exploitation Phase

Equation 13 produces values that are used to select one of two phases—equal to competition for adult females and following the silverback—for optimization operations during the exploitation phase. The w parameter is then used to compare the results of each phase. Considering that the silverback gorilla is the best solution in the whole population the other solutions move towards this solution as the silverback gorilla is the leader of the group. Equation 14 is used to simulate this process, and the condition for choosing this mechanism is equal to $C \geq W$.

$$GX(t-1) = L * M * (X(t) - X_{silverback}) + X(t) \quad (14)$$

Where $X_{silverback}$ represents the best solution for the whole population and has the lowest cost. M is calculated using Equation 15.

$$M = \left(\left| (1/N) \sum_{i=1}^N GX_i(t) \right|^g \right)^{1/g} \quad (15)$$

Where N represents the total number of the population and g is also calculated using Equation 16.

$$g = 2^L \quad (16)$$

The second strategy utilized in the DGTOA algorithm in the exploitation phase is the competition for mature females, the condition for this mechanism to be selected is $C < W$. When male gorillas reach maturity, they

start fighting with other males in the herd for the possession of female gorillas. This strategy is to simulate the described behavior of gorillas, which is expressed mathematically in Equation 17.

$$GX(i) = X_{siverback} - (X_{siverback} * Q - X(t) * Q) * A \tag{17}$$

$$Q = 2 * r_5 - 1 \tag{18}$$

$$A = \beta * E \tag{19}$$

$$E = \begin{cases} N_1, & rand \geq 0.5 \\ N_2, & rand < 0.5 \end{cases} \tag{20}$$

Where Q represents the impact force and A a randomly generated number between 0 and 1 is denoted by r_5 . Also, β is a constant parameter with fixed values that must be set before the binning operation. N_1 is a random number in the normal distribution and N_2 is a random number identical to the number of dimensions of the problem and in the normal distribution. If the newly created solutions outperform the previously produced ones at the end of the exploitation phase, the newly produced solution takes the place of the previously produced solution.

Crossover and Mutation Operators

Metaheuristic optimization algorithms are often introduced to encounter optimization problems in the beginning, but according to the nature of this type of algorithm, these types of trouble can be solved with good performance by integrating them with special operators that are implemented to solve discrete problems. Among the most widely utilized operators, we can mention the mutation operator and the crossover operator, because by using these two operators in the phases of exploration and exploitation, the two components of diversity and intensification can be obtained at the same time. Mutation and crossover operators are introduced in the genetic algorithm [23]. In the following, each operator is explained.

Crossover Operator

In the Crossover operator, two solutions are randomly selected and then two different and new solutions are created using these two solutions. It is possible to merge the important parts of two solutions and get an optimal solution. According to the explanations given, this operator is useful in the exploitation phase to obtain the intensification component. In this paper, the two-point crossover operator is used, in which two solutions are selected, and then two points are selected on the solutions, then the selected locations are cut from each other in both solutions and finally, Parts are swapped to create a new solution. Figure 1 shows an example of a crossover operation

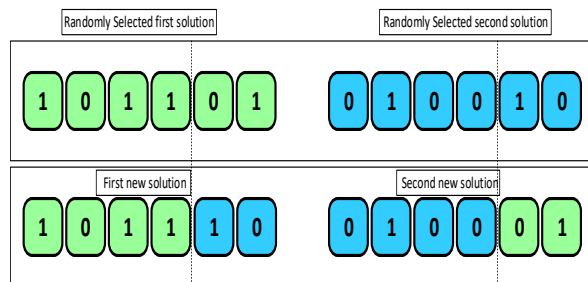


Figure 1: Crossover operator

Mutation Operator

In the mutation operator, each dimension of the solutions is mutated with a certain probability and the value of the cell changes. The mutation probability rate must be determined in advance and the higher the mutation probability is, the more diverse the new solution will be. Therefore, the above operator can be a better choice in the exploration phase to increase diversity. Figure 2 shows an example of a Mutation operation.

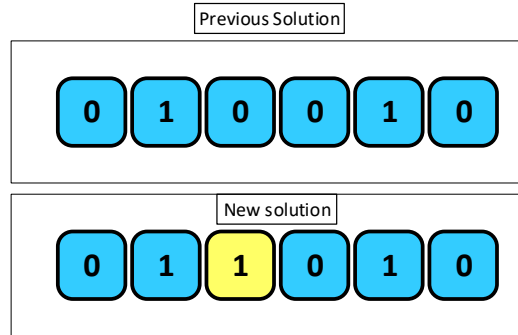


Figure 2: Mutation operator

K-MEANS Algorithm

K-MEANS was invented in 1967 [24], but Stuart Lloyd introduced the K-MEANS algorithm as a modulation technique in 1957.

