PFuzzyACO: Fuzzy-based Optimization Approach for Energy-aware Cluster Head Selection in WSN

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Abstract

Cluster head selection is one of the prime challenges in the routing of the Wireless Sensor Network (WSN). Literature works have introduced various techniques for finding the optimal cluster head for establishing the communication path. The uncertainty issues prevailing in the WSN makes way for the selection of the cluster head through the optimization algorithms. In this paper, the Fuzzy based optimization approach has been introduced for the optimal selection of the cluster head. This paper proposes the Penguin Fuzzy based Ant colony optimization (PFuzzyACO) algorithm for the cluster head selection in the WSN. The proposed PFuzzyACO algorithm utilizes a multi-objective fitness function based on the parameters, such as energy, distance, delay, traffic density, and link lifetime. The results prove that the proposed PFuzzyACO algorithm behaves better than the comparative models for the system of 50 nodes with the values of 10, 0.08783, and 0.67651 for the number of alive nodes, network energy, and the throughput, respectively. The proposed PFuzzyACO model has better values of 26, 0.10857, and 0.68116 for the nodes, network energy, and the throughput respectively for WSN with 100 nodes.

Keywords: Cluster head selection, Optimization, multi-objective fitness, Network energy, Throughput

1 Introduction

WSNs have the collection of various sensor nodes scattered through the large wireless environment. The nodes installed in the WSN are initially set up with the maximum battery power. Applications incorporating the WSN, design the WSN [28] to have the maximum network lifetime for the uninterrupted processing. The users prefer the incessant communication service in the WSN, and hence, the energy utilization of the hardware, operating system and communication protocols [1] within the WSN need a careful design structure. The sensors present in the WSN communicate with each other and send the information to the base station, also mentioned as the central hub. The communication over the sensor nodes in the WSN is preferred over the wireless medium due to the vast nature of the network [18]. Hence, the major design criteria for improving the lifetime of the network would be to reduce the energy consumption of the nodes [15]. Clustering the nodes in the WSN for the free flow communication is preferred nowadays due to the versatile nature of the clustering process. In clustering, the nodes in the WSN are grouped to form a cluster, with the node in the cluster selected as a cluster head [4-5]. The advantages of employing the clustering in the WSN are (1) reduced collision between the nodes, (2) Balancing the network load through constantly altering the cluster head, (3) condense the information update within the network, and (4) scalability [7].

One of the major challenges involved in the clustering process is the selection of the cluster head. In the optimization process, the selected cluster head changes optimally for each iteration round. Various QoS parameters are involved in the selection criteria for the selection of the best cluster head and thereby, increasing the network lifetime. The cluster head interconnects the clusters in the WSN [10, 13]. The clustering process requires energy-aware design and energy efficient operation since network structure differs for various environments [9]. The communication in the WSN [32-33] happens through the single hop or the multi-hop nature. Incorporating the clustering scheme in the WSN improves the communication between the nodes and the base station with the reduced energy consumption. Selection of the cluster heads improves the connectivity of the larger WSN [16]. Literature work contains various hierarchical protocols for the clustering of the nodes. The clustering protocols allow the communication between the nodes to reach faster to the base station without the loss of information and with improved energy consumption [15].

Several optimization based works [29-31] have been

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discussed in the literature. The optimization algorithms discussed in the literature have concentrated on improving the network lifetime of the WSN. In the literature [5], the Low Energy Adaptive Clustering Hierarchy (LEACH) [5] has been discussed. The LEACH algorithm performs the cluster head selection based on the hierarchical clustering. The LEACH protocol performs the cluster head selection process by reducing the energy utilization. In the LEACH protocol, a node in the local clusters within the WSN acts as a cluster head [12]. Other optimization algorithms such as Particle Swarm Optimization (PSO) [17, 19], and Genetic Algorithm (GA) [20] allow the optimization process for the NP-hard problem. The various predictable changes within the network are identified with the use of the fuzzy logic. The works [11, 14] have used the fuzzy-based system for the cluster head selection process. The advantages of using the fuzzy logic within the clustering process are flexibility and scalability [16-18].

The aim of the research is to develop a cluster head selection approach by proposing an algorithm, PFuzzyACO, in WSN. The objective of PFuzzyACO-based approach of cluster head selection is to select a sensor node as the cluster head, for the transmission of data from the cluster head to the sink, such that its energy is maximized and thereby, the lifetime of the network is improved. For the optimal selection of cluster heads, PFuzzyACO will be developed by integrating Fuzzy Ant Colony Optimization (Fuzzy ACO) [22] into Penguin Search Optimization Algorithm (PeSOA) [21]. The selection of the cluster heads in PFuzzyACO will be based on a newly developed fitness function that utilizes five parameters, such as energy, distance, delay, traffic density, and link lifetime. Thus, the proposed PFuzzyACO approach will select the feasible cluster heads that have the energy and the link lifetime in maximum, whereas the distance, the delay and the traffic density, are in minimum. The performance of the proposed approach will be analyzed using three measures, such as energy, throughput, and alive nodes.

The major contributions of this research work for improving the cluster head selection problem in the WSN are briefed as follows,

- Design of the PFuzzyACO algorithm for the cluster head selection in the WSN. The proposed PFuzzyACO algorithm mingles the PeSOA and the Fuzzy ACO algorithm and performs the selection of the suitable cluster head through the optimization process.
- Design of the multi-objective fitness function with the factors, such as energy, distance, delay, traffic density, and link lifetime of the nodes present in the WSN.

Here, the Section 1 deals with the selection of the cluster heads in the WSN. Section 2 provides literature survey of eight works providing information about the advantages of using fuzzy based optimization model. Section 3 presents the proposed PFuzzyACO algorithm for the cluster head selection. Section 4 provides the simulation results of the proposed PFuzzyACO algorithm and the comparative discussion. Finally, section 5 concludes the paperwork.

2 Motivation

The selection of the suitable cluster head for the WSN improves the connectivity among the nodes. The fuzzy logic based classifiers are more faults tolerant and have adaptable nature. Since the topology of the WSN has the dynamic nature, the use of the fuzzy logic classifier improves the cluster head selection.

2.1 Literature Survey

This section presents the eight literature works dealing with the optimization process.

Nayak and Vathasavai [1] had proposed the Type-2 Fuzzy Logic based clustering algorithm for the preservation of the energy of the nodes. The proposed model balances the load of the nodes more efficiently by selecting better cluster heads. The Type 2 fuzzy logic had improved results when implemented in the real time scenario. Besides, this work is suitable only for the small-scale applications. Twayej Wasan *et al.* [2] proposed the Self-Organising Cluster Head to Sink Algorithm (SOCHSA) depending on the integer based optimization. The SOCHSA algorithm could find the cluster head through the optimization algorithms, such as Discrete Particle Swarm Optimization (DPSO) and the GA. The SOCHSA algorithm is not suitable in the WSN environment.

