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On-demand fuzzy clustering and Ant-Colony optimisation based mobile data collection in wireless sensor network

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Abstract In a wireless sensor network (WSN), sensor nodes collect data from the environment and transfer this data to an end user through multi-hop communication. This results in high energy dissipation of the devices. Thus, balancing of energy consumption is a major concern in such kind of network. Appropriate cluster head (CH) selection may provide to be an efficient way to reduce the energy dissipation and prolonging the network lifetime in WSN. This paper has adopted the concept of fuzzy if-then rules to choose the cluster head based on certain fuzzy descriptors. To optimise the fuzzy membership functions, Particle Swarm Optimisation (PSO) has been used to improve their ranges. Moreover, recent study has confirmed that the introduction of a mobile collector in a network which collects data through short-range communications also aids in high energy conservation. In this work, the network is divided into clusters and a mobile collector starts from the static sink or base station and moves through each of these clusters and collect data from the chosen cluster heads in a single-hop fashion. Mobility based on Ant-Colony Optimisation (ACO) has already proven to be an efficient method which is utilised in this work. Additionally, instead of performing clustering in every round, CH is selected on demand. The performance of the proposed algorithm has been

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compared with some existing clustering algorithms. Simulation results show that the proposed protocol is more energy-efficient and provides better packet delivery ratio as compared to the existing protocols for data collection obtained through Matlab Simulations.

Keywords Clustering · Fuzzy logic · Particle Swarm Optimisation · Ant Colony Optimisation · Wireless Sensor Network

1 Introduction

In the last few decades, Wireless Sensor Networks (WSN) have gained huge popularity due to its capability of reliable monitoring in various application areas [16,9]. WSN consists of battery powered sensors which sense data from the environment and send this data to a base station or sink for further processing [55]

Now, the fact that the sensors are powered by low-cost irreplaceable batteries makes for an interesting area of designing new energy-efficient protocols [5]. Cluster-based protocols are one of these well accepted ideas as they can effectively organize the sensor nodes in the network [17,53]. In a clustering technique, one cluster head (CH) is selected from a cluster which serves as the leader of that cluster. Instead of sending the data directly to the base station, the sensors send the data to a CH. The CHs in turn transfer the data to a base station. Moreover, selecting the node with the least packet loss as a CH results in improved data delivery which is not fully exploited in the literature as yet.

Low Energy Adaptive Clustering Hierarchy (LEACH) [17] is one of the famous hierarchical routing protocols for homogeneous networks. As the nodes in LEACH are selected based only on probability value, the nodes with low energy may get chosen as a CH, thus degrading the performance of the network. So, a lot of new clustering protocols have been proposed to mitigate the shortcomings of LEACH.

Fuzzy logic [24,27,13,20] has been applied in many clustering protocols to overcome the deficiencies of LEACH. By appropriately selecting the fuzzy descriptors, the best candidates for becoming the CHs can be selected.

In most of the clustering protocols including those who have applied fuzzy logic, the CHs send data directly to a static base station [17]. This long range communication results in high energy dissipation of the CHs which in turn decreases the network lifetime. In [47], instead of directly sending the data to the sink, the authors have used a power-aware multi-hop routing to transfer the data to the static sink. But this may also not provide a very good result. Sink mobility [14,42] is another efficient solution which has been widely accepted to overcome this problem. E.g. in a firefighting system, an auto rescuer equipped with sensors can keep a lookout for survivors in a disaster area. In [30], Ma et.al introduced a mobile data collector in the network, called SenCar which works like a mobile base station and is either a mobile robot or a mobile vehicle equipped with a powerful transceiver and battery. This SenCar starts from the static data sink to traverse the entire network and then goes back to its initial starting point to transport the data to the static sink. The authors in [31] used a mobile data collector called an M-collector which works and behaves in a similar fashion as the SenCar. In the aforementioned works as the data is collected directly from a sensor node in a single-hop without any relays and collisions, the network lifetime is prolonged.

Now, finding an optimal trajectory for a mobile collector to shorten its tour length is an NP-Hard problem. In this work, ant-colony optimization (ACO) [50] technique has been implemented to provide a heuristic approach to find the optimal path between the CHs.

In ACO, the natural behavior of ants is simulated to solve several problems such as the Travelling Salesman Problem (TSP), Quadratic Assignment Problem and many such combinatorial optimization problems. The basic concept of ACO is based on the fact that the amount of accumulation of pheromones on a certain path is directly proportional to an ant choosing that particular path. Thus, after all the ants have built their individual tours, a global updating rule is applied to update the pheromone level on a particular edge. With the help of this mechanism, an ant can find the optimal path from its nest to a food source.

In this work, a fuzzy based clustering model along with ACO has been proposed to improve the performance of a sensor network in terms of energy consumption. The fuzzy based rules choose CHs based on certain predefined fuzzy descriptors. The nodes which have more number of neighbouring nodes, have a high node centrality and incurs less packet loss are selected as the final CH, thus resulting in good delivery ratio. Additionally, PSO is introduced to optimise the membership functions of the aforementioned parameters to achieve best reults in terms of CH selection resulting eventually in high network lifetime. The chosen CHs are then responsible for transferring the data to the mobile collector in a single-hop communication, thus saving energy.

PSO is an evolutionary algorithm used for the optimisation of continuous and multidimensional search spaces [23]. PSO has been used in [12] for optimisation of fuzzy logic controllers to improve the battery lifetime in Industrial Wireless Sensor Networks. In [38], the authors have used PSO and fuzzy clustering to determine the cluster heads. The initial clustering is based on fuzzy clustering according to their locations and the sensor nodes belong to a cluster with a specific probability. The energy consumption and the distance factors of a WSN are considered to design the fitness function. These works have shown the advantages of optimisation through PSO. To the best of our knowledge, there are no previous works which have used PSO to optimise node degree, node centrality and packet drop probability to find the cluster heads. Therein lies the novelty of this work.

The rest of the paper is organized as follows: Section 2 discusses the related works done so far in this area. Section 3 gives the problem formulation for the proposed model. The proposed algorithm is explained in details in Section 4. In Section 5 the experimental results are discussed. Finally, the work is concluded in Section 6.

2 Related Study

In this section, some relevant works on hierarchical clustering protocols are discussed. Some fuzzy logic based clustering protocols are also discussed here. Moreover, as mobile collector plays a major role in this work to combat high energy dissipation, the related study also focuses on different mobile element strategies. Some ACO based works are discussed to provide an insight on the application of ACO.

In LEACH [17], the CHs are selected in a probabilistic manner based on a threshold value which is calculated as:

$$T(n) = \begin{cases} \frac{p}{1-p(r mod \frac{1}{p})} & \text{if } n \in G \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where, r is the current round, p is the probability of a node to be a CH and G is the set of nodes which have not been selected to be a CH in the last $\frac{1}{p}$ rounds. While LEACH performs better than traditional routing protocols and it selects the CHs in a distributed manner but energy-distribution is not guaranteed in LEACH. Moreover, direct data transmission to a sink over a long distance results in high energy dissipation in LEACH. In contrast to LEACH, Threshold sensitive Energy-Efficient sensor Network protocol or TEEN [33] was designed such that the data is sent to the sink when a particular event occurs based on soft and hard thresholds. For soft threshold, the transmitter is just switched on in a node whereas for hard threshold the data is transmitted to the sink. An improved version of TEEN namely APTEEN [34] was proposed to incorporate both reactive and proactive data collection. Clustering communication based on number of neighbours (CCN) [43] was proposed in which consists of four phases that includes calculating the number of neighbours, Cluster head election, cluster formation and TDMA schedule determination. In CCN, the CHs are randomly selected and they adjust their transmission range based on the number of neighbours. In $(ACH)^2$ [4], the CHs get initially elected based on a threshold value. Furthermore, elected CHs whose residual energy is less than the average residual energy of the network get eliminated. For the final CH selection, one of the elected CH which is in the communication range of another elected CH gets selected. LEACH with Distance based threshold (LEACH-DT) was proposed in [22] which considers distances of the sensors from the sink to optimise the energy consumption. Hybrid Energy-Efficient Distributed Clustering (HEED) [53] selects CHs according to their residual energy and a secondary parameter which may be either proximity to its neighbours or node degree. It is an iterative approach and thus the overhead for CH selection is high. Kulia et.al [26] used a differential evolution approach to form clusters in the network in order to prolong the network lifetime. Cluster head election based on Bollinger Band has been proposed in [48]. In [18], an energy-efficient overlapping clustering protocol is proposed where the boundary nodes in the overlapping area are responsible to relay the aggregated data to the static sink. Prasad et.al [39] use hybrid differential evolution along with multi objective bee swarm optimisation for clustering. The CHs are selected based on communication energy, residual energy and energy constraint metric. Clustering based on spatial correlation was proposed in [32]. In this clustering approach, the spatial correlation between the sensed data was exploited to form clusters. In [46], the authors have selected the CHs based on chemical reaction optimisation technique. To ensure energy efficiency, the authors have used several parameters such as intra-cluster distance, sink distance and residual energy of the sensor nodes while selecting the CHs. In [25], the clustering technique is done in a hierarchical fashion where the CHs serve as the root. The distance to the CH decides the level of each member node in a cluster.

