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Energy-efficient clustering protocol in wireless sensor networks based on multi-objective binary dragonfly optimization algorithm and Mamdani fuzzy inference system

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Abstract

Clustering is an efficient method for designing routing algorithms in wireless sensor networks (WSNs) that enhances the network's lifespan and scalability. Considering the limited capabilities of sensor nodes, such as energy, processing power, and communication range, clustering-based routing protocols adapt network performance to these constraints. Recent related works have demonstrated that energy consumption in sensor nodes can be minimized using clustering methods. In the clustering approach, the selection of cluster heads and the formation of clusters play a critical role in data transmission. This article proposes a hybrid approach based on a multi-objective binary dragonfly optimization algorithm and Mamdani fuzzy inference system for clustering protocols in homogeneous wireless sensor networks. In this approach, the multi-objective binary dragonfly optimization algorithm is initially employed for cluster head selection, followed by the Mamdani-type fuzzy inference system for cluster formation. Finally, a multi-hop routing process is utilized for data packet transmission. The proposed clustering protocol has been simulated on WSNs with various topologies. Its performance has been evaluated based on multiple criteria, including average energy consumption, the first node to die, 50%of nodes dead, the last node to die, and the number of packets transmitted to the base station. The evaluation results indicate that the proposed clustering protocol outperforms previous protocols.

Keywords: Wireless sensor network, clustering, network lifetime, dragonfly optimization algorithm, fuzzy inference system
2020 MSC: 68M10, 68T20, 90C59, 94A05

1 Introduction

In recent years, wireless sensor networks (WSNs) have emerged as an attractive networking technology capable of deployment without considering traditional network infrastructure. A WSN consists of a large number of sensor nodes distributed across a geographical area, communicating with a central node called the base station. Generally,

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in a WSN, sensor nodes monitor their surrounding environment and transmit the collected information to the base station [1]. Sensor nodes in a WSN possess the capability to sense the environment, process data, and communicate with other nodes. These nodes monitor environmental parameters and convert them into electronic signals. One of the main advantages of WSNs is their ability to be deployed in geographical areas that are difficult for users to access [2]. Figure 1 illustrates a general schematic of a wireless sensor network. As depicted in Figure 1, sensor nodes are distributed within a geographical area to collect environmental data, which is then transmitted to the base station. The base station acts as a communication bridge between the environment and the users [3] .

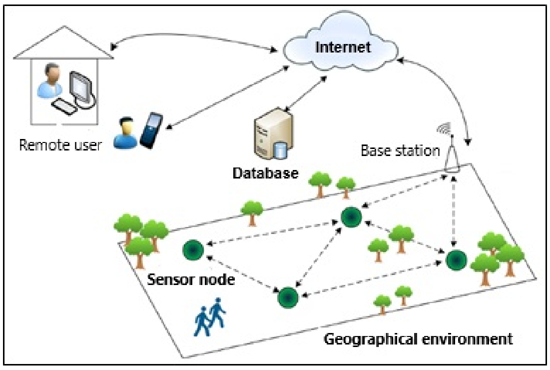

Figure 1: General schematic of a wireless sensor network [3].

Wireless sensor networks (WSNs) are widely used today in numerous application domains, including the Internet of Things (IoT) [4], vehicular ad hoc networks (VANETs) [5], personal health monitoring [6], traffic control [7], wildlife environmental monitoring [8], and geographical exploration [9]. Regardless of the application type, the design and development of WSNs face several challenges. Environmental coverage, network communication, network lifetime enhancement, and data validation are considered the four main challenges in designing and developing WSNs [10]. In this article, network lifetime enhancement is considered the primary focus of the study.

The energy source for sensor nodes in WSNs is typically a battery with limited capacity, and recharging or replacing the battery is usually not feasible. Therefore, improving energy efficiency and extending network lifetime is a critical issue in this field [11]. Clustering is one of the most widely used techniques in WSNs to conserve energy [12]. This technique consists of two main phases: cluster head selection and cluster formation. In the first phase, a limited number of sensor nodes in the network are selected as cluster heads. In the second phase, the remaining nodes are assigned to one of the cluster heads, forming clusters. Thus, in the clustering technique, sensor nodes are grouped into clusters, each of which has a cluster head. Since the cluster head is responsible for routing and data aggregation within the cluster, energy consumption among sensor nodes is effectively reduced. In clustering protocols, multi-hop communication replaces direct communication between sensor nodes, which further decreases energy consumption. Figure 2 illustrates the general model of the clustering technique in WSNs [12].

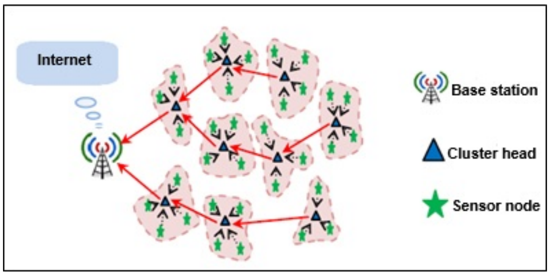

Figure 2: Model of the clustering technique in wireless sensor networks [12].

