Spatial Correlation-Based Clustering in Wireless Sensor Network

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Abstract

The wireless sensor networks generally comprise of a large number of sensors. The sensors are disposable and resource-constrained devices. Despite the significant improvement in battery technology, energy conservation is still an imperative function of wireless sensor networks to prolong the network operational lifetime. In the last decade, the clustering approach is normally employed to extend the network operational lifetime, where aggregated sensed information is sent to the base station. The cluster heads are responsible for managing cluster members, information accumulation, and data transmitting. Therefore, the selection of an efficient cluster is a primary concern in the clustered architecture. This paper proposes a correlation model and a localized clustering approach whose goal is to extend the network operational lifetime using fuzzy logic and spatial correlation characteristics. The fuzzy logic is utilized to key out the cluster heads and spatial correlation characteristics are employed to form clusters of closely located sensors in the observing field. Simulation results demonstrate that a significant improvement in energy efficiency can be attained utilizing the proposed approach as compared to the LEACH, CHEF, and DEC approaches.

Keywords: clustering, fuzzy logic, localized, wireless sensor network, correlation

1. Introduction

Today in this keen world, wireless sensor networks (WSNs) have many typical applications like in home automation, activity observing, health monitoring and persistent wellbeing checking. The most critical challenge in WSNs is the energy conservation because of limited accessibility and limited energy resources of the sensors [1]. The hierarchically clustered architecture is commonly practiced approach to expanding the network lifetime [2]. The clustering can be either static or dynamic. The dynamic clustering is more effective as compared to the static clustering [3]. The sensor nodes in the network can be controlled centrally or at the node level, but according to the [3], centralized clustering has limited application when contrasted with distributed techniques. The low-energy adaptive clustering hierarchy (LEACH) has been shown as a first dynamic clustering technique in WSNs [3]. In LEACH residual energy is not accounted for the cluster head election and sometimes inefficient sensor node gets selected as a cluster head. Therefore, in [4-5], the authors have highlighted various limitations of the LEACH and further presented the extension by an accounting number of parameters in the cluster head determination. However, with the increase in selection parameters, identification of efficient cluster head become more uncertain. Hence, in order to reduce uncertainty and to improve the decision-making process a cluster head selection using a fuzzy logic has been implemented [6]. This trend is further carried out in [7], where the authors have introduced a distributed fuzzy based clustering approach. The researchers have highlighted the shortcomings of the former fuzzy based approaches and further introduced modified approaches in [8-11]. Energy efficiency can be maximized by implementing optimization algorithms and neural network [12-13]. In WSNs, cluster head failure greatly affects the energy efficiency performance [16].

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Exploiting heterogeneity using fuzzy logic is another option to extend the network lifetime [17]. The concept of two-tier LEACH is further extended in [18]. It is seen that by implementing the fuzzy logic, there is a significant improvement in energy efficiency. Also, most of the techniques focused on residual energy and not took the advantage of correlated information between sensors. Therefore, in this paper, we developed a more realistic correlation model and proposed a fuzzy based clustering technique by exploiting spatial correlation characteristics. In proposing the technique, initially, the chance value of each sensor node is evaluated using the fuzzy system and based on that the cluster heads are identified. The correlation value is utilized for adding cluster members and to organize the clusters uniformly throughout the network.

The remainder of this paper is structured as follows. Related work is reviewed in section 2. The proposed correlation model and proposed clustering technique are given in section 3. The results and analysis are given in section 4. The paper is concluded in section 5.

2. Related Work

Anatasi et al. [1] have discussed various energy conservation issues and methods to achieve it. Singh et al. [2] have presented comprehensive review of fuzzy based clustering approaches and discussed various advantages and limitations of these approaches. Many clustering techniques have been presented for WSNs over the most recent couple of years. Reducing unnecessary energy wastage has been mainly addressed in the context of routing protocols, such as LEACH [3], DEC [4], and LEACH-C [5]. Most of them are inspired from the LEACH [3] and included a number of selection parameters for the cluster head election. Gupta et al. [6] have investigated the shortcoming of traditional cluster head selection methods and further proposed application of fuzzy logic in cluster head election by including more number of parameters in selection process. Kim et al. [7] and Tashtosh et al. [8] have primarily focused on energy efficiency and discussed limitations of the centralized clustering approaches. Further, they have proposed distributed clustering using fuzzy logic for WSNs. Haider et al. [9] have attempted to lower the energy consumption in routing and not addressed cluster formation issue. Gupta et al. [6] approach is further slightly modified by changing fuzzy input parameters and presented as LEACH-FL [10]. The network lifetime has been improved by deploying some nodes with higher energy resources [11]. The cluster head selection can be made more efficient by clubbing optimization algorithms like genetic algorithm with fuzzy logic CFGA [12].

The applications of optimization algorithms are limited to the centralized approach due to lower computation capabilities of the sensor nodes. Lee et al. [13] have presented LEACH-ERE, where energy expenditure in the next round is predicted by using the offline trained neural network for maximizing the energy efficiency. In order to improve the energy efficiency, the clustering can be divided into two-tier, where initially cluster heads are identified and then gateway nodes are selected GCHE-FL [14]. Mhemed et al. [15] have presented FLCEP, the main architecture of FLCEP is similar to the LEACH [3] except the cluster formation where fuzzy system output plays a vital role in latest. Izadi et al. [16] have addressed cluster head failure consequences and presented SCCH, where every cluster head selects backup cluster head based on the fuzzy system output value. The network lifetime has been extended by introducing high energy sensor nodes [17-18]. Shakya et al. [19] have developed Boolean disk model-based spatial correlation model, which depend upon the distance and sensing range of the sensor nodes. The distance between two entities can be calculated based on receiving signal strength in WSNs [20].

Liu et al. [21] have used Manhattan distance to find dissimilarity in the reading of two sensor nodes. Also, in every round each sensor node broadcast hello message in the network and to avoid collision between broadcasted packets MAC access technique has not been specified. This concept of finding the similarity using Manhattan distance has been carry forwarded by Shen et al. [22], where tree routing method has been used. Also, authors have not specified the node synchronization method.

