SOFT C USING MULTI OBJECTIVE METAHEURISTIC DRAGONFLY OPTIMIZATION FOR CLUSTER HEAD SELECTION IN WIRELESS SENSOR NETWORKS

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ABSTRACT

With development of low-power electronic devices, wireless communication capabilities are the leading areas in wireless sensor networks (WSNs).Many researchers carried out their research on cluster head selection in WSN. But the clustering accuracy was not improved and processing time was not reduced during cluster head selection. In order to overcome the existing problems, Soft CMultiobjectiveMetaheuristic Dragonfly Optimization (SCMMDO) Method is introduced. The main objective of this Method is to select the optimal cluster head for efficient data transmission in WSN.SCMMDOMethod performed two processes, namely clustering and optimization for data transmission in WSN. Simulation is carried out with different metrics such as energy consumption, clustering accuracy and processing time. The observed resultshows that the SCMMDOMethodeffectively increases theclustering accuracy and minimizes the energy consumption as well as processing time than the state-of-the art methods.

Keywords: electronic devices, wireless sensor networks, sensor nodes, Soft C clustering, multiobjective meta-heuristic dragonfly optimization, cluster head, source node

1. INTRODUCTION

Clustering is an essential one used for increasing the network lifetime in WSNs. It includes the grouping of sensor nodes into clusters and choosing the Cluster Head (CH) for all clusters. CH gathers the data from nodes and transmits aggregated 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 [11] for choosing the CH to perform data transmission between sensor nodes. But the clustering accuracy was not improved by TSBOA. For efficient cluster head selection in wireless sensor network, Diversity - Driven Multi-Parent Evolutionary Algorithm with Adaptive Non-Uniform Mutation was used [15]. The residual energy of sensor node and distance was optimized to reduce the fitness function. However, computational complexity was not reduced by designed algorithm. An innovative approach was introduced in [13] for selecting the cluster heads. The target of cluster head was based on the node distance and node energy. The cluster head selection minimized the energy utilization and increased the networklifetime through shortest path relay node concept. But the network lifetime was not improved by designed approach.

The Genetic Algorithm based Optimized Clustering (GAOC) protocol was created to allow for better CH selection by combining residual energy, distance, and node density. To address the Hot-Spot problem, multiple data sinks based GAOC (MS-GAOC) was introduced [6]. 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 [14] for choosing the cluster head within cluster for data recovery. CHSRDR considered the heterogeneity in power and preserved the cluster of vice-head on randomness inside the cluster. However, the computational overhead was not minimized by CHSRDR method. A new clustering algorithm was introduced in [18] for WSNs to minimize the energy consumption and increase the lifetime of WSNs. But, the processing time was not reduced by clustering algorithm. A genetic algorithm-based cluster head selection was introduced in [17] for centralized clustering algorithms with load balanced network. The designed algorithmidentifiedthe optimal cluster head and increased network lifetime. Though network lifetime was improved, the clustering accuracy was not improved by genetic algorithm. An energy efficient technique was introduced in [2] to reduce the attacks on improving cluster head selection mechanism. The honest nodes were determined to commend as cluster head during packets transmission phase. But the delay was not reduced by energy efficient technique. A hybrid Sparrow Search Algorithm with Differential Evolution algorithm was introduced in [12] to address the energy efficiency problem by cluster head selection in WSN. The designed algorithm employed high-level search efficiency with higher node lifetime. But, the processing time was not minimized by Hybrid Sparrow Search Algorithm.

2. RELATED WORKS

WSN are leading area of research for different applications. Firefly algorithm was introduced in [7] for increasing energy efficiency of network and node lifetime throughchoosing the optimal cluster head. Though the energy efficiency was improved, the delay was not minimized by Firefly algorithm. Firefly Algorithm (FA) and hesitant fuzzy was introduced in [16]with CH selection protocol. The designed protocol employed sensor node parameters to determine the score of each node for best CH selection. However, the energy efficiency was not improved by FA. Particle Swarm Optimization (PSO) approach was introduced in [10] for generating energy-aware clusters through optimal cluster head selection. PSO minimized optimal position cost for head nodes in cluster. But, the computational cost was not reduced by PSO approach. A multi-criteria decision-making method was introduced in [4] for choosing the CH based on residual energy, neighbors, distance below base station and transmission range for every node. But, the energy efficiency was not at required level by designed method.