Cluster head selection is a crucial step in implementing the clustering technique in wireless sensor networks (WSNs). Since cluster heads consume more energy than regular nodes, their optimal selection can significantly improve energy efficiency in WSNs [13]. The LEACH (Low-Energy Adaptive Clustering Hierarchy) technique is a well-defined clustering approach in WSNs that operates based on a distributed method [14]. However, the main drawback of the LEACH clustering technique is the potential selection of low-energy sensor nodes as cluster heads. As previously mentioned, the traffic load on cluster heads is higher than on regular sensor nodes. This issue causes the LEACH clustering technique to fail in optimally managing energy consumption. The cluster head selection problem can be considered an optimization problem, and metaheuristic algorithms can be employed to solve it. The dragonfly optimization algorithm is a metaheuristic algorithm inspired by the behavior of dragonflies [15]. This algorithm models the hunting behavior of dragonflies in searching for food resources and their collective movement to evade predators. The dragonfly optimization algorithm consists of two main steps: exploration and exploitation. As an iterative algorithm, it aims to approach the optimal solution in each iteration. Each dragonfly represents a potential solution within the problem's search space. To evaluate the quality of solutions (dragonflies), a fitness function is utilized, which is defined based on the specific optimization problem. The fitness function can generally be formulated as either a maximization or minimization problem. Once the termination condition of the dragonfly optimization algorithm is met, the best solution in the final population is considered the optimal solution to the problem. The dragonfly optimization algorithm demonstrates effective performance for solving continuous optimization problems.

The binary dragonfly optimization algorithm is an extended version designed to solve binary optimization problems. In the binary version, the algorithm employs a transfer function that maps the continuous search space to a discrete search space. S-shaped and V-shaped transfer functions are two well-known transfer functions used in metaheuristic algorithms to facilitate this mapping [16].

1.1 Motivation

By analyzing various clustering techniques, it can be concluded that solving the cluster head selection problem using metaheuristic algorithms is an effective approach for energy conservation. In this article, an energy-efficient clustering protocol for homogeneous wireless sensor networks is proposed. The proposed clustering protocol consists of two main steps. In the first step, cluster heads are selected based on a multi-objective fitness function using the binary dragonfly optimization algorithm. In the second step, regular nodes are assigned to the most suitable cluster heads using a fuzzy inference system, forming the clusters. The use of the binary dragonfly optimization algorithm for cluster head selection significantly enhances the lifetime of wireless sensor networks. Additionally, the use of a fuzzy inference system for cluster formation based on linguistic criteria, such as energy, distance, and neighborhood degree, also contributes to the extension of network lifetime.

1.2 Goals

The primary objective of this article is to design an energy-efficient clustering protocol for homogeneous wireless sensor networks. To achieve this main objective, the following sub-goals must be met:

- First Goal: Optimal cluster head selection based on a multi-objective binary dragonfly optimization algorithm is considered the first goal. The fitness function of the binary dragonfly optimization algorithm incorporates a weighted combination of three criteria: energy, distance, and neighborhood degree.

- Second Goal: Cluster formation based on the Mamdani-type fuzzy inference system is the second goal. The Mamdani fuzzy inference system utilizes three linguistic variables: the remaining energy of the cluster head, the distance between the regular node and the cluster head, and the neighborhood degree of the cluster head for decision-making.

- Third Goal: Improving the performance of the proposed clustering protocol in extending the lifetime of wireless sensor networks compared to other clustering protocols is the third goal. The performance of the proposed clustering protocol is evaluated using quantitative metrics such as the first node to die, 50%of nodes dead, the last node to die, the number of packets sent to the base station, and the average energy consumption of the network.

1.3 Organization

This article is organized into five main sections. Section 2 provides a review of previous works on extending the lifetime of wireless sensor networks based on clustering techniques. Section 3 presents the design of the proposed clustering protocol. Section 4 details the simulation and evaluation of the results. Finally, Section 5 concludes the article and offers suggestions for future work.

