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Extending the Lifetime of Wireless Sensor Networks Using Fuzzy Clustering Algorithm Based on Trust Model

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Abstract

Wireless sensor networks (WSNs) are the safest and most widely used existing networks, which are used for monitoring and controlling the environment and obtaining environmental information in order to make appropriate decisions in different environments. One of the very important features of wireless sensor networks is their lifetime. Two important factors come to mind to increase the lifetime of networks: These factors are maintaining the coverage of the network and reducing the energy consumption of sensor nodes simultaneously with the uniform consumption of energy by all of them. Clustering, as the optimal method of data collection, is used to reduce energy consumption and maintain the coverage of the network in wireless sensor networks. In clustered networks, each node transmits acquired data to the cluster head to which it belongs. After a cluster head collects all the data from all member nodes, it transmits the data to the base station (sink). Given that fuzzy logic is a good alternative for complex mathematical systems, in this study, a fuzzy logic-based trust model uses the clustering method in wireless sensor networks. In this way, cluster-head sensors are elected from among sensors with high reliability with the help of fuzzy rules. As a result, the best and most trusted sensors will be selected as the cluster heads. The simulation results in MATLAB software show that in this way, in comparison with K-Means, FCM, subtractive clustering, and multi-objective fuzzy clustering protocols, the energy consumption in clustered nodes will decrease and the network's lifetime will increase.

1. Introduction

One of the most difficult topics in computer and electronics sciences today is the discussion of remote monitoring and controlling systems [1]. Production and deployment of miniature, batterypowered nodes that communicate through wireless links have been made possible by earlier developments in information technology (IT), particularly in MEMS (micro electro-mechanical systems). A single node can collect information from the area that is in its coverage area. These nodes collaborate in order to have conceptually significant information from the whole area. Wireless sensor networks are made up of such nodes having sensing capabilities. Early implementation aimed to passively utilize these sensors for indoor applications. Scalar information like as temperature, humidity, pressure, and the location of nearby objects can all be sensed by these early nodes. These nodes are initially underpowered in terms of compute and storage, and their sole purpose is to send scalar data to the base station (sink). However, new sensor nodes outperform their predecessors in terms of compute power, storage capacity, and power management, and their main application domain switches from indoor to outdoor applications. Researchers are quite interested in the energy strategies of sensor nodes because they typically have batteries that cannot be recharged. For all of these reasons, one of the main objectives is still to reduce energy use through energy efficiency. To increase the lifespan of sensor nodes in this regard, energy-efficient algorithm design is essential [2].

Sensor nodes in the WSN can be organised into discrete groups known as clusters. A cluster-head (CH), also known as the leader, controls data aggregation from member nodes and transfer of the compiled data to the sink in each cluster. CH selection may be carried out centrally or decentralised. With a lot of sensor nodes, clustering in WSNs ensures strict performance requirements [3, 4]. Additionally, it makes WSNs more scalable [5]. Other benefits of clustering include route setup localisation, communication bandwidth conservation by minimising relayed packets, a decrease in the rate of energy consumption, and network topology stabilisation [6]. The literature has extensively examined the selection mechanisms since effective CH selection can lower energy consumption. The majority of strategies use a two-stage procedure, choosing CHs with more energy left over in the first step, and rotating the member nodes in the second step to balance energy consumption. This example demonstrates how these selection methods solely consider the nodes' energy and disregard their trust. Because the trust of the deployed nodes is not taken into account, clusters that are close to the sink are generated in lower sizes than clusters that are further away.

This study introduces a new clustering approach with the aim of prolonging the lifetime of WSNs, which is not only energy-efficient but also distribution-independent for wireless sensor networks. This protocol determines the radius of the sensors with the help of fuzzy logic and considering distance and energy variables, then determines the chance of becoming CH by considering the energy of the sensors and the number of neighboring sensors in the determined radius, and finally chooses sensors as cluster heads, which have high trust and a high chance of becoming CH.

The remainder of this paper is organized as follows: In Section 2, related studies are summarized. The system model is given in Section 3. Our proposed clustering algorithm, FCATM, is introduced and discussed in Section 4. Thereafter, simulation results and performance evaluations are explored in Section 5. Finally, in Section 6, our conclusions and possible future works are given.