Bhavana et al. [23] have used the Euclidean distance and Manhattan distance to find the location and similarity between the sensor nodes. Rango et al. [24] have evaluated correlation to aggregate the data at cluster head level. G. Pau [25] has reduced the power consumption by controlling the sleeping schedule with the help of fuzzy logic but not explored the correlation between sensor nodes. In above discussed approaches the real parameters like sensing range, transmission range, and battery power are not employed in the evaluation of the correlation between sensor nodes. Also, most of the approaches implemented the data correlation methods which were used in other application. Therefore, after reviewing various techniques, it is inferred that, first of all, none of them have taken the advantage of the spatial correlation between sensor nodes. Secondly, none of them tried to reduce the number of transmitting bits by debarring some nodes from sending data. Also, some general issues like the uniform organization of clusters, selection of efficient cluster heads and uniform load distribution still need more exploration. Therefore, these issues and unexplored areas motivated us to develop more realistic correlation model and a clustering technique which can maximize the energy efficiency as compared to the state of the art techniques.

3. Proposed Correlation Model

3.1. Mathematical model

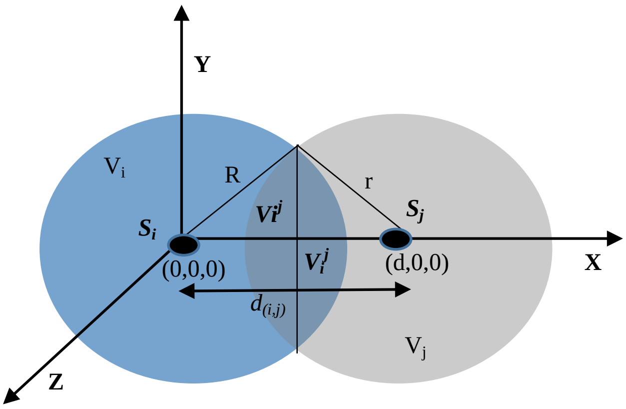


Fig. 1. Overlapped sensing region of sensors

Let two sensor nodes S_i and S_j are placed at the locations (0,0,0) and (d,0,0) respectively as shown in Fig. 1. The V_j and V_i are the sensing regions of the S_j and S_i sensor nodes having sensing radius r and R respectively. The region of overlap between S_i and S_j is defined by V_i^j and V_j^i. Spatial correlation depends upon the sensing range and location of sensors in the observing field [19]. The correlation in observed information depends upon the overlapped sensing region. Therefore, the correlation can be defined as the ratio of the overlapped region to the total sensing region of the sensor node [19]. In this context, we considered the three-dimensional region where the sensing region is spherical as shown in Fig. 1. The meaning of notations and symbols used in Fig. 1 is listed in Table 1. Therefore, the correlation between sensors can be expressed as follows:

$$\rho(d_{(i,j)}) = \frac{V_i^j + V_j^i}{V} \tag{1}$$

where, $\rho(d_{(i,j)})$ is a correlation coefficient which is a decreasing function of the distance, V_i^j and V_j^i both represent the area of overlap between S_i and S_j sensor nodes, and V is the total sensing region of a single sensor in the field. The maximum value of the correlation coefficient is equal to 1 when the distance between two sensor nodes is equal to the zero. Therefore, correlation coefficient has some positive value only if the distance between the ith and jth sensor node is less than the twice of the sensing radius i.e. $d_{(i,j)} < 2R$. The overlapped sensing volume as shown in Fig. 1 can be evaluated for different sensing ranges as follows:

$$V_{overlap} = \frac{\pi}{12d}(R+r-d)^2(d^2+2dr-3r^2+2dR+6rR-3R^2) \quad (2)$$

where, V_i^j and V_j^i are equal due to symmetry as shown in Fig 1. The R and r represent the sensing radius of the S_i and S_j nodes respectively. On putting $r = R$ in Eq (2), we get

$$V_i^j = V_j^i = \frac{\pi}{12}(2R-d)^2(d+4R) \quad (3)$$

From Eq (1), we obtain

$$\rho(d_{(i,j)}) = \frac{1}{16R^3}(\beta - d_{(i,j)})^2(d_{(i,j)}+2\beta) \quad (4)$$

where β = 2R is a control parameter. It is observed from the Eq (4) that if $d_{(i,j)} = 2R$ then $\rho(d_{(i,j)}) = 0$ and if $d_{(i,j)} < 2R$ then $\rho(d_{(i,j)}) < 0$. Therefore, the correlation model can be expressed as follows.

$$\rho(d_{(i,j)}) = \begin{cases} \frac{1}{16R^3}(\beta - d_{(i,j)})^2(d_{(i,j)}+2\beta), & if: 0 \le d_{(i,j)} < \beta \\ 0, & if: d_{(i,j)} \ge \beta \end{cases} \quad (5)$$

The Eq (5) is the desired correlation model. The meaning of symbols used in the above mathematical model is given in Table 1.

