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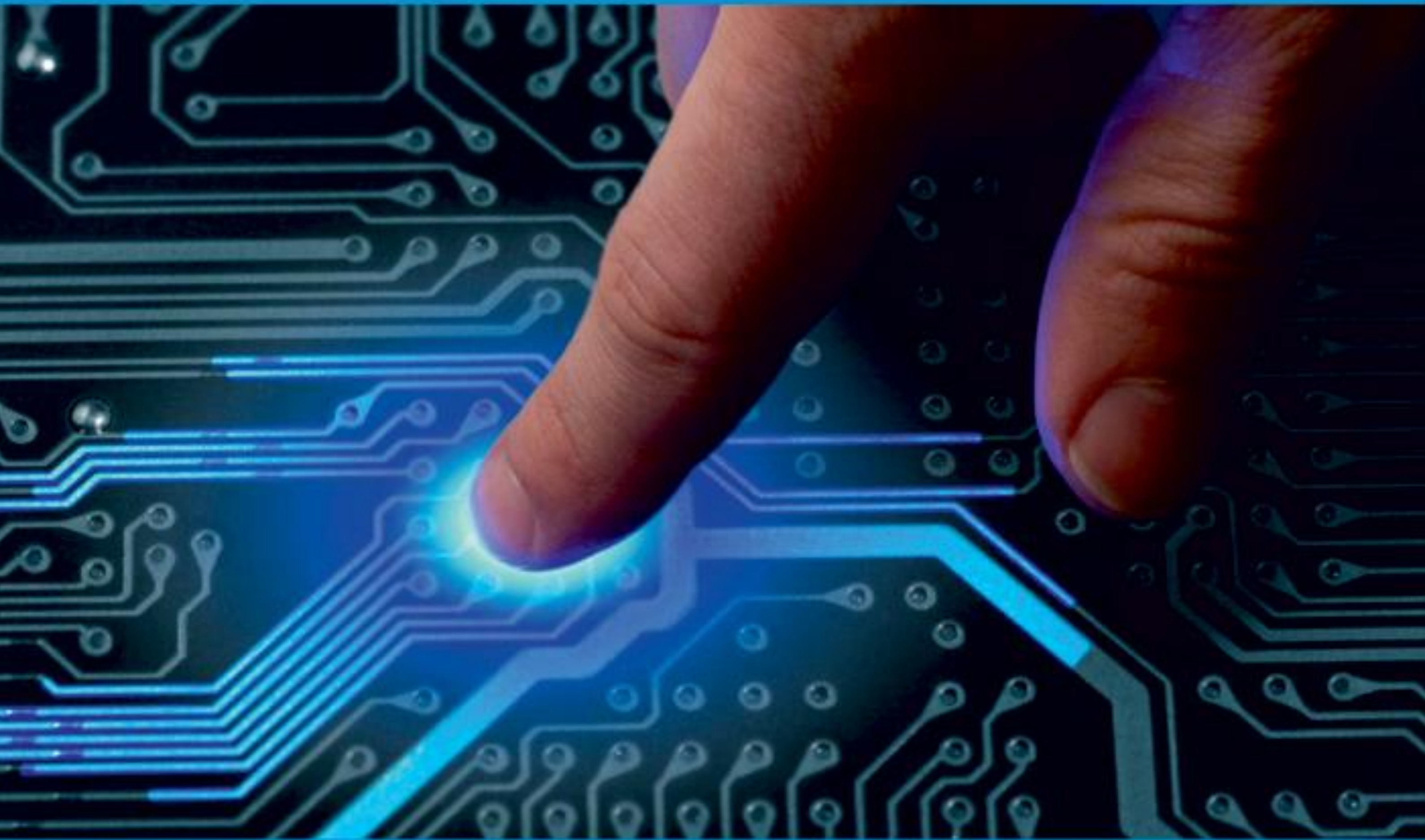

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WSN Genetic Algorithm –based Optimized Cluster Head Selection using Multiobjective Metaheuristic Dragonfly Optimization Techniques