To improve upon the approach for CH selection, fuzzy approaches were introduced. Fuzzy parameters like local distance and energy are used by CHEF [24] to find the CHs. The efficiency of CHEF over LEACH is by about 22.7%. An improvement over CHEF is proposed by Lee et al. [27]. The work considers residual energy and expected residual energy as the two fuzzy parameters. In FAMACROW [13], the network is divided into many layers and in each layer the CHs get selected based on certain fuzzy descriptors like residual energy, neighbourhood proximity and link quality indicator between the nodes. In [7], the authors have proposed fuzzy energy-aware unequal clustering algorithm (EAUCF) where the network is clustered with unequal clustering to handle the hot-spot problem. They have used fuzzy logic to tackle the cluster head radius estimation. Izadi et al. [20] have proposed a fuzzy logic based self-configurable clustering mechanism for early detection of failure of CHs and replace them with other nodes. This results in prolongation of network lifetime. In Energy Aware Dynamic Clustering Protocol (ECPF) [47], the CH selection takes place sporadically. The nodes with high residual energy become the tentative CHs. The final CHs are selected based on fuzzy parameters like node degree and node centrality. Finally, the CHs send data to the base by multi-hop routing. In [35], a multi-clustering algorithm based on fuzzy logic has been proposed where energy is conserved by reducing the number of cluster head elections. In this work, the cluster-heads are selected based on the round number. Depending on the round number, the fuzzy parameter also changes.

Now, the choice of the membership functions has a great impact on the performance of the fuzzy system. Thus, the optimisation of these functions plays a significant role in improving the performance of the system. Particle Swarm Optimisation algorithm has been used in many works to optimise the parameters of the fuzzy logic controller. In [21, 1], the authors combined fuzzy c-means clustering and particle swarm optimisation to propose a fuzzy clustering algorithm. The authors in [45] used PSO to optimise the fuzzy logic controllers (FLC) to improve power point tracking. Voltage sag has been improved in [36] due to the application of PSO to FLC. FLC has been used in [40] to control a quad rotor. PSO has then used to optimise the membership functions of the FLC. Fuzzy models have been optimised through PSO in [8] for electromagnetic actuated clutch systems.

Recently, mobility of sensor networks has attracted a lot of research interests due to its ability to decrease the overall energy consumption of the network. Animals were used as mobile sinks by Shah et al. [42] to collect data from wild surroundings. Maximum Amount Shortest Path (MASP) [14] was proposed to improve the network lifetime by optimizing the assignment of sensor nodes. In mobile element scheduling (MES) problem [44], a mobile element visits each sensor nodes individually to collect data from them. Weighted rendezvous planning (WRP) [41] is proposed to find the near-optimal trajectory of a mobile sink. In [54], the mobile collector moves around the network and pauses at some anchor points such that it falls within the transmission range of all sensors and directly collects data from them. To balance energy consumption in the network, [49] employed a mobile collector in the network. Mobility has been used in this work to overcome communication bottlenecks caused by spatial energy variation. An obstacle avoidance routing protocol with a mobile sink was proposed by Chanak et al. [10]. In this work, the mobile sink finds the shortest path to collect data from the static sensors while avoiding the obstacles. In Mobile Collector Data Path Planning (MCPP) [15], many mobile collectors are employed to visit only certain sojourn points to collect data from the sensors in a single-hop.

There are many clustering protocols which use mobility. A cluster based (CB) [6] approach uses binary search to find the RPs. In this work, initially five random CHs get selected. The rest of the nodes join a CH based on the hop count. The mobile sink then visits these CHs. Mobile Sink based adaptive Immune Energy-Efficient clustering Protocol (MSIEEP) [3] uses Adaptive Immune Algorithm (AIA) to find the sojourn locations of the mobile sink and the optimum number of CHs. Wang et al. [51] proposed two mobile sink based clustering protocols namely, EMCA and MECA to improve the network lifetime. In [52], the authors have used Particle Swarm Optimisation Technique to form a cluster head chain and then used a mobile sink to traverse the cluster heads. Nayak et al. [37] use LEACH to find the CHs and then selects a Super Cluster Head (SCH) from them using fuzzy logic. This SCH is responsible for collecting the data from the CHs and then upload this data to a mobile base station. In [11], the authors change the position of the sink in every round to mitigate the hot-spot problem and choose the nodes which are at one-hop distance from the sink as the cluster heads. In [2], the network is divided into clusters called Service Zones from which the data gets collected by the mobile data collectors. This helps in achieving scalability and load balancing of the network. Bio-Inspired Ant Colony Optimisation based Clustering Algorithm (ACO-CA) [50] selects the initial CHs based on a variation of LEACH which considers residual energy in each round. If there is another CH in its transmission range, then the one with the higher residual energy gets selected as the final CH. The CHs then get visited by a mobile sink based on Ant-Colony Optimisation technique.

Different aspects of ACO based technique have been incorporated by many researchers. To avoid blindness in WSN, ACO has been used by Hunag et al. [19]. A group-based connection mechanism is designed in this work to avoid blindness and reduce deployment cost. Lee et al. [28] used ACO to solve the energy coverage problem. This work uses three kinds of pheromones as opposed to a single pheromone in conventional ACO. Ant-Colony-based scheduling algorithm (ACB-SA) [29] is used for solving efficient-energy coverage (EEC) problem. To improve the effectiveness of ACB-SA, a new initialization method for the pheromone field and a modified construction graph is applied. FAMACROW [13] uses ACO as an inter-cluster routing protocol after it has selected some CHs based on fuzzy logic.

3 Problem Formulation

In this work, a network is considered in a deployment area $M \times M$ which is covered by a set of N randomly deployed nodes. Each node in the network is battery powered and has a microcontroller and sensors for sensing aspects of the physical environment. The aim of this work is to cluster these nodes using fuzzy logic and then collect data from the cluster heads using a mobile collector.

3.1 Network Characteristics

Let the set of nodes in the network be represented by a graph where N is the total number of nodes and E is the set of all possible links between two neighboring nodes n_i and n_j. To evaluate the network energy consumption, the first order radio model is used in this work. Depending on the distance between the transmitter and the receiver, both free space and multipath fading models are used. The amount of energy required for the transmission of l bits of data for a distance d is given by [50]:

$$E_{TX}(l,d) = E_{TX\_elec}(l) + E_{TX\_amp}(l,d) \tag{2}$$

Equation (2) can be written as

$$E_{TX}(l,d) = \begin{cases} lE_{elec} + l\epsilon_{fs}d^2 & d < d_0 \\ lE_{elec} + l\epsilon_{mp}d^4 & d \geq d_0 \end{cases} \tag{3}$$

Here, E_{elec} is the dissipated energy to run the circuit of the radio model, ϵ_{fs} and ϵ_{mp} respectively denote the amplifier energy for free space and multipath conditions. If the distance between the transmitter and the receiver is less than the threshold d_0 (given by $d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}$), the free space model is used. Else, the multipath model is considered. To receive bits, the amount of energy consumed is:

$$E_{RX} = lE_{elec} \tag{4}$$

3.2 Assumptions

Before delving into details, some assumptions are made regarding the network:

- The nodes have the capability to use power control to change their transmit power [47].
- All the nodes are homogeneous with the same initial energy E_{init} and they remain static throughout [47].
- The mobile collector has no energy constraints [50].
- The mobile collector ideally starts its journey from the base station.
- The distance between a transmitter and a receiver can be computed by the received signal strength [37].
- During communication there is no obstacle between a transmitter and a receiver [50].
- Each sensor knows its location via GPS module or certain localization techniques [3].

4 Proposed Algorithm

The proposed algorithm is divided into two phases: Setup phase and Steady phase.

