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Soft C-means Multi objective Metaheuristic Dragonfly Optimization for Cluster Head Selection in WSN

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Abstract*:* Wireless communication is a recent area in wireless sensor networks (WSNs) due to the advancement of electronic devices. WSN comprised spatially distributed sensors distributed over area. Clustering groups the sensor nodes for conserving the power. The cluster head (CH) selection balances the load with energy consumption. Many researchers carried out their research on cluster head selection in WSN. Therefore, clustering accuracy was not increased, and processing time was not reduced. In order to resolve the problems, Soft C-means Multiobjective Metaheuristic Dragonfly Optimization (SCMMDO) Method was introduced. The SCMMDO Method's main goal is to identify the ideal cluster head for effective data transmission in WSN. SCMMDO Method performed two processes, namely clustering and optimization in WSN. Initially, the sensor nodes are randomly distributed. The soft C-means method puts sensor nodes into clusters based on three factors. They are received signal strength, residual energy and bandwidth availability. The cluster head is then chosen using multi-objective meta-heuristic dragonfly optimization. The data packet is sent to the destination node by the source node using the cluster head that has been selected. Simulation is performed with the help of the metrics such as energy consumption, clustering accuracy and processing time, throughput and delay. The observed result illustrates that SCMMDO Method effectively increases the clustering accuracy and minimizes the energy consumption as well as processing time. The clustering accuracy of the proposed system is 96%.

Keywords*:* *Clustering, Cluster head selection, dragonfly optimization, energy consumption, wireless sensor network*

1. Introduction

Clustering is an essential one used for increasing the network lifetime in WSNs. An advanced clustering algorithm (HQCA) was created to produce high-quality clusters. [1]. For choosing the CH to carry out data transfer between sensor nodes, a Tunicate Swarm Butterfly Optimization Algorithm (TSBOA) was created. [2]. For optimal cluster head selection in WSN, the Diversity-Driven Multi-Parent Evolutionary Algorithm with Adaptive Non-Uniform Mutation was used. [3]. An innovative approach was introduced for selecting the cluster heads [4]. Genetic Algorithm-based Optimized Clustering (GAOC) protocol was designed for CH selection [5]. Cluster Head Selection by Randomness with Data Recovery in WSN (CHSRDR) method was designed for choosing the cluster head for data recovery [6]. In WSNs, a new clustering algorithm with low energy usage was introduced. [7]. For centralised clustering algorithms with load-balanced networks, a genetic algorithm-based cluster head selection was introduced. [8]. An energy efficient technique was introduced to reduce the attacks on improving cluster head selection mechanism [9]. A hybrid Sparrow Search Algorithm with Differential Evolution algorithm was introduced for solving energy efficiency problem issues [10]. The problems from literature are higher computational cost, higher processing time, higher energy consumption, lesser network lifetime, lesser clustering accuracy, higher computational complexity and so on. In order to address these problems, Soft C-means Multiobjective Metaheuristic Dragonfly Optimization (SCMMDO) Method is introduced for optimal cluster head selection in WSN.

The remaining paper is structured into six different sections. The related efforts of cluster head selection are described in Section 2. Section 3 provides a brief introduction of the SCMMDO Method, along with a neat architectural design in WSN. While Section 5 explains the simulation results, Section 4 describes the simulation setup. The conclusion is found in Section 6.

2. Related Works

WSN are leading area of research for different applications. Firefly algorithm was introduced in [11] for increasing energy efficiency and lifetime through. Though energy

