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Fuzzy-Based Firefly and ACO Algorithm for Densely Deployed WSN

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Most of the wireless sensor networks (WSNs) used in healthcare and security sectors are affected by the battery constraints, which cause a low network lifetime problem and prevents these networks from achieving their maximum performance. It is anticipated that by combining fuzzy logic (FL) approximation reasoning approach with WSN, the complex behavior of WSN will be easier to handle. In healthcare, WSNs are used to track activities of daily living (ADL) and collect data for longitudinal studies. It is easy to understand how such WSNs could be used to violate people's privacy. The main aim of this research is to address the issues associated with battery constraints for WSN and resolve these issues. Such an algorithm could be successfully applied to environmental monitoring for healthcare systems where a dense sensor network is required and the stability period should be high.

Keywords: clustering, firefly, WSN, ant colony optimization, fuzzy, wireless sensor healthcare network, FIS.

1. Introduction

In WSN, sensors are usually organized in high density and great amounts. The combination of IoT with WSNs will aid in reaching the maximum usage of applications and provide the new opportunities in various fields; however, this combination requires careful consideration. While WSNs have restricted resources, they possess the remarkable capability to make changes in almost every aspect of life. WSNs are a collection of small devices that work together to record and monitor a specific phenomenon. They can be used in a variety of situations.

Disasters, remote monitoring, pollution monitoring, military actions, different target tracking, security monitoring, health services, and other commercial uses are possible application areas of WSNs. Health is a very vital aspect of anyone's life. It is a condition in which an individual's psychological, physical, and social well-being works in sync with her/his metabolism. Nowadays, the innovation for sensing has the prospect for major developments not only in science and technology, but also in security, medical services, the environment, crucial surveillance, and in the economy [1]. In the case of wireless healthcare systems such as patient monitoring systems, there is a need for proper monitoring as it is directly concerned with patient life. In these systems, the WSN lifetime is the major issue. The sensor networks offer a potent arrangement of distributed sensing, communication, and computational capabilities. They are used in numerous fields and, in the meantime, experience frequent challenges due to their peculiarities. There are many architectural and design issues in WSNs.

Energy consumption, topology control, query processing, coverage, connectivity, production cost, hardware constraints, and security are some of the major issues that are continuously addressed by the researchers. To design energy-efficient WSNs that meet the requirement of most sensor network applications, several research areas need to be investigated [2]. In the literature, it has been proved that clustering algorithms play significant roles in the development of energy-efficient routing protocols; hence various clustering algorithms for cluster formation and selection of cluster heads (CHs) have been proposed. In clustering protocols, the cluster creation process and the number of clusters are critical. Clusters should be evenly distributed, and the number of messages sent during cluster creation should be kept to a minimum [3]. The data transferred by each sensor node (SN) is gathered and processed by the CH nodes. A CH node transmits this processed information to the sink. Though the energy intake gets reduced through clustering, it suffers from a major limitation: the structure's energy depletion is mostly connected with only on these CHs [4]. Researchers have proposed many algorithms based on fuzzy logic (FL) and various computation intelligence-based algorithms to develop energy-efficient algorithms for WSNs. In healthcare, wireless sensor networks are used to track ADL activities and collect data for longitudinal research. It is easy to understand how such WSNs could be used to violate people's privacy.

Various meta-heuristic algorithms have been applied in the implementation of various clustering algorithms. Swarm intelligence, glow-worm optimization, ant colony optimization, genetic algorithms, bee colony optimization, neural network, and firefly algorithm (FA) are some of the widely used algorithms to resolve the optimization issues.

To cope with the complexity of the dynamic system, there has been a significant development in communication and technological advancements in wireless media. The studies reveal that the fuzzy set theory proposed by Zadeh [5] has been widely investigated in the literature. Attempts were made to incorporate a new paradigm of FL-based approaches to handle uncertainty and impreciseness of the real-world system (process). Fundamentally, FL is the addition of dual logic, which incorporates the intermediary value computed between absolute true and absolute false [5]. It is expected that if the approximate reasoning power of FL is combined with WSN, it will be easier to handle the complex behavior of WSN [6] since it is very well suited for the implementation of clustering and routing algorithms, heuristics and optimizations such as link classification and selection of CHs.

A literature review reveals that FL is considered a significant tool in computational intelligence and could be used in the remote sensor system to resolve various challenges. It is very important to select the optimal CHs since a choice of accurate CH can extend the overall network lifespan and contribute to reducing energy intake. In a fuzzy-based firefly and ant colony algorithm (FF-ACO), the CH selection is based on the two fuzzy inputs: distance and energy.

FA is a meta-heuristic approach based onthe flashing lights of fireflies. The intensity of the light assists a firefly swarm in moving towards attractive and brighter positions. In the search space, these locations could be drawn to an optimal solution. Firefly algorithm has a fast convergence. The multimodal problems could be efficiently handled by the FAs, and they can be used for local, global, and general search heuristics [7]. The ability to discover the shortest and optimum path makes the ant colony optimization (ACO) the most promising and widely recognized application based on the behavior of ants. The ACO algorithms are now successfully used in various fields such as routing, scheduling, assignment, machine learning, and bioinformatics [8].

The formation of clusters in WSN is also a critical issue addressed in the literature. In the FF-ACO, the formation of clusters relies on the principle of the meta-heuristic FA. To discover the shortest route, routing is considered as a combinatorial optimization problem. In the proposed work, the routing or transmission of data packets relies on an ACO algorithm in which work has been done to minimize the energy loss in the transfer of redundant information.

The motivation of the research work: In an application such as environmental monitoring for healthcare systems, where dense sensor network are required, it is crucial to have higher stability period and longer network lifetime as sensors cannot be replaced again and again. The motivation of this research work is to design and implement an energy-efficient routing algorithm with an increased network lifespan as compared to other existing well-known algorithms in the case of densely deployed WSN, and this algorithm can deal with the low network lifetime problem and redundant information transmission problem, specifically in a densely deployed WSN.

WSNs are associated with battery constraints, which causes short network lifetime problems and prevents these networks from achieving their maximum performance. Hence, it is necessary to increase the lifespan as it is the major performance criterion.