- In the setup phase, CH election and cluster formation takes place.
- In the steady state phase, each CH creates a TDMA schedule by assigning time slots to its member nodes to avoid intra-cluster collisions. The member nodes send data to the CH according to its assigned time slot [3]. The mobile collector then collects data from the CHs based on Ant-Colony Optimisation (ACO).

Now, Fuzzy Logic can be appropriately used to model decision making behaviour where a lot of factors are involved. Furthermore, Particle Swarm Optimisation (PSO) can be used to tune the parameters of the fuzzy logic controllers for better performance of the network. The proposed algorithm uses fuzzy descriptors and PSO to form clusters in the network and the movement of the mobile collector is determined using ACO to mitigate the hot-spot problem in a wireless sensor network.

4.1 On demand clustering

To reduce the overhead during setup phase, the proposed algorithm performs clustering only on demand and not in every round. To achieve this, each CH checks its residual energy ($E_{residual}$) with respect to its initial energy ($E_{initial}$) based on $E_{residual} < \gamma E_{initial}$, $(0 < \gamma < 1)$. If this condition is satisfied, then the CH sends a control packet to the static sink in multi-hop fashion [47]. The sink upon receiving this packet, inform all the nodes in the network to perform re-clustering. Once the nodes receive this information they prepare themselves to perform clustering.

4.2 Cluster Formation

The proposed method for clustering is based on an extension of LEACH's cluster head selection algorithm [17]. In this method the threshold is considered based on an additional condition of a node's residual energy which is given as:

$$T(n) = \begin{cases} \frac{p}{1-p(rmod\frac{1}{p})} \times \frac{E_{residual}}{E_{initial}} \times k_{opt} & \text{if } n \in G \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

During clustering phase each node generates a random number between 0 and 1. If the number is below the predefined threshold value $T(n)$, then that node is elected to be the candidate for the selection of a cluster head. Let the number of CHs getting elected in each round be $C_i(i = 1, 2, ..., N)$. Equation (5) ensures that the responsibility of being a cluster head gets rotated among all the nodes and the nodes with higher residual energy than other nodes are elected to be the cluster heads. But to improve the network performance other factors can be incorporated to influence the decision of the final CH selection. Thus, the nodes need to be embedded with a fuzzy system to meet the said requirement.

For the final cluster head selection, the elected nodes make autonomous decision using Fuzzy Inference System (FIS) with Mamdani model. The fuzzy descriptors used in this work include

- Node Degree (ND)
- Node Centrality (NC) and
- Packet Drop Probability (PDP)

The inputs to the system are defined as follows:

1. **Node Degree (ND)** : Node Degree of an elected CH can be calculated as:

$$ND = \frac{T}{N} \tag{6}$$

   Here, T is the total number of neighbours of an elected cluster head.
2. **Node Centrality (NC)** : Node Centrality denotes how central the elected CH is among the other elected CHs within the entire network. NC is calculated as:

$$NC = \frac{\sqrt{\frac{\sum_{j \in T} d^2(C_i, j)}{T}}}{M} \tag{7}$$

   Here, $d(C_i, j)$ is the distance between an elected CH and its neighbours.
3. **Packet Drop Probability (PDP)**: Packet Drop Probability characterises the transmission quality of a link between a node and an elected CH. The packet drop in a network is attributed to the presence of attenuation, interference, noise etc. To calculate the same, uniform random distribution [4,3] is used in this work. The packet drop probability is dependent on

the distance between a node m and an elected CH C_i ($d(C_i, m)$) which is given in equation (8). If the link probability is larger than PDP, then the packet is supposed to be successfully delivered, else it will be dropped.

$$PDP = \begin{cases} 0 & \text{if } 0 \leq d(C_i, m) < 10 \\ \frac{1}{70} \times (d(C_i, m) - 10) & \text{if } 10 \leq d(C_i, m) \leq tr \\ 1 & \text{if } d(C_i, m) > tr \end{cases} \tag{8}$$

Here, tr is the transmission radius of a node.

The proposed algorithm evaluates *chance* using fuzzy if-then rules which is described in Section 4.3. A higher value of *chance* entails an elected CH to be selected as the final CH. With the increase in the value of node degree and decrease in the values of both node centrality and packet drop probability, the *chance* value of an elected CH to become a final CH is increased.

Once the final CHs are selected, the rest of the elected CHs become ordinary nodes and join a CH based on received signal strength [50] provided that if there are k optimal number of clusters, then each cluster will have $\frac{N}{k}$ number of nodes.

4.3 Fuzzy Logic Model

The fuzzy model used in this work is given in Fig. 1. It consists of four steps which include: Fuzzification, Rule evaluation, Fuzzy inference engine and defuzzification [37].

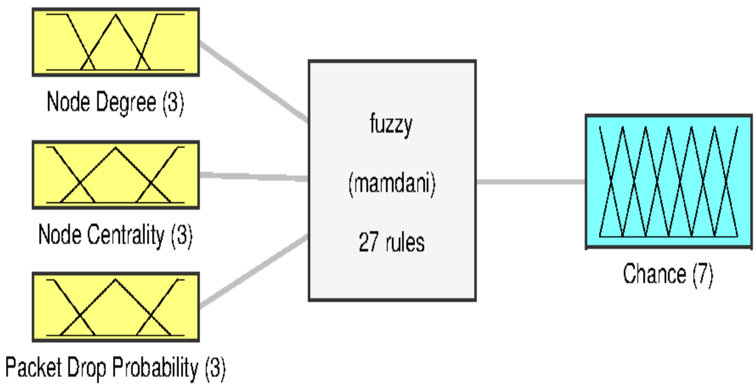
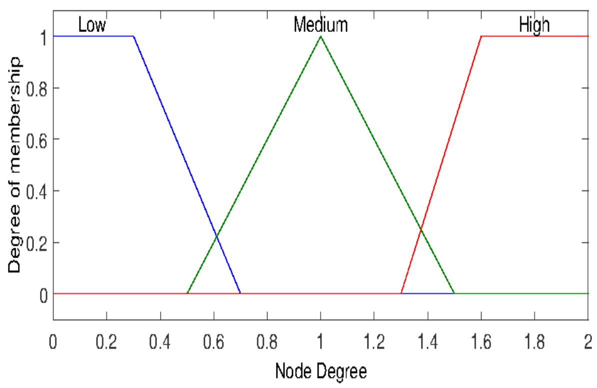
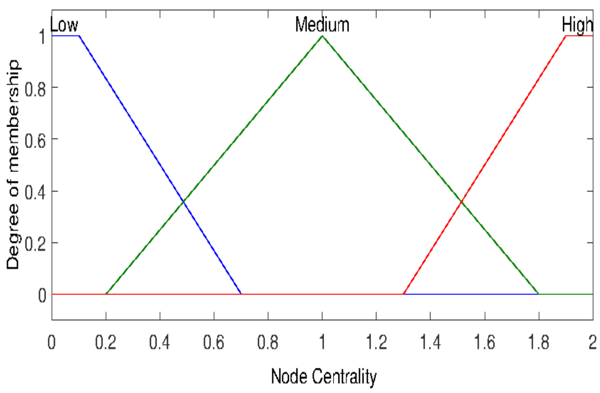


Fig. 1: Fuzzy model for the proposed work

In the proposed work, Mamdani fuzzy implication is used. As has already been discussed in Section 4.2, there are three fuzzy input variables taken for the final CH selection. For each of these three input variables, three linguistic variables have been considered. For all input variables, the linguistic variables are *low*, *medium* and *high* as shown in Figs. 2a, 2b and 2c. Trapezoidal membership functions are used to represent fuzzy input sets low and high whereas triangle function is used for medium input set. Fig. 2d shows the membership function plot for the output variable chance.