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efficiency was improved, the delay was not minimized by Firefly algorithm. Firefly algorithm (FA) and hesitant fuzzy was introduced in [12] with CH selection protocol. However, the energy efficiency was not improved by FA. Particle Swarm Optimization (PSO) approach was introduced in [13] for optimal cluster head selection. But, the computational cost was not reduced by PSO approach. A multi-criteria decision-making method was introduced in [14] for choosing the CH. But, the energy efficiency was not at essential level by designed method. [15] presented area double cluster head APTEEN routing protocol-based particle swarm optimization (DCA-PSO) for cluster head selection. But the optimal cluster head selection was not carried out by DCA-PSO. Using fuzzy method[16], presented a centralized method for selecting cluster head and distributed cluster formation scheme. The suggested technique, however, did not minimise clustering time. Several power-aware routing protocols for wireless sensor networks were introduced in [17]. But, the clustering accuracy was not improved by power-aware routing protocol. To increase network lifetime, [18] developed an algorithm that utilizes fuzzy-based energy-efficient cluster head selection. A novel ARSH-FATI-based Cluster Head Selection (ARSH-FATI-CHS) algorithm was introduced in [19] to minimize energy consumption. However, the computational complexity was not minimized. An efficient CH election scheme was introduced in [20] to rotate the CH position among nodes with higher energy level. However, the technique as planned did not reduce bandwidth use. The Multi-Objective Taylor Crow Optimization (MOTCO) algorithm, a mixture of the Taylor series and the Crow Search Algorithm, is used to select the best cluster head (CSA). [22] Introduced a simple and cost-effective modelling of a security system that provides security by providing secure cluster head selection during the data aggregation process in WSN. Using residual energy, nodes' positions, and the centrality of their nodes, an algorithm is proposed in [23] for selecting CHs. A hybrid optimization algorithm is used in [24] for energy-aware CH selection in hierarchical routing in WSNs. Based on determining the gain of each link in the network, this paper [25] provides a method of detecting link failure due to malicious nodes. A defective node identification system based on the Adaptive Neuro Fuzzy Inference System (ANFIS) classifier is created. [26]. The ANFIS classifier qualifies the conviction parameters that are retrieved from dependable and malicious nodes. With a rise in the number of rogue nodes, network performance will decrease.

From the literature, it is observed that the authors proposed various algorithms for clustering, cluster head selection, optimization in wireless sensor networks for efficient transmission of data. But it consumes more energy and high processing time.

3. Methodology

Sensor networks, also known as wireless sensor networks (WSN), are self-configured wireless systems used to monitor environmental conditions. Hundreds of sensor nodes made up the WSN. Clustering groups the sensor nodes with similar characteristics. Every cluster comprises one cluster head for performing efficient data communication in WSN. The information is collected from source node and sent to the base station through CH. Soft C-means Multiobjective Metaheuristic Dragonfly Optimization (SCMMDO) Method is introduced for choosing optimal cluster head in WSN. Figure 1 explains the architecture diagram of SCMMDO Method. SCMMDO Method is primarily concerned with selecting the optimal cluster head. WSNs begin with random distribution of sensor nodes. A soft C-means clustering method groups the sensor nodes according to received signal strength, residual energy, and bandwidth availability. Meta-heuristic dragonfly optimization is then used to select the cluster head among group members.

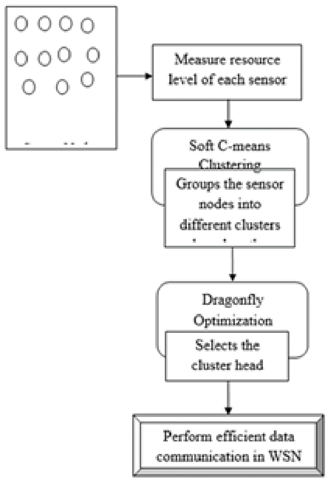

Fig 1. Architecture Diagram of SCMMDO Method

By using the optimal cluster head, the source node transmits the data packets to the destination nodes. Detailed descriptions of soft-c-means clustering and multi-objective meta-heuristic dragonfly optimization are provided in the following section.

1.1. Soft C-means Sensor Node Clustering

Clustering is the method of grouping the collection of similar objects into cluster. Soft c-means clustering is the process the where each data point is allocated based on probability score belong to cluster. During sensor node grouping process in soft c-means clustering, SCMMDO Method initializes the 'm' number of clusters '$Clu_1, Clu_2, Clu_3, \ldots Clu_m$' and their cluster centroid '$cc_1, cc_2, cc_3, \ldots cc_m$' in random manner. The soft c-means sensor node clustering process is carried out through allocating the membership to every sensor node 'SN_i' corresponding to each cluster centroid distance between centroid and sensor node. The sensor node 'SN_i' belongs to the cluster 'Clu_j' through membership function. The membership function is determined through residual energy, available bandwidth and received signal strength. The received signal strength is determined for performing efficient data transmission. The received signal strength (RSS) of sensor node is determined as follows,

$$RSS = 10\ \log_{10}\left(\frac{Transmitted\ signal\ power}{Received\ signal\ power}\right) \quad (1)$$