In this algorithm, the data is classified into K clusters and the number of clusters must be determined before the classification operation. In this algorithm, dissimilarity is calculated and estimated using Euclidean distance based on feature vectors. In this method, the data in one cluster is more similar to the data in another cluster. Also, the cluster markers represent the average locations of the data that belong to a cluster. The above process is briefly explained below.

- K is the center of the cluster to be placed randomly.
- Each data is placed in the closest cluster in such a way that the data with the center of the cluster is calculated using the Euclidean equation:

$$D(x_p, z_c) = \sqrt{\sum_{i=1}^d (x_{pi} - z_{ci})^2} \quad (21)$$

In Equation 21, d is the number of features of each vector, and x_p is the feature vector and is the center of the cluster.

- Recalculate the center of the cluster using Equation 15:

$$z_c = \frac{1}{n_c} \sum \forall x_p \in c_c x_p \quad (22)$$

In Equation 22, c_c is a set of data belonging to the cluster. And n_c is the number of instances in the cluster.

- Continue the above steps until the ending condition is met

In general, the ending condition in this algorithm can be the ultimate number of iterations or the improvement of results less than a threshold.

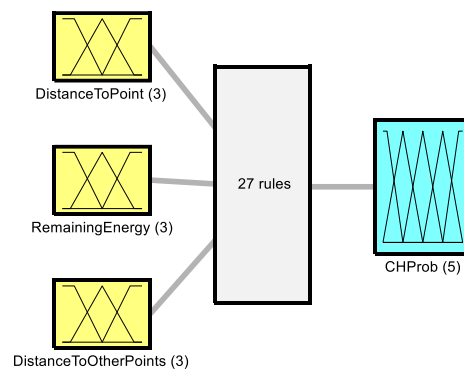
Cluster head selection based on Fuzzy

As explained in the explanation that follows, this subsection explores and discusses the fuzzy system's use in the cluster head selection process. A node is selected as the cluster head from among the nodes at each point in order to identify the nodes that are cluster heads. The fuzzy system depicted in Figure 3 serves as the hinge for choosing the cluster head.

Table 1: Fuzzy rules

No.	The chance to become the head of the cluster	Distance to other points	residual energy	distance to point
1	Medium	Low	low	Low
2	Medium	Low	medium	Low
3	Medium	Low	high	Low
4	High	Medium	low	Low
5	High	Medium	medium	Low
6	very high	Medium	high	Low
7	High	High	low	Low
8	very high	High	medium	Low
9	very high	High	high	Low
10	very high	Low	low	Medium
11	very high	Low	medium	Medium
12	Low	Low	high	Medium
13	Very low	Medium	low	Medium
14	Low	Medium	medium	Medium
15	Medium	Medium	high	Medium
16	Very low	High	low	Medium
17	Low	High	medium	Medium
18	Medium	High	high	Medium
19	Very low	Low	low	High
20	Very low	Low	medium	High

21	Very low	Low	high	High
22	Very low	Medium	low	High
23	Low	Medium	medium	High
24	Very low	Medium	high	High
25	Very low	High	low	high
26	Low	High	medium	high
27	Low	High	high	high



System Untitled: 3 inputs, 1 outputs, 27 rules

Figure 3: Used fuzzy model

Based on the inputs of this fuzzy system, a node has a higher chance of turning into a cluster head if its distance to the desired point is small, its distance to other points is large, and it has more energy. The odds of choosing a node as a cluster head is obtained depending on the fuzzy rules shown in Table 1. Inevitably the node with the best probabilities is chosen as the cluster head around the points.

Proposed Model

Meta-heuristic algorithms are often designed to optimize continuous problems, but these algorithms can solve problems in different search spaces because they can be easily integrated with different operators and at the same time maintain their search capabilities. The DGTOA algorithm is not an exception to this rule and this algorithm was originally presented to solve optimization problems in a continuous search space, so we need to integrate this algorithm with the Mutation and Crossover operators to encounter the clustering problem using the DGTOA algorithm. The main features of this algorithm are designed to solve continuous problems. In this article, we design and present a new version of the DGTOA algorithm, which is designed to solve discrete problems. In this version of the DGTOA algorithm, we used the mutation operator instead of the main operators of this algorithm in the exploration phase, and in the phase, we replaced the main operators of this algorithm with the Crossover operator, so that the algorithm can finally solve discrete problems and also maintain the search capabilities according to the components of diversity and intensification.