Major contribution: In the proposed approach, cluster-based hierarchy and fuzzy inference system (FIS) have been used for the CHs selection. Within the network, the FA is applied in the formation of clusters and the ACO algorithm is applied in the information transmission along with the selection of the optimal path. Cluster formation, cluster-head selection, and selection of an optimal path for the transmission of information are the key issues in WSN. All three issues have been addressed in the proposed algorithm.

Outcomes demonstrate that the FF-ACO has a prolonged network lifetime and an increased stability period. In the FF-ACO, a large number of data packets are acknowledged at the sink and it is superior to the intercluster ant colony optimization (IC-ACO) and low-energy adaptive clustering hierarchy (LEACH) algorithms, also in terms of energy efficiency.

The paper is arranged as follows: Sec. 2 briefs about the FL-based routing algorithms, FAs, and ACO algorithms. The radio model employed in the implementation of the algorithm is explained in Sec. 3. Section 4 consists of a detailed discussion about the implementation, process layout, and the flowchart of the proposed work. Section 5 discusses the simulation results, which reveal the significant improvement of various parameters in comparison to the existing approaches. Section 6 concludes the proposed work with suggestions that may be used in the future to improve the FF-ACO algorithm.

2. Materials and methods

This section explains the concept of ACO, FA, and the already available routing algorithm based on the concept of FL, FA, and ACO algorithm in the field of WSN. Cluster-based hierarchy and FIS are employed in the suggested technique to identify CHs. Within the network, the FA is used for clustering, while the ACO method is used for information transfer and route selection.

2.1. Ant colony optimization

In 1992 the concept of ACO was introduced by Marco Dorigo and it is named as ant system. This method is based on an ants' foraging activity when looking for a path between their colony and a source of food. It was first used to tackle the well-known dilemma of the traveling salesperson. It is used to solve a variety of difficult optimization issues. It is observed that the ACO is capable of developing the approximate answers to complex combinatorial problems in a reasonable calculation time [9]. Ants are constantly propelled from the several nodes to make a partial solution for the particular problem while going through the different phases of the task. These ants, who rely on trial data and attractiveness, are trailing a greedy local judgment [10].

A partial resolution is steadily delivered by all the agents during the traversal of various phases. The ACO attempts to determine an optimization issue by consistently succeeding in the steps listed below:

- solutions are made by utilizing a pheromone model;
- the arrangement is useful for revising the pheromones' evaluation vaues to designate them for future sampling to develop a superior arrangement.

2.2. Basic ant-based routing for WSN

The ACO approach is effectively used to deliver the estimated solution in various complex combinatorial optimization problems [11]. The description of the algorithm is given below:

1. At every regular interval, a forward ant is propelled to recognize the optimal route between the node and the last stop (destination). The identity of every node visited is saved in the memory of the ant.
2. Each ant follows a probabilistic approach for selecting the next hop in the optimized route and the probability of selection of a specific route is calculated as presented in Eq. (1):

$$p_k(r,s) = \begin{cases} \dfrac{[T(r,s)]^{\alpha}\,[E(s)]^{\beta}}{\sum\limits_{\mu \notin M_k} [T(r,\mu)]^{\alpha}\,[E(\mu)]^{\beta}} & \text{if} \quad s \notin M_k, \\ 0 & \text{otherwise}, \end{cases} \tag{1}$$

   where $p_k(r,s)$ is the likelihood of choosing a route between node r and s, T represents the pheromone values of the route (r,s), the visibility denoted by E is presented by Eq. (2):

$$\frac{1}{(c - e_s)}, \tag{2}$$

   where c – initial energy of nodes, e_s – node's current energy, α and β – determine the trail and visibility.
3. The forward ant starts transforming to the backward ant on reaching the destination node, which now refreshes the pheromone value of the path.
4. The quantity of pheromone dropped by the backward ant is presented by Eq. (3):

$$\Delta T_k = \frac{1}{N - Fd_k}, \tag{3}$$

   where N – number of nodes, Fd_k – distance traveled by the forward ant.

5. Pheromone information at a particular node is updated by the backward ant using Eq. (4):

$$T_k(r,s) = (1-\rho)T_k(r,s) + \Delta T_k, \tag{4}$$

where ρ is the trail evaporation parameter.

6. This backward ant is then eliminated on reaching the source node on which it was created.

2.3. Energy-efficient ant-based routing

In energy-efficient ant-based routing (EEABR), the distance and energy level of SN are considered for the selection of CH. EEABR employs a colony of artificial ants that move across the WSN in search of routes between sensor nodes and a destination node, both short and energy-efficient, extending the WSN's lifetime [12].

In the basic ant algorithm, each neighbouring SNs identity and their respective pheromone data are stored in the routing table; hence, a largememory is required to store this information. EEABR resolves this issue by keeping the data about the last two SNs, thus considerably decreasing the storage requirement. However, delay in packet delivery is the main shortcoming of this algorithm.

2.4. Firefly algorithm

Below are the prime considerations for the implementation of the fireflies' behavior as presented by Yang [13]. The algorithm was constructed based on the following assumptions:

1. One firefly can be pulled into all different fireflies because all the fireflies are unisexual.
2. Fireflies' attractiveness corresponds to their brightness, and for any two fireflies, the fireflies having less brigthness will be pulled towards the bright one; in any case, the brightness can diminish when the separation between them increases [14]. If no other fireflies are brighter than a given firefly, it will move at random [14].
3. The objective function is linked to the brightness.

Firefly algorithm: The steps of the FA [15] are as follows:

Create an underlying population of fireflies u_i with position x_i, $i = 1, 2, 3, ..., n$;
The objective function $f(x)$, where $x = (x_1, x_2, ..., x_d)^T$, is defined.
Produce an underlying populace of fireflies x_i, $i = 1, 2, 3, ..., n$;

$f(x_i)$ determines the light intensity I_i of a firefly u_i at point x_i.
Define the term "light absorption coefficient" y;
While ($t <$ max generation) do
 /*for all n-fireflies*/
   for $i = 1 : n$ do
    /*for all n-fireflies*/
    for j =1: n do
     if ($I_j > I_i$) then
      move firefly i towards j in d-dimension
    else
   end
  end
 Attractiveness shifts with the separation r by means of exp $[-yr]$;
Examine different arrangements and increase the intensity of light;
end
end
Rank the fireflies and identify the present best;
End

2.5. Low-energy adaptive clustering hierarchy

Low-energy adaptive clustering hierarchy (LEACH) is a clustering-based hierarchical routing protocol [16]. Formation of a cluster depends on the receiving signal strength, and the processed data are transferred to the sink via CHs. The energy of SNs is saved since the transfer of data has been performed by only such CHs. Data fusion and aggregation are accomplished within the cluster locally. In comparison to direct transmission, LEACH outperforms in terms of reduction of energy dissipation over a factor of 7 and 4–8, respectively.