2. **Related Works**

Effective data collection from deployed nodes is the focus of the data aggregation procedure. In this regard, clustering techniques offer energy-efficient infrastructure for the required activity. The established needs, such as reducing the quantity and size of data packets to be conveyed and offering effective delivery mechanisms for these routed packets, lead to the need for clustering. When taking into account the application kinds, which involve more multimedia streaming data every other day, this subject becomes even more important. Several WSN clustering techniques have been suggested in the literature. Key and differentiating characteristics of the popular clustering algorithms are described in the paragraphs that follow. It is helpful to think about what other existing clustering algorithms perform in order to assist identify the important elements of our suggested approach [4].

LEACH is a clustering-based system that uses random base station rotation to divide the energy load across the network's sensors in an equitable manner. In order to enable scalability and robustness for dynamic networks, LEACH employs localised coordination. Additionally, it adds data fusion into the routing protocol to lessen the quantity of data that needs to be broadcast to the base station. The probability that each node will become a cluster head in this round is determined by a stochastic method at the beginning of each round; in other words, this protocol chooses CHs using a probability model and then rotates CHs. Additionally, neither the gateway nor the nodes negotiate the CHs to be chosen in the following round. Before sending data to the sink in LEACH, the CHs compress the data. LEACH does not take into account the distribution of sensor nodes or the remaining energy on each node, hence it is not a lifetime-efficient algorithm for the network. [7].

Node equality is the main presumption of the Hybrid Energy Efficient and Distributed (HEED) algorithm, which is created for multi-hop networks [8]. It chooses cluster heads on a periodic basis using a hybrid of two node parameters: first cluster heads are chosen based on residual energy, and final cluster heads are chosen based on intra-cluster communication costs. However, because of its propensity to produce more clusters than predicted, the HEED algorithm suffers from the hotspots problem and results in uneven energy usage. [9].

Due to its effectiveness and simplicity in grouping huge data sets, the K-Means algorithm is one of the most often used clustering algorithms [10]. In the conventional K-Means technique, a collection of data, set D, is categorized using a set of initialized apriority clusters (k clusters). It first defines k centroids, one for each cluster, after which it takes into account data objects from the given data set and links them to the closest centroid. The distance between data objects and the centroids is often calculated using the Euclidean distance. When early grouping is complete and there are no more data objects, the first stage is finished. Here, new centroids must be calculated from scratch. The same data objects are bound to the nearest centroid and create a loop after acquiring fresh centroids. K-centroids gradually shift their points at the conclusion of the loop until they stop moving altogether [10, 11, 19]. The foundation of this approach is the squared error function minimization. The K-Means algorithm has issues with providing an initial seed value and a preliminary number of clusters. This approach also depends on the original cluster seed values and always converges to a local minimum. [10].

Fuzzy logic is being used by an increasing number of clustering algorithms to solve the issues that arise as a result of the uncertainties that exist in WSN nature. They are referred to as fuzzy clustering techniques as a result. Fuzzy logic is primarily used in these methods to combine the relevant input factors in a better way to produce the desired output, which in this case is CH election. [12, 18].

The data to be analyzed must be in the form of numerical vectors called feature vectors, and the number of clusters must be predefined in order to acquire the membership values of the feature vectors, according to Bezdek [13, 20]. The fuzzy c-means clustering algorithm's objective function that needs to be minimized is:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}{}^{m} \| x_i - c_j \|^2 \qquad 1 \le m < \infty \tag{1}$$

Where cj is the cluster-head of this cluster and uij is the degree of the membership function of xi in cluster j. The total number of nodes is N, the total number of clusters is C, and the parameter m, which affects the fuzziness of the generated clusters, is larger than 1.

The fuzzy c-means iterative algorithm has been described by Bezdek and Pal as a numerical procedure in their classification technique. With the update of membership uij and the cj cluster centres by [14], the goal function described above is optimised iteratively to perform fuzzy partitioning.

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left[\frac{\| x_i - c_j \|}{\| x_i - c_k \|}\right]^{\frac{2}{m-1}}} \tag{2}$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}{}^{m} . x_i}{\sum_{i=1}^{N} u_{ij}{}^{m}} \tag{3}$$

This iteration will stop when: maxij

$$\{|u_{ij}^{k+1} - u_{ij}^{k}|\} < \varepsilon \quad (4)$$

Where ε is a termination criterion between 0 and 1, and k is the number of iteration steps..