The sensor nodes in our proposed approach are first dispersed randomly throughout the issue area. Then, after the deployment of the nodes in the problem space and using the DGTOA algorithm, an adequate number of cluster heads and suitable points for the deployment of the cluster heads are made. The center points are then found using the K-MEANS method. The chief reason for using this algorithm is to estimate the number of

initial points and their coordinates in case of optimal selection and to obtain faster and better results. In other words, the output of the DGTOA algorithm forms the initial points and coordinates of the K-MEANS algorithm. Then, the fuzzy system is utilized to determine the cluster head nodes, which is implemented as the cluster head across the nodes close to the point of a node. A fuzzy system gives nodes that have more merit more chance to be cluster heads. A cluster is established when the cluster head sends a message to other nodes, asking them to select the nearest cluster head based on distance. These nodes then declare their selection to the cluster head. Ultimately, data is transmitted from the nodes that make up the cluster to the cluster head and the sinks. After sending information from the nodes to the sinks using the clustering technique, to harmonies the load in the network and not cause a quick shutdown of the current cluster heads, the clustering operation is repeated again and again so that other nodes have the opportunity to turn into the cluster head. The network ends with the shutdown of all nodes. Figure 4 illustrates the proposed model's main workflow.

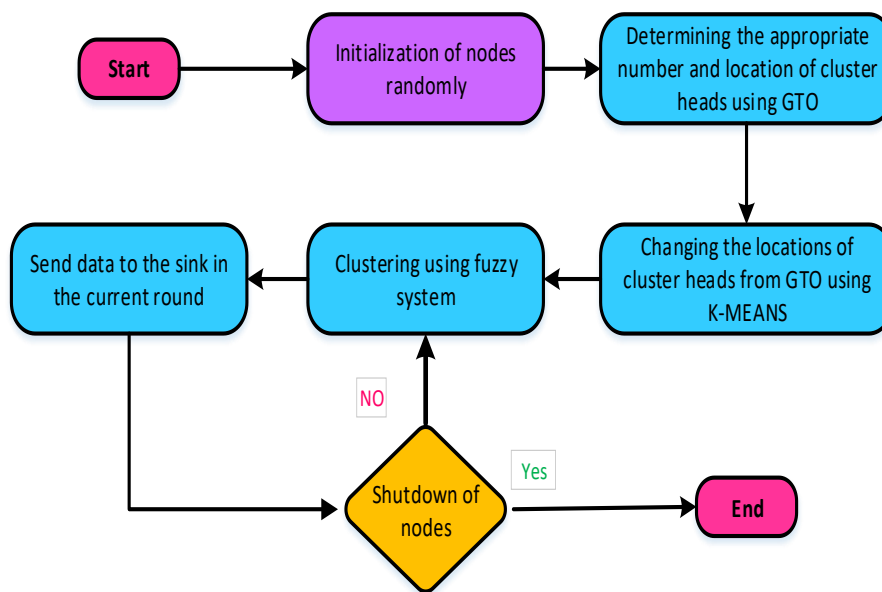


Figure 4: Flowchart of the Proposed Model

Simulation Result

In this section, we implemented two different scenarios to test the proposed model, in the first scenario we utilized 100 nodes in a 100x100 network area. But in the second scenario, to evaluate the proposed model against large networks, we establish the network's node count at 150 and its size at 150 by 150. Other parameters used for the network environment are illustrated in Table 2.

Table 2. Networks Models Parameters

Parameter name	Value
Nodes	100, 150
Network	100, 150
Initial Energy	0.5
Max Round	2000
Sink Location in the center of the Area	network/2

To check the quality of the results obtained from the designed model, the proposed model was measured with fuzzy system clustering (MOFCA), LEACH[25], and fuzzy clustering and ant colony routing algorithms (FUCARCH) Also this comparison is based on criteria such as the blackout of all nodes LND, the shutdown of the first FND node, blackout process of the nodes, the blackout of half of the nodes HND, and the amount of energy consumption were used and the results obtained are shown in the relevant graphs

Scenario 1

As was already established, there are 100 nodes and 100 network environments in the first scenario. The results obtained from the tests of the first scenario are shown in the graphs of dead nodes and energy in Figure 5.