2.6. Fuzzy master cluster head election LEACH

Fuzzy master cluster head election LEACH (FMCHEL) is a hierarchical homogeneous routing protocol developed for an application where the sink is positioned very far from the sensor network area [17]. In this protocol, the FL-based CH selection is used to maximize the lifetime of WSNs. The CH election mechanism is similar to cluster head election mechanism using fuzzy logic CHEF, but the proposed approach also has the master CH election mechanism in which only the master CH node forwards the processed data to the sink. FMCHEL is more energy-efficient, has a prolonged network lifetime and a more stable region than LEACH and CHEF protocols.

2.7. Energy-aware unequal clustering with fuzzy

Energy-aware unequal clustering with fuzzy (EAUCF) is an algorithm developed to increase the network lifespan of WSN [18]. EACUF chooses the CHs through the energy-based race between the tentative CHs. A probability-based model is being used for the CHs selection. The efforts are being made to lessen the energy consumption of CHs of each cluster by keeping them closer to the BS. The fuzzy rules were customized to grip the uncertainty in the estimation of CH radius.

2.8. Cluster-head election mechanism using FL

In cluster-head election mechanism using FL (CHEF), the fuzzy if-then rules are used to pick the CH [19]. The two linguistic characteristics used in CHEF to choose CHs are distance and energy. The CHEF has a longer stability period than LEACH. CHEF is a fuzzy-based algorithm in which CH election is performed in a distributed manner. It ensures that no two clusters-heads should be present within r distance via the candidate method. Additionally, FL control permits the SN, which is locally optimal and has higher energy than the other chosen as CH [19].

3. Energy model analysis

Heinzelman *et al.* [16] proposed a simple first-order model, and this model has been used in the proposed work. This model consists of a transmitting amplifier and transmitting and receiving electronics, as shown in Fig. 1. In this study, the multi-path fading channels free space and models are used.

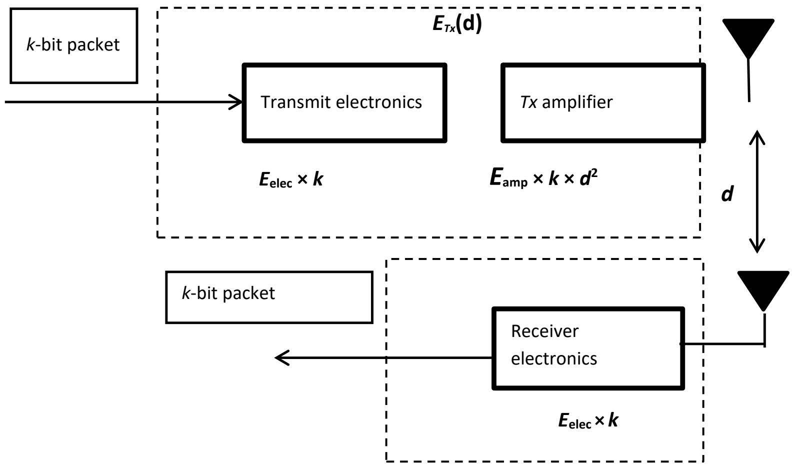

Fig. 1. Energy dissipation diagram.

The energy dissipated by the SN when it sends k-bit data from its transmitter is:

$$E_{Tx}(k,d) = E_{\text{elec}} \times k + E_{fs} \times k \times d^2 \qquad \text{if} \quad d < d_0, \tag{5}$$

$$E_{Tx}(k,d) = E_{\text{elec}} \times k + E_{mp} \times k \times d^4 \qquad \text{if} \quad d \geq d_0. \tag{6}$$

The following is the energy dissipation when receiving a k-bit data packet:

$$E_{Rx}(k) = E_{\text{elec}} \times k. \tag{7}$$

E_{elec} is the energy dissipation parameter, k is the packet size termed, d is distance, and E_{fs} and E_{mp} are the transmitter amplifier characteristics.

4. The FF-ACO algorithm

It is anticipated that if the approximate reasoning power of FL is combined with WSNs, it may be easier to handle the complex behavior of WSNs. Numerous soft computing technique-based methods are developed for enhancing the network lifetime through optimizing various processes such as selecting optimal CHs, forming the cluster, and finding an optimal route for routing. Fuzzy inference articulates the mapping from a specified input to output [20]. This mapping afterward offers a ground on which judgments can be formed. The inference engine marks inputs and fuzzy if-then rules to simulate reasoning by fuzzy inference. The interface converts the fuzzy set acquired by the inference engine into crisp output. In the proposed approach, fuzzy-if-then rules apply to the two input parameters, namely, the residual energy and distance. FL-based CHs election optimizes the process of selection of CHs, which was done randomly in the IC-ACO and LEACH algorithm.

In the FA, the main objective of a firefly's luminosity is to behave as a signal system to attract other fireflies. FA is a meta-heuristic approach for global optimization. The brightness is related to attractiveness, and both diminish as the distance between them increases. As a result, if there are two flashing fireflies, the less bright one will travel toward the brighter one.

The behavior of fireflies is modeled in the formation of clusters in the proposed approach. An ACO is an AI-based approach supported by the ant's pheromone-laying behavior. In this system, ants begin from a start point, pass through the neighboring SNs, and arrive at the last stop. When it is necessary to transmit the information from the start node, the launching of ants will be carried out. It has been observed that in a dense network the SNs are very likely to lie in close proximity. Hence, they sense the redundant information.