From (1), 'RSS'denotes the received signal strength. The signal strength is determined in terms of decibel (dB). The bandwidth availability is determined depending on variation between the total bandwidth and consumed bandwidth. It is given as,

$$Bw_{avilability} = Bw_{total} - Bw_{consumed\ bandwidth} \quad (2)$$

From (2), '$Bw_{avlailability}$' represent the bandwidth availability. 'Bw_{total}' represent the total bandwidth.'$Bw_{consumed\ bandwidth}$' symbolizes consumed bandwidth. After that, the residual energy of sensor node is computed. Every sensor node has residual energy that is equal to the difference between total and consumed energy. As a result, a sensor node's residual energy can be formulated as follows,

$$Energy_{Residual} = Energy_{Total} - Energy_{Consumed} \quad (3)$$

From (3), the residual energy is determined. Based on these above mentioned parameters, membership function of sensor node is determined. It is obtained as,

$$Mf_{ij} = \sum_{n=1}^{m}\left(\frac{d_{ij}}{d_{ic}}\right)^{-\left(\frac{2-fu}{fu}\right)} \quad (4)$$

From (4), 'Mf_{ij}'symbolizes the 'd_{ij}' denotes the parameter value distance between 'i^{th}' sensor node and 'j^{th}' cluster centroid. 'd_{ic}' portray the distance between 'i^{th}' sensor node and 'm^{th}' cluster. 'fu' denotes the fuzzifier. SCMMDO Method determines the cluster centroid because mean of all sensor node weighted by membership degree belongs to the cluster. Consequently, the centroid for each cluster is determined as,

$$Cluster\ centroid = \frac{\sum_{SN_i \in cluster\ centroid} Mf_{ij}^{fu} SN_i}{\sum_{SN_i \in cluster\ centroid} Mf_{ij}} \quad (5)$$

From (5), 'Mf_{ij}' is amembership degree. Cluster centroid and sensor node distance are calculated as follows,

$$d_{ij} = \left(\sum_{i=1}^{z}(|(SN_i - cluster\ centroid)|)^q\right)^{1/q} \quad (6)$$

From (6), 'SN_i' represent the 'i^{th}'sensor node in WSN. 'z' symbolizes the number of sensor node. 'q' denotes the parameter. The minimal distance between the sensor node and cluster centroid is suitable to group sensor node to that cluster. The algorithmic process of Soft c-means sensor node clustering is given as,

Algorithm 1: Soft C-means Sensor Node Clustering

Input: Number of sensor nodes $\boldsymbol{SN_i = SN_1, SN_2, SN_3 \ldots . SN_n}$

Output: Number of clusters

1. Begin
2. For eachnumber of input sensor nodes '$\boldsymbol{SN_i}$'
3. Initialize 'c' number of clusters in network
4. Calculate received signal strength, residual energy and bandwidth availability
5. Compute the membership function for every sensor node
6. Determine the centroid for every cluster
7. Calculate the distance between centroid and parameter value for every sensor node
8. Groups the sensor node to the minimum distance cluster
9. End for
10. End

Algorithm 1 explains the process of soft c-means clustering in SCMMDO Method. Initially, number of clusters is initialized. After that, received signal strength, residual energy and bandwidth availability is determined of every sensor node. Then, the membership function is calculated for every sensor node. The centroid value of every cluster is determined to perform node clustering. After that, the distance between the centroid and parameter value of sensor node is determined for every cluster. Finally, the sensor node is grouped to the cluster with minimum distance in WSN. In next sub-section, cluster head selection in SCMMDO Method is explained briefly.

1.2. Multiobjective Metaheuristic Dragonfly Optimization based Cluster Head Selection

Dragonfly optimization is a meta-heuristic method for finding better solutions to optimization problems. In SCMMDO Method, In dragonfly optimization, a multiobjective optimization algorithm is used to solve more than three objective problems at the same time. The dragonfly behavior is the movement and search of their food source. In every cluster, the dragonfly represents the number of sensor nodes '$P = df_1, df_2, \ldots df_p$' and their food source is considered as the multiobjective functions (i.e., received signal strength, residual energy and bandwidth availability). Multiobjective Metaheuristic Dragonfly Optimization in SCMMDO Method functioned with the population based approach termed as the swarm. An optimization initializes the population of 'h' number of dragonfliesin the search space. It is formulated as,

$$P = df_1, df_2, \ldots df_h \tag{7}$$

The fitness value is computed for every dragonfly in current swarm population. Depending on the estimation, the fitness value is determined as,

$$Fitness\ Function = (\ Energy_{Residual} > Energy_{threshold} \&\& (RSS > RSS_{th}) \&\& \ (Bw_{availability} > Bw_{threshold})) \tag{8}$$