Mary and Gnanadurai [3] proposed the Enhanced Zone Stable Election Protocol (ZSPE) for the efficient cluster head selection. The ZSPE algorithm performed the optimization based on the Fuzzy Logic. The ZSPE model considered various parameters, such as residual energy, density distance, for the cluster head selection. Besides, the model has not considered the fuzzification functions and the rules during the optimization. Sarkar and Murugan [4] had performed the optimization based on the Firefly with Cyclic Randomization (FCR). The FCR model extended the existing firefly algorithm for reducing the complexity of the network during the data transmission. Even though, the proposed FCR model had high computational cost for the large networks. Khan et al. [5] had presented the Fuzzy-TOPSIS based Cluster Head selection algorithm. They had also proposed the predictable mobility model with the use of the octagonal trajectory for improving the load distribution among the sensor nodes. The model provided robustness to the network, but the algorithm suffered due to vagueness.

Jung et al. [6] proposed the adaptive cluster head selection algorithm with the use of the teen protocol and the fuzzy logic. The model had gathered the attributes of the sensor nodes for the cluster head selection. The adaptive cluster head selection algorithm had majorly improved the lifetime of the network. Increase of the fuzzy input impacted the performance of the model. Gajjar et al. [7] presented the Low Energy Fuzzy based Unequal Clustering algorithm for the cluster head selection. The model had a multihop architecture and thus, increased the inter-cluster communication among the network. The model increased the stability among the network. The absence of the global routing in work had reduced the performance of the work. Alagirisamy and Chow [8] had proposed the unequal clustering algorithm with dual sink (ECH-DUAL) for the cluster head selection. The ECH-DUAL algorithm had considered the hot spot problem present in the WSN. Factors, such as dynamic path and delay of the node, were not considered for the analysis.

2.2 Challenges

The selection of the cluster head through the optimization approaches faces the following difficulties,

- The nodes present in the WSN has restricted energy and computing capacity. The open nature of the nodes in the WSN arise to new challenges, such as link breakage, data loss, etc. [1].
- The dynamic nature of the WSN gives rise to various cluster configurations. Hence, the automatic organization of clustering and the cluster head selection becomes more complex [20].
- The WSN model with the hierarchical clustering has the hotspot problem. The cluster near the base station do more works than the other cluster heads. Hence, the workload of the nodes is not evenly distributed. Besides, due to the heavy workload of the nodes near the base station, they tend to die more early than other nodes in the WSN [7]. This leads to the coverage and the connectivity issues.
- The WSN with the complex structure has uncertainty issues [3], and hence, the cluster head selection can be done as an optimal problem.
- In [23], for the selection of cluster heads in the WSN, only three objectives, such as energy, delay, and distance, are considered. As the objective of the work is maximizing the network lifetime, it is essential to consider other important objectives like link lifetime, traffic density, and so on, for the effective communication. Moreover, the ABC algorithm employed in the work for the optimal selection does not utilize the global best solution.

3 Proposed Method: PFuzzyACO Algorithm for the Selection of the Optimal Cluster Head

This research allows the selection of the effective cluster head for the establishment of the routing path for the communication in the WSN. Figure 1 presents the block diagram of the proposed PFuzzyACO algorithm. The proposed PFuzzyACO algorithm integrates the Fuzzy ACO algorithm and the PeSOA algorithm for the optimization process. The proposed model derives a multiobjective fitness function based on the energy, distance between the nodes, delay, LLT, and the traffic present in the network. The proposed fitness function is derived as the maximization function. Based on the fitness function, the proposed PFuzzyACO model finds the optimal cluster head.

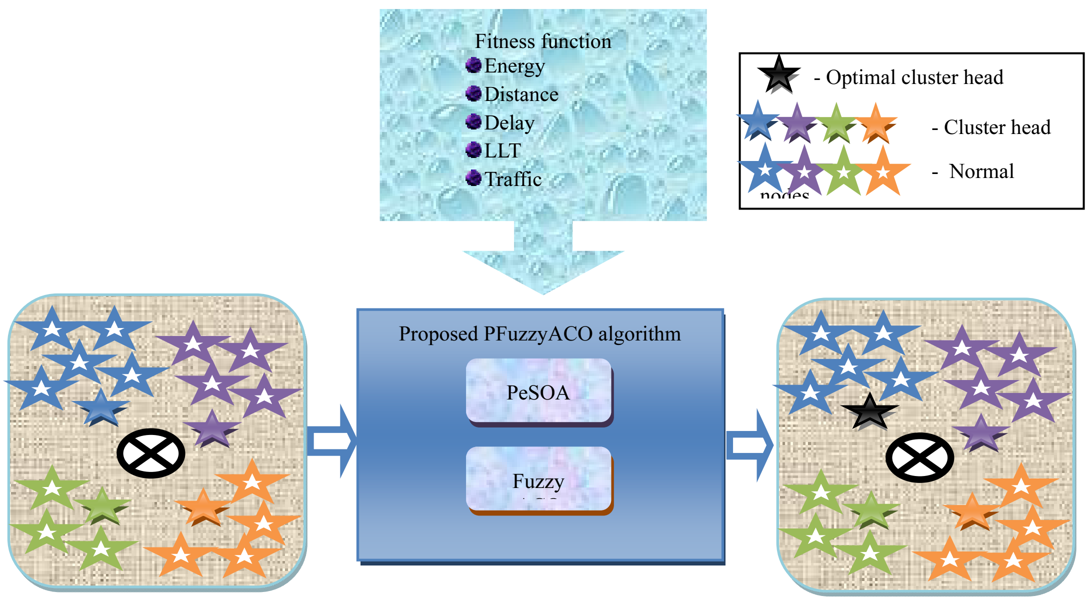


Figure 1. Block diagram of the proposed PFuzzyACO algorithm for cluster head selection

3.1 Radio Model

Here, the standard network model [26] of the WSN is presented. The WSN network contains the combination of the sensor node and the base station. Since the network has a dynamic nature, the nodes within the network move from one position to another position rapidly. The nodes in the WSN acts as a cluster head node and the normal node. The communication between the nodes of the WSN is established with the use of the wireless link. Consider the WSN with A normal nodes and B cluster head nodes. The normal and the cluster head node in the WSN is represented as D^N and D^H, respectively. The position of the base station within the WSN is represented as $(0.5U, 0.5V)$. The sensor nodes present in the WSN are battery operated. The movement of the nodes from its initial position to random position also results in energy dissipation. Equation 1 presents the energy dissipation in the normal node.