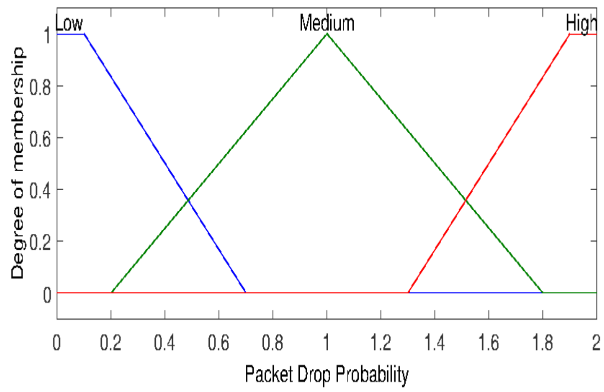


(a) Membership function plot for Node Degree

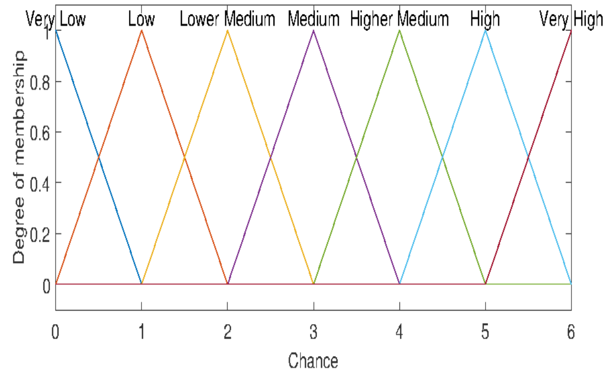


(b) Membership function plot for Node Centrality

Fig. 2: Parameters for Fuzzy Logic Controller



(c) Membership function plot for Packet Drop Probability



(d) Membership function plot for the output variable Chance

Fig. 2: Parameters for Fuzzy Logic Controller (contd...)

Table 1 gives the linguistic variables for each input variables.

ND	NC	PDP
Low	Low	Low
Medium	Medium	Medium
High	High	High

Table 1: Linguistic Variables

As there are three input variables and three linguistic variables for each of the three inputs, there are total $3^3 = 27$ rules to be considered for the selection of CHs. The linguistic variables that the output chance is composed of are: very low, low, lower medium, medium, higher medium, high and very high.

Table 2 depicts the fuzzy rules and the corresponding chance for the final CH selection.

Rule No.	ND	NC	PDP	Chance
1	Low	Low	Low	Higher Medium
2	Low	Low	Medium	Medium
3	Low	Low	High	Lower Medium
4	Low	Medium	Low	Medium
5	Low	Medium	Medium	Lower Medium
6	Low	Medium	High	Low
7	Low	High	Low	Lower Medium
8	Low	High	Medium	Low
9	Low	High	High	Very Low
10	Medium	Low	Low	High
11	Medium	Low	Medium	Higher Medium
12	Medium	Low	High	Medium
13	Medium	Medium	Low	Higher Medium
14	Medium	Medium	Medium	Medium
15	Medium	Medium	High	Lower Medium
16	Medium	High	Low	Medium
17	Medium	High	Medium	Lower Medium
18	Medium	High	High	Low
19	High	Low	Low	Very High
20	High	Low	Medium	High
21	High	Low	High	Higher Medium
22	High	Medium	Low	High
23	High	Medium	Medium	Higher Medium
24	High	Medium	High	Medium
25	High	High	Low	Higher Medium
26	High	High	Medium	Medium
27	High	High	High	Lower Medium

Table 2: Linguistic Variables

The time complexity of Mamdani Inference technique is $O(N_r+N_{id})$ where N_r is the number of rules and N_{id} is the input dimension.

Now, the ranges for the membership functions for each of the fuzzy inputs and output have been chosen randomly. This may not always provide the satisfactory results. To this end, particle swarm optimisation (PSO) can be used to manage the membership functions. The next subsection illustrates PSO in details along with the method to optimise the fuzzy functions using PSO.

4.4 Particle Swarm Optimisation

PSO is one of the most popular nature-inspired stochastic optimisation model which provides solutions to multi-variable objective functions.. In PSO, a swarm of particles moves in a search space to solve a problem over a population of candidate solutions. The performance of the particle is based on its position. Initially the position of each particle is generated randomly and in each iteration the position is updated based on its personal best position and the overall best positions of the other particles. Thus, the position and velocity of each particle in a single swarm of size S and dimension D can be updated as:

$$\overrightarrow{V}_{i,j}^{k+1} = w\overrightarrow{V}_{i,j}^{k} + c_1 r_1(\overrightarrow{P}_{i,j}^{k} - \overrightarrow{X}_{i,j}^{k}) + c_2 r_2(\overrightarrow{G}_{j}^{k} - \overrightarrow{X}_{i,j}^{k}) \tag{9}$$

$$\overrightarrow{X}_{i,j}^{k+1} = \overrightarrow{X}_{i,j}^{k} + \overrightarrow{V}_{i,j}^{k+1} \tag{10}$$

where $1 \leq i \leq S$ and $1 \leq j \leq D$. $\overrightarrow{X}_{i,j}^{k}$ and $\overrightarrow{V}_{i,j}^{k}$ represent respectively the position and the velocity vector of the i^{th} at the k^{th} iteration. $\overrightarrow{P}_{i,j}^{k}$ represents the personal best j^{th} component of the i_{th} particle and $\overrightarrow{G}_{j}^{k}$ is the j^{th} component of the best particle of the population in iteration k. r_1 and r_2 are two random numbers which take the values between 0 and 1. w is the inertia factor which varies between $[w_{min}, w_{max}]$ and c_1 and c_2 are the cognitive coefficients. PSO is explained in Algorithm 1.

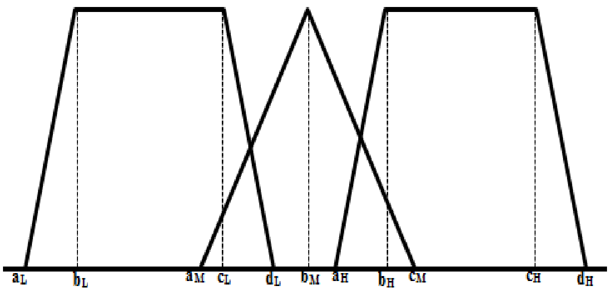
Algorithm 1: Particle Swarm Optimisation

Input : w_{min}, w_{max}, c_1, c_2, $maxite$
Output: Optimum solution of the objective function

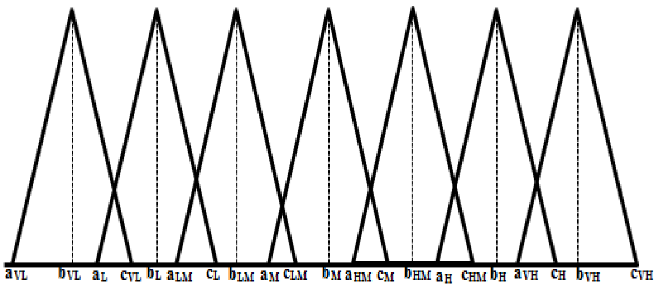
begin
  for *each particle* **do**
    Initialise population with positions $\overrightarrow{X}$ and velocities $\overrightarrow{V}$
    Calculate fitness of the particles
    Find the global best position
  end
  while $k < maxite$ **do**
    Set $w = w_{max} - \frac{k(w_{max} - w_{min})}{maxite}$
    Update velocity and position of each particle
    Calculate fitness of the particles
    Find the global best position
  end
end

The initial population is taken randomly and the initial velocity is set as $\overrightarrow{V}_{i,j}^{k} = 0.1 \times \overrightarrow{X}_{i,j}^{k}$. *maxite* gives the maximum number of iterations which is the termination condition for the PSO algorithm.

To use PSO for the optimisation of the membership functions is equivalent to the optimisation of each parameter of the membership functions. The representation of the variables is for the input and output are given in Fig. 3a and Fig. 3b respectively.



(a) Representation of input variables



(b) Representation of output variables

Fig. 3: Representation of input and output variables

For the simplicity of implementation, the parameters a_L, b_M and c_H for each input are fixed. The parameters a_{VL}, b_M and c_{VH} are fixed for the output. Thus apart from these fixed parameters, there are other forty two parameters that need to be optimised which is the input to the PSO algorithm (N_{ip}). Now, to optimise these parameters some criteria need to be fulfilled. For the input and the output parameters, the criteria can be specified as follows:

Input Parameters	***Output Parameters***	(11)
1. $a_L < b_L < c_L < d_L$	a. $a_{VL} < b_{VL} < a_L < c_{VL}$	
2. $b_L < a_M < c_L < d_L < b_M$	b. $c_{VL} < b_L < a_{LM} < c_L$	
3. $b_M < a_H < c_M < b_H$	c. $c_L < b_{LM} < a_M < c_{LM}$	
4. $b_H < c_H < d_H$	d. $c_{LM} < b_M < a_{HM} < c_M$	
	e. $c_M < b_{HM} < a_V < c_{HM}$	
	f. $c_{HM} < b_H < a_{VH} < c_H$	
	g. $c_H < b_{VH} < c_{VH}$	

While considering the position of each particle the constraints of eq. 11 need to be checked in each iteration. Thus it is necessary that the boundary of each of the particle lies within

$$\overrightarrow{X}_{i,j}^{k} \in [LB_{i,j}^{k}, UB_{i,j}^{k}] \tag{12}$$

and the boundaries $LB^k_{i,j}, UB^k_{i,j}$ for each particle are so considered that they satisfy the constraints of eq. 11. So, the main steps of PSO to optimise the input and output parameters are:

1. During any iteration the positions of the particles are adjusted as: If $\overrightarrow{X}^k_{i,j} < LB^k_{i,j}$, then

$$\overrightarrow{X}^k_{i,j} = LB^k_{i,j} \tag{13}$$

   else if $\overrightarrow{X}^k_{i,j} > UB^k_{i,j}$

$$\overrightarrow{X}^k_{i,j} = UB^k_{i,j} \tag{14}$$

2. The velocity and position of each particle are updated as given in eqs. 9 and 10.

In the proposed algorithm, energy conservation of the entire network is the primary concern. So, the main aim is to maximise the *Chance* value of each node such that the best cluster heads are chosen. Thus, *Chance* is considered to be the fitness function which can be written as:

$$Chance = \frac{\sum_{i=1}^{n} x_i \times c_i}{\sum_{i=1}^{n} c_i} \tag{15}$$

Here, x_i represents the output of rule base i and c_i is the centroid of the output membership function.