2 Related Work

Kola and colleagues proposed a new clustering algorithm based on a differential evolutionary algorithm to enhance the lifetime of wireless sensor networks [17]. In this approach, the cluster head selection problem is solved using a novel differential evolutionary algorithm. The improved version of the differential evolutionary algorithm proposes a strategy to escape local optima. Moreover, an efficient fitness function has been defined to maximize the network lifetime. The fitness function considers the energy consumption of regular nodes and cluster head nodes. Zhi and colleagues introduced a clustering-based routing protocol for wireless sensor networks [18]. In this method, second-order fuzzy logic and the Ant Colony Optimization algorithm are used. In the first step, second-order fuzzy logic is used for cluster head selection, and in the second step, a multi-hop routing strategy based on the Ant Colony Optimization algorithm is proposed. This method aims to improve the network's lifetime cycle and balance network traffic load. Sharma and colleagues presented an improved version of the Ant Colony Optimization algorithm to improve energy consumption in wireless sensor networks [19]. This method uses the enhanced Ant Colony Optimization algorithm to find optimal paths between sensor nodes and the base station. In this strategy, each sensor node has the ability to communicate with its neighbors, and the best neighbors are selected during the routing process for the network's sensor nodes.

Zheng and colleagues proposed an improved Harmony Search algorithm for energy-efficient routing in wireless sensor networks [20]. The Harmony Search algorithm suggests a strategy for escaping local optima. Additionally, the genetic algorithm's roulette-wheel selection operator is used to generate the initial population. The fitness function of the improved Harmony Search algorithm is defined based on energy consumption and path length criteria. Singhman and colleagues proposed an energy-efficient clustering protocol for wireless sensor networks [21]. In this approach, an enhanced version of the Ant Colony Optimization algorithm is suggested for cluster head selection. The improved version of the Ant Colony Optimization algorithm proposes a strategy to prevent premature convergence and local optima trapping. Maximizing the remaining energy, minimizing the distance between sensor nodes and cluster heads, and minimizing the energy consumption of the cluster heads are considered the three main criteria in the fitness function.

Singhman and colleagues, in another study, presented an efficient clustering protocol based on an enhanced Artificial Bee Colony algorithm [22]. In this metaheuristic algorithm, an improvement strategy for searching the problem space and enhancing exploration capacity is proposed. The enhanced Artificial Bee Colony algorithm is used for selecting cluster heads in the clustering technique. In the cluster formation phase, each regular node connects to the nearest cluster, and each node will be connected to only one cluster. Gupta and colleagues presented an integrated routing and clustering protocol based on the Harmony Search algorithm and Cuckoo Search algorithm [23]. In this method, cluster head selection is based on metaheuristic algorithms, and routing between cluster heads and the base station is considered. The Cuckoo Search algorithm is used for selecting cluster heads, and uniform distribution of cluster heads is taken into account in its fitness function. The Harmony Search algorithm is used for optimal routing between cluster heads and the base station.

Gupta, in another study, proposed an improved Cuckoo Search-based clustering protocol for wireless sensor networks [24]. In this method, the improved Cuckoo Search algorithm is used for selecting cluster heads, followed by a multi-hop strategy for communication establishment. In the improved version, a method for generating the initial population based on elitism is proposed, where part of the initial population is assigned values based on the best solutions obtained from the fitness function. Verma and colleagues presented a genetic algorithm-based cluster head selection method for heterogeneous wireless sensor networks [25]. In heterogeneous wireless sensor networks, sensor nodes have different hardware and software capabilities, such as initial energy, coverage radius, and communication radius. In this method, simulation is performed on wireless sensor networks with one or multiple base stations. Additionally, a multi-hop routing protocol is proposed to reduce communication distance.

Dataraya and colleagues presented a hybrid method based on the Firefly algorithm and the Fly optimization algorithm for cluster head selection in wireless sensor networks [26]. The performance of the proposed hybrid method is compared with other metaheuristic algorithms such as the Cuckoo Search algorithm, Genetic Algorithm, Grasshopper Optimization Algorithm, and Ant Colony Optimization algorithm. Energy and distance criteria are considered as the objectives in the fitness function. Mehta and colleagues proposed a multi-objective optimal routing algorithm based on clustering in wireless sensor networks [27]. In this method, a multi-objective clustering algorithm based on cost, remaining energy, and coverage criteria is designed, and then an optimal path from cluster heads to the base station is selected using the Fish School Optimization algorithm. Simulation of this methodology shows that the network lifetime has increased. Sahoo and colleagues presented a clustering technique based on Particle Swarm Optimization (PSO) in heterogeneous wireless sensor networks [28]. In this method, the base station's position changes over time, and it is referred to as a moving base station. In the fitness evaluation of particles in the PSO algorithm, the optimal cluster head selection problem is calculated considering the current position of the base station. The PSO algorithm's fitness function is defined as a five-objective function.

Alazab and colleagues proposed a cluster head selection strategy based on the Multi-Objective Swarm Rider

Optimization algorithm for wireless sensor networks with Internet of Things (IoT) applications in smart cities [29]. The Swarm Rider Optimization algorithm is a new metaheuristic algorithm inspired by the idea of a number of riders moving toward a target position. For selecting the best combination of cluster heads, distance, energy, and delay are used as criteria. Ran and colleagues proposed an improved LEACH clustering protocol based on fuzzy logic [30]. In the fuzzy inference system, three linguistic variables are used: remaining energy of the node, distance from the node to the base station, and the degree of node connectivity. The cluster head selection process is centralized, and the base station calculates the chance of nodes becoming cluster heads.