For cluster head selection, the area double cluster head APTEEN routing protocol-based particle swarm optimization (DCA-PSO) was introduced [5]. DCA-PSO employed classification adaptive change inertia weight for optimization process. But, the optimal cluster head selection was not carried out by DCA-PSO.A centralised cluster head selection and distributed cluster formation scheme was introduced in [9] with fuzzy methods. The fuzzy was employed by sink to identify the cluster centerand associatedmember nodes. But, the clustering time was not reduced by designed scheme. A power-aware routing protocol was introduced in [3] for WSNdepending on threshold rate and fuzzy logic for increasing the energy efficiency. The cluster heads were chosen based on probability values of every node in WSN calculated from residual energy of every node. But, the clustering accuracy was not improved by power-aware routing protocol. A fuzzy-based energy-efficient cluster head selection algorithm was designed in [8] to increase the network lifetime. K-means algorithm was employed to form cluster and cluster head was selectioncarried out with fuzzy logic system

3. METHODLOGY

WSN is a self-configured wirelessnetwork to examine the environmental conditions. 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 the source node and transmitted to the base station through CH. But efficient clustering is not carried out by existing techniques for CH selection. Therefore, SCMMDO method is introduced for choosing optimal cluster head in WSN. The main objective ofSCMMDO method is to select the cluster head in wireless sensor networks. The brief description of SCMMDO is carried out in below sub-section.

3.1 Soft C using Sensor Node Clustering Clustering is the method of grouping the collection of similar objects into cluster. Soft c-is the process allocating data points based on probability score belong to cluster. During sensor node grouping, SCMMDO initializes the 'm' number of clusters '$Clu_1, Clu_2, Clu_3, \dots Clu_m$'and their cluster centroid '$cc_1, cc_2, cc_3, \dots cc_m$' in random manner. The soft c sensor node clustering process is carried out throughallocating 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 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, $RSS = 10\ \log_{10}\left(\frac{Transmitted\ signal\ power}{Received\ signal\ power}\right)$(1)

From eqn.1, 'RSS'denotes the received signal strength. The signal strength is determined in decibel (dB). The bandwidth availability between cluster head is determineddepending on difference between the total bandwidth and consumed bandwidth. It is given as, eqn. 2

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

'$Bw_{avlailability}$'represent the bandwidth availability.'Bw_{total}' represent the total bandwidth.'$Bw_{consumedbandwidth}$'symbolizes consumed bandwidth. After that, the residual energy of sensor node is 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, eqn. 3

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

(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 eqn. 4, 'Mf_{ij}'symbolizes the 'd_{ij}' denotes theparameter 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 Methoddetermines 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 eqn. 5

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

'Mf_{ij}' is amembership degree. The distance between the sensor node and cluster centroid is computed as eqn. 6,

$d_{ij} = (\sum_{i=1}^{z}(|(SN_i - cluster\ centroid)|)^q)^{1/q}$(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 thesensor node and cluster centroid is suitable to group sensor node to that cluster.

It describes the step by step process of soft c 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.

3.2 Multiobjective Metaheuristic 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 movement of dragonflies and their search for food is their behaviour. Every cluster's dragonfly represents the number of sensor nodes. '$P = df_1, df_2, \dots df_p$' and their food source is considered as themultiobjective functions(i.e., received signal strength, residual energy and bandwidth availability). Multiobjective Metaheuristic Dragonfly Optimization in (MMDO) Methodfunctioned 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,

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

Once initialization process was completed, the fitness value is determined for every dragonfly in current swarm population. Depending on the estimation, the fitness value is determined as, $FitnessFunction = (Energy_{Residual} Energy_{threshold} \&\& (RSS > RSS_{th})$(8)

From eqn. 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 the analysis, the fitness function is computed as given below in eqn. 9.

$FitnessFunction = argmax\{RSS, Bw_{availability}, Energy_{Residual}\}$(9)

'$argma$'represents the maximum function argument. In search space, four swarming behaviours of dragonflies are determined based on the fitness measure. To identify the global optimal solution among population, the four behaviours are separation, alignment, cohesiveness, and attraction towards food supply. Initially, the separation method is used to determine the dragonfly's current and nearby positions. It is given as,

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

From eqn. 10, 'δ_1' denotes the separation of dragonflies, '$P_{a(t)}$'represents the dragonfly's current location. The position of nearby dragonflies is represented by $P_{b(t)}$. The letter 'h' stands for the number of nearby dragonflies in the search space. The second process is alignment, which refers to the speed with which dragonflies migrate towards their neighbours. It is formulated as,

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

From eqn.11, 'δ_2' denotes the alignment. '$\tau_j(t)$'symbolize the speed of dragonflies in close proximity finally, the cohesion process is used to determine the dragonfly's tendency to fly to the centre of the neighborhood's mass.

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

From eqn.12, 'δ_3'denotes the cohesion process of dragonfly. Finally, the dragonfly's attraction to the food source is governed by the current position of the food source and the dragonfly's position. It is given as eqn. 13

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

'δ_4'Symbolizes the attraction towards the food source.'P_f'represent the position of food source. The current dragonfly's location is updated with their surroundings.