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ABSTRACT: The advancement of electronic gadgets has led to the emergence of wireless communication as a contemporary field within wireless sensor networks (WSNs). These networks consist of sensors spread out across a designated space. To preserve energy, sensor nodes are grouped through a process known as clustering. The cluster head (CH) is chosen to evenly distribute the workload and minimize energy usage. Despite numerous attempts by researchers to enhance the selection of cluster heads in WSNs, there has been limited improvement in clustering accuracy. To address these challenges, a solution known as the Soft C-means Multiobjective Metaheuristic Dragonfly Optimization (SCMMDO) Method has been introduced. The primary goal of the SCMMDO Method is to carefully choose the most effective cluster head to facilitate efficient data transmission within a wireless sensor network (WSN). This method employs two key procedures: clustering and optimization, both of which are aimed at enhancing data transmission in the WSN. At the outset, sensor nodes are scattered in a random manner. Following this, the Soft C-means clustering process is implemented to assemble these sensor nodes into clusters. These clusters are established based on three critical factors: received signal strength, remaining energy, and available bandwidth. Subsequently, the cluster head is chosen for each individual cluster utilizing a multiobjective meta-heuristic dragonfly optimization process. Once the cluster heads are determined, the Source nodes are able to transmit data packets to their intended destination nodes. To assess the performance of the SCMMDO Method, simulations are carried out, employing metrics such as energy consumption and clustering accuracy. The results of these simulations demonstrate that the SCMMDO Method significantly enhances clustering accuracy while concurrently reducing energy consumption.

KEYWORDS: Electronic Devices, Wireless Sensor Networks, Sensor Nodes, Soft C-Means Clustering, Multi objective Meta-Heuristic Dragonfly Optimization, Cluster Head, Source Node

I. INTRODUCTION

Clustering is an essential one used for increasing the network lifetime in WSNs. CH gathers data and transmits data to the base station. A high-quality clustering algorithm (HQCA) was introduced in [1] for forming the high-quality clusters. But the bandwidth utilization rate was not improved by HQCA. A Tunicate Swarm Butterfly Optimization Algorithm (TSBOA) was introduced in [2] for choosing the CH to perform data transmission between sensor nodes. But the clustering accuracy was not improved by TSBOA.

Diversity-Driven Multi-Parent Evolutionary Algorithm with Adaptive Non- Uniform Mutation was carried out in [3] for optimal cluster head selection in WSN. However, computational complexity was not reduced by designed algorithm. An innovative approach was introduced in [4] for selecting the cluster heads. The target of cluster head was based on the node distance and node energy. But, the network lifetime was not improved by designed approach. Genetic Algorithm-based Optimized Clustering (GAOC) protocol was designed in [5] for optimized CH selection. But, the computational complexity was not reduced by GAOC protocol. Cluster Head Selection by Randomness with Data Recovery in WSN (CHSRDR) method was designed in [6] for choosing the cluster head for data recovery. However, the computational overhead was not minimized by CHSRDR method.

A new clustering algorithm was introduced in [7] for WSNs to minimize the energy consumption and increase the lifetime of WSNs. A genetic algorithm based cluster head selection was introduced in [8] for centralized clustering algorithms with load balanced network. Though network lifetime was improved, the clustering accuracy was not improved by genetic algorithm. An energy efficient technique was introduced in [9] to reduce the attacks on improving cluster head selection mechanism. But, the delay was not reduced by energy efficient technique. A hybrid Sparrow Search Algorithm with Differential Evolution algorithm was introduced in [10] to address the energy efficiency problem by cluster head selection. The key aim of the article is given as; the key objective of SCMMDO Method is to choose the optimal cluster head for efficient data transmission in WSN.Initially, the sensor nodes are distributed randomly. Soft C-means clustering process groups the sensor nodes to form the cluster based on received signal strength, residual energy and bandwidth availability. In SCMMDO Method, Soft c-means sensor node clustering process allocates the membership to every sensor node corresponding to each cluster centroid depending on the distance between the centroid and sensor node. Then, the cluster head is chosen for every cluster using multi objective meta-heuristic dragonfly optimization in SCMMDO Method. The dragonfly optimization algorithm solves more than two objective problems. With help of selected cluster head, source node transmits the data packet to destination node. The remaining paper is structured into six different sections. In Section 2, the related works of cluster head selection are discussed. Section 3 gives brief description of SCMMDO Method with neat architectural diagram in WSN. In section 4, the simulation settings are presented and the simulation results are discussed in Section 5. The conclusion of the research work is listed in section.

II. 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 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 generating energy-aware clusters through 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 required level by designed method.

Area double cluster head APTEEN routing protocol-based particle swarm optimization (DCA-PSO) was introduced in [15] for cluster head selection. But, the optimal cluster head selection was not carried out by DCA-PSO.A centralized cluster head selection and distributed cluster formation scheme was introduced in [16] with fuzzy methods. But, the clustering time was not reduced by designed scheme.

A power-aware routing protocol was introduced in [17] for WSN depending on threshold rate and fuzzy logic for increasing the energy efficiency. But, the clustering accuracy was not improved by power-aware routing protocol. A fuzzy-based energy-efficient cluster head selection algorithm was designed in [18] to increase the network lifetime. .