From (8), 'RSS'symbolizes the received signal strength.'RSS_{th}' symbolizes the threshold of the RSS. '$Bw_{availability}$' symbolize the availability of bandwidth. '$Bw_{threshold}$' symbolizes the threshold of availability of bandwidth. Depending on analysis, the fitness function is computed as given below,

$$Fitness\ Function = arg\ max\{RSS, Bw_{availability}, Energy_{Residual}\} \tag{9}$$

From (9), '$arg\ max$' denotes the argument of maximum function. Depending on the fitness measure, four swarming behavior of dragonflies are determined in search space. Global optimal solutions are found by using the four behaviors. Initially, the separation process identifies the current and neighboring position of dragonfly. It is given as,

$$\delta_1 = -\sum_{k=1}^{h} \left(P_{a(t)} - P_{b(t)}\right) \tag{10}$$

From (10), 'δ_1' denotes the separation of dragonflies, '$P_{a(t)}$' symbolizes the current position of dragonfly.'$P_{b(t)}$' represent position of neighboring dragonflies. 'h' denotes the count of adjacent dragonflies in the search space. The second one is alignment to the movement velocity of dragonflies. It is formulated as,

$$\delta_2 = \frac{1}{h} \sum_{j=1}^{n} \tau_j(t) \tag{11}$$

From (11), 'δ_2' denotes the alignment. '$\tau_j(t)$'symbolize the velocity of 'neighboring dragonflies. Thirdly, the cohesion process finds the tendency of dragonflies towards center of their neighborhood.

$$\delta_3 = \frac{1}{h} \sum_{k=1}^{h} [P_{b(t)} - P_{a(t)}] \tag{12}$$

From (12), 'δ_3'denotes the cohesion process of dragonfly. The process of attracting to a food source is determined by the current position of the food source and the dragonfly's position. It is given as,

$$\delta_4 = \left|P_f - P_{a(t)}\right| \tag{13}$$

From (13), 'δ_4'symbolizes the attraction towards the food source. 'P_f'represent the position of food source. The position of the current dragonfly gets updated with their neighborhoods,

$$P_{a(t+1)} = P_{a(t)} + \nabla P_{a(t+1)} \tag{14}$$

From (14), '$P_{a(t+1)}$'denotes the updated position of dragonfly, '$P_{a(t)}$' symbolizes the current position of dragonfly. '$\nabla P_{a(t+1)}$'symbolizes the step vector to identify the movement direction of dragonfly. It is given as,

$$\nabla P_{a(t+1)} = \{we_1\delta_1 + we_2\delta_2 + we_3\delta_3 + \rho_f\delta_4\} + \ \theta * P_{(t)} \tag{15}$$

From (15), 'we_1'denotes the weight of separation function. 'we_2' represent weight of alignment function. 'we_3' symbolizes weight of cohesion.'ρ_f' represent the food vector. 'θ'symbolize the inertia weight to control convergence behavior of optimization, '$P_{(t)}$' indicates the position of the dragonfly at time 't'.

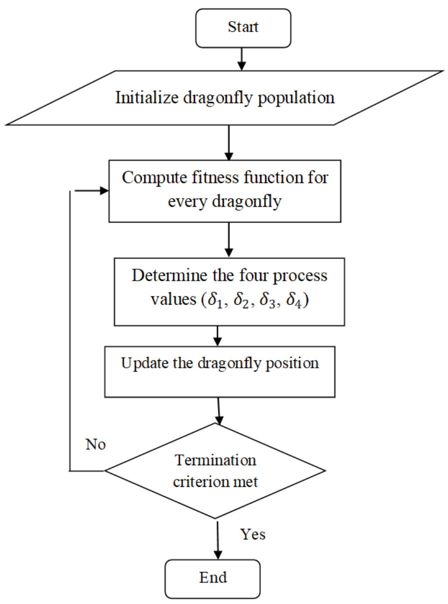

Fig 2. Flow diagram of Multiobjective Metaheuristic Dragonfly Optimization based Cluster Head Selection

Figure 2 describes the flow diagram of Multiobjective Metaheuristic Dragonfly Optimization based Cluster Head Selection in SCMMDO Method. The drangonfly populations are initialized and fitness function is determined based on different parameters for identifying the cluster head. The process gets iterated until the all sensor nodes are analyzed. By this way, cluster head is selected in SCMMDO Method for efficient data transmission in WSN.

