



Clustering Optimization using Fuzzy C-Mean Clustering and Artificial Bee Colony Algorithm for Wireless Sensor Network

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Article History

Volume 6, Issue 9, 2024

Received: 17 Apr 2024

Accepted: 06 May 2024

doi: 10.33472/AFJBS.6.9.2024.3383-3390

Abstract

The Wireless Sensor Network (WSN) plays an important role in various industrial automation, commercial, robotics, environmental monitoring, landslide detection, earthquake detection, transport and logistics, habitat monitoring, etc. WSN clustering provides efficient way to improve the network lifetime, throughput, scalability and packet delivery ratio. However, performance of the WSN network is limited due to low power battery operated sensor node and improper positioning of the cluster heads during cluster formation. This paper presents Fuzzy C-mean algorithm (FCM) for WSN clustering and Artificial Bee Colony Algorithm for selection of optimal cluster heads. The proposed algorithm provides optimized cluster selection that provides better network lifetime and throughput.

Keywords: Artificial Bee Colony Algorithm, Data Aggregation, Fuzzy C-Mean Clustering, Wireless Sensor Network.

1 Introduction

Wireless sensor network (WSN) is widely used in many industrial, commercial and social application because of vast of Internet of Things (IoT). WSN is group of homogeneous or heterogeneous sensor nodes distributed over the plane. It consists of sensor node, processing unit, memory, transmitter, receiver and battery. The lifetime of the network is usually lower because of use of low power battery. WSN distributed over larger area needs clustering of sensor nodes in group to provide efficient routing and data aggregation. Selection of cluster head (CH) is crucial because it accepts the data from sensor nodes and transmits it towards base station. Many times the CH is selected based on its position in the cluster and often chances are given to centrally located node irrespective of its energy, load balancing capacity, connectivity, and distance from the base station [1][2].

Various clustering techniques have been presented in past for the WSN data aggregation and routing. Janaki Raam et al. [3] have presented the paper on a parallel ant colony optimization algorithm and k-means clustering algorithm for grouping the sensor nodes to detect the optimal path in the WSN routing. It proved a longer life span of the network and an efficient routing algorithm. Liu et al. [4] have proposed an unsupervised clustering problem based on ant colony optimization algorithm. They have used ant colony optimization with stochastic best solution kept-ESacc. Gupta et al. [5] proposed a modified version of the ACO base LEACH clustering algorithm for effective CH selection. In their work, data transmission took place in three phases from the sensor node to CH, from CH to cluster leader and from cluster leader to BS. It resulted in an improvement in average energy consumption. They have not considered data redundancy which affects the data aggregation. Aadil et al. [6] have proposed CACONET (Clustering based ACO for VANETs) for the clustering. They have performed extensive experimentation by varying the size of the network, sensor nodes in the network, coverage area of the network, sensor node transmission range, speed and direction of VANETs node. The performance of CACONET algorithm has been compared with the multi objective particle swarm algorithm (MOPSO) and clustering algorithm based ACO (CLACO) and the proposed algorithm outperformed these algorithms. Yang et al. [7] presented the ant colony optimization algorithm along with dynamic clustering based multipath routing protocol (MRP) for the burst event monitoring in the reactive WSN to maximize the sensor network lifetime and to minimize the energy consumption. In the MRP algorithm, CHs were selected based on residual energy and multiple paths between the sensor node and CH have been selected using ACO. It resulted in efficient data aggregation, better load balancing, maximizes the sensor network lifetime and lowers energy consumption in the WSN. The authors found the parameter setting for the algorithm challenging and slower speech due to parameter tuning.

This paper presents WSN clustering using Fuzzy C-Mean (FCM) algorithm for the clustering of the sensor nodes. Further, a biologically inspired artificial bee colony algorithm is used for the selection of optimal cluster head (CH) based on its connectivity, distance from base station, residual energy and position in cluster. The performance of the proposed algorithm is estimated based on network throughput, lifetime and packet delivery ratio.

Rest of the paper is systematized as follow: Section II provides detailed information about proposed clustering and CH selection strategy. Section III focuses on simulation results and discussions on results. Further, section IV gives concise conclusion and future scope.

2 Proposed Methodology

The proposed methodology consists of four chief phases such as initialization phase, clustering phase, cluster selection phase and data aggregation phase. The initialization phase consists of the network parameter initialization such as simulation area, number of sensor nodes, base station position, sensor node energy and locations. It also consists of initialization of the radio model parameters such as number of bits in the transmission frame, energy required for transmission and reception of single bit, amplification factor, traffic pattern, MAC protocol, etc.