A novel ARSH-FATI-based Cluster Head Selection (ARSH-FATI-CHS) algorithm was introduced in [19] with ranked-based clustering (NRC) to minimize the communication energy consumption of sensor nodes. 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. The designed scheme considered initial energy, residual energy and an optimum value of cluster head for cluster head selection. But, the bandwidth consumption was not minimized by designed scheme.

III. METHODLOGY

Wireless Sensor Networks (WSNs) is a self-configured wireless networks to examine the environmental conditions.WSN comprised the hundreds of sensor nodes. Clustering process is carried out to group the sensor nodes with similar characteristics. Each cluster comprises one cluster head for performing efficient data communication in WSN The information is collected from source node and sent to base station through CH. Soft C-means Multi objective Metaheuristic Dragonfly Optimization (SCMMDO) Method is introduced for choosing optimal cluster head in WSN. The architectural diagram of SCMMDO Method is illustrated in figure.

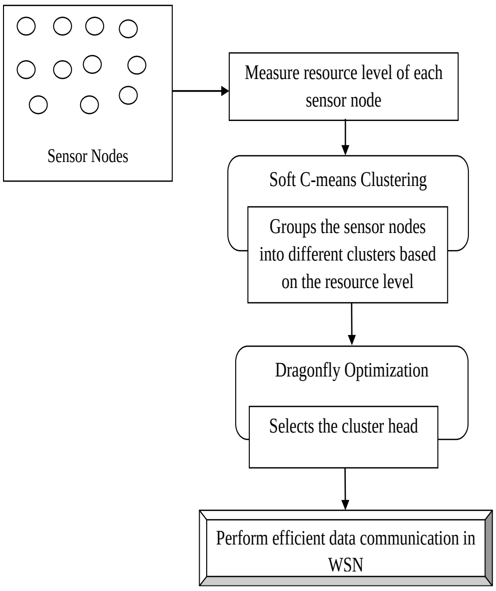

Figure 1. Architecture Diagram of SCMMDO Method

1 explains the architecture diagram of SCMMDO Method. The main objective of SCMMDO Method is to select the optimal cluster head. Initially, the sensor nodes are distributed randomly in WSN. Soft C-means clustering is carried out for grouping the sensor nodes based on received signal strength, residual energy and bandwidth availability. Then, the cluster head is selected among group members using meta-heuristic dragonfly optimization. Finally, the source node transmits the data packet to destination node through the optimal cluster head. The brief description of soft c-means clustering and multi-objective meta-heuristic dragonfly optimization is carried out in below sub-section.

3.1 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 based on distance between the 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 of the sensor node 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 decibel (dB). The bandwidth availability between the cluster head is computed depending on variation between the total bandwidth and consumed bandwidth. It is given as,

$$Bw_{avilability} = Bw_{total} - Bw_{consumed\ bandwidth}$$

(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

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calculated. The residual energy of sensor node is defined as the difference of total energy and consumed energy of sensor node. The residual energy of sensor node is formulated as,

$$Energy_{Residual} = Energy_{Total} - Energy_{Consumed}$$

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

From (4), 'Mf_{ij}'symbolizes the 'd_{ij}' denotes the parameter value distance between '$i^{t□}$' sensor node and '$j^{t□}$' cluster centroid. 'd_{ic}' Portrays the distance between '$i^{t□}$' sensor node and '$m^{t□}$' 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 membership degree. The distance between the sensor node and cluster centroid is computed as,

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

From(6), 'SN_i' represent the '$i^{t□}$'sensor node in wireless sensor network. '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 sensornode clustering is given as,

Algorithm 1: Soft C-means Sensor Node Clustering	
Input: Number of sensor nodes $SN_i = SN_1, SN_2, SN_3 \ldots SN_n$	
Output: Number of clusters	
1.	**Begin**
2.	**For** each number of input sensor nodes '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**

3.2 Algorithm 1 describes the step by step 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 the 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.