Kang and colleagues proposed an improved LEACH clustering protocol based on distance [31]. The researchers introduced a distance-aware clustering routing protocol aimed at balancing the energy consumption of all sensor nodes. The probability of each node becoming a cluster head is determined based on the distance to the base station. Shokouhi and colleagues proposed a clustering routing protocol based on evolutionary algorithms [32]. In this paper, two evolutionary algorithms—Genetic Algorithm and Simulated Annealing—are combined for optimizing control parameters. Since the combined evolutionary algorithm runs on the base station, it does not incur computational overhead for the network. Zahidi and colleagues proposed a clustering routing protocol where the cluster formation phase is conducted before cluster head selection [33]. In this protocol, the cluster formation phase is carried out using the c-means algorithm, followed by the selection of the appropriate cluster head based on a fuzzy inference system.

3 Proposed Clustering Protocol

In this section, the proposed clustering protocol is described. The wireless sensor network is homogeneous, meaning all sensor nodes are identical in both hardware and software. The proposed wireless sensor network consists of many sensor nodes randomly distributed across the network's working environment. The base station is a high-energy central node capable of communicating with all the sensor nodes in the network. All sensor nodes are aware of their positions in the network, and this information remains constant throughout the network's lifetime. The energy consumption of each sensor node for transmitting or receiving data is calculated based on the Heinzelman energy model [14]. In this model, the energy consumption of sensor nodes is determined by the size of the data packet and the distance between the transmitting and receiving nodes. Equation (1) shows the energy consumption for the transmitting sensor node, and equation (2) shows the energy consumption for the receiving sensor node.

$$E_T = \begin{cases} (L \times E_{elec}) + (L \times \epsilon_{fs} \times d^2) & d < d_0 \\ (L \times E_{elec}) + (L \times \epsilon_{mp} \times d^4) & d \geq d_0 \end{cases} \tag{1}$$

$$E_R = L \times E_{elec} \tag{2}$$

In these equations, the variable LLL represents the data packet size, the variable d indicates the distance between the transmitting and receiving sensor nodes, and the variable E_{elec} represents the energy consumed per bit during the operation of the transmitter circuit. Additionally, the variables e_{fs} , e_{mp} represent the amplification coefficients for the free-space and multipath models, respectively. Finally, the variable d_0 represents the threshold distance, which is expressed through equation (3).

$$d_0 = \sqrt{e_{fs}/e_{mp}}. \tag{3}$$

In this section, an energy-efficient clustering protocol for homogeneous wireless sensor networks is designed. The proposed clustering protocol consists of four main stages: network setup, cluster-head selection, cluster formation, and multi-hop routing, as illustrated in Figure 3. The details of the proposed clustering protocol are outlined below.

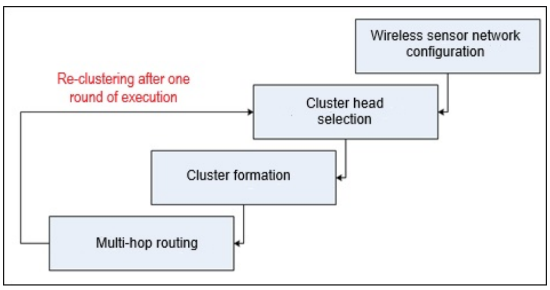

Figure 3: Schematic of the proposed clustering protocol.

3.1 Network Setup

The network setup stage takes place after the random distribution of sensor nodes within the network's geographical area. In this stage, all nodes initiate the neighbor discovery process by broadcasting a packet containing the node's ID and location. Each sensor node also stores a neighbor table containing information about neighboring nodes. After the neighbor discovery process, each sensor node sends a "Hello" packet to the base station at most once. The "Hello" packet includes three subfields: node ID, node location, and node energy. The base station stores the specifications of all the sensor nodes. After this stage, the base station is able to establish the network topology and can begin the clustering process.

3.2 Cluster-Head Selection

Cluster-head selection is one of the primary tasks of clustering protocols, which significantly impacts network performance. The optimal selection of cluster-heads can be viewed as a multi-objective optimization problem. In this method, a multi-objective binary dragonfly optimization algorithm is used to solve the cluster-head selection problem.