This procedure converges to a local minimum or a saddle point of Jm.

The algorithm is composed of the following steps:

1. Initialize U = [uij] matrix, U (0)
2. At k-step: calculate the centers vectors C(k)=[cj] with U(k)

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} . x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \quad (5)$$

3. Update U(k), U(k+1)

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left[\frac{\| x_i - c_j \|}{\| x_i - c_k \|} \right]^{\frac{2}{m-1}}} \quad (6)$$

If ||U(k+1) - U(k)||<ε then STOP; otherwise return to step 2.

The best data point to use to construct a cluster centroid based on the density of nearby data points is found using subtractive clustering [15]. Chiu's mountain method is expanded upon by this strategy. The mountain method for clustering is relatively straightforward and efficient. The mountain approach's accompanying computing method is solved using the subtractive-clustering algorithm. The calculation of this approach is proportional to the size of the problem and uses data points as candidates for the cluster centre. It makes an estimate regarding the cluster centres' initial size and position. The potential for each data point is calculated based on its distance from the actual data point once the data space is divided into grid points. The grid point with the highest potential value will be selected as the initial cluster centre since it will have a high potential value due to the proximity of many data points. We will attempt to locate the second cluster centre by determining the grid point with the highest potential value after choosing the first cluster centre. The next cluster centre will be a grid with numerous data points nearby in addition to the first cluster centre grid point because grid points close to the first cluster centre will lower its potential worth. Up until the potential of every grid point drops below a threshold value, this process of gaining new cluster centres and lowering the potential of neighbouring grid points is repeated. As a result, this technique is among the easiest and most efficient ways to identify cluster centres. However, the complexity of its processing exponentially increases as data dimensions increase.

Take a look at the following set of n data points: X = x1, x2, x3,..., xn. Each point is then taken into account as a potential cluster centre. The following is a definition of the data point's xn potential:

$$p_n = \sum_{i=1}^{n} e^{\frac{-4 x_n - x_i^2}{r_a^2}} \quad (7)$$

The neighbourhood is defined by the positive constant ra, where ra is the hypersphere cluster radius in the data space. Choose the data point with the highest potential after determining each data point's ability to serve as the first cluster centre. Consider x1 and p1 to be the first cluster centre and their respective potentials. Use the formula below to then update each data point's potential.

Think of a set of n data points:

X is equal to "x1, x2, x3,..., xn". Each point is then taken into account as a potential cluster centre. The following is a definition of the data point's xn potential:

$$p_n = p_n - p_1 e^{\frac{-4 x_n - x_1^2}{r_b^2}} \quad (8)$$

The positive constant rb is the hypersphere penalty radius in data space. Find the next highest potential to serve as the following cluster centre after computing the revised potential of each data point. These procedures keep going until there are enough cluster centres.

The Multi-objective Fuzzy Clustering Algorithm (MOFCA) [2] is built with two key considerations in mind: first, it must be energy efficient in all circumstances where it can be used, and second, it must be light enough to be installed on actual sensor hardware boards. It is a distributed unequal fuzzy clustering algorithm that uses local judgements to choose the tentative and final CHs and determine the node competition radius. To determine the competition radius for tentative CHs, MOFCA takes into account three variables: the distance to the sink, the node's remaining energy, and the node's density. Like several other methods, MOFCA uses fuzzy logic in addition to these factors to determine the competition radius. Compared to the protocols discussed above, this protocol's algorithm is more energy-efficient, and its performance scales well.

3. System Model

The system model, together with its network and energy model subsections, is thoroughly explained in this section.