Table 1 Notations and symbols used in the correlation model

Notation/Symbol	Description
R	Sensing range S_i
r	Sensing range S_j
S_i	the i^{th} sensor node
S_j	the j^{th} sensor node
V	The spherical volume of the sensing region
$d(i,j)$	The distance between node S_i and S_j
V_i^j	Volume of region of S_i in S_j
V_j^i	Volume of region of S_j in S_i
$\rho(d_{(i,j)})$	Correlation coefficient
β	Control parameter
d	Distance between nodes
h	Height of spherical cap

3.2. Network model

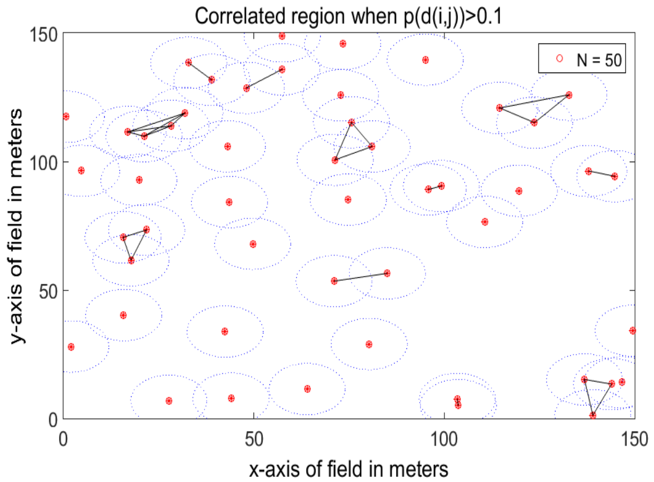
Let an observing field where N number of sensors having local identities s_i, $i \in \{1,2,.., N\}$ are randomly deployed as shown in Fig. 2. Sensing range is fixed and transmission range is adjustable. Only the selected cluster heads are allowed to communicate with the base station. The sensor nodes not associated with any cluster are acting individually as a cluster head. The sensor nodes are static and their geographical locations are known. The base station is placed outside the field. The sensor nodes can calculate the distance from the base station based on received signal strength indicator (RSSI) as follows [20]:

$$d = 10\hat{}\left[\left(P_0 - F_m - P_r - 10\times L\times\log_{10}(f) + 30\times L - 32.44\right)/10\times L\right] \quad (6)$$

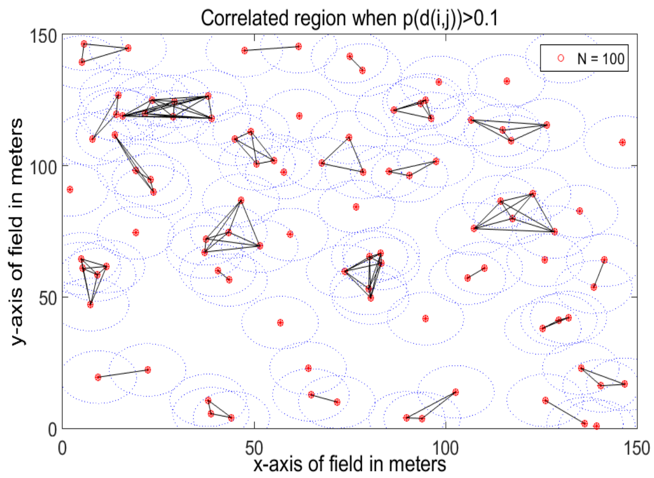
where P_0 is the power of the signal at distance d_0. The distance d_0 is the square root of the ratio of the amplification factor of free space to the amplification factor of multipath. The L, f, F_m and P_r are a path loss exponent, frequency, fade margin and received signal power respectively. After distancing calculation sensor nodes can calculate the required energy to transmit k bits at a distance d as follows [3]:

$$E_{TX}(k,d)=\begin{cases}(E_{elec}+\varepsilon_{fs}\times d^{2})\times k, & d<d_{0}\\(E_{elec}+\varepsilon_{mp}\times d^{4})\times k, & d\geq d_{0}\end{cases} \tag{7}$$

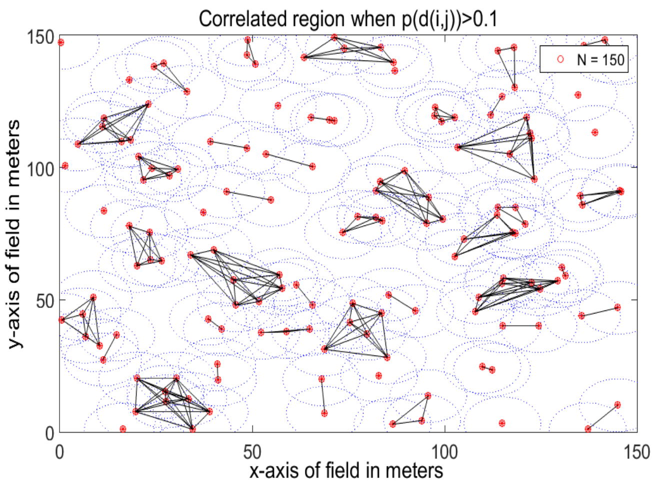
where E_{elec} is the energy consumed per bit by an electrical circuit in the transmitter. The ε_{fs} and ε_{mp} are an amplification factor for free space and multipath respectively. The correlation coefficient between sensor nodes is evaluated using Eq (5).



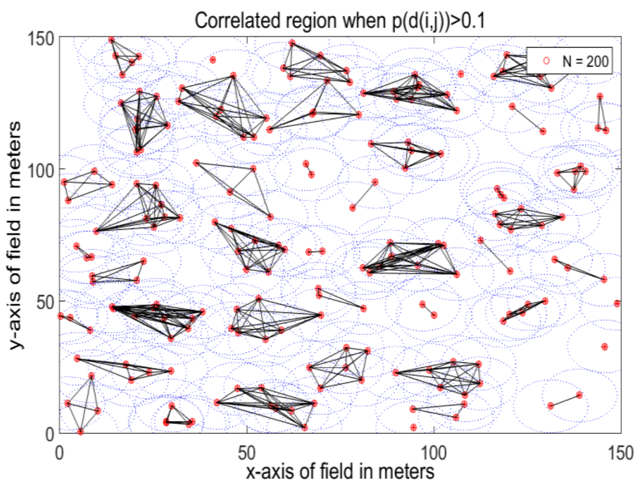
(a) Number of deployed nodes (N) = 50



(b) Number of deployed nodes (N) = 100



(c) Number of deployed nodes (N) = 150



(d) Number of deployed nodes (N) = 200

Fig. 2 Correlated sensor nodes (The solid line represents correlated sensors.)