3.2.1 Multi-objective Fitness Function

To extend the network lifetime, an optimal subset of cluster-heads must be selected in each round. In this context, the multi-objective fitness function is formulated based on energy, neighborhood degree, and distance parameters. The first objective in the fitness function of the multi-objective binary dragonfly optimization algorithm is the average remaining energy of the cluster-heads. This objective is defined as a maximization function. The average remaining energy of the cluster-heads is expressed through equation (4), where E_{CHi} denotes the remaining energy of the i-th cluster-head. The second objective in the fitness function of the multi-objective binary dragonfly optimization algorithm is the average neighborhood degree of the cluster-heads. This objective is also defined as a maximization function. The average neighborhood degree of the cluster-heads is expressed through equation (5). In this equation, the variable $Degree_{CHi}$ represents the neighborhood degree of the i-th cluster-head node. The third objective in the fitness function of the multi-objective binary dragonfly optimization algorithm is the average distance between the cluster-heads and the base station. This objective is defined as a minimization function. The average distance between the cluster-heads and the base station is expressed through equation (6), where the variabl Dis_{CHi} represents the distance of the i-th cluster-head node from the base station. The final fitness function is a weighted combination of the three parameters mentioned, which can be expressed through equation (7). The sum of the weights defined in the final fitness function is always equal to one, as shown in equation (8).

$$Fit_1 = \frac{1}{m} \times \sum_{i=1}^{m} E_{CHi} \tag{4}$$

$$Fit_2 = \frac{1}{m} \times \sum_{i=1}^{m} Degree_{CHi} \tag{5}$$

$$Fit_3 = \frac{1}{m} \times \sum_{i=1}^{m} Dis_{CHi} \tag{6}$$

$$Fit = w_1 \times Fit_1 + w_2 \times Fit_2 + w_3 \times (1 - Fit_3) \tag{7}$$

$$w_1 + w_2 + w_3 = 1 \tag{8}$$

3.2.2 Multi-objective Binary Dragonfly Optimization Algorithm

The multi-objective binary dragonfly optimization algorithm is used to solve the cluster-head selection problem. Algorithm 1 presents the pseudocode of the multi-objective binary dragonfly optimization algorithm for solving the cluster-head selection problem. The details of the multi-objective binary dragonfly optimization algorithm are outlined below.

• **Separation:** Separation is considered as the avoidance behavior, which is formulated based on equation (9). In this equation, the variable XX represents the current position of the dragonfly, X_j represents the position of the j-th neighboring dragonfly, and NN denotes the number of neighboring dragonflies.

• **Alignment:** Alignment is considered as the behavior of flying in coordination with the group of dragonflies, which is formulated based on equation (10). In this equation, the variable V_j represents the velocity of the j-th

Algorithm 1: The Multi-objective Binary Dragonfly Optimization Algorithm
1. Randomly initialize position vectors of dragonflies (X)
2. Initialize step vectors of dragonflies to zeros
3. while (maximum iteration)
4. Evaluate the fitness function of dragonflies \\\\ multi-objective
5. Update the best solution (X^+)
6. Update the worst solution (X^-)
7. Update the parameters (s, a, c, f, e , w)
8. for $i = 1$ to number of dragonflies (M)
9. Update S based on (9)
10. Update A based on (10)
11. Update C based on (11)
12. Update F based on (12)
13. Update E based on (13)
14. Update step vector using (14)
15. Update position vector using (15)
16. Recode position vector using (16) and (17) or (18) and (19)
17. end for
18. end while
Output: the best solution (X^+)

$$S_i = -\sum_{j=1}^{N} X - X_j \tag{9}$$

neighboring dragonfly, and NN denotes the number of neighboring dragonflies.

$$A_i = \frac{\sum_{j=1}^{N} V_j}{N}. \tag{10}$$

• **Cohesion:** Cohesion is considered as the behavior of dragonflies moving closer to each other, which is formulated based on equation (11). In this equation, the variable XX represents the current position of the dragonfly, X_j represents the position of the j-th neighboring dragonfly, and NN denotes the number of neighboring dragonflies.

$$C_i = \frac{\sum_{j=1}^{N} X_j}{N} - X. \tag{11}$$

• **Attraction:** Attraction is considered as the foraging behavior, which is formulated based on equation (12). In this equation, the variable XX represents the current position of the dragonfly, and X^+ represents the position of the best dragonfly found in the population based on the fitness function.

$$F_i = X^+ - X. \tag{12}$$

• **Distraction:** Distraction is considered as the behavior of fleeing from a predator, which is formulated based on equation (13). In this equation, the variable XX represents the current position of the dragonfly, and X^- represents the position of the worst dragonfly found in the population based on the fitness function.

$$E_i = X^- + X. \tag{13}$$

• **Dragonfly Update:** The dragonflies in the population perform the update operation based on the five introduced behaviors. To update the positions of the dragonflies in the problem's search space, two vectors, named the step vector (ΔX) and the position vector (X), are defined and formulated based on equations (14) and (15). In these equations, the variables s, a, c, f, e are the coefficients of the five behaviors: separation, alignment, cohesion, attraction, and distraction, respectively. Additionally, the variable ww represents the inertia weight, and tt denotes the iteration number of the algorithm.