The time complexity for any evolutionary algorithm is $O(N_{ip} \times pop\_size + f_c \times pop\_size)$ where N_{ip} is the input dimension, pop_size is the population size and f_c is the cost of the fitness function. For the PSO method used in this work, the time complexity thus evaluates to $O(N_{ip} \times S + n^2 \times pop\_size)$.

4.5 Mobile Collector Movement Strategy

In this work, the CHs are treated as cities which are being traversed by a collector (salesman), thus mapping the proposed work to a travelling salesman problem (TSP) which is an NP-Hard Problem. Therefore, a heuristic approach namely, Ant Colony Optimisation (ACO) technique has been used in this work to maneuver the mobile collector through the network.

According to ACO problem, the probability that an ant a in city i visits city j at time t is given by:

$$p^a_{ij}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum\limits_{h \in allowed_a(t)} [\tau_{ih}(t)]^\alpha [\eta_{ih}(t)]^\beta} & \text{if } j \in allowed_a(t) \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

Here, τ_{ij} represents the intensity of the path pheromone between two cities i and j, $\eta_{ij} = \frac{1}{d_{ij}}$,where d_{ij} is the Euclidean distance between two cities and $allowed_a(t)$ represents the set of cities that are yet to be visited. Finally, $\alpha(> 0)$

and $\beta(>0)$ are the parameters to control the influence of τ_{ij} and η_{ij}. Then once all ants have built their tours, pheromone is updated on all edges as:

$$\tau(i,j) = (1-\rho) * \tau(i,j) + \sum_{a=1}^{m} \Delta\tau_a(i,j) \tag{17}$$

In eq. (17), $\rho \in [0,1]$ is the pheromone decay parameter responsible for taking care of the evaporation of the pheromone from the visited edges. $\Delta\tau_a(i,j)$ can be expressed as:

$$\Delta\tau_a(i,j) = \begin{cases} \frac{1}{d_{ij}^a} & \text{if } (i,j) \in \text{tour done by ant a} \\ 0 & \text{otherwise} \end{cases} \tag{18}$$

Thus, based on the above policy of ACO as given by eqns. (16), (17) and (18), the mobile collector moves throughout the network and collects data from the CHs in a single-hop fashion. This reduces the network energy consumption for data collection by the sink.

The time complexity for ACO is the same as PSO that is $O(N_{ip} \times pop\_size + f_c \times pop\_size)$. For the ACO method used in this work, the time complexity is $O(N_{ip} \times no\_of\_ants + n^2 \times pop\_size)$, as the graph to be considered for TSP must be connected where n is the number of cluster heads.

5 Simulation Results

The simulations have been conducted in MATLAB R2015a to compare the performance of the proposed algorithms with three other existing algorithms: ACO-CA [50], Tree-Cluster [11] and LEACH-FD [37].

To evaluate the values for ACO and γ, a network area of 100 m $\times$ 100 m (base station is placed at the centre of the network) have been considered where 100, 200, 300 and 400 sensor nodes are randomly deployed. The expected number of clusters is considered to be approximately 5% of the total number of nodes. Thus, k_{opt} and the transmission radius is such chosen that for each deployment the aforementioned criterion of 5% is satisfied. For these simulations, results with 90% confidence interval has been taken after running the simulation for 30 times. The other simulation parameters are given in Table 3.

Parameters	Value
Data packet size	800 bits
Control packet size	200 bits
Initial Energy (E_{inital})	2J
Energy Consumption on Circuit (E_{elec})	50 nJ/bit
Energy Consumption for data aggregation(E_{DA})	5nJ/bit/signal
Free-space channel parameter (ϵ_{fs})	10p pJ/bit/m^2
Multi-path channel parameter(ϵ_{mp})	0.0013p pJ/bit/m^4
Swarm Size (S)	50
Minimum inertia weight ($w_m in$)	0.4
Maximum inertia weight ($w_m ax$)	0.9
Cognitive coefficients (c_1, c_2)	2
Number of iterations ($maxite$)	20

Table 3: Simulation Parameters

5.1 Assigning ACO values

Now, ACO provides near-optimal solution to TSP. Thus, increasing the number of ants essentially will provide a better result. Performance evaluation of ACO for different number of ants for different node deployments and some values for α, β and ρ are given in Table 4.

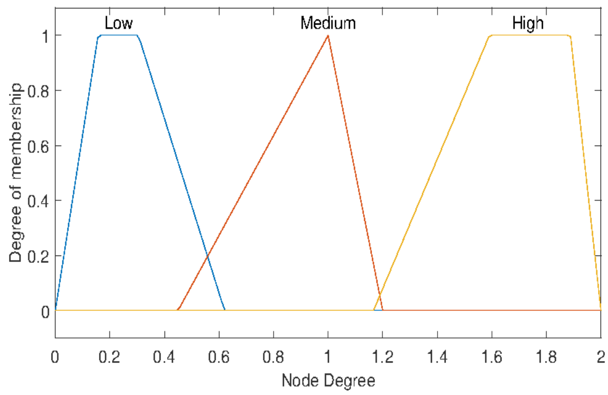
Number of nodes	Number of ants	α	β	ρ	Path Length (in m)
100	2	1	1	0.5	257.3583
100	2	1	2	0.5	238.9774
100	2	1	3	0.5	238.9774
100	2	2	2	0.5	238.9774
100	2	3	2	0.5	286.5522
100	2	2	3	0.5	252.0718
100	2	3	3	0.5	252.0718
100	5	1	1	0.5	238.9774
100	5	1	2	0.5	238.9774
100	5	1	3	0.5	275.1873
100	5	2	2	0.5	238.9774
100	5	3	2	0.5	252.0718
100	5	2	3	0.5	238.9774
100	5	3	3	0.5	238.9774
100	10	1	1	0.5	262.7224
100	10	1	2	0.5	238.9774
100	10	1	3	0.5	238.9774
100	10	2	2	0.5	252.0718
100	10	3	2	0.5	238.9774
100	10	2	3	0.5	238.9774
100	10	3	3	0.5	238.9774
200	2	1	1	0.5	292.8147
200	2	1	2	0.5	310.7888
200	2	1	3	0.5	246.6427
200	2	2	2	0.5	320.9747
200	2	2	3	0.5	323.7838
200	2	3	2	0.5	278.4948
200	2	3	3	0.5	250.4311
200	5	1	1	0.5	328.3104
200	5	1	2	0.5	246.6427
200	5	1	3	0.5	278.3324
200	5	2	2	0.5	246.6427
200	5	2	3	0.5	250.4311
200	5	3	2	0.5	278.4948
200	5	3	3	0.5	250.4311
200	10	1	1	0.5	246.6427
200	10	1	2	0.5	246.6427
200	10	1	3	0.5	246.6427
200	10	2	2	0.5	250.4311
200	10	2	3	0.5	250.4311
200	10	3	2	0.5	250.4311
200	10	3	3	0.5	246.6427
300	2	1	1	0.5	252.2317
300	2	1	2	0.5	297.3668
300	2	1	3	0.5	252.2317
300	2	2	2	0.5	252.2317
300	2	2	3	0.5	252.2317
300	2	3	3	0.5	252.2317
300	2	1	3	0.5	344.8646
300	5	1	1	0.5	297.3668
300	5	1	2	0.5	252.2317
300	5	1	3	0.5	252.2317
300	5	2	2	0.5	252.2317
300	5	2	3	0.5	252.2317
300	5	3	3	0.5	304.7903
300	5	1	3	0.5	252.2317
300	10	1	1	0.5	252.2317
300	10	1	2	0.5	252.2317
300	10	1	3	0.5	252.2317
300	10	2	2	0.5	252.2317
300	10	2	3	0.5	252.2317
300	10	3	3	0.5	252.2317
300	10	1	3	0.5	252.2317
400	2	1	1	0.5	355.1309
400	2	1	2	0.5	264.4772
400	2	1	3	0.5	327.2346
400	2	2	2	0.5	381.5152
400	2	3	2	0.5	362.4062
400	2	2	3	0.5	299.6898
400	2	3	3	0.5	264.4772
400	5	1	1	0.5	334.7100
400	5	1	2	0.5	299.6898
400	5	1	3	0.5	264.4772
400	5	2	2	0.5	264.4772
400	5	3	2	0.5	264.4772
400	5	2	3	0.5	327.2346
400	5	3	3	0.5	299.6937
400	10	1	1	0.5	303.7209
400	10	1	2	0.5	338.8272
400	10	1	3	0.5	264.4772
400	10	2	2	0.5	264.4772
400	10	3	2	0.5	264.4772
400	10	2	3	0.5	264.4772
400	10	3	3	0.5	264.4772