3.3. Proposed clustering technique

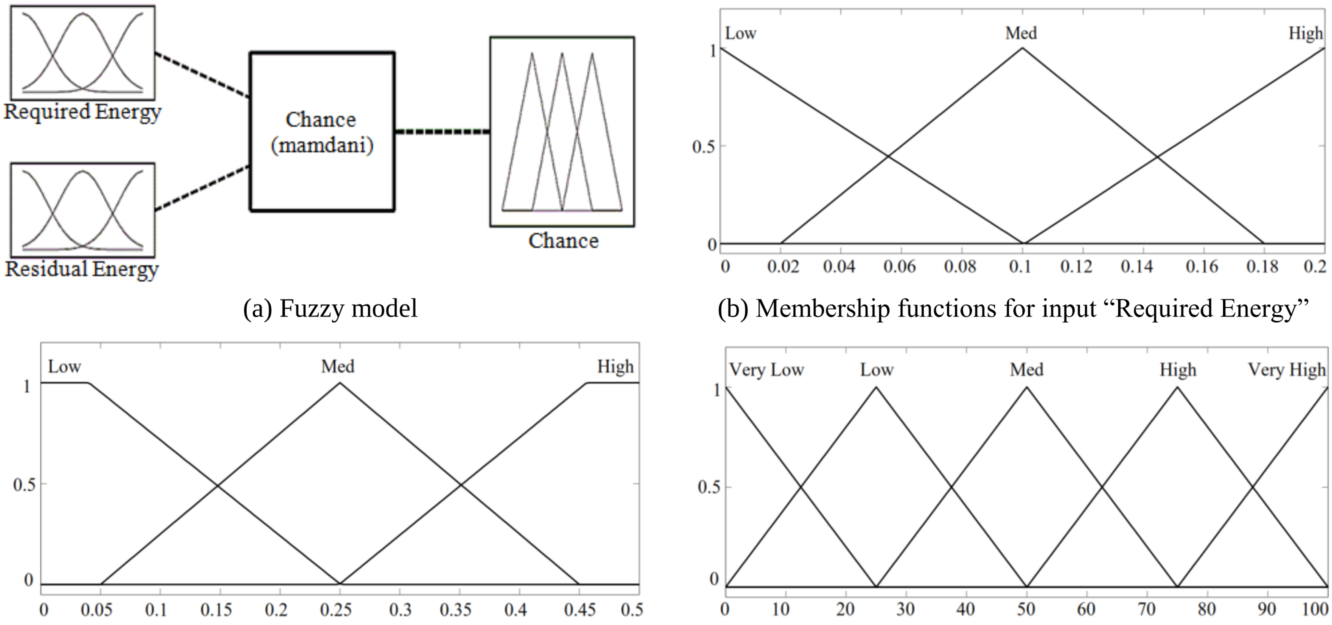
In the proposed technique, the clusters are configured in two phases like LEACH [3], DEC [4], and CHEF [7]. The two input parameters, residual energy and required energy to transmit are two fuzzy input parameters to evaluate the chance value of each sensor node. After deployment of the sensor nodes, the base station evaluates the correlation coefficient matrix using Eq (5) and broadcast it on the network. The sensor nodes evaluate the required energy to transmit k bits to the base station using Eqs (6) and (7) respectively based on the received signal strength. After evaluating required energy to transmit in the next step every sensor node runs the fuzzy system to find the chance value (*chance*(i)) according to the fuzzy if-then rules given in Table 2. The fuzzy system and membership functions are depicted in Fig. 3. The sensor nodes set its initial timer value as follows:

$$s(i).timer = \frac{\gamma}{chance(i)} \tag{8}$$

where $s(i).timer$ is the timer value of s_i corresponding to the chance value $chance(i)$. The γ is the adjustment parameter to differentiate timer value between sensors. According to the fuzzy if-then rules the sensor node having high residual energy and require low energy to transmit possess higher chance value. Therefore, the initial timer value for more eligible sensor nodes is less as compared to the other sensor nodes. In the next step, the base station coordinates all the sensor nodes and on receiving a message from the base stations all sensor nodes begin countdown simultaneously and broadcasts itself as a cluster head candidate on reaching zero.

Table 2 Simulation Parameters

Parameters	Value
The base station position	Outside the field at (75,175)
Initial energy (E_0)	0.5 Joule
ε_{fs}	10×10^{-12} J/bit/m^2
ε_{mp}	0.0013×10^{-12} J/bit/m^4
Number of Nodes (N)	50, 100, 150, 200
E_{elec}	50 nJ/bit
E_{DA}	5 nJ/bit/message
Cluster competition radius	20 m
Number of the base stations	1
Adjustment parameter (γ)	2
Path loss exponent (L)	2
Frequency (f)	2.4GHz
F_m	10 dB



(a) Fuzzy model

(b) Membership functions for input “Required Energy”

(c) Membershp functions for input “Residual Energy”

(d) Membership functions for Output “Chance”

Fig. 3 Fuzzy model and membership functions for inputs and output

The sensor with a higher chance value broadcast itself as a cluster head candidate earlier than the lower chance value sensor nodes. If a sensor node receives cluster head candidate messages, it stops its countdown and checks the correlation value between them and if $\rho(d_{(i,j)}) = 0$ then it continues its countdown and broadcast itself as a cluster head candidate on reaching to zero. The sensor node joins the cluster head candidate with highest correlation value. The two cluster heads cannot exist within the twice the sensing range due to the correlation coefficient value condition. This process continues and after some time the cluster formation takes place in the network. In the second phase, selected cluster head design the schedule for its cluster members and collect data to transmit collectively to the base station similar to the LEACH [3]. As shown in Algorithm 1, after the first round the sensor nodes evaluate their chance value but do not undergo the clustering process again. Only the role of cluster head is rotated among the cluster members on the basis of fuzzy chance value. The sensor node having highest chance value within a cluster becomes the cluster head in the next round. This process will continue until approximately half of the sensor nodes died, after that again all the alive nodes undergo clustering process similar to the first round. Therefore, the sensor nodes undergo clustering process only two times and the rest of the time the role of cluster head is rotated among the cluster members according to the chance value. The energy expended by cluster head in each round is given as follows [3]:

Algorithm 1

```
1.  Start
2.    BS_eval (ρ(d_(i,j))) = eq (5);
3.    BS_broadcast(ρ(d_(i,j)))
4.    s(i).required-energy = eqs (6)&(7);
5.    r = 1;
6.    γ = 2;
7.  For i = 1:N
8.    fis=readfis('Chance');
9.    chance(i)=evalfis([s(i).energy s(i).required-energy], fis);
10.   s(i).timer= γ /chance(i);
11. end
12.   s(.)_countdown_begin;
13.   a=1;
14. For i=1:N
15.   if s(i).timer ==0;
16.      s(i) = 'CH_candidate';
17. elseif  CH_rx_s(j) ρ(d_(i,j)) >0
18.     stop countdown;
19.     send = CH_join_msg;
20. else
21.    s(i)_broadcast = 'CH_candidate_itself';
22. end
23.    accept = s(j).CH_join;
24.    s(i).Chnum = a;
25.    a = a+1;
26.    design= TDMA;
27.    perform = steady state;
28.    eval(energy_expenditure) = eqs.(8)&(9);
29. end
30. end
31. if alive node>0
32. For r = 2:rmax
33.    For i = 1:N
34.       chance(i)=evalfis([s(i).energy s(i).required-energy], fis);
35.    end
36. For i = 1:a
37.    s(i).Chnum.chance.highest = s(i).CH;
38. end
39.    eval(energy_expenditure) = eqs.(8)&(9);
40. if dead_node >= N/2
41.    go to step 7;
42. end
43. end
44. end
```

$$E_{CH} = nE_{elec}B_0 + nE_{DA}(B_0 + 1) + E_{Tx}(n, d_{toBS}) \tag{9}$$

where E_{CH}, E_{elec}, E_{DA}, and E_{Tx} are the total energy expenditure of cluster head in one round, energy expended in an electrical circuit, energy expenditure for data aggregation, and energy expenditure for transmitting n bits at a distance d_{toBS} to the base station respectively. B_0 denotes the number of cluster members in the present cluster.

The energy consumption for non-cluster head sensor nodes is evaluated as follows:

$$E_{nonCH} = nE_{elec} + n\varepsilon_{fs}d_{toCH}^2 \tag{10}$$

where E_{nonCH} is the energy expended by each cluster member and n is the number of bits in one packet. ε_{fs} and d_{toCH} represents amplification factor for free space and distance with respect to the cluster head.

4. Analysis and Results

To examine and analyze the algorithm, MATLAB is used to create the WSN network. The number of alive nodes, the first node die (FND) round, the last node die (LND) round, cluster heads distribution per round and average energy consumption are the metrics used to determine the network lifetime. The field of 150m $\times$ 150m is created, where sensor nodes are randomly deployed. The base station is positioned outside the observing field at the position (x = 75 m, y = 175 m). In order to evaluate the performance of the proposed scheme, the number of nodes deployed varied from 50 to 200. The energy expenditure is modeled according to the Eqs (7), (9) and (10). The simulation parameters are listed in Table 3. Firstly, the results of correlation model are analyzed and then performance metrics are discussed.

Table 3 Fuzzy if-then rules for the proposed approach

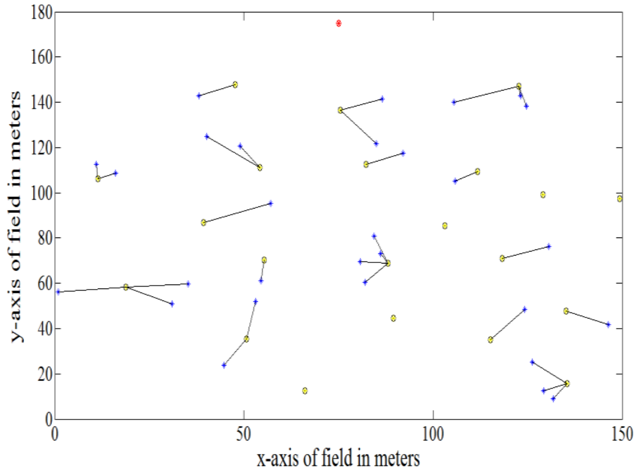
Rule No.	Required Energy	Residual energy	Chance
1	L	L	L
2	L	M	H
3	L	H	VH
4	M	L	VL
5	M	M	M
6	M	H	VH
7	H	L	VH
8	H	M	L
9	H	H	M
L = Low, M = Medium, H = High, VH = Very High, VL= Very Low			

4.1. *Correlated sensors*

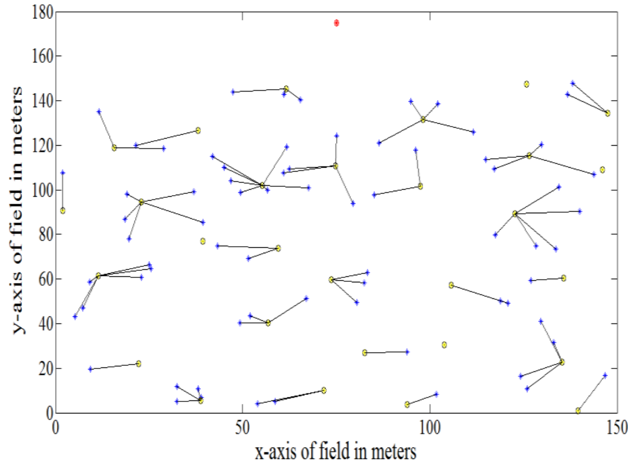
The correlation coefficient $\rho(d_{(i,j)})$ is evaluated for two-dimensional field using the Eq (5). As shown in Fig. 4, the solid line represents the correlation between sensors. In this experiment, sensor nodes are correlated to each other only if the value of $\rho(d_{(i,j)}) > 0.1$. This correlation threshold can be adjusted according to the requirement. It is observed from Fig. 2 that correlated sensors increase with an increase in node density within the same observing field. Therefore, after identifying correlated sensors, the cluster can be organized between spatially closed sensors.