3.3 Multiobjective Met heuristic Dragonfly Optimization based Cluster Head Selection

The dragonfly optimization is the meta-heuristic method used to find better solution for optimization problem. In SCMMDO Method, Multiobjective denotes the dragonfly optimization algorithm that solves more than three objective problems such as received signal strength, residual energy and bandwidth availability. The dragonfly behavior is the movement and search oftheir food source. The dragonfly is considered as the number of sensor nodes in every cluster '$P = df_1, df_2, \ldots df_p$' and their food source is considered as themulti objective functions (i.e., received signal strength, residual energy and bandwidth availability). Multiobjective Meta heuristic Dragonfly Optimization in

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SCMMDO Method functioned with the population based approach termed as the swarm. An optimization initializes the population of 'h' number of drag on flies in the search space. It is formulated as,

$$P = df_1, df_2, \dots df_h \quad (7)$$

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

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

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

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

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. The four behaviors are used to find the global optimal solution among the population. Initially, the separation process identifies the current and neighboring position of dragonfly. It is given as,

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

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 number of neighboring dragonflies in the search space. The second one is alignment to the movement velocity of dragonflies. It is formulated as,

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

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.

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

From (12), 'δ_3'denotes the cohesion process of dragonfly. Finally, the attraction process towards food source is determined depending on the current position of food source and the position of the dragonfly. It is given as,

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

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,

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

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,

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

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'. Depending on the updated results, the global best solution is identified. By this way, cluster head is selected in SCMMDO Method for every cluster. The flowchart of dragonfly optimization is given in below diagram.

Table 2. Simulation Parameters

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

The performance of proposed SCMMDO Methodis determined using four parameters, namely

- Energy consumption
- Clustering Accuracy

IV. RESULTS AND 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. The performance of proposed method and existing methods is evaluated with help of table and graphs.

4.1 Impact of Energy Consumption

Energy consumption is defined as the amount of energy consumed to perform clustering process for efficient data transmission in WSN. It is the product of number of sensor nodes and amount of energy consumed by one sensor node to perform clustering process. It is formulated as,

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

From (16), 'EC' represent the energy consumption of sensor node. 'N' symbolizes the number of sensor nodes.

Table 3. Tabulation for Energy Consumption

Number of sensor nodes	Energy Consumption (J)		
	HQCA	TSBOA approach	Proposed SCMMDO Method
50	45	38	27
100	47	40	29
150	50	43	32
200	52	45	35
250	55	48	38
300	58	51	41
350	60	54	44
400	62	57	47
450	65	59	49
500	68	61	52

Table 2illustratessimulation results of energy consumption using three methods, namely proposed SCMMDO Method, existing high-quality clustering algorithm (HQCA) [1] and existing Tunicate Swarm Butterfly Optimization Algorithm (TSBOA) [2] approach with respect to number of sensor nodes. The energy consumptions determined based on the amount of energy consumed to perform cluster head selection. The ten simulation results illustrates that the energy consumption is considerably minimized when compared to existing techniques. Let us consider that number of sensor

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nodes is 200, the energy consumption by proposed SCMMDO Method is 35J whereas the energy consumption by existing HQCA [1] and existing TSBOA [2] approach is 52J and 45J respectively. The diagrammatic representation of energy consumption is given in figure 3.

Figure 2describes the flow diagram of Multiobjective Metaheuristic Dragonfly Optimization based Cluster Head Selection in SCMMDO Method. The dragonfly 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.

V. SIMULATION SETTINGS

The proposed SCMMDO Method replica is simulated 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 simulation parameters used for conducting the experimental process is illustrated in Table2.

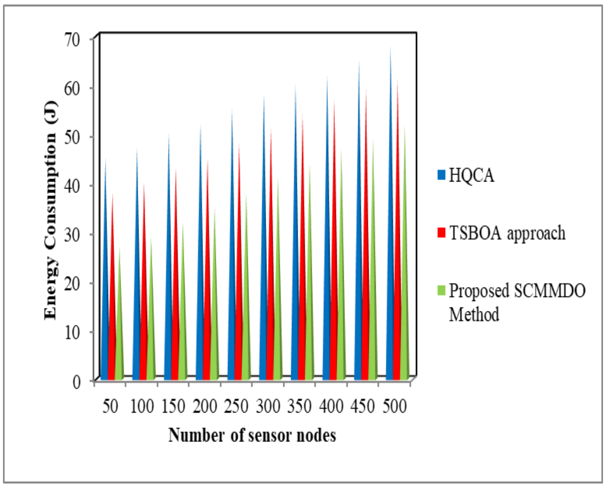

Figure 2. Measurement of Energy Consumption

Figure 3illustrates the simulation results of energy consumption ofdifferent number of sensor node varied from 50 to 500. From figure, the green color pyramid denotes the energy consumption of proposed SCMMDO Method whereas the blue color pyramid and red color pyramid denotes the energy consumption of existing HQCA [1] and existing TSBOA [2]. As described in the graphical results, the proposed SCMMDO Method reduces the energy consumption while transmitting the data packet through optimal cluster head selection. As described in the graphical results, the proposed SCMMDO Method reduces the energy consumption while transmitting the data packet through optimal cluster head selection. This is because of the application of soft c-means sensor node clustering and multi objective met heuristic dragonfly optimization for optimal cluster head section in WSN. Soft c-means sensor node clustering process groups the sensor node to form the cluster based on the residual energy, bandwidth and received signal strength. After that, cluster head is selected for every cluster. Through optimal cluster head, efficient data transmission is carried out in WSN. This helps to reduce the energy consumption in WSN. Therefore, the energy consumption of proposed SCMMDO Method is reduced by 31% and 21% when compared to existing HQCA [1] and existing TSBOA [2] respectively.