$$E_{diss}(N_i) = \begin{cases} E_g * h + E_a * h * \left\| D_j^H - D_i^N \right\|^4; \; if \; \left\| D_j^H - D_i^N \right\| \geq \kappa \\ E_g * h + E_{fs} * h * \left\| D_j^H - D_i^N \right\|^4; \; if \; \left\| D_j^H - D_i^N \right\| < \kappa \end{cases} \quad \textbf{(1)}$$

where, the term E_g refers to the electronic energy and E_a represents the energy within the amplifier. The term h represents the data bytes and κ refers to the initial distance. When the normal gets altered from its initial position, the energy dissipation depends on,

$$E_{diss}(N_i) = E_g * h + E_o * h * \left\| D_j^H - D_i^N \right\|^4 \quad \textbf{(2)}$$

where, the term E_o refers to the free space energy. The expression for the E_g is represented by the following expression,

$$E_g = E_I + E_W \quad \textbf{(3)}$$

where, E_I and E_W indicates the energy of the transmitter and the energy used for the data aggregation. Equation 4 express the energy dissipation for the cluster head.

$$E_{diss}(H_j) = E_g * h \quad \textbf{(4)}$$

The energy update for both the normal node and the cluster head is expressed as follows,

$$E_{x+1}(N_i) = E_x(N_i) - E_{diss}(N_i) \quad \textbf{(5)}$$

$$E_{x+1}(H_j) = E_x(H_j) - E_{diss}(H_j) \quad \textbf{(6)}$$

where, the term $E_x(N_i)$ and $E_x(H_j)$ refers to the energy remaining on the sensor node and the cluster head node.

3.2 Proposed Multi-objective Fitness Function for the Proposed PFuzzyACO Algorithm

Selection of the optimal cluster head through the proposed PFuzzyACO algorithm requires a fitness function. This work considers various network parameters, such as energy, distance, delay, LLT, and traffic density of the nodes present in the WSN. The proposed fitness function for the PFuzzyACO algorithm is designed as the maximization function. Equation (7) presents the proposed multi-objective fitness function for the PFuzzyACO algorithm.

$$Fitness, \; \eta = \left[c_1 * M + c_2 * Z + c_3 * O + c_4 * P + c_5 * Q \right] \quad \textbf{(7)}$$

where, the term M indicates the energy remaining on the network, and Z represents the distance between the cluster head and the normal nodes in the WSN. The term O indicates the delay during the transmission and P represents the LLT of the link established between the nodes. The term Q defines the traffic density. Other terms, such as c_1, c_2, c_3, c_4, and c_5, represent the constants for the fitness function. The mathematical expression for each objective used in the proposed fitness function is briefed as follows,

Energy M**:** The energy factor depends on the energy of the normal node and the cluster head node. The transmission and the reception of the data packets by the nodes result in energy dissipation. The energy remaining on the network is represented by the expression (8).

$$Energy \; M = \alpha \left[\frac{1}{A} \sum_{i=1}^{A} M_i^N \right] + \beta \left[\frac{1}{B} \sum_{j=1}^{B} M_j^H \right] \quad \textbf{(8)}$$

where, the term M_i^N and M_j^H shows the energy remaining on the normal node and the cluster head node and the index terms i and j vary as $1 \leq i \leq A$ and $1 \leq j \leq B$. The terms A and B indicate the total number of normal nodes and the cluster head nodes within the network. The term α and β represent the weighted constants used for the normalization of the energy factor.

Distance Z**:** For the error-free communication, the distance parameter needs to consider the following conditions,

(1) Minimum distance between the cluster head and the normal node, and

(2) The maximum distance between two cluster heads, i.e., a larger separation between the clusters.

By considering the above conditions, the expression for the distance Z is represented as follows,

$$Dis\tan ce,\ Z = \gamma\left[1 - \frac{\sum_{i=1}^{A}\sum_{j=1}^{B}\left\|D_j^H - D_i^N\right\|}{G*A*B}\right] + \delta\left[1 - \frac{\sum_{j=1}^{B}\sum_{k=1}^{B}\left\|D_j^H - D_k^H\right\|}{G*B*B}\right] \quad (9)$$

where, the term $\left\|D_j^H - D_i^N\right\|$ represents the distance between the j^{th} cluster head and the i^{th} normal node in the WSN. The term $\left\|D_j^H - D_k^H\right\|$ represents the distance between the cluster head of j^{th} and k^{th} cluster. The term G points to the simulation area of the WSN. The term γ and δ are the weighted constants for the distance.

Delay O **:** The delay factor is defined to be in minimum. In this work, the individual delay of the cluster is calculated. Expression for the delay of the cluster is expressed as follows,

$$Delay\ \ O = \left[1 - \frac{\underset{j=1}{\overset{B}{Max}}\left\|C_j\right\|}{A}\right] \quad (10)$$

where, the term $\left\|C_j\right\|$ expresses the total number of cluster members in the j^{th} cluster.

LLT P **:** The next objective defined in the proposed fitness function is the LLT. The LLT depends on each link established between the cluster head and the normal node. The expression for the LLT is expressed as follows,

$$LLT,\ \ P = \frac{1}{A*B}\sum_{i=1}^{A}\sum_{j=1}^{B} L_{ij} \quad (11)$$

where, the term L_{ij} represents the link established between the i^{th} normal node and the j^{th} cluster head, A and B indicate the total number of normal nodes and the cluster head nodes in the network. The expression for the L_{ij} is expressed as follows,

$$L_{ij} = \frac{2*M_i^N*M_j^H}{V*S_s*S_r*R + \left\|D_j^H - D_i^N\right\|} \quad (12)$$

where, the term V indicates the constant value for the estimation of the link path and the term R represents the network range. The terms S_s and S_r indicate the packet sending and the receiving rate, respectively.

Traffic density Q **:** The final factor involved in the proposed fitness function is the traffic density. The traffic density must be low and it is expressed as follows,

$$Traffic\,density\ \ Q = \left[1 - \frac{(b+p)}{2}\right] \quad (13)$$

where, the terms b and p represent the bandwidth utilized and the packet drop. The expressions for the bandwidth utilized and the packet drop are given in the following equations,

$$b = \frac{1}{A*B}\sum_{i=1}^{A} b_i^u \quad (14)$$

$$p = \frac{1}{A}\sum_{i=1}^{A}\frac{p_i^d}{p_i^m} \quad (15)$$

where, the term b_i^u express the bandwidth utilized by the i^{th} normal node. The terms p_i^d and p_i^m express the total packets dropped by the i^{th} node, and the total packets sent by the i^{th} node when the link is established.

3.3 Cluster Head Selection: Proposed PFuzzyACO Algorithm

This work proposes the PFuzzyACO algorithm for finding the optimal cluster head. The optimization process using the proposed work uses the proposed multi-objective fitness function. The proposed PFuzzyACO algorithm blends the Fuzzy ACO algorithm [22] and the PeSOA [21]. The existing Fuzzy ACO algorithm modifies the ACO algorithm with the fuzzy-based logic. The Fuzzy ACO algorithm was primarily designed to solve the routing behaviour in the WSN, but it needs more performance improvements and more computational time. The use of the PeSOA algorithm with the FuzzyACO algorithm improves the speed of convergence since the solutions in the PeSOA is divided between the local and the global minimum values. The hybridization of PeSOA algorithm with other algorithms can be potentially fruitful. Hence, we combine these two algorithms for optimally selecting the cluster head in WSN. The use of the PeSOA algorithm with the FuzzyACO algorithm improves the speed of convergence since the solutions in the PeSOA is divided between the local and the global minimum values. Also, we develop the new multi-objective fitness function, by considering various factors, such as energy, distance, delay, traffic density, and link lifetime of the nodes present in the WSN.