4.2. *Cluster formation*

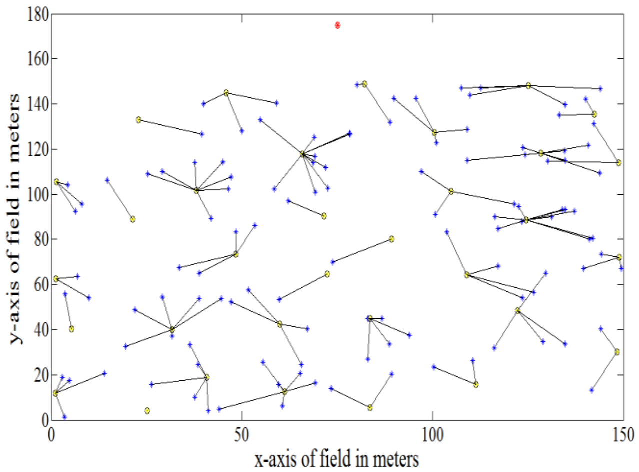
Fig. 4 represents the cluster formation after the first round. The solid line represents a link between the cluster members and their cluster head. The yellow color nodes represent cluster heads and the blue color nodes represent cluster members. It is distinctly understood from the Fig. 4, the cluster heads distribution is uniform in the network. As shown, for N = 50, N= 100, N = 150, and N = 200 total number of clusters 22, 28, 32, and 34 are framed in the network, respectively.



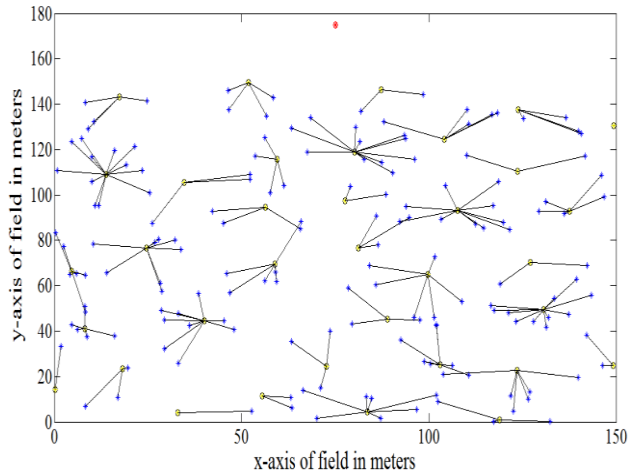
(a) Number of deployed nodes (*N*) = 50



(b) Number of deployed nodes (*N*) = 100

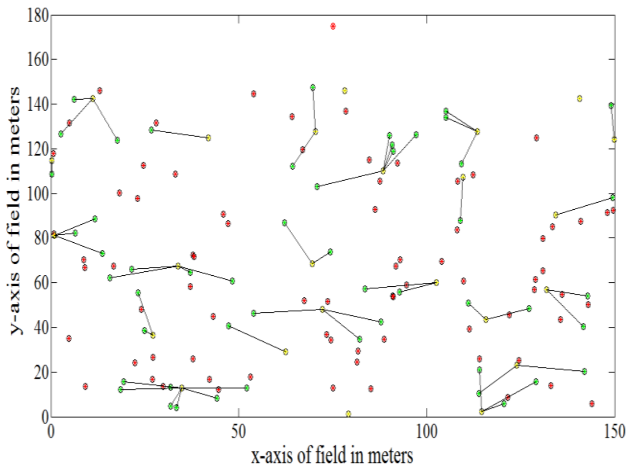


(c) Number of deployed nodes (*N*) = 150

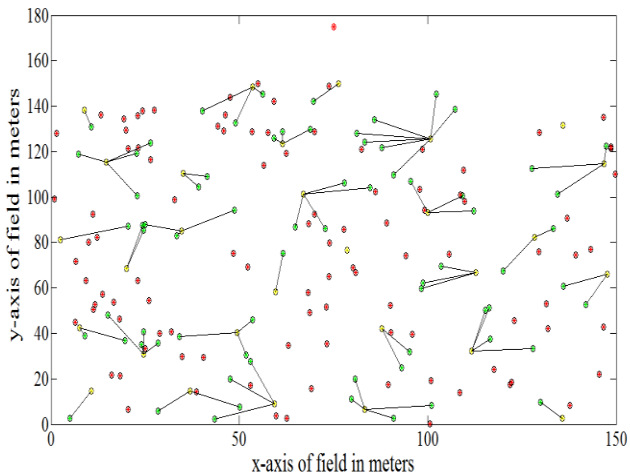


(d) Number of deployed nodes (*N*) = 200

Fig. 4 Cluster formation using the proposed clustering technique in the first round.
(Yellow color the cluster heads, blue color: the cluster members)



(a) Number of deployed (*N*) = 150



(b) Number of deployed (*N*) = 200

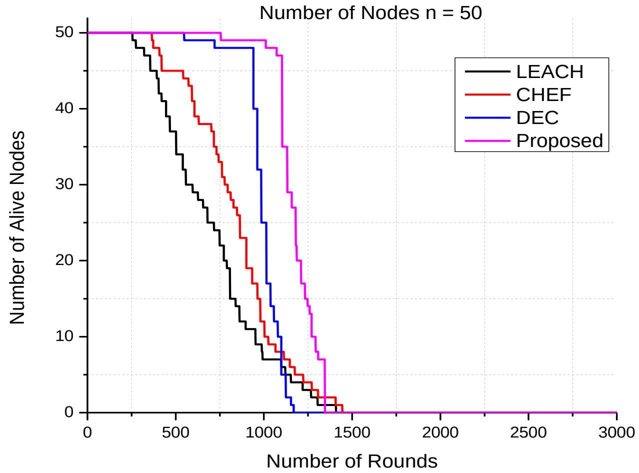
Fig. 5 Cluster formation when N/2 node, left alive using the proposed clustering technique.
(Red color dead nodes, green color: alive nodes)

When *N* is increased from 50 to 100, there is 27.27% increment in the number of cluster heads. Similarly, for 100 to 150 and 150 to 200, there is 14.28% and 6.25% increment in the number of cluster heads.