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

From eqn. 14, '$P_{a(t+1)}$'denotes the current position of the dragonfly'$P_{a(t)}$' is symbolized by the updated position of the dragonfly. '$\nabla P_{a(t+1)}$'symbolizes the step vector to identify themovement direction of dragonfly. It is given aseqn. 15

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

(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 The position of the dragonfly at time ‘t’ reflects the convergence behaviour of optimization$P_{(t)}$. The global best solution is determined based on the updated results. By this way, Every cluster's cluster head is chosen using the SCMMDO Method. The flowchart of dragonfly optimization is given in below diagram.

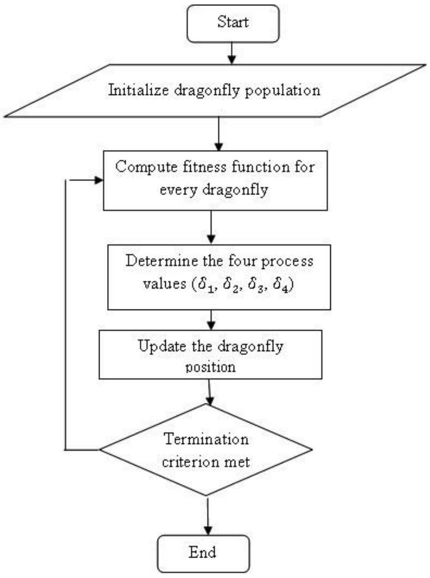

Figure 1 Flow diagram of Multiobjective Metaheuristic Dragonfly Optimization based Cluster Head Selection.

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 formulated as eqn. 16.

$EC = N * Energy\ consumed\ by\ one\ sensor\ node$ (16), ‘EC’ represent the energy consumption of sensor node. ‘N’ symbolizes the number of sensor nodes.

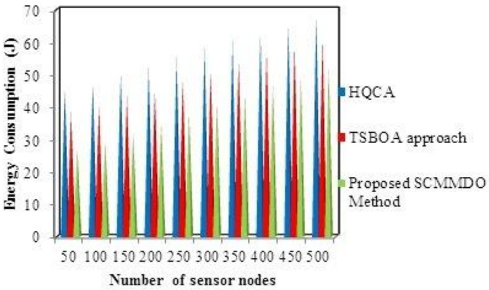

Figure 2 Measurement of Energy Consumption

Figure 2illustrates the simulation results of energy consumption of different 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 and existing TSBOA. 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.

5.2 Impact on Clustering Accuracy

Clustering accuracy is defined as the proportion of successfully grouped sensor nodes to the total number of sensor nodes. It is measured in terms of percentage (%). It is formulated as,

$$CA = \frac{Numberofsensornodesthatarecorrectlyclustered}{N} \quad (17)$$

From eqn. 17, ‘CA’ symbolizes the clustering accuracy. ‘N’ symbolizes the number of sensor nodes.

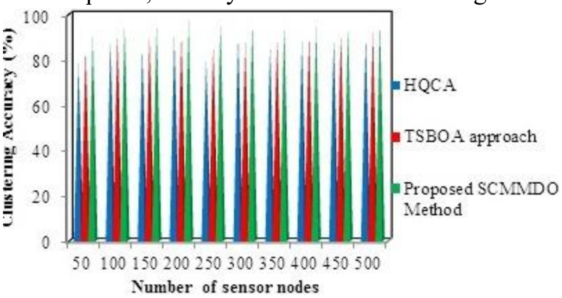

Figure 3 Measurement of Clustering Accuracy

Figure 3 illustrates the simulation results of clustering accuracy of different number of sensor node varied from 50 to 500. The green color pyramid denotes the clustering accuracy of proposed SCMMDO Method whereas the blue and red color pyramid denotes the clustering accuracy of existing HQCA and TSBOA. As illustrated in results, the proposed SCMMDO Method increases the clustering accuracy while grouping the sensor nodes in WSN by using soft c-using residual energy, bandwidth, and received signal strength, the sensor node clustering procedure groups the sensor nodes to form the cluster. 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.

6. CONCLUSION

An efficient SCMMDO Method is developed for efficient data transmission through optimal cluster head selection with minimum processing time in WSN environment. The scattered sensor nodes are grouped into the diverse clusters using soft c clustering. The clustering based data transmission minimizes the energy consumption and increases clustering accuracy. After that, the cluster head ischosen by using multiobjective metaheuristic dragonfly optimizationfor every cluster and manages all sensor nodes within the cluster. This process reduces the processing time. Simulation of proposed SCMMDO methodis carried out with three different performance metrics such as energy consumption, clustering accuracy and processing time. The observed resultshows that the proposed SCMMDOMethodincreases theclustering accuracy by 8% and minimizes the energy consumption by 26% as well as processing timeby 28% than the existing HQCA [1] and existing TSBOA [2].

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