The transmission, sensing, and processing of redundant information is a serious issue since it is combined with energy consumption, time, and delay, thus leading to waste of various network resources. Since the proposed approach is implemented in the dense environmentthe work has been done to reduce the redundant data transfer similar to IC-ACO [21]. Further, the CHs have been chosen randomly in IC-ACO and LEACH, whereas the fireflies' behavior inspired cluster formation and fuzzy-based CH selection makes the proposed approach superior to IC-ACO and LEACH.

The entire rounds initiate with a setup phase to identify the FL-based CHs selection, and the cluster formation is performed in this phase, followed by a steady-state phase where the data packets are transmitted from the SNs to the CHs and to the sink. In FF-ACO, cluster formation relies on the algorithm inspired by firefly behavior. The FF-ACO algorithm's steady-state phase and setup phase are described below.

4.1. Setup phase

4.1.1. Cluster heads selection based on FL. Classical techniques only consider the true and false values, while FL can consider the partial truth value of parameters. The FL model consists of a defuzzifier, fuzzifier, fuzzy inference engine, and fuzzy rules, as shown in Fig. 2.

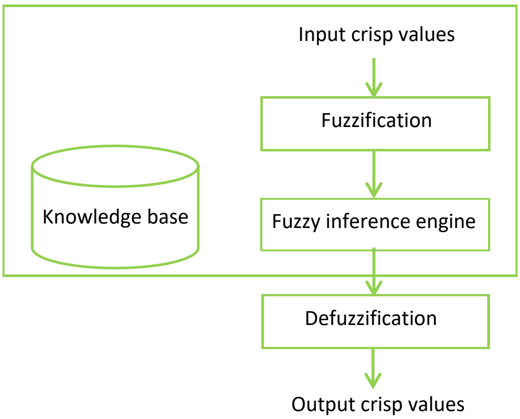

Fig. 2. Structure of the FL model.

In the proposed approach, the Mamdani model is used. The crisp values are converted into fuzzy sets by the fuzzifier. In order to produce an output as fuzzy sets, the fuzzy if-then-else rules are applied to the fuzzy sets [22]. By using the defuzzification technique, the output fuzzy set is converted into crisp output by the defuzzifier.

4.1.2. Knowledge representation. In FF-ACO, the nine different fuzzy if-then rules are applied and two input functions are used. The functions are as follows:

- Distance: This parameter signifies the distance between the SNs and the sink.
- Residual energy: This parameter represents the SN's remaining energy.

With the help of these two parameters, the chance is calculated. The distance and the energy are delivered to the FIS to convert it to the fuzzy sets. Then, they are signified using membership functions. The two parameters here are known as input variables. For each input variable there are three different membership functions, shown in Table 1.

TABLE 1. Fuzzy set for energy and distance.

Input	Fuzzy set		
The residual energy of the battery	low	average	high
Distance	near	medium	far

The proposed approach is homogeneous; hence, all the SNs have similar initial energy. Thus, the value of residual energy could lie between 0 to 0.5, as shown in Fig. 3. The network plots in a range of 100×100, and the value of distance is between 0 to 75. The distance is represented as three fuzzy sets: far, medium, and near. Table 1 presents the fuzzy sets for distance and energy. The membership functions for residual energy and distance are presented in Figs. 3 and 4, respectively.

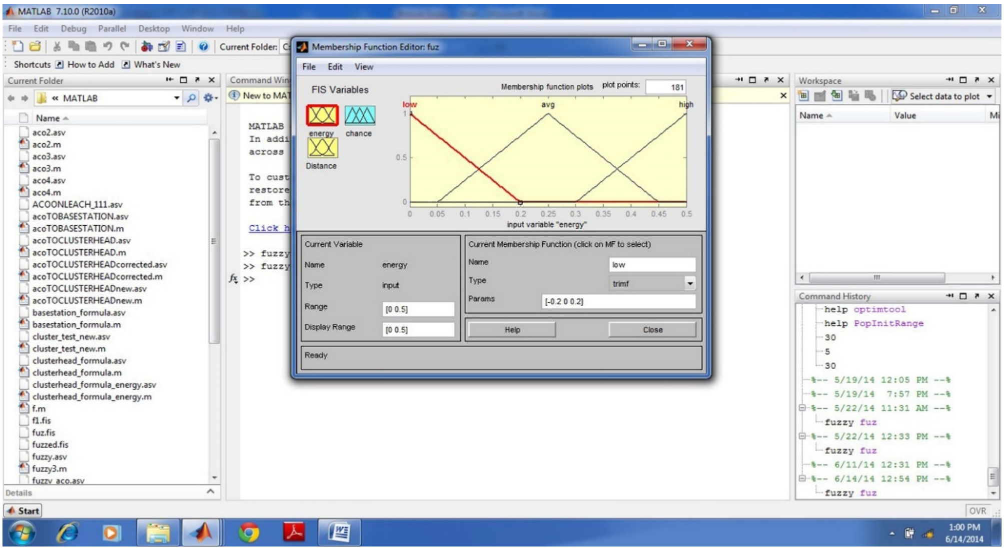

FIG. 3. Membership function of residual energy.

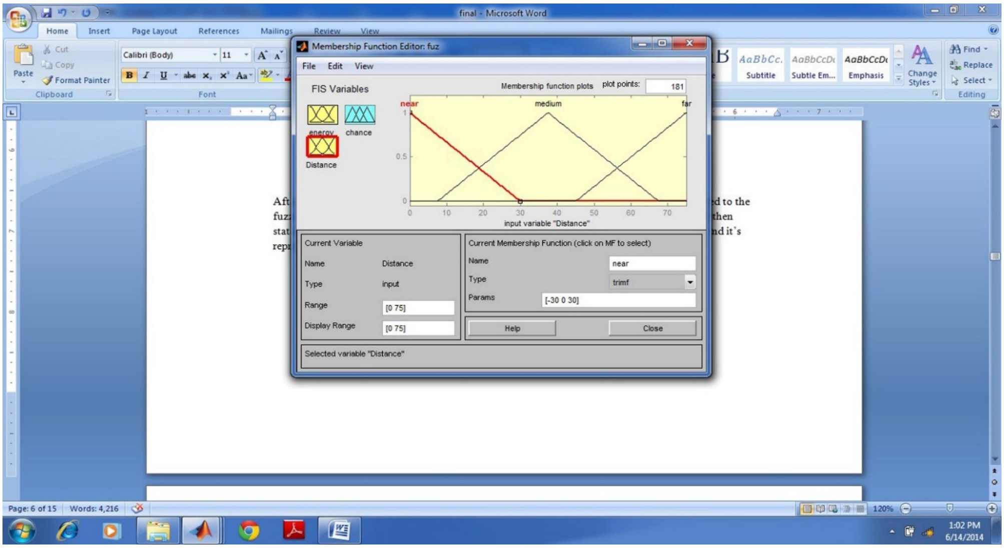

FIG. 4. Membership function of distance.