3.3.1 Solution Encoding

The solution encoding for the proposed PFuzzyACO algorithm is defined in this section. Figure 2 presents the solution encoding for the proposed PFuzzyACO algorithm. The proposed work aims to find the optimal cluster head node among various nodes present in the WSN. The solution vector for the proposed

PFuzzyACO algorithm contains various cluster head nodes, represented as $H_1, H_2, ...H_J$. Consider the WSN network with B number of cluster heads. The proposed algorithm retains J optimal cluster heads from the optimization process.

Figure 2. Solution encoding for the cluster head selection using the proposed PFuzzyACO algorithm

3.3.2 Algorithmic Procedure of the Proposed PFuzzyACO Algorithm

The proposed PFuzzyACO algorithm finds the optimal cluster head based on the results of the Fuzzy ACO and the PeSOA algorithm. Various steps involved in the optimization of the proposed PFuzzyACO algorithm are briefed as follows,

Step 1. Population initialization. The initial step in the optimization procedure of the proposed PFuzzyACO algorithm is the initialization of the population. The population of the proposed model is randomly initialized with the size of J . The randomly initialized population for the proposed PFuzzyACO algorithm is expressed in the following expression,

$$X = \{X_1, X_2, X_3, ...X_n, ...X_J\} \quad \textbf{(16)}$$

where, the term X_n represents the n^{th} solution of the proposed PFuzzyACO algorithm.

Step 2. Fitness evaluation. The fitness of the each random solution initialized in the population is found in this step. The fitness of each solution obtained through the optimization process depends on the proposed multi-objective fitness function. In this step, the fitness of the solution is found based on the equation (7).

Step 3. Find X^{PeSOA} based on the PeSOA algorithm. The next step in the proposed PFuzzyACO algorithm is the utilization of the existing PeSOA algorithm for the optimization process. The solution is directly fed to the existing PeSOA algorithm and the solution update is found. The PeSOA algorithm finds the optimal solution based on the prey search behavior of the penguins. The penguins communicate with the other penguins through the vocalization. The vocalization allows unique identification of the other penguins. The food for the penguins is found through the holes. The food present in the holes vary based on the hole level. When a group of whales finds the food in the hole, the whale alerts the other groups. When the hole contains no food the penguin move into other hole position. The position update of the penguin is represented by the following equation.

$$X^{PeSOA}(t+1) = X_{best} + rand().\left|X_{localbest}(t) - X^{PeSOA}(t)\right| \quad \textbf{(17)}$$

where, the term X_{best} represents the best solution for the PeSOA, and the term $rand()$ represents the random value. The term $X_{localbest}(t)$ represents the value of the local best. Based on the above value, the probability of the holes and the levels are found.

Step 4. Find the worst solution based on the fitness function. The proposed PFuzzyACO algorithm requires the worst solution from the PeSOA algorithm. The worst solution is found based on the proposed fitness value. For the each iteration t, the fitness of the each solution $X^{PeSOA}(t+1)$ is found and then the solution with the worst fitness value is retained at the end. The worst solution from the PeSOA algorithm is represented as, $X^{PeSOA}_{worst}(t+1)$

Step 5. Find $X^{F\,ACO}$ based on the fuzzy ACO algorithm. In the next step, the solution $X(t)$ is directly fed to the conventional Fuzzy ACO algorithm. The existing Fuzzy ACO algorithm provides improved results since it acts on the pheromone behaviour of the ants. When the population is fed to the existing Fuzzy ACO algorithm, the solution gets updated based on the pheromone update provided by the ants. The ants move towards the destination based on the pheromone left by the previous ant. The memory of the ant gets updated to avoid the search in the same path. The following expression represents the required update for the pheromone factor,

$$\Delta v = w * (e - f) * E \quad \textbf{(18)}$$

where, the term w represents the variable parameter, the term e and f express the maximum hops and remaining hops to reach the destination. Based on the equation (18), the pheromone concentration of the solution gets update. The pheromone update is represented as follows,

$$v = (1 - \xi) * v + \Delta v \quad \textbf{(19)}$$

where, the term ξ refers to the pheromone concentration. The value of the ξ varies between $[0,1]$ and the term $(1-\xi)$ represent the residue factor of the pheromone concentration. Based on the pheromone update, the solutions of the Fuzzy ACO algorithm gets updated. Then the solution is primarily fed to the fuzzy logic. The various parts involved in the fuzzy logic system are the Fuzzification inference engine, and defuzzification. Figure 3 presents the general architecture of the fuzzy logic system provided with the objectives of the proposed fitness function.

The fuzzy logic system is provided with the pheromone update and the objectives of the fitness function derived in the equation (7) as the input. The fuzzy logic system utilized for this work contains the Mamdani inference engine. Each block present in the fuzzy logic system is represented as follows:

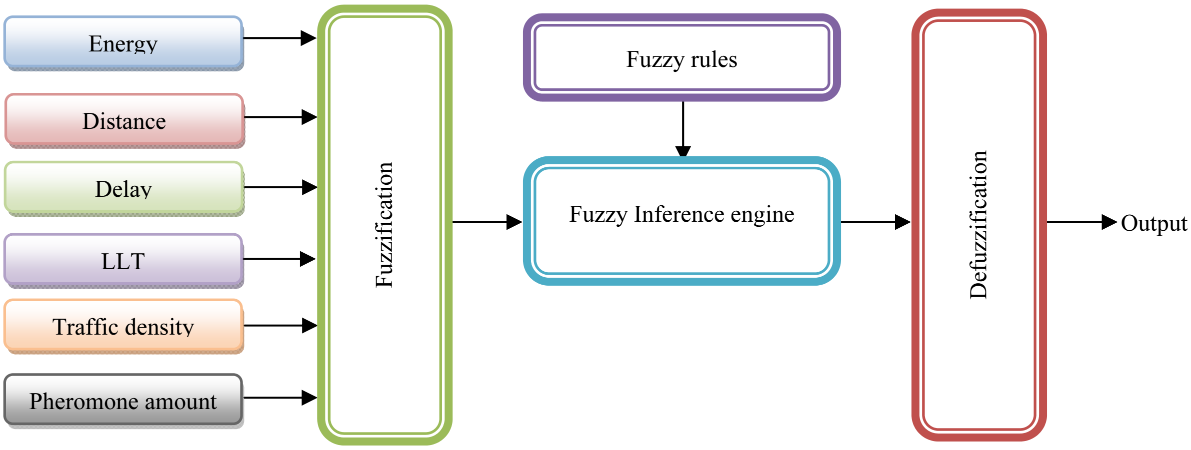


Figure 3. General architecture of the Fuzzy ACO with the proposed multiobjective fitness function

(1) Fuzzification: In the Fuzzification block, the objective functions of the proposed fitness function and the pheromone update are provided as the input value. Based on the input values provided to the system, the fuzzy system obtains the membership degree. Hence, the input values of the system are converted to the crisp values in the Fuzzification block.