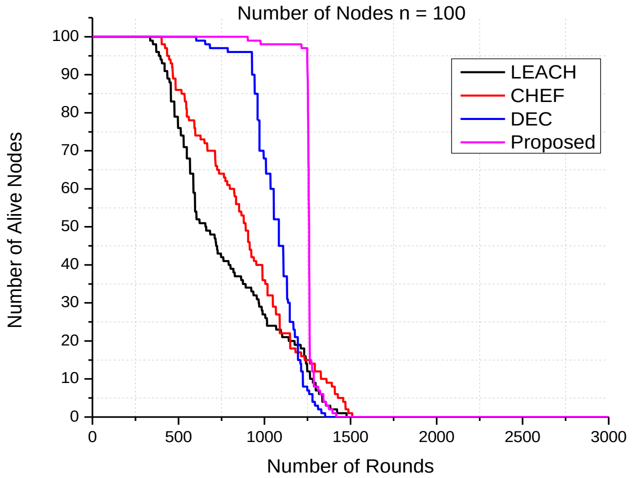
In LEACH [3], CHEF [7], and DEC [4], the percentages of cluster heads in the network are predefined by the user, but in proposed approach cluster heads percentage depend upon the node density and correlation value. Therefore, a number of cluster heads in the network automatically get selected with the change in node density. Fig. 5 illustrates that the cluster formation after the death of around 50% nodes, where the red color and green color nodes represent dead and alive nodes respectively.

4.3. Number of alive nodes

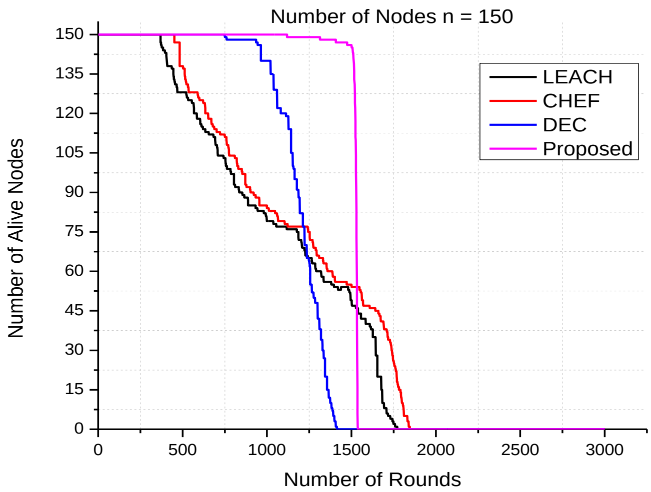
Alive nodes in each round are depicted in Fig. 6. As shown, the first node death occurs after 550 rounds for proposed and DEC [4], where the first node dies before 550 rounds in LEACH [3] and CHEF [7]. This difference arises due to the uneven distribution of clusters in LEACH [3] and CHEF [7]. In DEC [4], clustering performed only one time and the rest of the time role of cluster head is rotated based on residual energy. In the proposed approach, clusters are redistributed when about 50% alive left in the network. Therefore, the proposed approach performs better than the DEC [4]. The first node death is an important attribute to define the network lifetime [3, 4, 7]. For higher node density (*N* = 150, 200) as shown in Fig. 6 deaths of the first node occur after 1000 rounds. The nodes die uniformly after the first node death as compared to the other techniques. Therefore on the basis of the first node death round, it can say that proposed approach improves the network lifetime as compared to the other three approaches.