The Mamdani rule-based model is used by the SNs for the decision-making, and existing fuzzy if-then rules are used to select the neighboring SN as chance [23]. The rule base and its representation of the FF-ACO approach are given below in Table 2. The inputs are provided to FIS when the rule base is applied to them. The fuzzified output thus created requires defuzzification. The output linguistic variable defines the chance of selection and has two levels, high and low.

TABLE 2. Fuzzy rules.

S. No.	Distance	Energy	Chance
1	far	high	high
2	far	average	low
3	far	low	low
4	medium	high	high
5	medium	average	high
6	medium	low	low
7	near	high	high
8	near	average	high
9	near	low	low

4.2. Formation of cluster

After the CHs are identified based on the two fuzzy inputs of distance and remaining energy,the balanced cluster formation with the associated CHs will take place in this phase only. After CHs are elected through the fuzzy inference, they start broadcasting the desired packet by presenting the intensity value, which is presented by Eq. (8):

$$I(x) = \frac{I_0}{(1 + \gamma\, x_i^2)}, \tag{8}$$

where $I(x)$ is the source light intensity at a distance x_i, and the absorption coefficient of the medium is denoted as γ. A firefly's attractiveness is proportionate to the light intensity observed by the neighboring fireflies [24, 25]. β the attractiveness coefficient, is calculated by the Eq. (9):

$$\beta = \beta_0 \exp(-\gamma\, r_{ij}), \tag{9}$$

where β_0 is the attractiveness at $r = 0$, r_{ij} is the distance between any two fireflies i and j, which are located at x_i and x_j, respectively, and calculated using Eq. (10):

$$r_{ij} = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2}. \tag{10}$$

The greater the distance between the ordinary SN and the CHs, the lower the values determined by the Eq. (8), where I_0 represents the initial intensity. All the CHs accumulate higher intensity values than the normal SNs in the network in a particular round. Here, x_i is computed using FA Eq. (11):

$$x_i = x_i + \beta \exp\left[-\gamma r_{ij}^2\right](x_j - x_i) + \alpha \times \varepsilon, \tag{11}$$

where x_i, and x_j are the location of CH and normal SNs, respectively. Only the x coordinates are used for the intensity calculation. The distance between the normal SNs and CHs is calculated with the help of α, β, γ, and ε parameters (the adjustable parameters). Here, ε provides the randomness in the above equation.

After obtaining the intensity values from the CHs, the normal SNs calculate their intensity value using Eqs. (8) and (11). Each SN stores its own intensity values and the intensity values of other CHs chosen based on two fuzzy inputs of distance and energy. All normal SNs then compare the values of their intensity with the intensity values of all the CHs. The SNs create an association with the CHs, which has the highest value compared to their value. The process leads to cluster formation.

4.3. Steady-state phase

If the network is densely deployed, it is highly probable to transmit the redundant data [26]. In this phase, the redundant data minimization, routing, and ACO-based data transmission take place within the clusters. The subsequent stages are repeated untill all the SNs are alive.

1. Minimization of redundant information: The minimization of redundancy is similar to IC-ACO. The SNs that lie in high density or very close to each other have maximum probability to transmit the repetitive data [27]. To conserve the energy that is lost while transmitting this repetitive data, a radius has been picked up experimentally. As in the case of intercluster ant colony optimisation, 5 is chosen as the optimum radius in the (100×100) network. Out of the SNs in the chosen range, an SN with maximum residual energy is chosen for the data transfer to the CH only if the chosen SN is nearer to the CH than the sink. The rest of the SNs inside the radius does not participate as they are in sleep mode in the present round and will not take part in data transfer [28]. If the chosen SN is nearer to the sink, at that point, it will not transmit information to the CH. However, it will participate with the rest of the SNs that are not in the range. Afterward, the information received at CHs is processed and transferred to the sink.

2. Routing of data packets within the cluster using ACO: In every cluster, the SNs that are neither in rest mode nor chosen for the information transmitted to the sink within the cluster will start the routing by transmitting the information to the neighboring SNs [29]. Every SNs then identifies its neighbor SN. The optimal path to the sink is shaped by the ants to accomplish effective routing [21]. It shadows the probable attitude in the construction of the solution, i.e., choosing an appropriate route for transferring the information towards the sink. The probabilistic selection relies on pheromone and heuristic information, and it is constantly updated. During this routing process, ants choose their optimal path based on heuristic and pheromone information. The evolving solution for this procedure is described below.

4.4. The evolving solution for FF-ACO

In this phase, information transmission takes place. The ACO algorithm is being used to determine the optimal route between the CHs and SNs. In addition, an adaptive routing strategy based on ACO is created. The excess energy remaining in the nodes is used to determine which route to take.

The following steps are undertaken to recognize the ACO route:

1. At each source, SN forward ants are presented.
2. The ants practice the intermediate SNs with the ultimate objective of targeting their respective CHs [23].
3. The ants have a probabilistic approach for settling on the choice of which SN is to be explored subsequently. The pheromone and heuristic information is the emphasis of this probabilistic strategy. The probability is calculated as follows:

$$p = \frac{(\tau_{ij})^{\alpha 1} (\eta_j)^{\beta 1}}{\sum\limits_{j \in N} (\tau_{ij})^{\alpha 1} (\eta_j)^{\beta 1}}, \tag{12}$$

where τ_{ij} signifies the pheromone data and it is calculated as:

$$\tau_{ij} = \frac{1}{d_{ij}}, \tag{13}$$

where the distance between SN and its related CH is d_{ij}, η_j indicates the heuristic information desribing the SN's energy and it is determined as:

$$\eta_j = \frac{E_0 - E_{\text{residual}}}{\sum\limits_{k \epsilon N} E_k}, \tag{14}$$

where E_0 is the starting energy and E_{residual} is the leftover energy. The parameters α_1 and β_1 control the relative weight of the heuristic and pheromone trail, respectively.