3.1. Network Model

The following properties are assumed with regard to the sensor network being studied:

- The nodes are determined as the base station (the sink), root, and member nodes.
- All nodes are identical.
- The capabilities of all nodes, such as processing and communicating, are similar.
- All sensors are located in a two-dimensional space, and information on the location of each one, known as a basic premise.
- The nodes are deployed either manually in order to form a non-uniform or randomly.
- The base station may be located anywhere within the WSN's Area of Interest (AOI). It is not necessary for it to be far from the sensing area. But it can also be outside the AOI.
- Following the deployment phase, every sensor node must be stationary. However, the forcible modification of the initial placement by remote control is not included in the definition of "mobility" in this context. It only includes changes to locations brought on by tectonic movements like erosion or displacement brought on by outside things. The inclusion of this supposition also targets emerging networks.
- Because mobility is assumed to be generated by external sources, it does not cause nodes to consume energy.
- All sensor nodes have the same amount of energy when they are deployed.
- All sensor nodes have the same rate of production data and send information periodically.
- The base station’s power level in comparison with the energy of sensors is unlimited.
- The nodes are capable of adjusting transmission power according to the distance of the receiving nodes.
- The distance between nodes can be calculated based on radio signal strength.

3.2. Energy Model

Sensor nodes consume energy mainly during packet transmitting, packet receiving, sensing, and data processing. We used the energy model given in [2, 16]. Depleted energy measurement in transmitting or receiving l bits over a distance of d is done as in Eqs. (9) and (10), respectively. E_{elec}= 50 nJ/bit, E_{fs}= 10 pJ/bit/m2, Emp= 0.0010 pJ/bit/m4, and d0 = 20 m. E_{elec} is the energy consumption per bit in the transmitter and receiver circuitry, Emp is the energy dissipated per bit in the RF amplifier, and L is the length of packets.

$$E_{TX}= \begin{cases} L \times E_{elec} + L \times E_{fs} \times d^2 & d < d0 \\ L \times E_{elec} + L \times E_{mp} \times d^4 & d \geq d0 \end{cases} \quad (9)$$

$$E_{RX} = L \times E_{elec} \tag{10}$$

In a wireless sensor network, cluster heads are responsible for collecting data from the sensors and sending it to the base station. Therefore, the energy consumed in cluster heads during a round is calculated by the following equation:

$$ECH = (\frac{n}{k} - 1) L \cdot E_{elec} + \frac{n}{k} L \cdot E_{DA} + L \cdot E_{elec} + L \cdot E_{fs} \cdot d^4_{to\text{-}BS} \tag{11}$$

Where n is the total number of nodes, k is the total number of clusters, EDA is the energy or cost of gathering relevant data from all sensors in a cluster by the cluster head, and $d_{to\text{-}BS}$ is the average distance between the cluster head and the base station.

The energy used in any typical sensor node is calculated by the following equation:

$$E_{CM} = L \cdot E_{elec} + L \cdot E_{fs} \cdot d^2_{to\text{-}CH} \tag{12}$$

$d_{to\text{-}CH}$ is the average distance between the cluster head and the typical sensor node.

4. Fuzzy Clustering Algorithm Based on Trust Model (FCATM)

In this study, it is assumed that the sensor nodes get a message from the base station and calculate their distance to the base station. Also, each sensor is aware of the situation and the extent of its residual energy.

The proposed protocol selects local cluster heads so that the base station doesn't need to gather all nodes' information and determine all cluster nodes. Furthermore, the proposed protocol is similar to the LEACH protocol, since time is divided into sections called rounds and clusters are configured in each round. In each round, there are two phases: startup and steady state.

In the startup phase, the impact radius and CH chance of the sensors are calculated. Then cluster heads are elected based on chance and the trust of their neighbours.

In the steady state phase, CH data collection, aggregation, and transmission to the base station are done.

4.1. Determining the impact radius with the help of fuzzy logic

As previously mentioned, each sensor is aware of the extent of its residual energy and its distance to the base station. FCATM considers an impact radius for each sensor node to reduce energy consumption according to residual energy and the distance to the base station. This radius limits the sensor node to its impact radius if elected as CH and prevents rapid depletion of energy. In the fuzzy function, fuzzy rules use three fuzzy variables to determine the impact radius. They are:

- Energy: the amount of remaining energy in the sensor node.
- Distance: the separation between the sensor node and the base station.
- Radius: The sensor node's impact radius.

Fuzzy rules used to calculate the impact radius of sensor nodes are shown in Table 1:

Table 1

Fuzzy rules to determine impact radius.