(2) Inference Engine. The inference engine contains a set of fuzzy values obtained from the Fuzzification block. Then, these values are processed based on the set of fuzzy rules. The fuzzy inference engine finds the suitable rule sets for the input values and based on the rules, the output is provided as the linguistic value.

(3)Defuzzification: In the defuzzification block, the linguistic values are converted to the nonfuzzy values. The fuzzy model makes use of the centroid technique for finding the fuzzy output.

The fuzzy ACO classifier system provides the required solution update represented as $X^{F\,ACO}(t+1)$. The term $X^{F\,ACO}(t+1)$ represents the required fuzzy score from the Fuzzy ACO algorithm.

Step 6: Find the best solution based on the fuzzy score. Then from the fuzzy score $X^{F\,ACO}(t+1)$ value, the best solution of the Fuzzy ACO algorithm is retained for the update of the general solution. The best solution of the fuzzy ACO algorithm is represented as $X_{best}^{FACO}(t+1)$.

Step 7. Replacement strategy. The next step in the proposed PFuzzyACO algorithm is the update of the solution based on the fuzzy score. The worst value obtained in the PeSOA algorithm given in the step 4 is replaced with the best solution $X_{best}^{FACO}(t+1)$ and it is given as follows,

$$X_{worst}^{PeSOA}(t+1) = X_{best}^{FACO}(t+1) \tag{20}$$

Based on the updated value of the $X_{worst}^{PeSOA}(t+1)$, the solution $X(t+1)$ gets further updated.

Step 8. Termination. In the final step, the proposed PFuzzyACO algorithm gets the updated value $X(t+1)$. At end of the termination $t = T_{\max}$, the final solution is provided as the output by the proposed PFuzzyACO algorithm. The final best value of the Fuzzy ACO $X_{best}^{FACO}(t+1)$ acts as the optimal cluster head at the final iteration.

3.4 Pseudo Code of the Proposed PFuzzyACO Algorithm

Figure 4 presents the pseudo-code of the proposed PFuzzyACO algorithm.

Algorithm. Proposed PFuzzyACO algorithm

Inputs: Cluster heads of the WSN
Output: Optimal cluster head
Begin
Initialize the population of the PFuzzyACO algorithm
For ($t<T_{max}$)
    Find the fitness of the each solution
    Call PeSOA algorithm
    For(n=1; n=J)
        Find the value of the $X^{PeSOA}(t+1)$
        Find the fitness of the solution based on equation (7)
        Find the value of the $X_{worst}^{PeSOA}(t+1)$
    End for
    Call Fuzzy ACO algorithm
    For(n=1; n=J)
        Find the value of the $X^{F\,ACO}(t+1)$
        Find the fuzzy score of the solution
        Find the value of the $X_{best}^{FACO}(t+1)$
    End for
    Replace $X_{worst}^{PeSOA}(t+1)$ with $X_{best}^{FACO}(t+1)$ // Replacement strategy
    t=t+1; //Increment iteration
End for
Return $X_{best}^{FACO}(t+1)$ // Optimal cluster head
End

Figure 4. Pseudo code of the proposed PFuzzyACO algorithm

4 Results and Discussion

This section presents various simulation results achieved by the proposed PFuzzyACO algorithm. The performance of the PFuzzyACO proposed model is analyzed based on the metrics, such as number of alive nodes, throughput and the network energy. Here, 10 experiments are performed and the average of these experiments is plotted.

4.1 Experimental Setup

The simulation of the proposed model requires the NS2 simulator and the PC with certain system configurations. The entire simulation of the proposed PFuzzyACO model is done in a PC with the 4GB RAM, Windows 10 OS, and the Intel I3 processor.
Parameters to be Fixed. Number of cluster head - 5, populations (J) -10.

4.2 Simulation Setup

Table 1 presents the simulation setup used for the proposed PFuzzyACO algorithm. The simulation of the proposed PFuzzyACO model uses the network with 50 and 100 nodes.

Table 1. Simulation setup for the proposed PFuzzyACO algorithm

Simulation parameters	Values
Area of the network dimension	100*100
Total number of nodes present in the WSN	50, 100
Bit rate for the transmission	4000 bit
Initial energy of the each node in the WSN	0.5
Energy utilized by the node for the transmission of the bit	50 nJ/bit/m^2
Number of iterations for the simulation	2000

4.3 Evaluation Metrics

In this work, the evaluation metrics, such as number of alive nodes, throughput and the network energy analyze the performance of the proposed model. The expression for the evaluation metrics is briefed as follows,
Number of alive nodes. This measure defines the number of nodes with the minimum energy based on the iteration rounds.
Throughput. The throughput measure [27] in this work defines the ratio of the number of packets received by the nodes in the WSN to the time. The expression is defined as follows,

$$Throughput = \frac{Number\ of\ packets\ recieved}{time} \tag{21}$$

Network energy: The cluster head selection process need to utilize low energy through the cluster head selection process. The network energy depends on the equation (1).

4.4 Comparative Models Used in the Experimentation

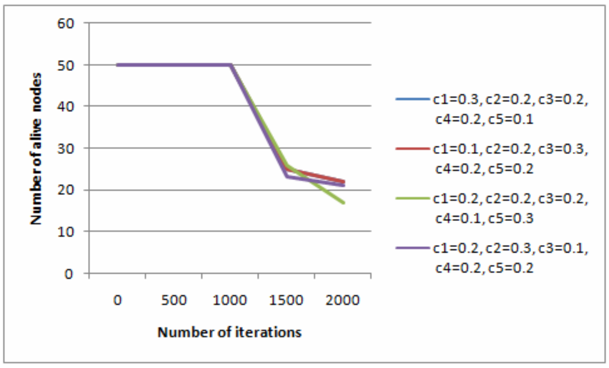
For the performance evaluation, this research uses four existing techniques, namely Fractional Artificial Bee Colony algorithm (FABC) [23], Artificial Bee Colony algorithm (ABC) [24], LEACH [25] and Ant Colony Optimization (ACO) algorithm [26]. The comparative models used in the experimentation find the optimal cluster head using the same simulation setup as the proposed model.