4. An SN with the greatest likelihood is picked as the next hop for the transmission of sensed data to its associated CHs.

4.5. The algorithm for FF-ACO

The following algorithm characterizes the stages to be monitored in the development of the proposed FF-ACO algorithm for the cluster formation, CHs selection, and the discovery of an optimal route to the target SN:

1. The below steps are recurrent till all the SNs are alive.
2. The distance and energy are the two parameters transferred to the FIS. Afterward, it is processed based on the predefined fuzzy if-then rules, and the CHs are identified – the SNs with the maximum chance are selected as CHs.
3. Clusters are shaped around these selected CHs using the FA.
4. After cluster formation using the FA, efforts are made to minimize the redundant information as all the SNs in close proximity (i.e., 5 in the proposed approach) will not participate in transmission. Only one of the SNs with higher energy will participate in transmission in that particular round. The pheromone and heuristic information is required to calculate the ant colony optimized path between every SN and associated CH. This optimized ant colony algorithm-based path depends on the pheromone and heuristic information.
5. Before transmitting information to the sink, the immediate route between the sink and each SN is compared with the ACO-based route created in the past stride.

6. Based on the above comparison one of the paths is chosen as follows:
   - if an ACO-based route has less distance than the direct route, the SN transfers the information to the CHs. Next, CH node forwards this information to the sink;
   - if the direct route is smaller than the ant colony-based route then the processed information is directly transferred to the sink.

Figure 5 presents the flowchart for the FF-ACO algorithm.

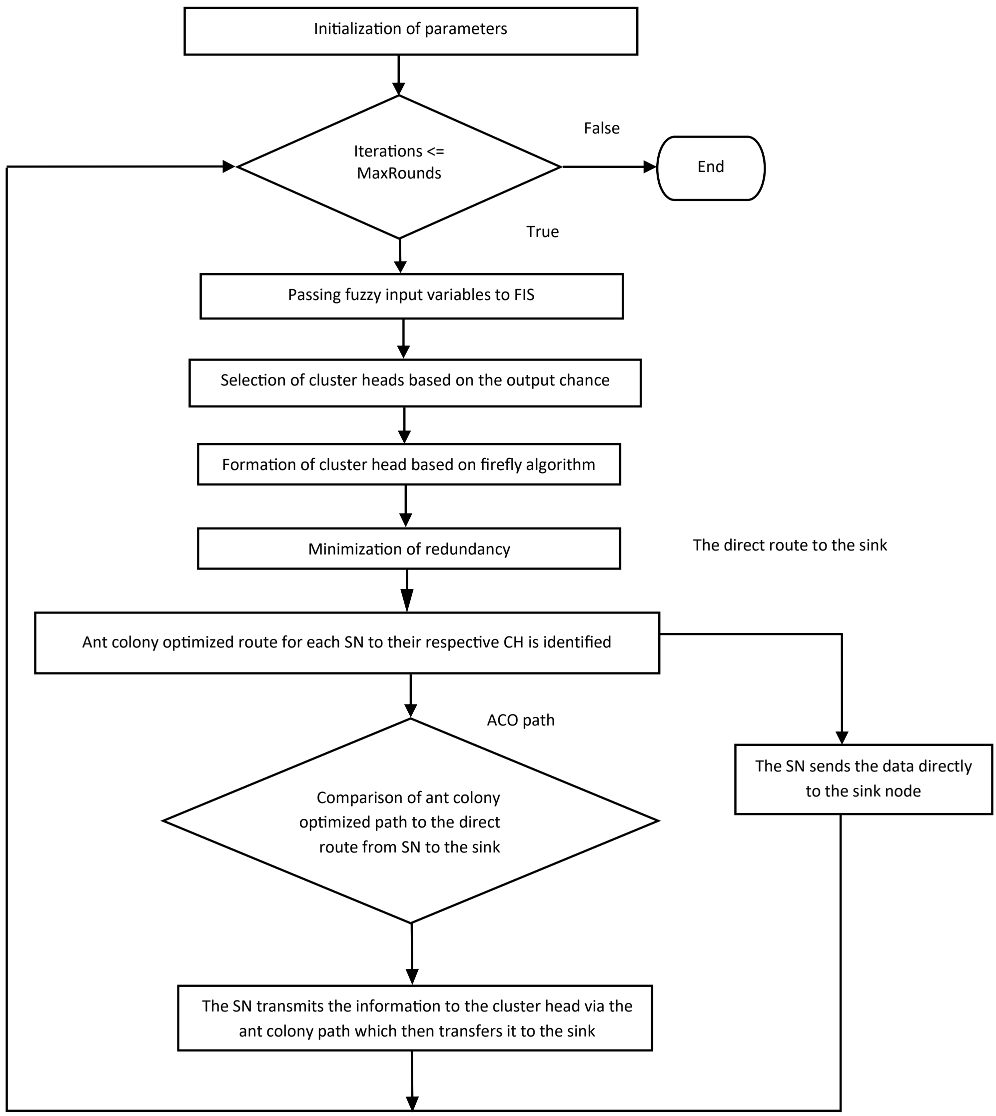

Fig. 5. Flowcharts for the proposed approach.

5. Results and discussions

This part briefly discusses the simulation results of the FF-ACO algorithm. The performance of FF-ACO algorithm is compared to IC-ACO and LEACH with similar network and parameter settings. These algorithms have two similar parameters, distance (the range between the SNs and the sink is indicated by this parameter) and residual energy (the residual energy of the SN is represented by this parameter). The range of transmission for all the SNs is similar. The sink lies at position (50, 50). The results obtained depict that the fuzzy method calculates the linguistic rules in an instinctive way and that the requisite for the correct illustration of the surroundings could be averted. In an experimental setup, 100 and 200 SNs are randomly positioned in a 100×100 area. Table 3 presents the parameters used for simulations.