NO.	ENERGY	DISTANCE	RADIUS
1	Low	Far	Very Small
2	Low	Medium	Very Small
3	Low	Close	Small
4	Medium	Far	Small
5	Medium	Medium	Medium
6	Medium	Close	Large
7	High	Far	Medium
8	High	Medium	Large
9	High	Close	Very Large

4.2. Calculating the chance of becoming CH with the help of fuzzy logic

After determining the radius, the extent of the CH chance is calculated. In the fuzzy function, fuzzy rules use three fuzzy variables to calculate CH chance. They are:

Energy: the amount of remaining energy in the sensor node.

Neighbours: The number of neighbours who are located within the effect radius.

Probability: the likelihood that the sensor will lead the cluster.

Fuzzy rules used to calculate the sensor’s chance of becoming cluster head are shown in Table 2:

Table 2

Fuzzy rules to calculate the sensor’s chance for becoming cluster head.

NO.	Energy	Neighbor	Chance
1	Low	Little	Very Low
2	Low	Normal	Low
3	Low	Many	Rather Low
4	Medium	Little	Medium Low
5	Medium	Normal	Medium
6	Medium	Many	Medium High
7	High	Little	Rather High
8	High	Normal	High
9	High	Many	Very High

4.3. Clustering and determining CHs based on trust model

FCATM employs fuzzy logic in determining impact radius and calculating CH chance. This protocol elects CHs based on the greatest chance and the level of trust. Each sensor node in its radial range checks to see if other sensor nodes have any more chances, selects itself as cluster head, and publishes a notification message on the network. Other sensor nodes check, after receiving the message, if they are in the range of a few heads, to select the CH with the highest level of trust as their cluster head and send a joining message to this head.

4.4. Calculating trust level

In fuzzy logic, trust can be classified into two classes:

- Fuzzy direct trust
- Fuzzy indirect trust
-

4.4.1. Calculating fuzzy direct trust level

The trust extent of each sensor node is determined based on the history of communications between sensor nodes. In order to calculate the level of fuzzy direct trust or fuzzy membership function, each sensor node keeps track of successful and unsuccessful interactions with its neighbours. If, in the past, sensor A had successful interactions for S times and unsuccessful interactions for U times with sensor B, the fuzzy direct trust membership function for the relationship between A and B can be calculated as follows:

$$TD_{AB} = \frac{S_{AB}}{S_{AB} + U_{AB}} \tag{13}$$

4.4.2. Calculating fuzzy indirect trust level

In order to calculate the level of fuzzy indirect trust from sensor A to sensor B, each sensor node sends the calculated trust to other neighbours. When sensor A transmits the trust to sensor B from other neighbors, by using its trust level and the trust level received from other neighbors, it calculates the extent of trust to sensor B:

$$T_{AB} = w_1 \times TD_{AB} + w_2 \times \frac{\sum_{j \in N_B} TD_{jB}}{Length(N_B)} \quad (14)$$

Where NB represents the neighbors of sensor A that send their trust to sensor A. In addition, w1 and w2 are coefficients or weights of direct trust and neighbors' recommended trust, respectively, that have the following conditions:

$$w_1 + w_2 = 1 \quad (15)$$

The remarkable point is that at the beginning of the startup phase, the trust level to all sensors is considered equal and trust calculating is repeated at the beginning of each clustering step.

4.5. The pseudo code of FCATM

The pseudo code of the FCATM protocol is explained in Algorithm 1.

Algorithm1. FCATM protocol

Input: field dimensions, sensor position, sink position, maximum number of rounds, and initial energy

Output: A Clustered WSN, Average of Sensors' Energy, Average of Alive Nodes, Time of the First Sensor Death, Time of the First Cluster-Head Death

1. Computation of d0
2. Creation of the random sensor network
3. While all sensors have energy
4. Every time, the time of clustering
5. When the update finishes, do
6. 1. Clustering with consideration of the fuzzy-based radius
7. 2. Candidate Selected Cluster-Heads with Fuzzy-Based Chance
8. 3. Selection Cluster-Heads Based on Trust Model
9. Every time, beginning with the time
10. Calculate the average of the sensors' energy.
11. Calculate the average of alive nodes
12. Calculate the time of the first sensor death.
13. Calculate the time of the first cluster-head death.
14. End while

5. Simulation results and performance evaluations

We implemented FCATM, K-Means, FCM, subtractive clustering, and multi-objective fuzzy clustering algorithms in a MATLAB simulator to test and compare their performances in terms of average total remaining energy in the network, number of alive nodes, death time of the first sensor, and death time of the first CH. Simulation parameters are given in Table 3.