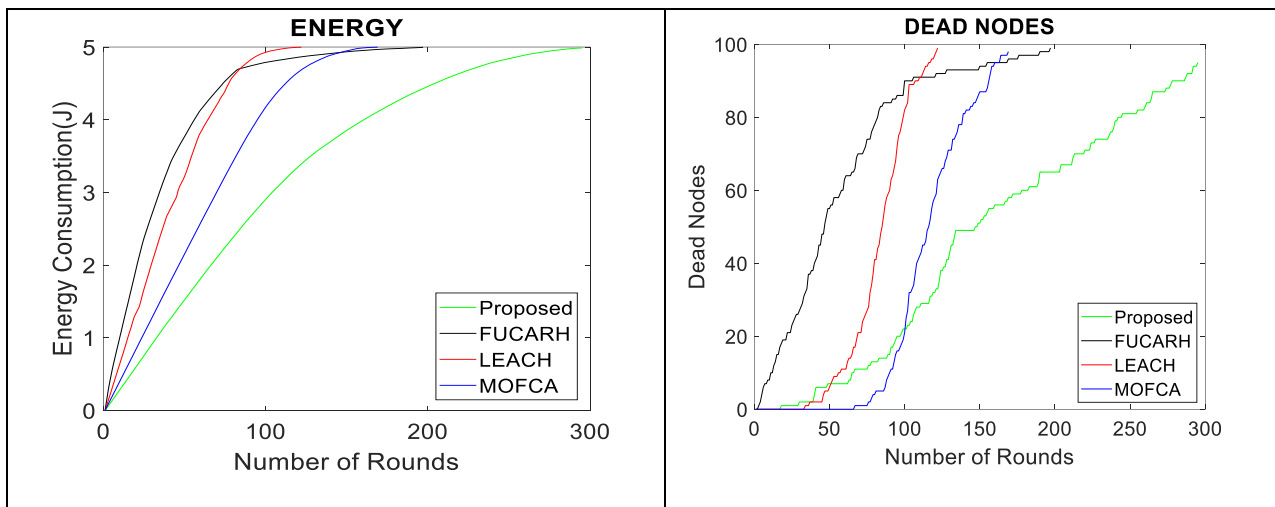


Figure 5: Energy and Dead Nodes Graphs for 100 nodes

According to the graphs shown in Figure 5, the proposed model has a much softer and better process in shutting down the nodes and was able to keep the nodes active for a longer period, if the compared methods are almost from the cycle of After 100, most of the nodes have lost and become inactive, while the proposed model in the 200th cycle, which is double, almost half of the nodes are active. However, according to the energy criteria, the proposed model consumes much less energy than other methods, which makes the network remain active for a longer period.

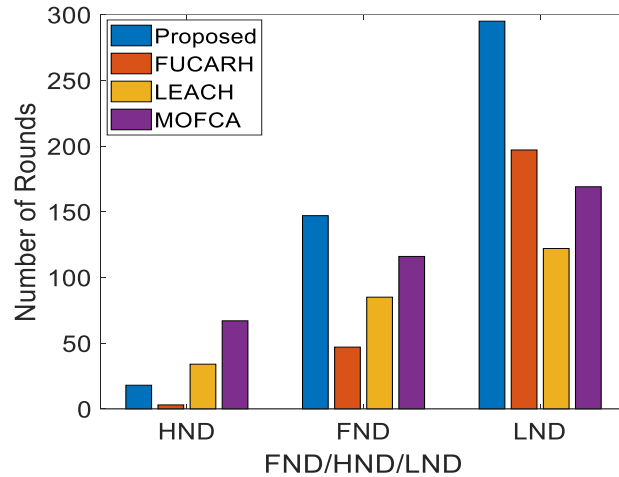


Figure 6: FND / HND/ LND Metrics for 100 nodes

As can be seen in Figure 6, the designed model was capable of performing superior to the other compared methods because it was able to keep the nodes on for a longer period. The same issue indicates that the proposed model has a good ability to cluster operations and create shorter paths.

Scenario 2

We have utilized 150 nodes in the second scenario for the evaluations and in an environment equal to 150 for the tests of the proposed model. We have tended to check the efficiency of the suggested model against larger networks, and on the other hand, the scalability of the proposed model is also shown.