Table 3. Simulation parameters.

Parameters	Values
Location of the sink	50, 50
Radius of CH	5 m
Initial energy in each SN	0.5 J
EDA (data aggregation energy)	5×0.000000001 J
Electronic energy (Efs)	10×0.000000000001 J
Amplifier energy (Emp)	$0.0013 \times 0.000000000001$ J
ETX = ERX	50×0.000000001 J
α (Pheromone control parameter)	0.5
β (Heuristic control parameter)	4
Firefly algorithm parameter	$\alpha = 0.2$, $\beta = 1$, $\gamma = 1$
Maximum rounds	3500

The comparison of the three algorithms (LEACH, IC-ACO, and FF-ACO) is based on the following:

1. Stable region: It is the region up to which all SNs are alive.
2. The total consumed energy: It is the sum of energy of all the nodes. All the nodes are homogeneous and all have the same initial energy of 0.5 J. Thus, the total energy in the case of 100 nodes is 50 J and 100 J in the case of 200 nodes.
3. The total number of data packets received at the sink.

It is clearly understood from the results that compared to IC-ACO and LEACH, the FF-ACO has progressed in the stable region and has a better overall network lifetime. The FF-ACO is also found to be superior in terms of energy utilization compared to IC-ACO and LEACH. Table 4 shows the comparison of IC-ACO, LEACH, and FF-ACO in terms of first node dead (FND) values with 100 and 200 SNs. Table 5 shows the improvement of the FF-ACO in terms of stability period over LEACH and IC-ACO. Table 6 shows the decline in unstable period of FF-ACO over LEACH and IC-ACO.

Table 4. Comparison of FF-ACO, IC-ACO, and LEACH in terms of FND.

Description	LEACH	IC-ACO	FF-ACO
FND_round SNs: 100	436	930	1138
FND_round SNs: 200	222	948	1177

Table 5. Improvement in stability period over LEACH and IC-ACO.

Description	An improvement over LEACH [%]	An improvement over IC-ACO [%]
SNs: 100	161	22.36
SNs: 200	430	24.16

Table 6. The decline in unstable period over LEACH and IC-ACO.

Description	An improvement over LEACH [%]	An improvement over IC-ACO [%]
SNs: 100	13.45	40.93
SNs: 200	28.15	45.01

Figure 6 reveals the total alive SNs versus rounds, which specifies the network lifetime when 100 SNs are installed. It is clearly understood from the figure that the performance of the FF-ACO algorithm is much better compared to IC-ACO and LEACH. In LEACH, the FND value is 436 rounds compared to 930 rounds in IC-ACO and 1138 in FF-ACO, which illustrates the substantial progress in the stability period.

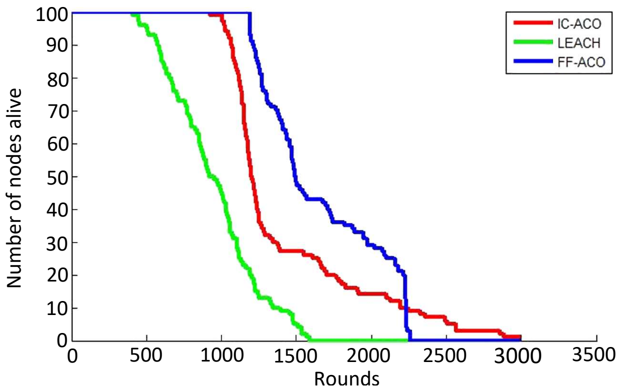

Fig. 6. The number of live SNs versus rounds (SNs: 100).

Figure 6 shows the total number of live SNs at various rounds, with 100 SNs introduced into the system. Here, the performance of FF-ACO is better than that of LEACH and IC-ACO. Figure 7 portrays the total number of live SNs at various rounds, which specifies the network lifetime when the network is more dense as 200 SNs are introduced inside the system. Figure 7 shows that the performance of FF-ACO is superior to IC-ACO and LEACH in a dense environment. In LEACH protocol, the FND value is 222 rounds, in IC-ACO it is 948, and 1177 in FF-ACO. The figure shows that the performance of the LEACH protocol is degraded in a denser network. However, the performance of the IC-ACO algorithm is considerably overshadowed by the LEACH protocol, whereas the performance of FF-ACO is better than IC-ACO.

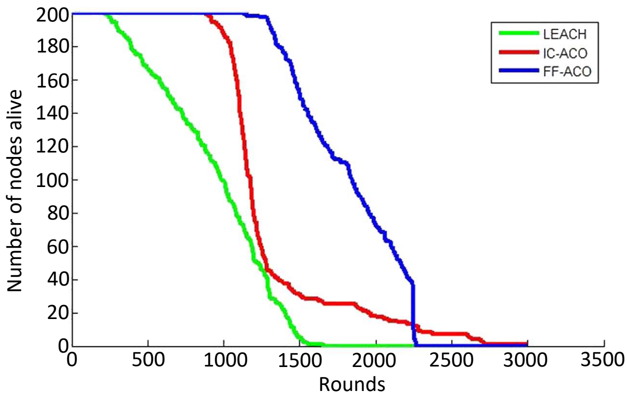

Fig. 7. The number of live SNs versus rounds (SNs: 200).

Figure 8 portrays the evaluation of total energy consumed versus rounds for all three protocols, and it can be seen that the FF-ACO is more energy efficient in comparison to IC-ACO and LEACH. The total residual energy at

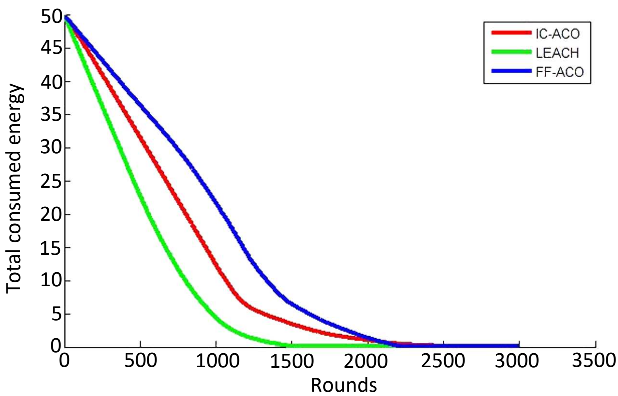

Fig. 8. Total consumed energy versus rounds (SNs: 100).

different rounds can be observed in the figure, provided all the SN have the same initial energy of 0.5 J.