4.5 Performance Analysis of the Proposed PFuzzyACO Algorithm

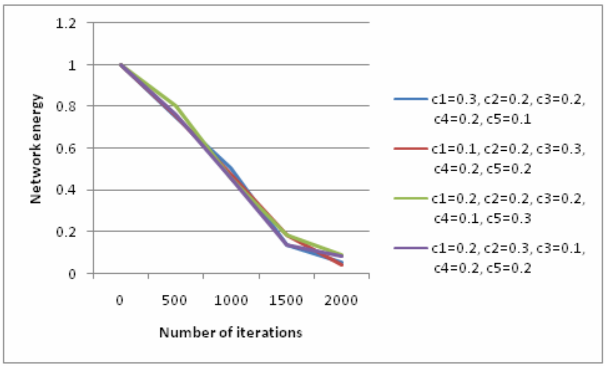
Here, the performance of the proposed PFuzzyACO algorithm is analyzed with the metrics, such as a number of alive nodes, network energy, and the throughput parameters. The analysis is done in the WSN with 50 and 100 nodes. For varying number of iterations, the performance of the proposed model is analyzed. The proposed PFuzzyACO algorithm uses a multi-objective fitness function for defining the feasibility of the optimal cluster head. The fitness function utilizes five constant values c_1, c_2, c_3, c_4, and c_5, for the optimization process. In the performance analysis, the performance of the proposed PFuzzyACO algorithm is measured against the different values of c_1, c_2, c_3, c_4, and c_5.

4.5.1 Performance Analysis on the WSN with 50 Nodes

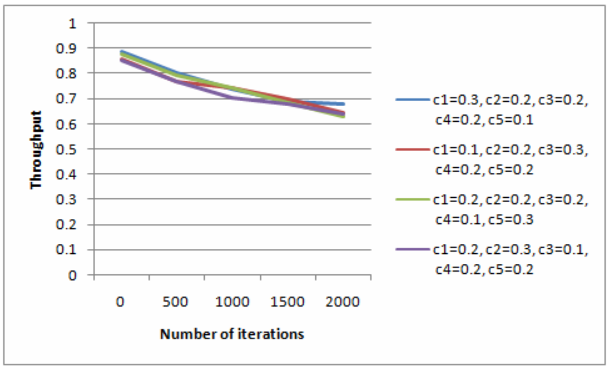
Figure 5 depicts the performance of the proposed PFuzzyACO algorithm for the WSN with 50 nodes. For various values of the constant in the fitness measure, the performance of the proposed PFuzzyACO is measured. Figure 5(a) shows the performance of the proposed PFuzzyACO algorithm based on the number of alive nodes for the WSN with 50 nodes. For the values of c_1=0.3, c_2=0.2, c_3=0.2, c_4=0.2, and c_5 =0.1, the proposed PFuzzyACO model has 25 and 22 alive nodes at the end of 1500 and 2000 round of iteration. Figure 5(b) presents the performance analysis of the proposed system based on the network energy for the WSN with 50 nodes. For the values of c_1=0.3, c_2=0.2, c_3 =0.2, c_4 =0.2, and c_5 =0.1, the proposed PFuzzyACO model has an energy value of 0.13395 and 0.05168 at the at the iterations 1500 and 2000, respectively. Figure 5(c) shows the performance of the proposed PFuzzyACO algorithm based on the throughput. For the values of c_1=0.3, c_2=0.2, c_3=0.2, c_4=0.2, and c_5=0.1, the proposed PFuzzyACO model has throughput value of 0.68904 and 0.67754 for the iterations 1500 and 2000.



(a) Number of alive nodes



(b) Network energy

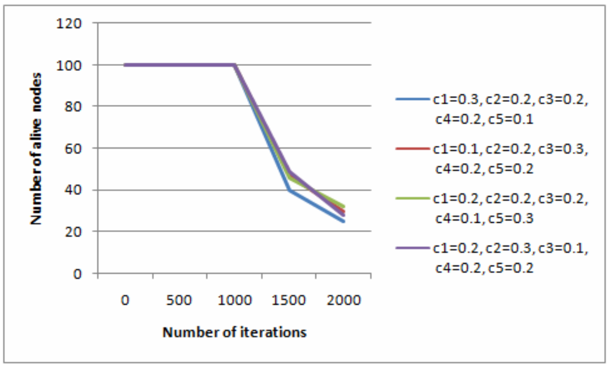


(c) Throughput

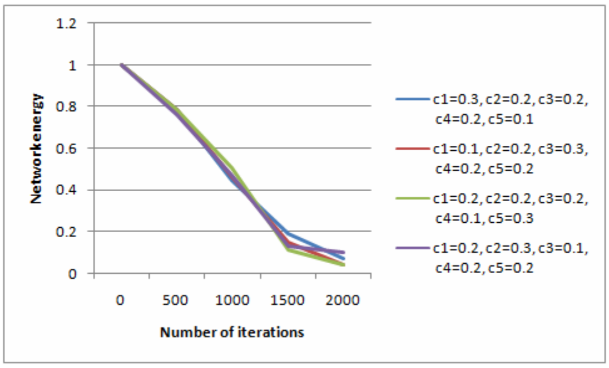
Figure 5. Performance analysis of the proposed PFuzzyACO algorithm for 50 nodes based on

4.5.2 Performance Analysis on the WSN with 100 Nodes

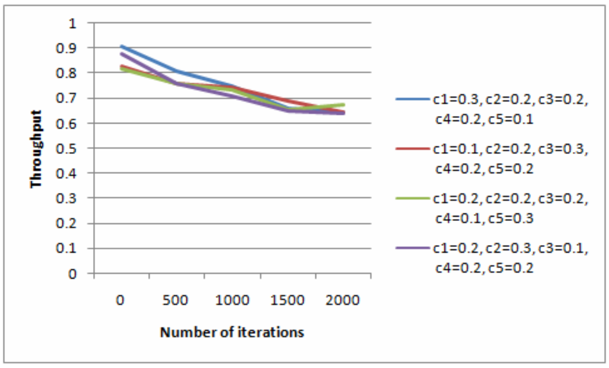
Here, the performance of the proposed PFuzzyACO model is analyzed for the WSN with 100 nodes. Figure 6(a) presents the performance analysis of the proposed model based on the number of alive nodes for the variation in the iteration round. For the values of c_1 =0.3, c_2 =0.2, c_3 =0.2, c_4 =0.2, and c_5 =0.1, the proposed PFuzzyACO model has 100 and 25 alive nodes at the end of 500 and 2000 round of iteration. Adjusting the constant value to c_1=0.1, c_2=0.2, c_3=0.3, c_4=0.2, and c_5=0.2, results in 100 and 30 alive nodes for the iterations 500 and 2000. Figure 6(b) presents the performance analysis of the proposed system based on the network energy for the WSN with 100 nodes. Figure 6(c) shows the performance of the proposed PFuzzyACO algorithm based on the throughput. For the values of c_1 =0.3, c_2 =0.2, c_3 =0.2, c_4 =0.2, and c_5 =0.1, the proposed PFuzzyACO model has throughput value of 0.80826 and 0.64523 at the end of 500 and 2000 round of iteration.



