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ABCRF: Atomic Bond Connectivity Based Range Optimized Fuzzy Clustering Algorithm for WSN

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Wireless sensor networks (WSNs) have a significant contribution in different applications. WSNs perform the data collection, processing, and transmission through sensor nodes. Sensor nodes work for a limited time due to battery constraints; clustering of sensor nodes reduces the loss in battery power. We propose a new clustering algorithm (ABCRF) to enhance the network lifetime by reducing the battery loss of the sensor nodes. The proposed work selects a suitable cluster head (CH) for data collection. The decision for the CH performs based on the chance value. Next, the chance value calculation requires fuzzy logic-based technique, total coupling index, and residual energy of sensor node. The total coupling index is a newly proposed parameter utilizing the communication range information of sensor nodes. The communication range of a sensor node has significant importance so, double range optimization carries out. Final range calculation requires distance to base station, residual energy, and initial range of sensor nodes. The formulation of the initial communication range of sensor nodes works on the atomic bond connectivity (ABC)-based index. The presented protocol is compared with some of the well-known clustering protocols such as LEACH, EEUC, EAUCF, MCFL, and FBUCA. The simulation results reveal; that the ABCRF performs much better in different scenarios over other algorithms under consideration regarding the number of nodes alive and remaining energy metrics.

Keywords: wireless sensor network, fuzzy logic technique, atomic bond connectivity, double range optimization, clustering

1. INTRODUCTION

Researchers are showing interest in the area of wireless sensor network (WSN) applications due to their wide use in real scenarios, like environmental pollution control, disaster management, and border surveillance [1-3]. A collection of low battery power tiny devices, cooperatively performing a single task defines a wireless sensor network [4]. Each sensor is capable of working in a remote area or even in an isolated area. Due to huge costs, it is not practical to replace the batteries specifically in remote areas [5, 6]. The primary aim of clustering in WSN is to reduce the energy consumption of sensor nodes and improve the network's lifetime [7]. Clustering partitions the network into multiple groups called clusters. Each cluster contains a CH dedicated to collect, aggregate, and transmit data to the base station (BS) [8]. The modeling of the scenarios where decision-based on input

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parameters is required take place using fuzzy logic. WSN uses fuzzy logic to find suitable CHs and evaluate the competition range of a sensor node [9, 10]. There is a lot of uncertainty in the WSN environment, and hence obvious and efficient decision making happen using fuzzy logic. Combination of certain specific input parameter's value calculates crisp output value based on fuzzy logic. In the WSN environment, required input parameters are residual energy, centrality, degree, and BS distance. CHs near the BS lose their energy quickly due to heavy traffic generated by using the multi-hoping technique. The network is partitioned because of the premature death of CHs; this problem is termed as a hot spot problem. The hot spot problem mitigates by using the fuzzy logic technique. Unequal clustering reduces the hot spot problem generated due to multi-hop routing protocol in WSN. The design of several protocols uses fuzzy logic techniques for clustering in WSN [11-17]. Residual energy-based unequal clustering protocols utilize to find suitable CH without using the fuzzy logic technique [18-22]. Clustering protocols based on parameters like node degree [23], processing capability, and node's ID [24-27] are also energy-efficient protocols for WSN. Atomic bond connectivity (ABC) index introduced in [28] is a popular structure descriptor of molecules utilizing the concept of degree of a vertex. The ABC index of a connected graph G is defined as

$$ABC(G) = \sum_{uv\in E} \sqrt{\frac{d_u+d_v-2}{d_u d_v}}. \tag{1}$$

The above degree-based molecular structure is a valuable predictive tool in studying the heat of formation in alkanes. Following are also similar connectivity indices for a graph G as defined in [29, 30].

$$R_{-\frac{1}{2}}(G) = \sum_{uv\in E} \frac{1}{\sqrt{d_u d_v}} \tag{2}$$

$$R_{-1}(G) = \sum_{uv\in E} \frac{1}{d_u d_v} \tag{3}$$

Where d_u and d_v are degree (number of incident edges) of vertex u and vertex v. E is set of edges of graph G.

Double range optimization is the newly introduced term. The purpose of double-range optimization is to calculate each node's final range based on two different sets of parameters. At the first level we calculate the range without using the fuzzy logic concept but at a second level fuzzy logic concept with different sets of parameters is applied to calculate the final range of each node.

1.1 Motivation

Wireless sensor networks, as an active field of research with broad implementation, are concerned with enhancing the current solutions in the same way as other fields of technology and science. There is several research issues in this field that still need focus, such as energy constraints, designs that are reliable for communication within the network, and quality of services. It is becoming increasingly difficult to solve all these problems due to their conflicts with one another. However, we are now searching for a solution that is both time-saving and cost-effective that uncovers new methods and concepts in the area under consideration. The research areas of WSNs are large, and these networks are becoming more common due to their scope of expansion. Clustering is an instance of these techniques and is seen as a scalable and effective method of energy consumption for WSNs. Thus, the main motivation for this work is to develop the new parameter and combine the fuzzy logic techniques for clustering in WSNs. Further it motivates in the detection of shortcomings and also mentioning the benefits of utilizing clustering to prolong the life of the network. Some benefits are: – clustering can avoid the redundancy of the communication messages along with keeping up with the bandwidth for communication. Clustering decreases the communication overhead and also balances the topology of the network. Clustering makes it possible to implement an optimized network management strategy. The methodologies presented in this paper for selecting the cluster head differ from other protocols. Some utilize simple parameter for CH election while in other many parameters are merged to get some new parameters for selection. So along with introducing new parameter and ideas for the clustering process, a detailed evaluation of clustering and clustering-based routing protocols is presented with a more accurate analysis of the method.