In the clustering phase, fuzzy C-mean clustering algorithm is used to form the cluster of sensor nodes having same initial energy based on position of sensor node in simulation area. Fuzzy c-means (FCM) is a data clustering technique in which a dataset is grouped into n clusters with every sensor node in the network belonging to every cluster to a certain degree. For example, a certain node that lies close to the center of a cluster will have a high degree of belonging or membership to that cluster and another node that lies far away from the center of a cluster will have a low degree of belonging or membership to that cluster [8][9].

$X = \{x_1, x_2, x_3 \dots, x_n\}$ be the set of sensor nodes and $V = \{v_1, v_2, v_3 \dots, v_c\}$ be the set of centers of clusters.

Step 1: Randomly select 'c' cluster centers.

Step 2: Calculate the fuzzy membership u_{ij} using

$$\mu_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{d_{ij}^2}{d_{ik}^2} \right)^{\frac{2}{m-1}}} \quad (1)$$

Step 3: Compute the fuzzy centers 'v_j' using ;

$$V_j = \frac{\left(\sum_{i=1}^n (\mu_{ij})^m x_i \right)}{\left(\sum_{i=1}^n (\mu_{ij})^m \right)}, \forall j = 1, 2, \dots, c \quad (2)$$

Step 4: Repeat step 2 and 3 until the minimum 'J' value is achieved or $\|U(k+1) - U(k)\| < \beta$.

where,

k is the iteration step.

β is the termination criterion between $[0, 1]$.

$U = (\mu_{ij})_{n \times c}$ is the fuzzy membership matrix.

J is the objective function.

Further, the CHs are selected using improved artificial bee colony algorithm. The improved ABC consider the network cluster head energy, cluster head density, cluster head location, Gini coefficients and other similar factors to improve the clustering and cluster head position. ABC is inspired by biological phenomenon and was proposed by Dervis Karaboga in 2005. It consists of three groups of bees: employed, onlookers and scouts [10][11].

- **Employed bees:** A bee going to the food source visited by itself
- **Onlooker bees:** A bee waiting on the dance area for making decision to choose a food source

– **Scout bees:** A bee carrying out random search

Number of employed bees is equal to the number of food sources around the hive. Employed bee whose food source has been exhausted becomes a scout bee. The phenomenon of ABC algorithm is described in Fig. 1.

The ABC generates a randomly distributed initial population of SN solutions (food sources).

Let

x be the initial population, where $i = 1, 2, 3 \dots, SN$

Where

– X_i : i^{th} food source in the population

– SN denotes the swarm size (food sources)

Onlooker bees chooses a food source depending on the probability

$$P_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \quad (3)$$

Here, fit_i fitness value of the solution i which is proportional to the nectar amount of the food source in the position i .

The fitness function for the selection of CH is designed as follow based on connectivity, distance from base station, residual energy and position in cluster (see equation 4). Here, d_{ik} is distance between CH and BS, C_i is connectivity of node (no of neighboring nodes connected to particular node), and RE represent residual energy. The weight factors w_1, w_2 and w_3 are selected as 0.2, 0.3 and 0.5 respectively.

$$fit_i = w_1 * \frac{1}{d_{ik}} + w_2 * C_i + w_3 * RE \quad (4)$$

It produces new solution (position) from the old one in memory (position update equation for j^{th} direction of i^{th} candidate) using equation 5.

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \quad (5)$$

Where

- $\phi_{ij}(x_{ij} - x_{kj})$ is called step size and ($i \neq k$)
- $k \in (1, 2, \dots, SN)$
- $j \in (1, 2, \dots, D)$
- ϕ_{ij} : random number within $[-1, 1]$

If a position cannot be improved over a predefined number (called *limit*) of cycles, then the food source x_i is abandoned.