Table 4: Analysis of ACO

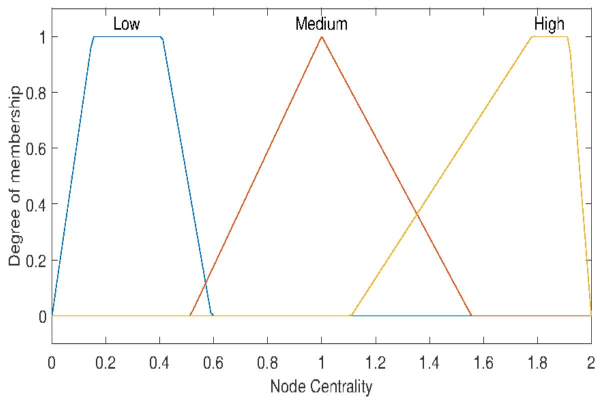
As can be seen from Table 4, with the increase in the number of visiting points, using more number of ants provides better results. Thus, in this work for different node deployments 10 ants have been considered and as α, β and ρ values of 1, 3 and 0.5 give the shortest path for most cases, these values are used for the simulation purposes.

5.2 Optimisation of parameters

The optimisation results by applying PSO on the input and output parameters of the membership functions are given Figs. 4a, 4b, 4c and 4d.

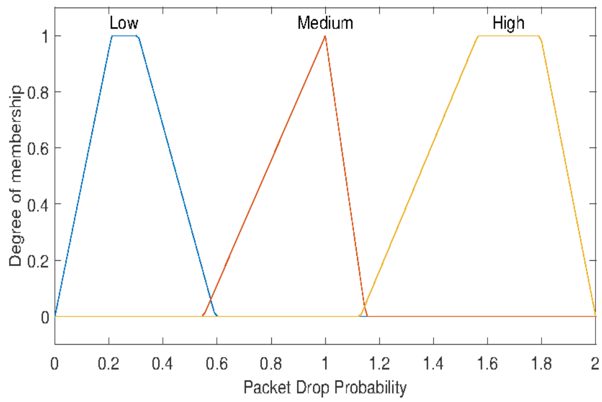


(a) Optimised input for Node Degree

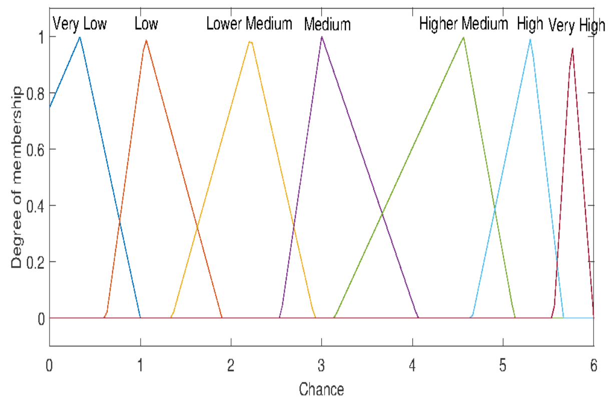


(b) Optimised input for Node Centrality

Fig. 4: Optimised parameters for fuzzy logic controllers



(c) Optimised input for Packet Drop Probability



(d) Optimised output for Chance

Fig. 4: Optimised parameters for fuzzy logic controllers (contd...)

As can be noted from the figures, although the range of each membership function is different from that of Figs. 2a, 2b, 2c, but the overall boundaries remain the same. The rest of the performance analysis have been done considering the above fuzzy inputs and outputs.

5.3 Assigning γ value

Since the clustering follows an on demand process, setting a proper value of γ is of utmost importance. To achieve this, the proposed algorithm has been implemented for different values of γ by varying the node numbers from 100 to 400 in a network area of 100 m $\times$ 100 m which is given in Figs. 5 and 6. When γ is equal to 0, it implies that the clustering process is fixed. And γ equals to 1 implies that the clustering is done in every round. As, both delivery ratio (packet drop probability being a fuzzy parameter) and node longevity are important parameters in our algorithm, so γ value is such taken that there is a trade-off between these two values. As can be seen from the figures, setting γ=0.7 fulfills our criteria. Thus, this value has been taken for the simulation purposes.

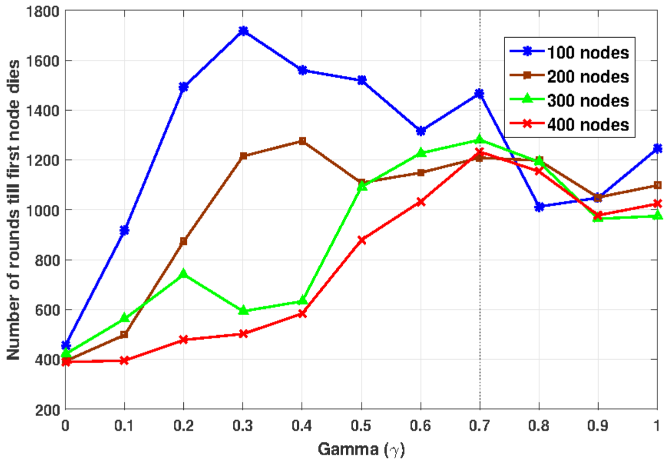


Fig. 5: γ value for different node densities

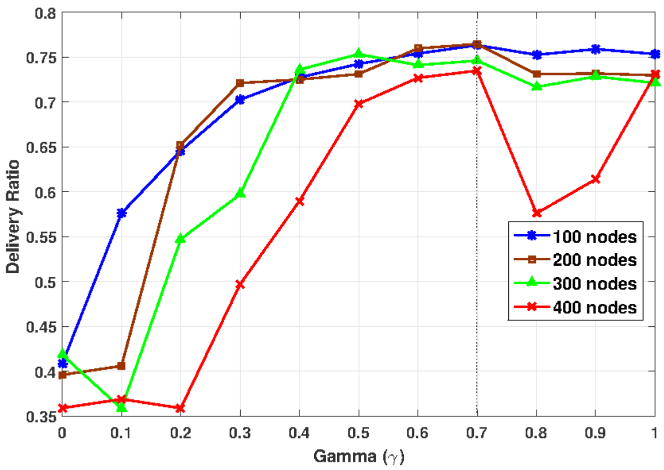


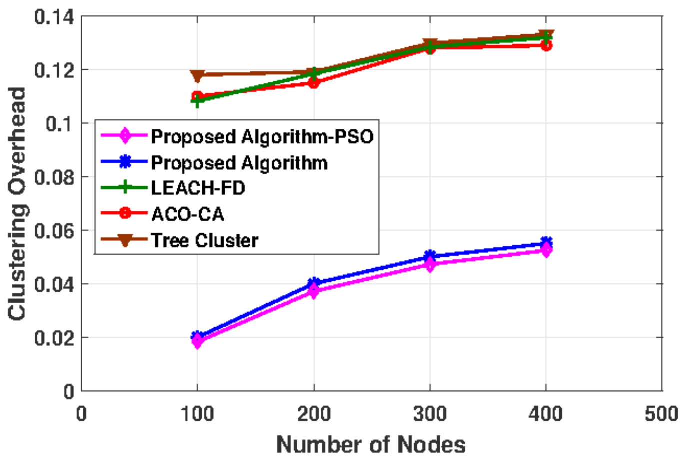
Fig. 6: γ value for different node densities

5.4 Comparison with existing algorithms

For comparison with existing algorithms two scenarios with 100, 200, 300 and 400 nodes have been considered. For both the scenarios, the other parameters are the same as in Table 3.