(a) Number of alive nodes



(b) Network energy



(c) Throughput

Figure 6. Performance analysis of the proposed PFuzzyACO algorithm for 100 nodes based on

4.6 Comparative Analysis of the Proposed PFuzzyACO Algorithm

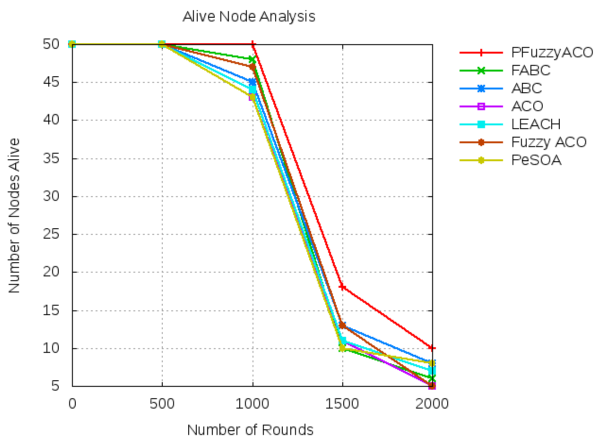
Here, the performance of the proposed PFuzzyACO algorithm is compared with various models, such as FABC, ABC, ACO, LEACH, Fuzzy ACO and PeSOA. The analysis is done by varying the number of iteration rounds against the number of alive nodes, network energy, and the throughput.

4.6.1 Comparative Analysis for the System with 50 Nodes

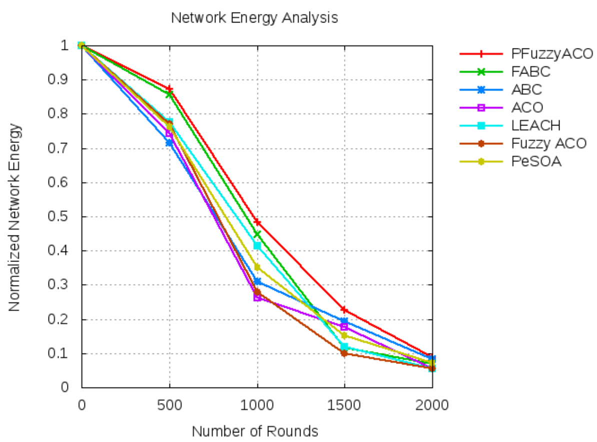
The comparative analysis of the proposed PFuzzyACO algorithm with the comparative models for the WSN with 50 nodes is presented in Figure 7. The performance of each model is measured against a various number of iteration rounds. Figure 7(a) shows the comparative analysis of each model in the WSN with 50 nodes against the number of alive node metric. At the iteration round 1000, the existing ABC, ACO, FABC, LEACH, Fuzzy ACO and PeSOA algorithms have 45, 43, 48, 44, 47, and 43 alive nodes. Meanwhile, the proposed PFuzzyACO algorithm has 50 alive nodes at the iteration 1000. At the end of the iteration, the proposed model has 10 alive nodes, clearly outperforming the comparative ABC, ACO, FABC, LEACH, Fuzzy ACO and PeSOA algorithms which have only 8, 5, 6, 7, 5, and 8 alive nodes, respectively. Figure 7(b) indicates the comparative analysis of the models based on the network energy for the WSN with 50 nodes. Initially, each node in the WSN has a maximum energy of 1. The transmission and the reception of the data packets at each iteration reduce the energy. The model with the higher energy at the end of the iteration has the overall better performance. At the iteration round of 2000, the existing ABC, ACO, FABC, LEACH, Fuzzy ACO and PeSOA algorithms have the energy value of 0.08328, 0.05545, 0.07024, 0.05579, 0.05506, and 0.07304 respectively. The proposed PFuzzyACO model has the high network energy value of 0.08783 at the iteration 2000. Figure 7(c) presents the comparative analysis for the system with 50 nodes based on the throughput. For the iteration of 2000, the existing ABC, ACO, FABC, LEACH, Fuzzy ACO and PeSOA algorithms have the throughput value of 0.60978, 0.61934, 0.6223, 0.63233, 0.63871, and 0.63880 respectively. The PFuzzyACO model achieved the overall higher throughput value of 0.67651 at the iteration 2000.

4.6.2 Comparative Analysis for the System with 100 Nodes

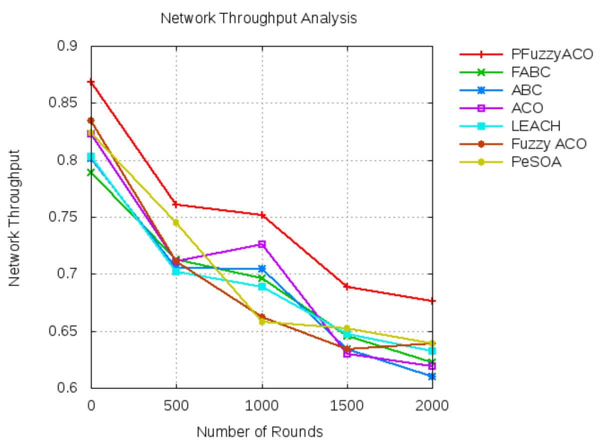
Figure 8(a) shows the comparative analysis of each model in the WSN with 100 nodes against the number of alive node metric. At the iteration round of 1500, the existing ABC, ACO, FABC, LEACH, Fuzzy ACO and PeSOA algorithms have 19, 17, 15, 22, 18, and 16 alive nodes. Meanwhile, the proposed PFuzzyACO algorithm has 48 alive nodes at the iteration 1500. At the end of the iteration, the proposed model has 26 alive nodes, which clearly shows the outperforming behavior of the proposed algorithm against the comparative ABC, ACO, FABC, LEACH, Fuzzy ACO and PeSOA algorithms that have only 15, 13, 15, 8, 12,