$$\Delta X_i(t+1) = (sS_t + aA_t + cC_t + fF_t + eE_t) + w\Delta X_i(t), \tag{14}$$

$$X_i(t+1) = X_i(t) + \Delta X_i(t+1). \tag{15}$$

• **Binary Encoding:** In the dragonfly optimization algorithm, all dragonflies update their positions based on equations (14) and (15). Accordingly, dragonflies can move to any point in the problem's search space. Since the cluster-head selection problem is a binary encoding problem, all dragonflies must be mapped from the continuous space to the binary space. For this purpose, transfer functions are used. Let's assume that the variable $X_i(t)$ represents a dragonfly before the update, and $Z_i(t)$ represents the same dragonfly after the update. Using an S-shaped transfer function or a V-shaped transfer function, dragonflies can be mapped to binary encoding. The S-shaped transfer function is defined based on equations (16) and (17). Additionally, the V-shaped transfer function is defined based on equations (18) and (19).

$$S(Z_i(t)) = \frac{1}{1+e^{-Z_i(t)}} \tag{16}$$

$$X_i(t+1) = \begin{cases} 0 & \text{rand} < S(Z_i(t)) \\ 1 & \text{rand} \geq S(Z_i(t)) \end{cases} \tag{17}$$

$$V(Z_i(t)) = \left| \text{erf}\left(\frac{\sqrt{\pi}}{2} Z_i(t) \right) \right| \tag{18}$$

$$X_i(t+1) = \begin{cases} 0 & \text{rand} < V(Z_i(t)) \\ 1 & \text{rand} \geq V(Z_i(t)) \end{cases} \tag{19}$$

3.3 Cluster Formation

In this phase, the ordinary sensor nodes are connected to one of the cluster-heads. The Mamdani-type fuzzy inference system is used to determine the connection of each ordinary sensor node to the cluster-heads. The fuzzy inference system uses three linguistic variables: the remaining energy of the cluster-head, the neighborhood degree of the cluster-head, and the distance between the sensor node and the cluster-head. In the proposed fuzzy inference system, 27 fuzzy rules are defined, and the output of the system is the probability of each cluster-head for every ordinary node. Figure 4 illustrates the schematic of the fuzzy inference system. Additionally, Table 1 shows the fuzzy rules used in the fuzzy inference system.

Based on the proposed Mamdani-type fuzzy inference system, each ordinary sensor node calculates the probability of connecting to all cluster-heads and then connects to the cluster-head with the highest probability. The proposed Mamdani-type fuzzy inference system is designed to reduce the energy consumption of the sensor nodes. After all ordinary sensor nodes are connected to the cluster-heads, the cluster formation phase is completed, and all clusters are established.

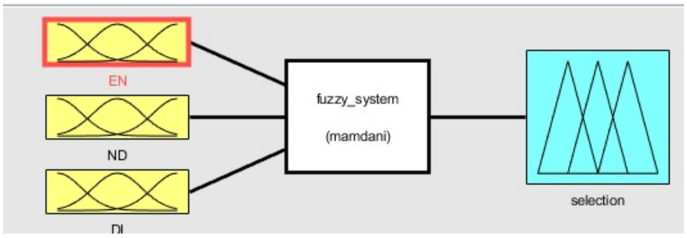

Figure 4: Schematic of the fuzzy inference system.

3.4 Multi-hop Routing

After the clusters are formed, the ordinary sensor nodes need to send their data to the respective cluster-heads. The ordinary sensor nodes rely on other sensor nodes within the cluster to help forward their data to the cluster-head. To do this, the target sensor node first uses the route discovery process to find its neighbors within the respective cluster. Then, the shortest path between the target sensor node and the cluster-head is determined based on the neighbors within the cluster. Finally, the routing process is applied based on the shortest path found between the target sensor node and the respective cluster-head, and the energy levels of the sensor nodes involved in the routing process are updated.

4 Results Evaluation

The proposed clustering protocol was simulated using MATLAB software version 2017. To obtain accurate scientific results, the proposed clustering protocol was implemented on various wireless sensor network topologies. The protocol was evaluated based on several metrics: the first node death, half of the nodes dead, last node death, average energy consumption of nodes, and the number of data packets sent to the base station.