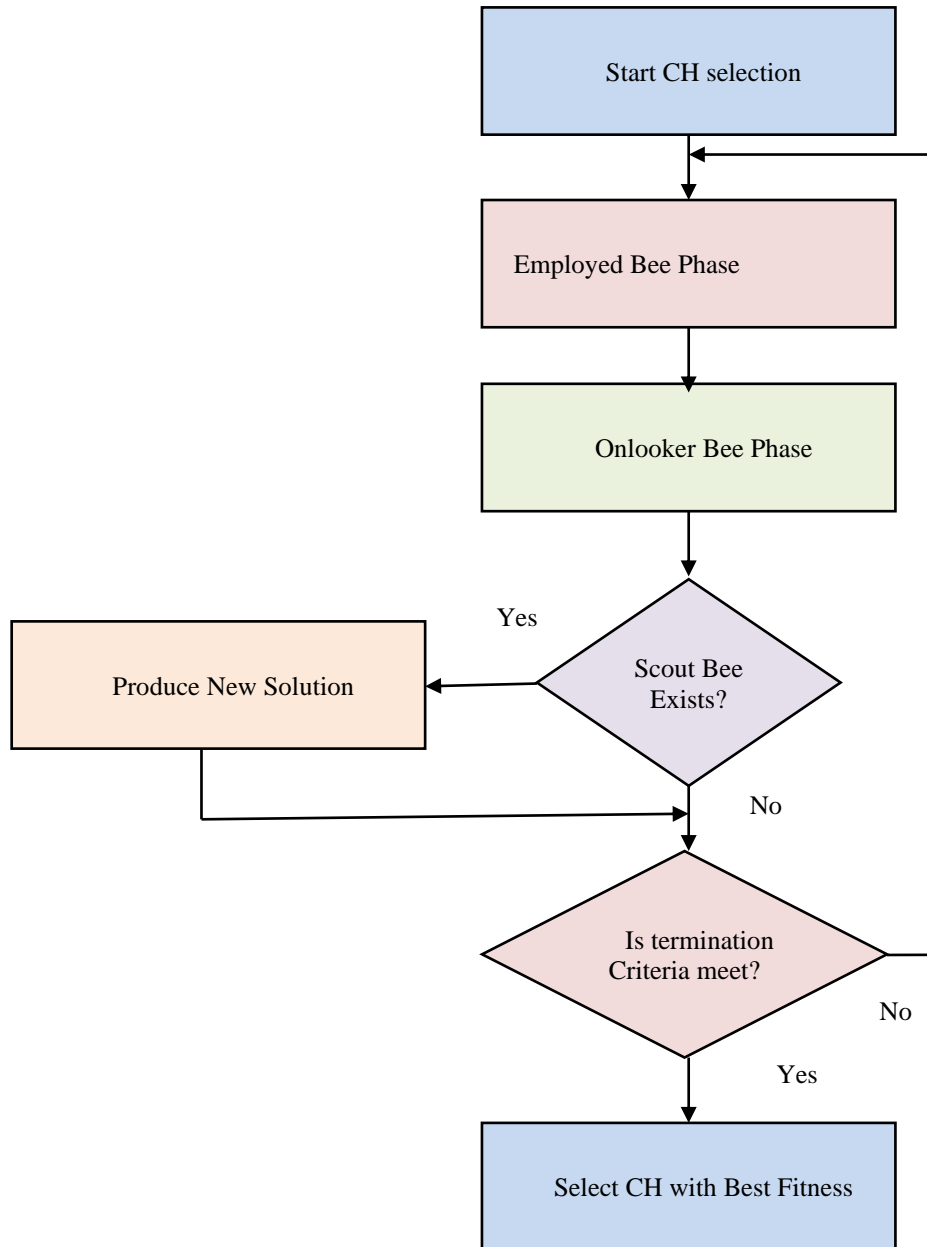


Fig. 1 Flowchart of proposed ABC Cluster Head selection algorithm

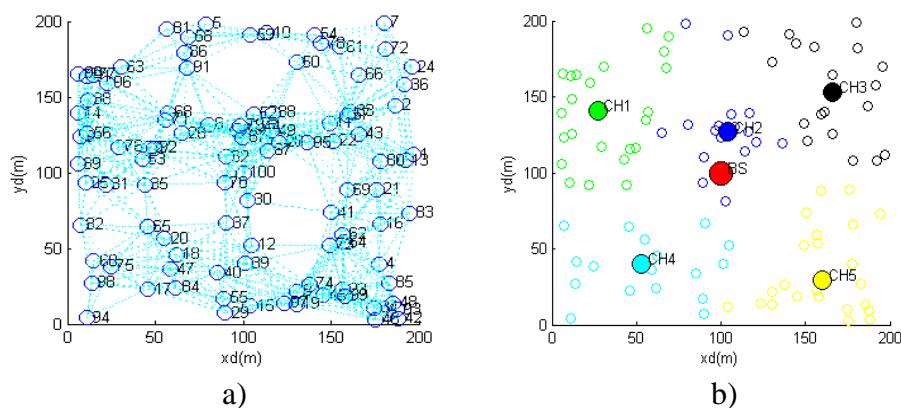
3 Simulation Results and Discussions

The proposed system is simulated using MATLABR2018b on windows environment using personal computer having 8 GB RAM and core i5 processor with 2.64GHz speed. The network parameters and its specifications are given in table 1.