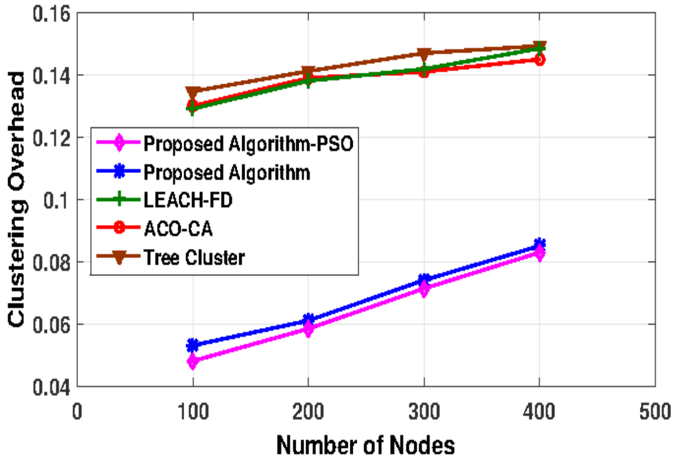
- ***Scenario 1***: A 100 m × 100 m network where the base station is located at the centre of the network.
- ***Scenario 2***: A 200 m × 200 m network where the base station is located at the coordinate (50,175).

In Fig. 7, comparisons of clustering overhead for the proposed algorithm with PSO and without PSO with the existing algorithms [50, 11, 37] are given. Clustering overhead represents the ratio of the amount of energy consumed during set up phase to the total energy dissipation for each algorithm. The proposed algorithms (with/without PSO) perform on-demand clustering, thus the overhead is very less for them in both the scenarios. On the other hand ACO-CA, Tree-Clustering and LEACH-FD suffer from high overhead as they perform clustering in every round.



(a) Scenario 1

Fig. 7: Comparison for clustering overhead

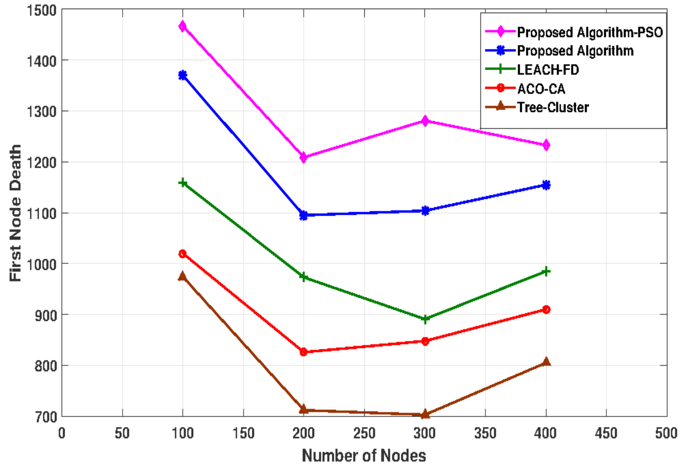


(b) Scenario 2

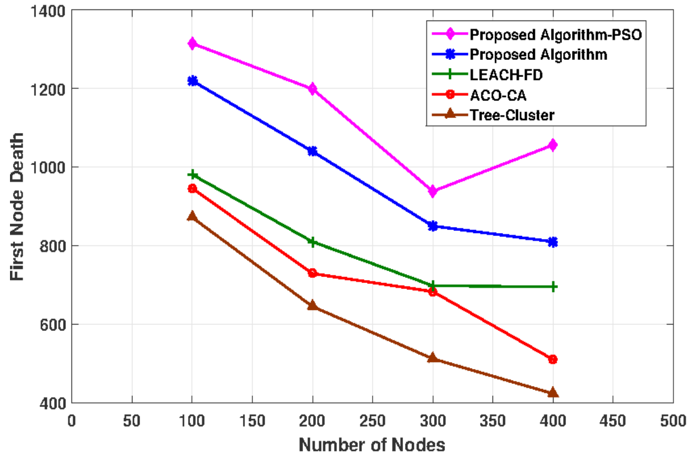
Fig. 7: Comparison for clustering overhead (contd...)

Comparisons for network lifetime for the proposed algorithm with ACO-CA, Tree-Cluster and LEACH-FD are given in Fig. 8 in terms of first node death (FND), half of alive nodes (HNA) and last node death (LND). In Fig 9 the network lifetime is given in terms of the number of alive nodes.

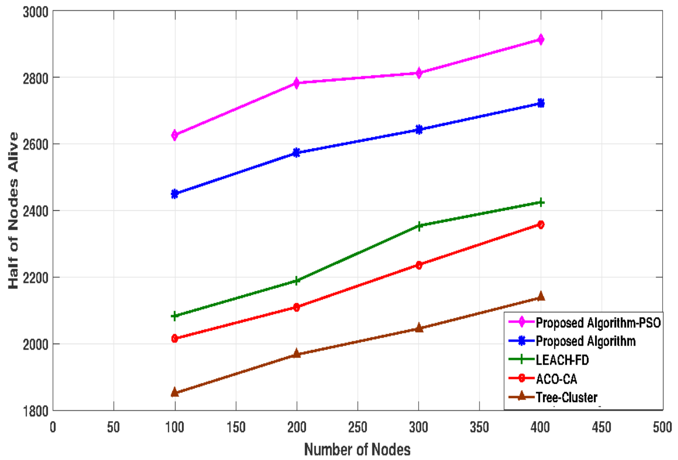
Tree-Cluster chooses cluster-heads which are at one-hop distance from the sink and the rest of the nodes send data to these CHs by multi-hop routing. But this procedure does not cause hot-spot problem as the sink is mobile. ACO-CA selects its CH based on only residual energy and does not take other factors into consideration which have a huge impact on network lifetime but it showcases better performance than Tree-Cluster for the presence of a mobile sink and one-hop data gathering from the CHs. In LEACH-FD all the CHs send their data to the Super Cluster Head thus causing extra burden on only one node. As is evident from the figures, the proposed algorithm has the highest network lifetime as compared to the other algorithms due to the joint application of fuzzy logic for the selection of CHs and the presence of a mobile collector and performs even better when the fuzzy parameters are optimised by using Particle Swarm Optimisation. The figures (Figs. 8 and Fig 9) show that the proposed algorithms with and without PSO performs better than the compared algorithms for all network densities. Furthermore, the energy consumption of all nodes in the network for the proposed approaches is less than the compared algorithms as can be seen from Fig. 10.