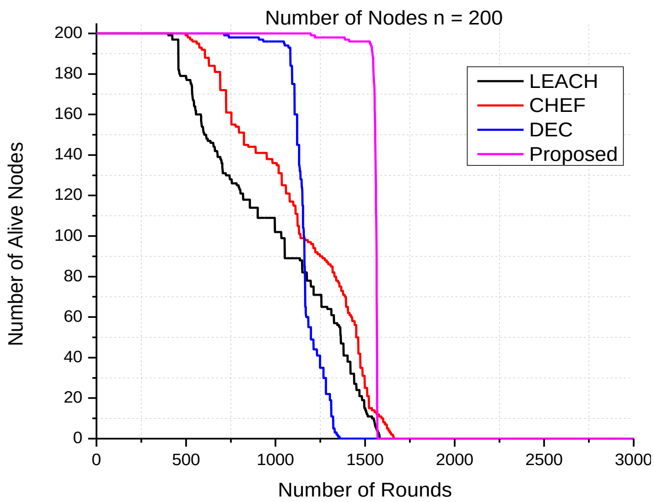
(a) Number of deployed nodes (*N*) = 50



(b) Number of deployed nodes (*N*) = 100



(c) Number of deployed nodes (*N*) = 150



(d) Number of deployed nodes (*N*) = 200

Fig. 6 A number of alive nodes for every round for different values of *N*

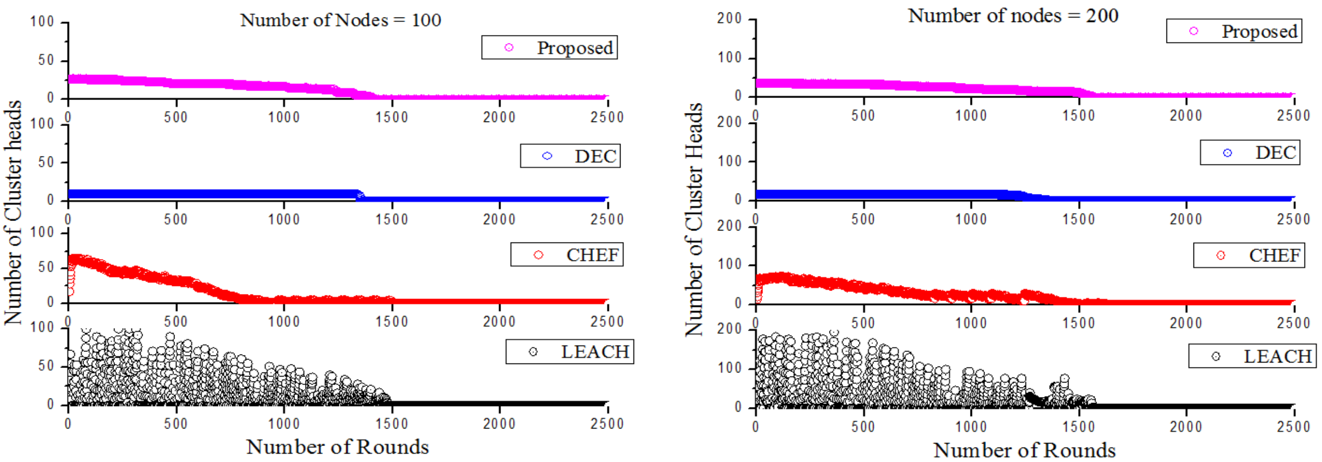
4.4. First node die round and last node die round

The first node dies round comparison is illustrated in Fig. 6. For *N* = 50 the first node dies nearby 750^{th} round and for *N* = 200 is the first node dies nearby 1000th round. In the first node dies round comparison, proposed approach clearly outer perform LEACH [3], DEC [4], and CHEF [7]. The last node die comparison is shown in Fig. 6. It is seen that LND round performance is comparable for all approaches. Generally, the first node dies round define the network lifetime [3], because the death of node affects its overall performance. Therefore, on the basis of the first node die round proposed approach improve network lifetime by 55%, 47%, and 40% as compared to the LEACH [3], CHEF [7], and DEC [4] respectively, when $N = 100$.

4.5. *Number of cluster heads in every round*

The cluster head distribution for every round is shown in Fig. 7, it is clearly seen that selected cluster heads in the proposed approach vary from 22 to 40 for different values of N. As shown, the number of cluster heads are constant in DEC [4] upto 1200 rounds because of one time cluster formation. In CHEF [7], number of cluster heads vary from 50 to 65 due to the small optimal cluster radius.

In LEACH [3] variation in the number of cluster heads selected is large due to the probability-based selection of cluster heads. In the proposed approach, clusters are framed using correlation characteristics. Hence, it can say that proposed approach uniformly distributes the cluster heads.



(a) Number of deployed nodes (N) = 100 (b) Number of deployed nodes (N) = 200

Fig. 7 Cluster heads distribution for every round

4.6. *Average energy consumption*

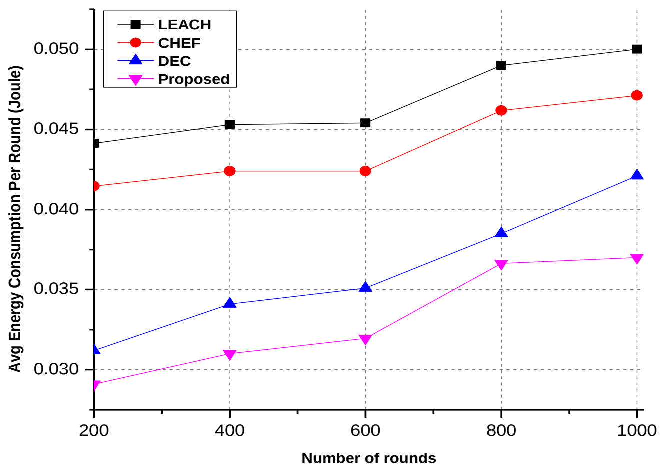


Fig. 8 Average energy consumption for first 1000 rounds

For $N = 100$, the average energy consumption for first 1000 rounds is shown in Fig. 8. The average energy consumption for LEACH [3], CHEF [7], and DEC [4] are 51%, 42%, and 7.2% higher than the proposed approach after the first 200 rounds respectively. Also, it is observed that after 1000 rounds energy consumption for proposed approach is lower as compared to the other three approaches. In WSNs, most of the energy expended in transmitting and receiving information [1]. According to Eq (7) energy expenditure directly proportional to the distance between sender and receiver. Therefore, proposed approach reduces the average energy consumption by creating clusters between closely placed sensor nodes. From above analysis, it can be inferred that the proposed technique extends the network lifetime as compared to the LEACH [3], CHEF [7], and DEC [4] respectively.

5. Conclusion

This paper introduced a correlation model to represent the spatial correlation between the sensors and a localized clustering approach to virtually dividing the network into clusters. The different key elements are discussed, it is found that the cluster formation between spatially closed sensors reduce the overall average energy consumption and improved the network lifetime. The effectiveness of the proposed approach is assessed on the basis of the first node die round, the last node dies round, a number of alive nodes for every round, cluster formation, cluster heads distribution, and average energy consumption. It is found that the proposed approach performs better in terms of all above-mentioned attributes as compared to the LEACH, CHEF, and DEC approaches. Simulation results show that network lifetime is extended about 40%, 47% and 55% as compared to DEC, CHEF, and LEACH. It is also found that the death of the nodes is more uniform with an increase in node density, which replicates the uniform load distribution in the network. Energy consumption is also lower for the proposed approach as compared to the others. Therefore, the proposed approach improves energy efficiency and extend the network lifetime as compared to LEACH, CHEF, and DEC. As a future work, this work can be extended by including correlation between the event and sensor nodes rather than only exploiting the correlation between sensors. Also, there is more work to do in optimizing the value of adjustment parameter for more better results. The designing of fuzzy-if-then rules and membership functions need more attention. The testing of the proposed approach in real testbed will be left we as future work.

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