Table 1: System and network parameters and specifications

System Parameter	Specification
Number of Nodes	50,100,200,300,...500
Node Position	Fixed and Mobile
Simulation area	1000m x 1000 m
Base Station Position	Fixed and Mobile
Initial energy (Eo)	2 J
Traffic Patterns	CBR (Constant Bit Rate)
MAC Protocol	802.11
Threshold Distance(do)	$\sqrt{\frac{E_{fs}}{E_{mps}}}$
Energy Dissipated per bit (Eelec)	50 nJ /bit
Transmission Power Dissipation (ETX)	50 nJ /bit
Receiver Power Dissipation (ERX)	50 nJ/bit
Amplification Factor for Free Space(Efs)	10pJ/bit/m ²
Amplification Factor for Multi Path (Emp)	0.0013pJ/bit/m ⁴
Message bits (K)	2000 bits

The results for the FCM and FCM-ABC for WSN clustering and CH selection are shown in Fig. 2.



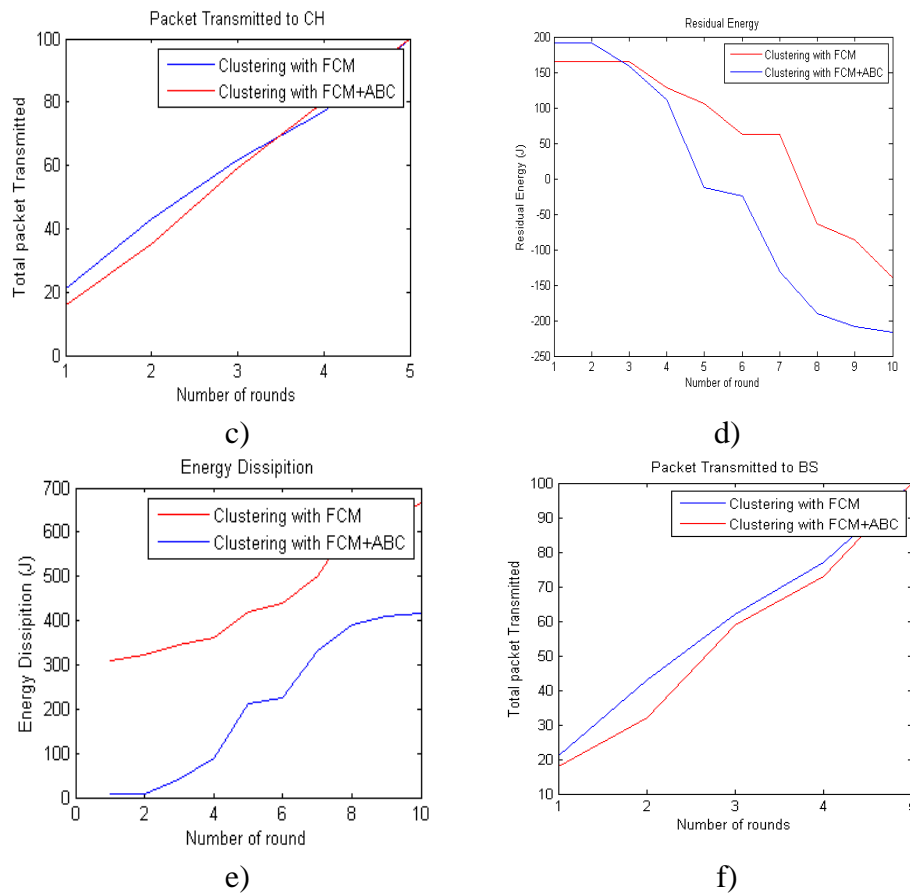


Fig. 2 a) Network scenario for $N=100$ b) Clustering and CH optimization using FCM-ABC c) Packet transmitted to CH d) Residual energy e) Energy dissipation f) Packet transmitted to BS

The experimental results show that optimal selection of CH improves the lifetime of the network and thus results in higher packet throughput towards CH and BS and higher residual energy. The variability in number of nodes shows that proposed algorithm can perform efficiently for dense network also.

4 Conclusions and Future Scope

Thus, this paper presents optimal clustering and cluster head selection using Fuzzy C-Mean and improved Artificial Bee Colony Optimization algorithm to tackle the problem of less energy efficiency and poor network lifetime of WSN. The cluster selection based on connectivity, distance from base station, residual energy and position in cluster. It has shown significant improvement over the centralized CH selection using FCM algorithm for various network density conditions and scalability conditions. The proposed algorithm is capable of giving better performance for real time scenarios because of its adaptability to the environment change. In future, the performance of the proposed system can be validated on real time mobility models of WSNs.

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