(a) FND in Scenario 1

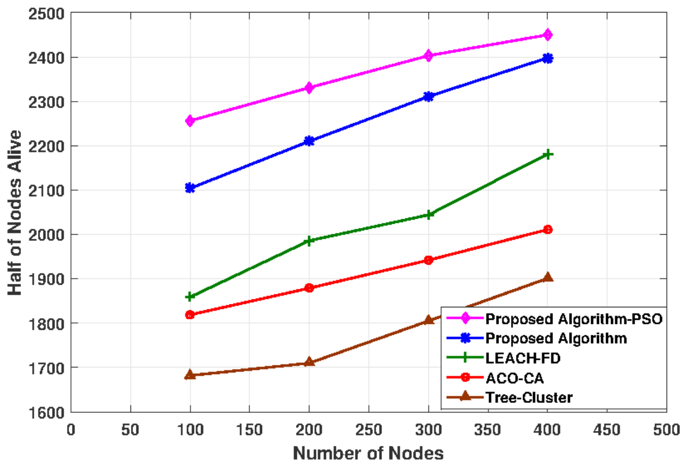


(b) FND in Scenario 2

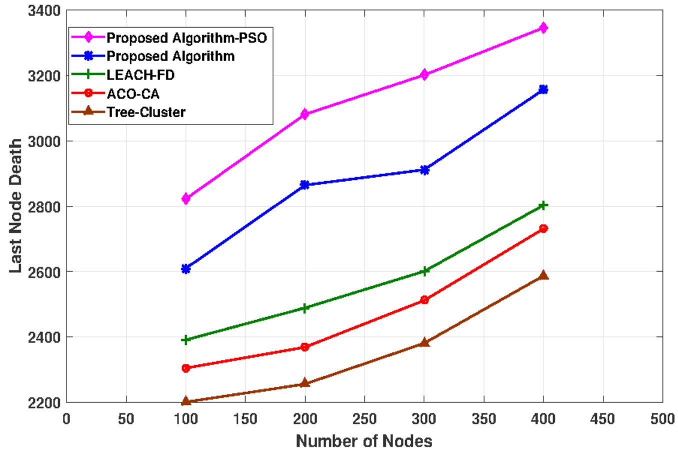


(c) HNA in Scenario 1

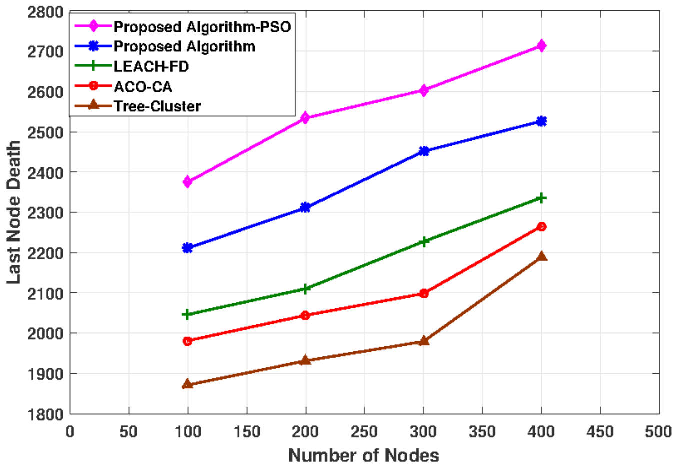
Fig. 8: Comparison for network lifetime with increasing node density



(d) HNA in Scenario 2

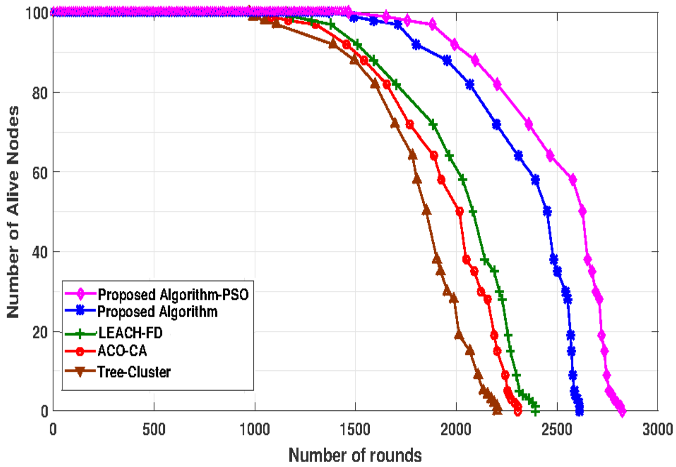


(e) LND in Scenario 1

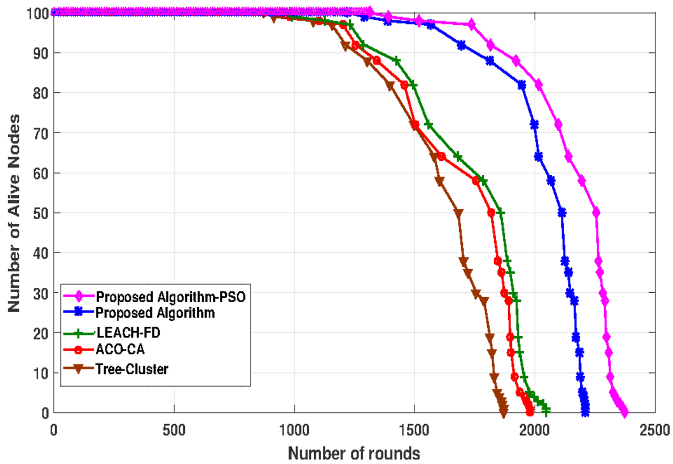


(f) LND in Scenario 2

Fig. 8: Comparison for network lifetime with increasing node density (contd...)

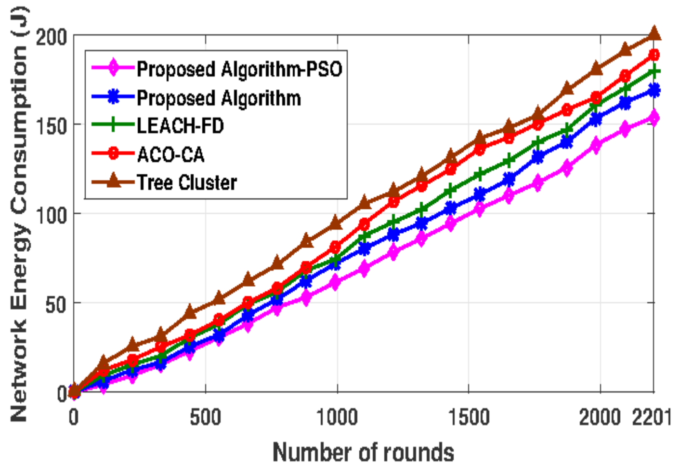


(a) Scenario 1 (100 nodes)

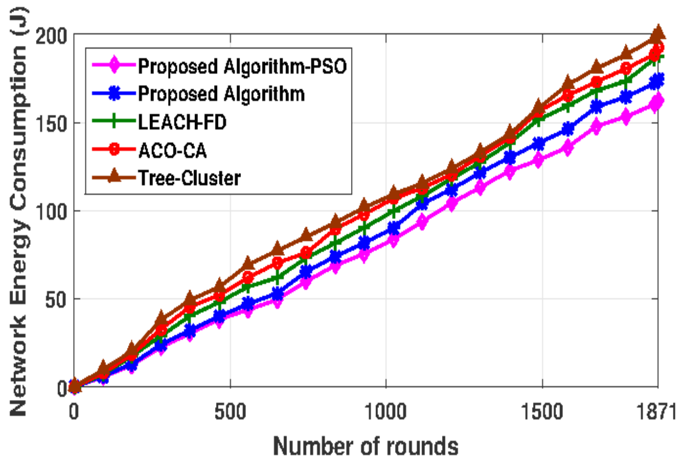


(b) Scenario 2 (100 nodes)

Fig. 9: Comparison for network lifetime



(a) Scenario 1 (100 nodes)



(b) Scenario 2 (100 nodes)

Fig. 10: Comparison for energy consumption

As packet drop probability is an important fuzzy parameter for CH selection in the proposed algorithm, it scores over other algorithms in terms of delivery ratio as given in Table 5 which is further improved by the application of Particle Swarm Optimisation to the proposed algorithm.

Packet delivery ratio (%)	Protocol	Number of nodes			
		100	200	300	400
Scenario 1	Tree-Cluster	0.6518	0.6672	0.6546	0.6592
	ACO-CA	0.6659	0.6734	0.6646	0.6704
	LEACH-FD	0.6829	0.6905	0.6757	0.6815
	Proposed Algorithm	0.7202	0.7142	0.7034	0.7242
	Proposed Algorithm-PSO	0.7634	0.7647	0.7462	0.7356
Scenario 2	Tree-Cluster	0.6128	0.6054	0.5826	0.7713
	ACO-CA	0.6212	0.6114	0.6011	0.6127
	LEACH-FD	0.6285	0.6295	0.6602	0.6035
	Proposed Algorithm	0.6719	0.6728	0.6621	0.6607
	Proposed Algorithm-PSO	0.7196	0.7206	0.7084	0.7071

Table 5: Simulation results for packet delivery ratio

6 Conclusion

In this work, a fuzzy-based on demand energy efficient clustering approach has been put forward along with ant colony based optimization for mobile collector movement to deal with the problem of energy consumption and packet delivery ratio in wireless sensor networks. To optimise the membership functions of the fuzzy logic controllers, Particle Swarm Optimisation has been used to provide improved results in terms of network lifetime and packet delivery. Combining all the aforementioned techniques provide better results than the existing clustering protocols. The paper provides extensive simulation results to verify the claim of the superiority of the proposed algorithms when compared to existing works like ACO-CA [50], Tree-Cluster [11] and LEACH-FD [37].

Although, this work provides good results regarding network lifetime and packet delivery, there are some limitations which can provide future research directions. Once the nodes start dying some part of the network may become uncovered. So full network coverage is a parameter which may be considered to determine the cluster heads. Also the proposed method has been designed for proactive networks. The work can be extended to support a reactive network to detect intrusions. The authors would also like to test the proposed work in a practical scenario to verify the applicability of the protocols.

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