Table 1: Fuzzy rules in the proposed Mamdani-type FIS

Rule	residual energy of the CH	distance between the CH and the sensor node	neighborhood degree of the CH	Chance
1	High	Close	High	Very Strong
2	High	Close	Medium	Very Strong
3	High	Close	Low	Very Strong
4	High	Medium	High	Very Strong
5	High	Medium	Medium	Strong
6	High	Medium	Low	Medium
7	High	Far	High	Medium
8	High	Far	Medium	Medium
9	High	Far	Low	Medium
10	Medium	Close	High	Strong
11	Medium	Close	Medium	Medium
12	Medium	Close	Low	Medium
13	Medium	Medium	High	Strong
14	Medium	Medium	Medium	Medium
15	Medium	Medium	Low	Weak
16	Medium	Far	High	Weak
17	Medium	Far	Medium	Weak
18	Medium	Far	Low	Weak
19	Low	Close	High	Medium
20	Low	Close	Medium	Medium
21	Low	Close	Low	Weak
22	Low	Medium	High	Weak
23	Low	Medium	Medium	Weak
24	Low	Medium	Low	Very Weak
25	Low	Far	High	Very Weak
26	Low	Far	Medium	Very Weak
27	Low	Far	Low	Very Weak

4.1 Simulation Settings

Table 2 shows the values assigned to the parameters of the multi-objective binary dragonfly optimization algorithm. The simulation results of the proposed clustering protocol were provided for 10 different wireless sensor networks with a random distribution of 150 sensor nodes. The base station was considered to be at the center of the network's operational area. Additionally, all the wireless sensor networks were homogeneous, and the initial energy of all sensor nodes was set to 0.5 Joules. The values of the parameters for the wireless sensor networks are shown in Table 3.

Table 2: Setting the parameters of the IVBDA

No	Parameters	Value
1	Maximum iteration	100
2	Population size	200
3	Number of dimensions	150
4	W	0.9
5	S	0.1
6	A	0.1
7	C	0.7
8	F	1
9	E	1

Table 3: Network parameters

No	Parameters	Value
1	Simulation Area	100×100 m^2
2	BS location	$(50, 50)$
3	No. of Sensor nodes	150
4	Initial Energy of nodes	0.5 J
5	E_{elec}	50 nj/bit
6	e_{fs}	100 pj/bit/m^2
7	e_{mp}	0.0013 pj/bit/m^4
8	L	4000bit

4.2 Results Evaluation

Table 4 presents the simulation results of the proposed clustering protocol based on the multi-objective binary dragonfly optimization algorithm on 10 different wireless sensor network topologies. The table evaluates the metrics of the first node death, half of the nodes dead, and last node death. Additionally, the multi-objective binary dragonfly optimization algorithm was implemented using both the S-shaped and V-shaped transfer functions. Figure 5 shows the average network lifetime across 10 different topologies for the metrics of the first node death, half of the nodes dead, and last node death. As observed from the results, the multi-objective binary dragonfly optimization algorithm using the V-shaped transfer function performs slightly better than the S-shaped transfer function.

Table 4: The result of the proposed protocol on 10 WSNs based on BDA

#WSN	BDA					
	S-shaped			V-shaped		
	FND	HND	LND	FND	HND	LND
1	**2237**	**2761**	**2901**	2227	2759	2887
2	**2650**	**3414**	**3633**	2637	3389	3604
3	**2402**	**2974**	**3127**	2389	2891	3056
4	1933	2178	2361	**2001**	**2224**	**2459**
5	2268	2745	2888	**2277**	**2764**	**2911**
6	2168	2678	2804	**2251**	**2727**	**2847**
7	3007	3101	3198	**3011**	**3121**	**3245**
8	2658	2967	3074	**2666**	**2991**	**3119**
9	**2133**	**2435**	**2556**	2118	2418	2501
10	**2091**	**2451**	**2565**	2047	2438	2479

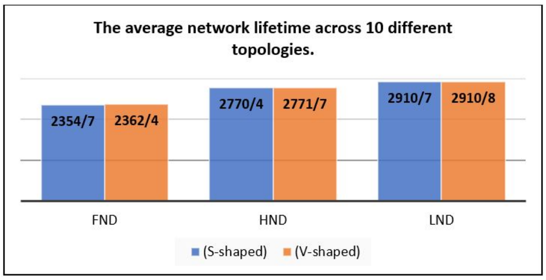

Figure 5: Average network lifetime across 10 different topologies.

In Table 5, the average energy consumption of sensor nodes at iteration numbers 500, 700, and 900 is presented. Additionally, the multi-objective binary dragonfly optimization algorithm was executed based on both the S-shaped and V-shaped transfer functions. The results of the average energy consumption of sensor nodes across 10 different network topologies are provided. In these various topologies, 150 sensor nodes are randomly distributed in the network's operational area. Table 6 presents the number of packets sent to the base station in 10 different wireless sensor networks.