4. Simulation Settings

The presented SCMMDO technique replica is implemented in NS-2 simulator in the wireless network region of $1500\, m * 1500\, m$ with help of 500 sensor nodes. For conducting the simulation, SCMMDO Method used Random Waypoint model as mobility and DSR as routing protocol. The parameters utilized for conducting the experimental process is illustrated in Table 2.

Table 2. Simulation Parameters

Simulacrum Parameters	**Assesses**
Network Simulator	NS 2.34
Number of runs	10
Number of sensor nodes	500
Mobility standard	Random Waypoint model
Square space	1500m × 1500m
Speed of sensor nodes	0 – 20 m/s
Counterfeit time	250sec
Protocol	DSR

The performance of proposed SCMMDO Method is computed using four parameters, namely: Energy consumption, Clustering Accuracy and Processing Time.

5. Result Discussion

The simulation performance of SCMMDO Method is analyzed and compared with two existing methods namely high-quality clustering algorithm (HQCA) [1] and Tunicate Swarm Butterfly Optimization Algorithm (TSBOA) [2] approach.

5.1 Energy Consumption

The amount of energy consumed by the process of clustering in WSN to efficiently transfer data is known as energy consumption. It is formulated as,

$$EC = N * Energy\ consumed\ by\ one\ sensor\ node \quad (16)$$

From (16), 'EC' represent the energy consumed by the sensor nodes. 'N' symbolizes the amount of sensor nodes. The diagrammatic representation of consumption of energy is given in figure 3.

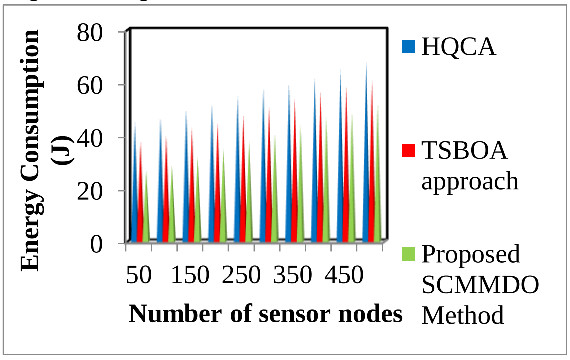

Fig 3. Measurement of Energy Consumption

Figure 3 illustrates energy consumption results of different number of sensor node varied from 50 to 500. As described in the graphical results, the proposed SCMMDO method reduces the consumption of energy consumption while transmitting the data packet through optimal cluster head selection. In comparison to existing HQCA [1] and existing TSBOA [2], the proposed SCMMDO Method has a 31% and 21% reduction in energy consumption, respectively.

5.2 Clustering Accuracy

It is the ratio of correctly clustered sensors to the total number of sensors that determines the clustering accuracy. It is formulated as,

$$CA = \frac{Number\ of\ sensor\ nodes\ that\ are\ correctly\ clustered}{N} \quad (17)$$

From (17), 'CA' symbolizes the clustering accuracy. 'N' symbolizes the number of sensor nodes. The diagrammatic representation of clustering accuracy is given in figure 4. Figure 4 illustrates the simulation results of clustering accuracy of different number of sensor node varied from 50 to 500. As illustrated in results, the proposed SCMMDO Method increases the clustering accuracy while grouping the sensor nodes in WSN.

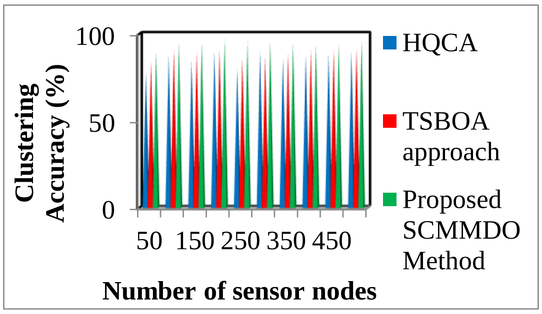

Fig 4. Measurement of Clustering Accuracy

This is due to the application of soft c-means sensor node clustering in proposed SCMMDO Method. Consequently, the clustering accuracy of proposed SCMMDO Method is improved by 10% and 6% than the existing HQCA [1] and existing TSBOA [2] correspondingly.