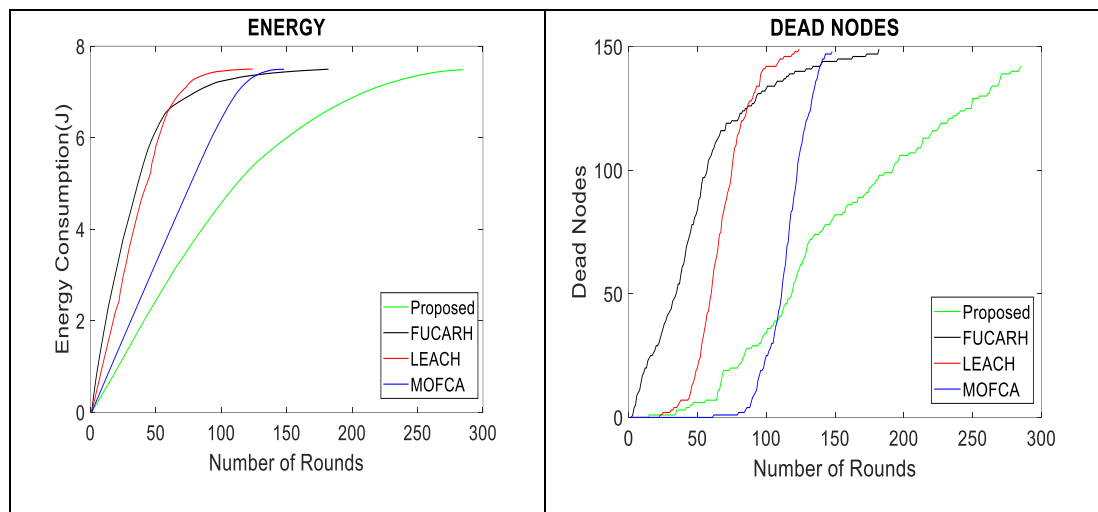


Figure 7: Energy and Dead Nodes Graphs for 150 Nodes

In Figure 7, the suggested model has demonstrated exceptional performance in comparison to the compared methodologies and has maintained network activity for a longer duration. It also consumes less energy than the compared methods. However, by carefully looking at the dead nodes diagram, it can be observed that the recommended model has a very monotonous reduction pattern and tries to keep the network active throughout the operation. It can also be seen in the energy diagram that the suggested model has reduced energy consumption to a great extent in contrast to large and complex networks and the difference between the proposed model and other methods is very significant.

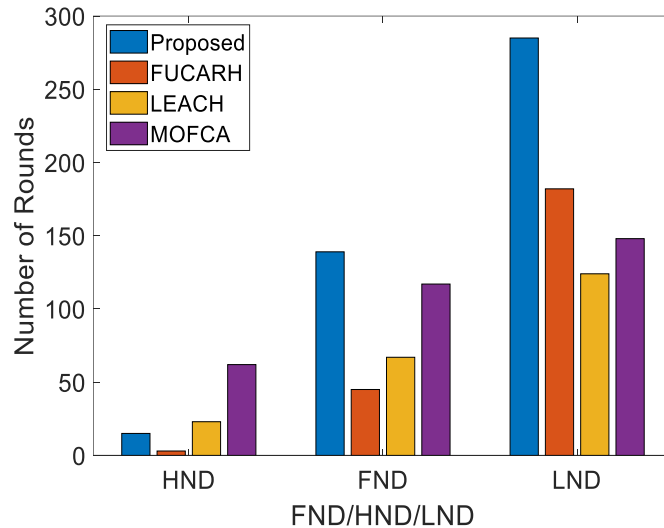


Figure 8: FND / HND/ LND Metrics for 150 nodes

Figure 8 shows the graph related to FND, HND, and LND criteria. About this diagram, it can be observed once again that the recommended model was able to perform very well in clustering and reducing energy consumption in large networks. It managed to keep almost half of the nodes active during the network activity compared to the compared methods, which indicates the significant performance of the suggested model in clustering and reducing WSN network energy consumption.

Conclusions and Future works

Balancing the computing load using clustering methods to reduce energy consumption is one of the most efficient methods in WSN networks. However, an efficient protocol in clustering should achieve capabilities such as connectivity in WSN networks and reliability in various dimensions of the environment. We presented a novel hierarchical clustering approach for WSNs. One reason is that in WSN, the most energy consumption occurs during the transmission of messages such as data and packets, therefore we presented a clustering algorithm to reduce transmission packets. Moreover, in this paper, taking into account the uniform energy consumption among the nodes, the cluster heads are chosen in such a way that they have more competence in terms of location and extra-cluster and intra-cluster transmission trees. The three parameters of the degree of adjustment and energy consumption and the exact distance that each data travels to reach the station determine the probability of the cluster head being selected. The results indicate a reduction in energy consumption in both large and small dimensions of the network, and the lifespan of the network has also increased substantially.

In the future, the presented algorithm can be used for clustering and reducing the energy consumption of different types of networks. Also, other types of meta-heuristic discrete algorithms can be presented to solve this problem. Furthermore, it is possible to evaluate the types of neighborhood operators that have been used to solve discrete problems to solve this problem.

Conflict of interest

The authors confirm that they are not affiliated with or involved in any organization or entity with financial interests.

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