Figure 9 presents the correlation of total consumed energy versus rounds for all three protocols. It can be observed in the figure that the FF-ACO is more energy efficient in comparison to IC-ACO and LEACH. The figure illustrates the total energy remaining when there are 200 SNs.

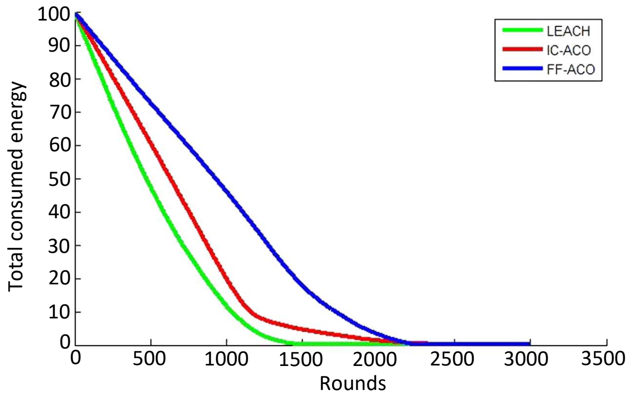

Fig. 9. Total consumed energy versus rounds (SNs: 200).

Figure 10 illustrates the data packets acquired by the sink while 100 SNs are installed. It can be observed that the total amount of packets acknowledged at the sink is improved as the FF-ACO has a higher network lifetime in contrast to LEACH and IC-ACO.

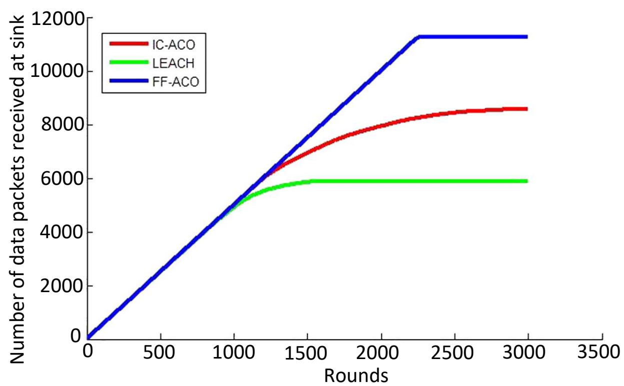

Fig. 10. Data packets received at sink versus rounds (SNs: 100).

Figure 11 shows the data packets acquired by the sink when 200 SNs are installed. It can be observed that in the FF-ACO there is more information

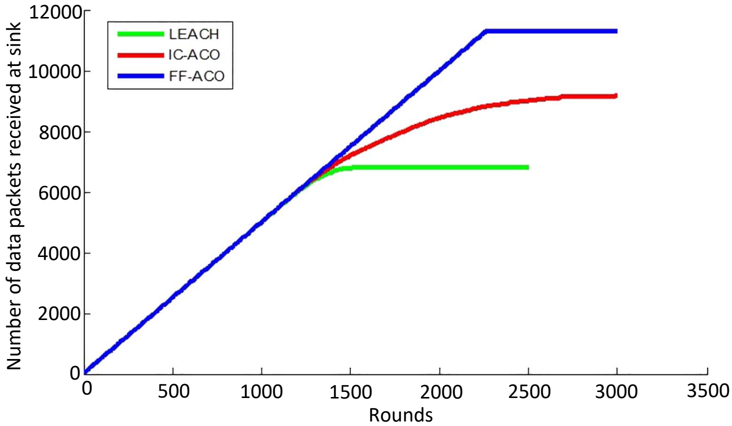

FIG. 11. Data packets received at sink versus rounds (SNs: 200).

transmitted to the sink compared with IC-ACO and LEACH in a dense environment.

Simulation results have the following conclusions:

1. The stability period is significantly improved compared with the existing IC-ACO and LEACH protocols in dense environments.
2. The FFACO is more energy efficient as the overall network lifetime and the rounds with FND are improved.
3. There is a considerable improvement in the number of packets received at the sink in similar network scenarios.

6. Conclusions

Selecting CH, cluster formation, and identifying the best route in a progressive, intense environment of a SN are very challenging issues. The primary objective of this work was to expand the network lifespan when it is highly dense. It was observed that in a dense network, the SNs are usually placed in close proximity and used to transmit the redundant data to the sink. Hence, energy is wasted in processing these similar data. In the FF-ACO algorithm, the application of FL, the FA, and the ant colony meta-heuristic approach were all used for the CH election, cluster formation and to find out the route between SNs and the sink. The experimental results show that despite the additional overhead of selection of CHs, the FF-ACO is efficient as it provides improved outputs such as higher numbers of data packets transmitted, extended network lifetime, improved stable region, and more energy-efficiency in dense networks. The FF-ACO algorithm has been considered for various network setups through increasing the SNs in a densely deployed network. Simulation results noticeably underline the extended lifetime, enhanced data transmission, and improved energy efficiency. Additionally, they reveal that when we compare the FF-ACO with IC-ACO, which is also specifically designed for densely deployed sensor networks, it could be seen that there is an improvement of 22.36% in the stability period when the number of nodes is 100 and there is an improvement of 24.16% when the number of nodes is increased from 100 to 200.

In the FF-ACO protocol, the simulations were conducted considering that the network is homogeneous. Future research could be further expanded and upgraded for the heterogeneous network. As it is evident, different methods such as the SN's mobility context and the incorporation of the mobile sink for a high-density network could be explored, and these are considered as great challenges in WSNs. In the FF-ACO, the SNs are randomly arranged, which could be further improved for future enhancement by incorporating any systematic deployment methodology. The future scope of this research will consider providing increased output in terms of higher numbers of data packets sent, prolonged network lifetime, improved stable region, and energy efficiency in dense networks. Thus, systematic deployment could further increase the overall energy efficiency with improved and enhanced coverage region.

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