5.1 Impact on Clustering Accuracy

Clustering accuracy is defined as the ratio of number of sensor nodes that are correctly clustered to the total number of sensor nodes. It is measured in terms of percentage (%). It is formulated as,

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

From (17), 'CA' symbolizes the clustering accuracy. 'N' symbolizes the number of sensor nodes.

Table 4. Tabulation for Clustering Accuracy

Number of sensor nodes	Clustering Accuracy (%)		
	HQCA	TSBOA approach	Proposed SCMMDO Method
50	78	84	90
100	88	91	95
150	85	90	95
200	90	91	97
250	80	86	96
300	90	87	96
350	86	89	95
400	88	91	94
450	89	91	94
500	90	92	96

Table 3illustratessimulation results of clustering accuracy using three methods, namely proposed SCMMDO Method, existing high-quality clustering algorithm (HQCA) [1] and existing Tunicate Swarm Butterfly Optimization Algorithm (TSBOA) [2] approach with respect to number of sensor nodes. The clustering accuracy is determined based on the number of correctly clustered sensor nodes in WSN. The ten simulation results illustrates that the clustering accuracy is considerably increased when compared to existing techniques. Let us consider that number of sensor nodes is 400, the clustering accuracy by proposed SCMMDO Method is 94% whereas the clustering accuracy by existing HQCA [1] and existing TSBOA [2] approach is 88% and 91% respectively. The diagrammatic representation of clustering accuracy is given in figure 4.

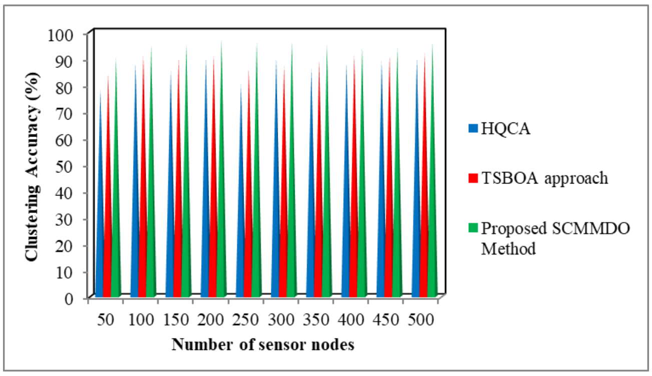

Figure 3. Measurement of Clustering Accuracy

Figure 4illustrates the simulation results of clustering accuracy ofdifferent number of sensor node varied from 50 to 500. From figure, the green color pyramid denotes the clustering accuracy of proposed SCMMDO Method where as the blue color pyramid and red color pyramid denotes the clustering accuracy of existing HQCA [1] and existing TSBOA [2]. As illustrated in the graphical results, the proposed SCMMDO Method increases the clustering accuracy while grouping the sensor nodes in WSN. This is due to theapplication of soft c-means sensor node clustering in proposed SCMMDO Method. Soft c-means sensor node clustering process groups the sensor node to form the cluster based on the residual energy, bandwidth and received signal strength. This helps to increase the clustering accuracy in WSN. Therefore, the clustering accuracy of proposed SCMMDO Method is increased by 10% and 6% when compared to existing HQCA [1] and existing TSBOA [2] respectively.

VI. CONCLUSION

An efficient SCMMDO Method is developed for efficient data transmission through optimal cluster head selection with minimum processing time in WSN environment. The distributed sensor nodes are grouped into the different clusters using soft c-means clustering. The clustering based data transmission minimizes the energy consumption and increases clustering accuracy. After that, the cluster head is chosen by using multi objective met heuristic dragonfly optimization for every cluster and manages all sensor nodes within the cluster. Simulation of proposed SCMMDO Method is carried out with three different performance metrics such as energy consumption, clustering accuracy. The observed result shows that the proposed SCMMDO Method increases the clustering accuracy by 8% and minimizes the energy consumption by 26% than the existing HQCA [1] and existing TSBOA [2].

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