(a) Number of alive nodes



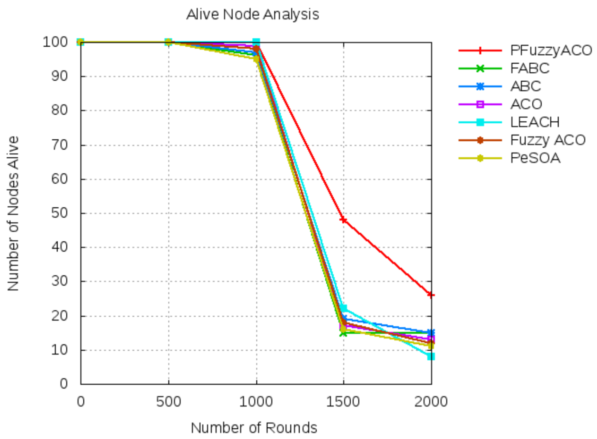
(b) Network energy



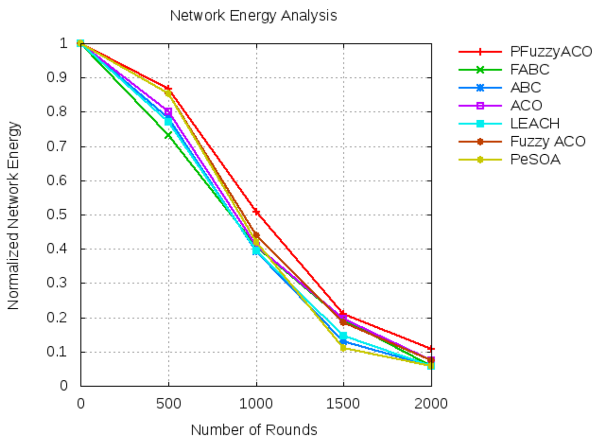
(c) Throughput

Figure 7. Comparative analysis for 50 nodes based on

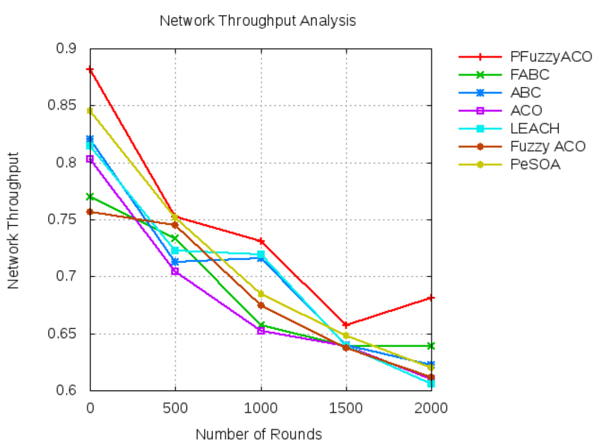
and 11 alive nodes, respectively. Figure 8(b) indicates the comparative analysis of the models based on the network energy for the WSN with 100 nodes. At the iteration 2000, the existing ABC, ACO, FABC, LEACH, Fuzzy ACO and PeSOA algorithms have the energy value of 0.05856, 0.0759, 0.05759, 0.0577, 0.07516, and 0.05681 respectively. The proposed PFuzzyACO model has the high network energy value of 0.10857 at the iteration 2000. Figure 8(c) presents the comparative analysis for the system with 100 nodes based on the throughput. For the iteration of 2000, the existing ABC, ACO, FABC, LEACH, Fuzzy ACO and PeSOA algorithms have the throughput value of 0.62201, 0.60979, 0.63855, 0.60591, 0.61192, and 0.61969 respectively. The PFuzzyACO model achieved the overall higher throughput value of 0.68116 at the iteration 2000.



(a) Number of alive nodes



(b) Network energy



(c) Throughput

Figure 8. Comparative analysis for 100 nodes based on

4.6.3 Replacement Status

Figure 9 shows the replacement status of the proposed model based on iteration. In the proposed model, total numbers of iterations are 2000. Among 2000 iterations, the replacement is done at 30% of iterations, i.e., 600 iterations.

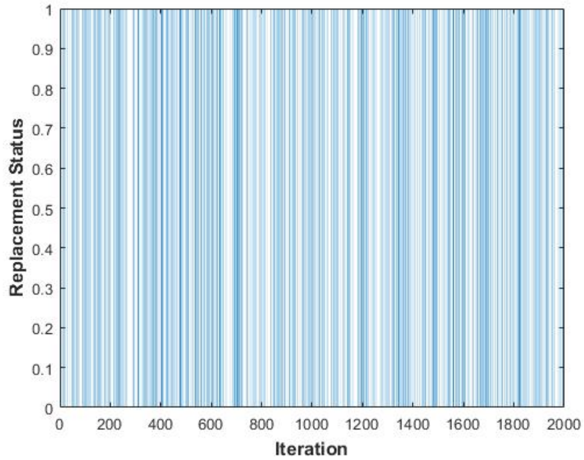


Figure 9. Replacement status of the proposed model

4.7 Discussion

This section presents the comparative analysis of the models under various simulation conditions. Table 2 presents the performance of the comparative models against the proposed PFuzzyACO model with their maximum values. From the simulation results, it is evident that the proposed PFuzzyACO model has the overall better performance than the comparative techniques. For the WSN with 50 nodes, the proposed PFuzzyACO model has the values of 10, 0.08783, and 0.67651, as the number of alive nodes, network energy, and the throughput, respectively. For the system with 100 nodes, the proposed model has better values of 26, 0.10857, and 0.68116 as the nodes, network energy, and the throughput, respectively.

Table 3 provides the comparative analysis of the proposed method and the existing methods based on computational time. The computational time of the existing methods, such as ABC, ACO, FABC, LEACH, Fuzzy ACO, and PeSOA is 3 sec, 4.5 sec, 2 sec, 3.5 sec, 2.5 sec, and 4 sec respectively, while the proposed PFuzzyACO has the computational time of 1.5 sec which is smaller than the other existing methods.

5 Conclusion

This paper introduces the PFuzzyACO algorithm for finding the optimal cluster head in the WSN environment. The proposed PFuzzyACO model integrates the PeSOA, Fuzzy logic and the ACO algorithm for the optimization procedure. Besides, the fitness for the selection of the optimal cluster head is done based on the proposed multiobjective fitness

Table 2. Comparative analysis of the proposed PFuzzyACO for varying number of nodes

Evaluation metrics	Number of nodes	Comparative models						
		ABC	ACO	FABC	LEACH	Fuzzy ACO	PeSOA	Proposed PFuzzyACO
Number of alive nodes	50	8	5	6	7	5	8	10
	100	15	13	15	8	12	11	26
Network energy	50	0.08328	0.05545	0.07024	0.05579	0.05506	0.07304	0.08783
	100	0.05856	0.0759	0.05759	0.0577	0.07516	0.05681	0.10857
Throughput	50	0.60978	0.61934	0.6223	0.63233	0.63871	0.63880	0.67651
	100	0.62201	0.60979	0.63855	0.60591	0.61192	0.61969	0.68116

Table 3. Comparative analysis based on computational time

Comparative Methods	Computational Time (Sec)
ABC	3
ACO	4.5
FABC	2
LEACH	3.5
Fuzzy ACO	2.5
PeSOA	4
Proposed PFuzzyACO	**1.5**

function. The proposed multiobjective fitness function defines the fitness of the optimization procedure based on the five factors namely, energy, distance, delay, traffic density, and link lifetime of the nodes. The simulation of the proposed PFuzzyACO algorithm is done with the experimental setup of WSN with the 50 and 100 nodes. The evaluation metrics such as network energy, number of alive nodes, and throughput define the efficiency of the algorithms. For the WSN with 50 nodes, the proposed PFuzzyACO model has the values of 10, 0.08783, and 0.67651 for the number of alive nodes, network energy, and the throughput respectively. For the system with 100 nodes, the proposed model has better values of 26, 0.10857, and 0.68116 for the nodes, network energy, and the throughput respectively.

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