Table 3

Simulation parameters.

Parameters	Values	Description
xm	300m	Field Dimensions: x maximum
ym	300m	Field Dimensions: y maximum
Sink.x	150m	Sink Position: x
Sink.y	400m	Sink Position: y
n	200	Number of Sensors
E0	0.5J	Initial Energy
Emp	0.0013pJ/bit/m4	Energy Consumed by power amplifier
Efs	10pJ/bit/m2	Energy Consumed by power amplifier
Eelec	50nJ/bit	Energy Consumed by transmitter and receiver circuits
ETX	50nJ/bit	Energy Consumed by radio electronics
ERX	50nJ/bit	Energy Consumed by radio electronics
EDA	5nJ/bit/signal	Energy Consumed for data aggregation
rmax	5000	maximum number of rounds

Fig. 1 represents the location of elected CHs, and Fig. 2 represents clustering the nodes in the network with different colors in FCATM.

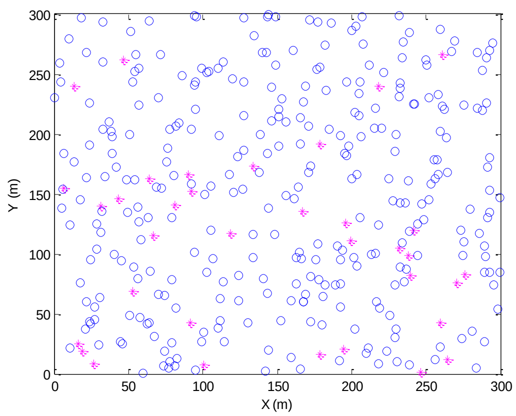

Fig 1. The location of elected CHs in FCATM.

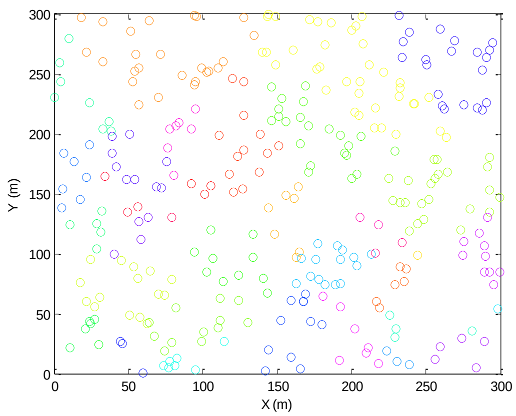

Fig 2. Clustering the nodes in the network with different colors in FCATM.

Fig. 3 compares the average total remaining energy in the algorithms after a certain period of 2500 rounds. It can be seen from the figure that the highest average of total remaining energy is obtained in FCATM, while the least is obtained in the K-Means algorithm for 200, 300, 400, 500, and 600 sensor nodes, respectively. Because in FCATM, determining the impact radius of the sensors based on fuzzy logic allows the best sensors to be selected as cluster heads, cluster heads away from the base station do not lose their energy quickly.

Fig. 4 compares the number of alive nodes after a certain period of 2500 rounds. Alive nodes are the nodes that have enough energy for data collection and processing. As can be seen from the figure, the number of alive nodes in FCATM is much higher than in the other algorithms because cluster head and cluster size election are based on fuzzy logic and load distribution is optimal, so the sensors will have a longer lifetime and the number of alive nodes is much higher than in the other algorithms.

Fig. 5 shows the comparison of the death time of the first sensor in the algorithms for 200, 300, 400, 500, and 600 sensor nodes, respectively. For each comparison, the death time of the first sensor in FCATM is the highest, while in the K-Means algorithm it is the least.

Figure 6 compares the initial CH's death time for several simulations by 200, 300, 400, 500, and 600 sensor nodes using various techniques. Because the cluster size in FCATM is inversely related to the CH's distance from the base station and distant CHs are the centres of smaller clusters, their energy consumption can be properly controlled, and the network loses them later, the death time of the first CH in FCATM is higher than that of the other algorithms for each comparison.