Table 5: The average energy consumption of the network)

#WSN	Round	BDA (S-shaped)	BDA (V-shaped)
1	500	0.08615	0.08655
	700	0.12061	0.12117
	900	0.15507	0.15579
2	500	0.06880	0.06935
	700	0.09632	0.09707
	900	0.12384	0.12483
3	500	0.07990	0.08180
	700	0.11186	0.11452
	900	0.14382	0.14724
4	500	0.10585	0.10165
	700	0.14819	0.14231
	900	0.19053	0.18297
5	500	0.08655	0.08585
	700	0.12117	0.12019
	900	0.15579	0.15453
6	500	0.08915	0.08780
	700	0.12481	0.12292
	900	0.16047	0.15804
7	500	0.07815	0.07703
	700	0.10941	0.10784
	900	0.14067	0.13865
8	500	0.08132	0.08015
	700	0.11382	0.11221
	900	0.14634	0.14427
9	500	0.09784	0.09961
	700	0.13692	0.13944
	900	0.17604	0.17928
10	500	0.09745	0.10084
	700	0.13643	0.14112
	900	0.17541	0.18144

In Figure 6, the average number of packets sent to the base station across 10 different topologies is shown. It can be observed that the multi-objective binary dragonfly optimization algorithm based on the V-shaped transfer function performs slightly better than the S-shaped transfer function. To evaluate the performance of the proposed clustering protocol, it has been compared with respect to the metrics of the first node death, half of the nodes dead, last node death, and the number of data packets sent to the base station. The comparison results are based on the average obtained from executing the protocols across 10 different topologies.

Table 6: The total number of data packets received in the BS based on BDA

#WSN	BDA					
	S-shaped			V-shaped		
	FND	HND	LND	FND	HND	LND
1	**335550**	**387426**	**401286**	334050	386718	399390
2	**397500**	**473136**	**494817**	395550	469998	491283
3	**360300**	**416928**	**432075**	358350	408048	424383
4	289950	314205	332322	**300150**	**322227**	**345492**
5	340200	387423	401580	**341550**	**389763**	**404316**
6	325200	375690	388164	**337650**	**384774**	**396654**
7	451050	460356	469959	**451650**	**462540**	**474816**
8	398700	429291	439884	**399900**	**432075**	**444747**
9	**319950**	**349848**	**361827**	317700	347400	355617
10	**313650**	**349290**	**360576**	307050	345264	349818

Table 7 presents a comparison of the proposed clustering protocol with other methods in terms of network lifetime. The proposed clustering protocol exhibits very high performance in terms of network lifetime. In Table 8, a comparison of the proposed clustering protocol with other methods in terms of the number of packets sent to the base station is provided. The proposed clustering protocol also demonstrates very high performance in terms of the number of data packets sent to the base station.

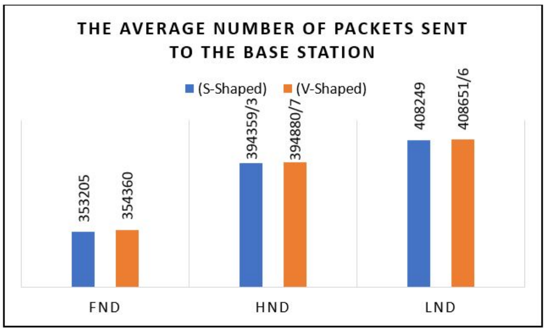

Figure 6: Average number of packets sent to the base station across 10 different topologies.

Table 7: Comparison of the proposed protocol with other protocols based on network lifetime

Protocol	FND	HND	LND	Rank
LEACH	387.8	507.4	689.6	7
LEACH-DT	445.6	625.9	857.2	6
LEACH-FL	648.3	717.9	733.5	5
ASLPR	722.4	745.5	757.2	4
SIF	755.6	772.7	781.6	3
Proposed (BDA-S)	2354.7	2770.4	2910.7	2
Proposed (BDA-V)	2362.4	2771.7	2910.8	1

Table 8: Comparison of the proposed protocol with other protocols based on TPT

Protocol	FND	HND	LND	Rank
LEACH	58170	72793.5	76830	7
LEACH-DT	68840	88537.6	93455.3	6
LEACH-FL	97245	107083.1	107478	5
ASLPR	108360	110915	111138	4
SIF	113340	115196.6	115369.7	3
Proposed (BDA-S)	353205	394359.3	408249	2
Proposed (BDA-V)	354360	394880.7	408651.6	1

5 Conclusions

Clustering is a well-defined method for improving the energy consumption of sensor nodes and extending the lifetime of wireless sensor networks. In this paper, a new clustering-based routing protocol was designed to enhance energy consumption in sensor nodes. In the cluster head selection phase, a multi-objective binary dragonfly optimization algorithm was used to optimally select cluster heads. In the fitness function of the metaheuristic algorithm, three parameters—energy, neighborhood degree, and distance—were considered. Additionally, in the cluster formation phase, a Mamdani fuzzy inference system was used. The remaining energy of the cluster head, neighborhood degree, and the distance between the cluster head and the base station were considered as inputs to the fuzzy system. Simulation results showed that the multi-objective binary dragonfly optimization algorithm based on the V-shaped transfer function performs better than the one based on the S-shaped transfer function. The proposed protocol was compared with other protocols introduced in related works in terms of network lifetime, and the results showed that the proposed protocol performs efficiently.

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