5.3 Processing Time

The time consumed in the process of selecting cluster head is known as processing time. This is defined as the difference between the ending and starting times of cluster head selection. It is measured in terms of milliseconds (ms). It is formulated as,

$$Processing\ time = Ending\ time - starting\ time\ of\ CH\ selection \quad (18)$$

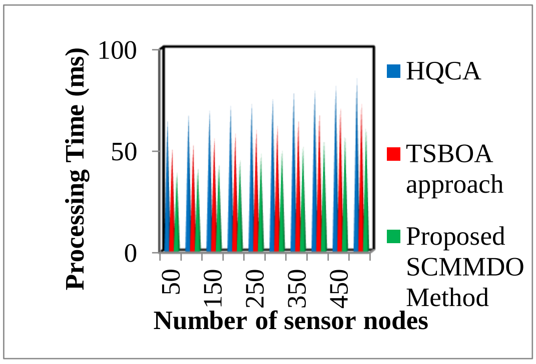

Fig 5. Measurement of Processing Time

From (18), the processing time is calculated. Methods are considered more efficient when their processing time is less. Figure 5 illustrates how processing time is represented diagrammatically. A simulation of multiple sensor nodes varied from 50 to 500 is shown in Figure 5. According to results, the proposed SCMMDO Method is effective in reducing processing time when choosing cluster heads. Therefore, the processing time of proposed SCMMDO Method is reduced by 35% and 21% than the existing HQCA [1] and existing TSBOA [2] respectively.

5.4 Impact on Throughput

A throughput is the rate at which data is successfully transferred between two points.

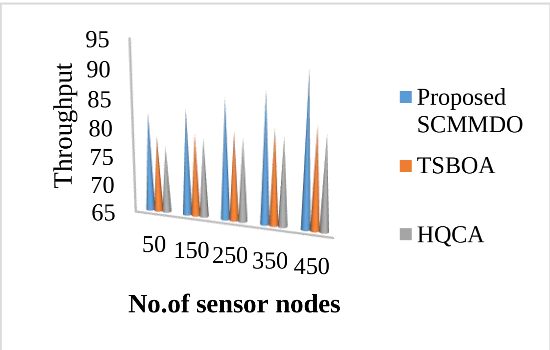

Fig 6. Measurement of Throughput

From the figure 6, we can make out the difference in throughput, between the existing algorithms and the proposed algorithm. The throughput for the existing algorithm increases with the increasing number of nodes, but in slow progression. While for the proposed algorithm the throughput increases in progression. Hence it is clearly visible that the proposed algorithm gives significantly improved throughput, when put to use.

5.5 Impact on delay

A packet's delay is how long it takes the link to push its bits onto it.

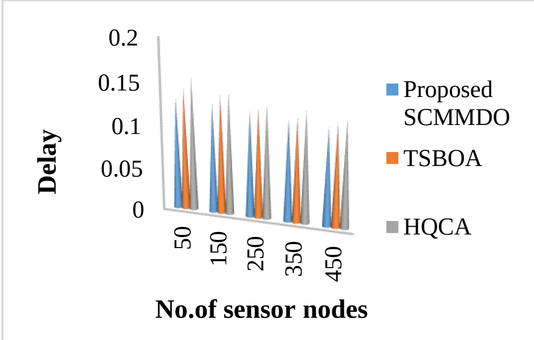

Fig 7. Measurement of Delay in packet delivery

The graphs plotted in figure 7 shows that the delay time for packet delivery is less in the case of proposed algorithm as compared to the existing algorithm. For instance when the number of the nodes is 50, the delay time is 0.12 secs for the proposed architecture. When the number of nodes becomes 450, the delay is 0.009 for the proposed algorithm.

6. Conclusion

An efficient SCMMDO Method is developed for efficient data transmission through optimal cluster head selection with minimum processing time in WSN environment. A multiobjective metaheuristic dragonfly optimization is used to select the cluster heads while minimizing the energy consumption and improving clustering accuracy. The observed result shows that the proposed SCMMDO Method increases the clustering accuracy by 8% and minimizes the energy consumption by 26% as well as processing time by 28% than the existing HQCA (high-quality clustering algorithm and existing TSBOA.

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