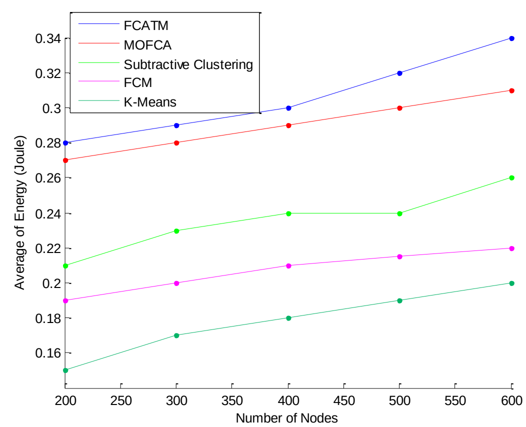

Fig 3. Comparison of the average total remaining energy with respect to the number of nodes.

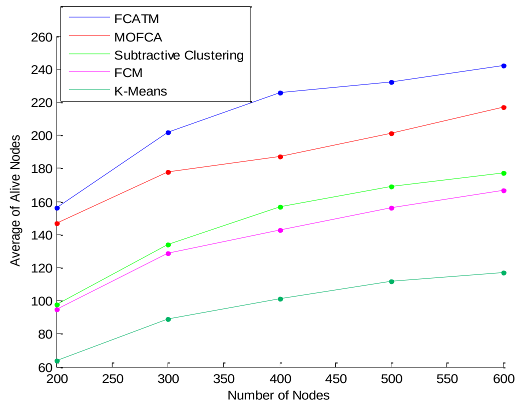

Fig 4. Comparison of the number of alive nodes after a certain period of 2500 rounds with respect to the number of nodes.

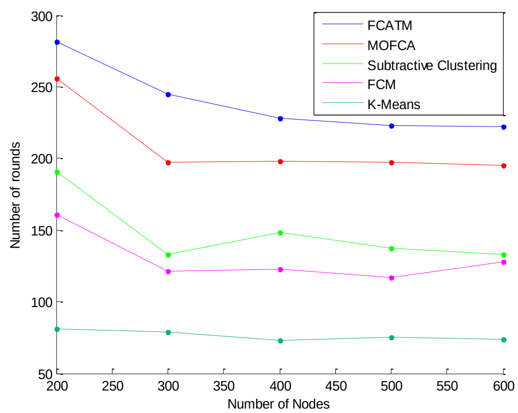

Fig 5. Comparison of the death time of the first sensor in the algorithms.

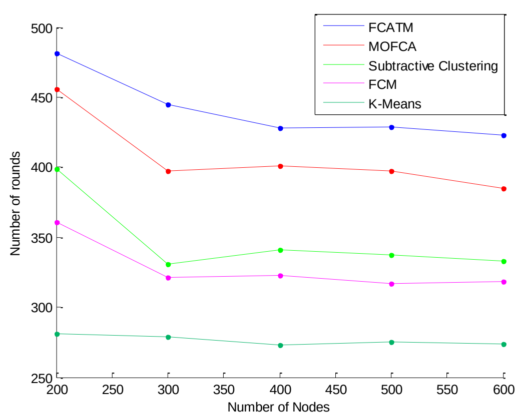

Fig 6. Comparison of the death time of the first CH in the algorithms.

6. Conclusions and future directions

In this study, a fuzzy clustering algorithm based on the trust model is proposed for wireless sensor networks. Our proposed algorithm, FCATM, considers nodes' energy levels, distance to the sink, impact radius, number of neighbours within the impact radius, and trust level parameters in selecting the cluster heads and joining the clusters while making use of fuzzy logic to overcome the uncertainties occurring in the WSN. We implemented FCATM in MATLAB software and compared the average of total remaining energy, the number of alive nodes, the death time of the first sensor, and the death time of the first CH with K-Means, FCM, subtractive clustering, and multi-objective fuzzy clustering algorithms for different simulation times and node numbers. We determined from simulation results that, FCATM performs best when compared with the other algorithms.

In future studies, the proposed study is planned to be organised for mobile wireless sensor networks. Also, applying useful parameters in the formation of clusters and using neural network topics in the algorithm will help to develop the proposed protocol. Moreover, using newer trust management systems to ensure security and determine the most reliable factors to evaluate the sensors' interactions can properly optimise the proposed protocol.

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