1.2 Major Contributions

Competition radius calculation and further use it to model fuzzy logic system makes the unequal clustering more successful. Following are notable contributions of this paper:

- In unequal clustering, the range of a sensor node decides the list of competitors for CH. We define the Atomic bond connectivity-based index of sensor nodes and used it to calculate the initial range of the node.
- Earlier research work does not consider double range optimization. We define the fuzzy logic technique considering the initial range as one of its input parameters to calculate the final range value.
- A sensor node's location to other nodes is an indicative parameter for its role in the network. We define a new parameter (total coupling index) to better cater to the node's location value. We also establish the fuzzy logic system based on the total coupling index as the input parameter.
- We perform the comparison of the ABCRF protocol with other popular unequal clustering algorithms of WSN.

2. RELATED WORKS AND CURRENT RESEARCH PROGRESS

2.1 Related work

In the current section, we explain some related algorithms on hierarchical clustering structure and also illustrate some relevant fuzzy logic-based clustering algorithms. Low Energy Adaptive Clustering Hierarchy (LEACH) [31] protocol divides the nodes into different clusters by utilizing the probabilistic threshold value calculation. The threshold is evaluated by

$$T(n) = \begin{cases} \frac{p}{1-p(r \bmod \frac{1}{p})} & \text{if } n \in G \\ 0 & \text{otherwise} \end{cases}. \tag{4}$$

In Eq. (4), p defines the node's probable value for CH selection in a particular algorithm execution round. G consists of all the nodes which were not CH for the last round. Cluster formation carries out in various rounds. Each round consists of a cluster set-up and a steady-state phase. Sensor nodes compute a threshold value and compare it with a randomly generated number during the set-up phase. A smaller random value than the threshold value is a qualifying condition for the nodes to work as CHs. Each member node joins the nearest CH node for cluster formation. CHs directly transmit aggregated data to BS and pure randomization leads to pre-mature energy loss.

In Hybrid Energy-Efficient Distributed Clustering (HEED) [32] decisions for CHs finalizes jointly by the remaining energy of the node and degree of the node.

CHEF [33] is a fuzzy logic-based clustering approach. Like LEACH, the CHEF forms clusters by reconfiguring the network in each round. Each node generates a random number and compares it with the optimal probability value. A smaller random value than optimal probability permits the node to calculate a fuzzy chance value. Energy and local distance are input parameters for fuzzy chance value. Each qualified node advertises chance value in its neighborhood. The node with the largest chance value is assigned the final CH responsibility and informs all other nodes in its neighborhood.

EAUCF [34] is also one of the distributed fuzzy logic-based clustering protocols. It also considers energy and distance to BS as two fuzzy input parameters for competition radius selection. The probabilistic model-based approach defines tentative CHs. EAUCF protocol generates a random number and compares it with some predefined threshold parameters. If the random number is smaller than the threshold value, the node works as a tentative CH. The residual energy is compared with all other tentative node's residual energy in its competition radius. The highest residual energy node works as a CH. The base station and nodes are stationary during the execution of the algorithm. Smaller is the range of sensor nodes whose residual energy is less. The primary aim of the EAUCF algorithm is to decide the range of each sensor node, which is the basis of an unequal clustering algorithm.

DUCF [15] performs clustering by utilizing the fuzzy logic concept. Energy, degree, and distance to BS are input parameters of FIS. Chance and cluster size are output values of the FIS. The restriction of the maximum number of cluster members may not permit some of the nodes to join a CH and hence more energy will be spent in data transmission.

MCFL [16] is a fuzzy logic-based multi-cluster algorithm. It performs clustering in different rounds. Each round uses a separate combination of input-output FIS parameters. In some of the rounds, no CHs selection takes place and the CHs of the previous round carry out the data aggregation task. Multi-clustering does not improve the performance significantly when the BS is at a distant location. Three different clustering algorithms are considered to perform cluster head selection. The first clustering algorithm runs in rounds 1, 4, 7, …, and uses residual energy and the number of neighbors as input parameters. The second clustering algorithm executes in rounds 2, 5, 8, …, and uses the cluster heads of previous rounds. The third clustering algorithm executes in rounds 3, 6, 9, …, and uses the residual energy and the distance to cluster head as input parameters. The sensor node's energy is the primary parameter so the MCFL algorithm uses the residual energy in each execution rounds.

UCF [17] is an unequal cluster-based protocol. UCF distributes the workload evenly among the nodes to resolve the hot spot problem. Competition range optimization carries out employing the fuzzy logic technique. Local density and distance to BS are the input parameters of the fuzzy inference system. Residual energy is the main parameter for CH selection and it does not use a random function.

Unequal clustering protocol decides the final cluster heads successfully. All these protocols perform a single-step calculation for competition radius.

2.2 Current Research Progress

In recent decades, WSNs have emerged as a critical area of research for various applications. Many popular applications for instance habitat monitoring, smart transport systems, underwater monitoring necessitate WSNs to be movable rather than stationary [35]. WSNs are the main building block to gather, process, and broadcast the information in the IoT. WSN is a fundamental part of IoT; it raises billions of devices to share environmental data for improving user control [36]. Exiting work mainly performs optimization of energy consumption of sensor nodes. Fuzzy-logic methods handle uncertainties of the parameter's values to reduce the difficulties of tuning the relative importance of the parameters for selecting CHs. Current progress [37-41] in the area of WSN fuzzy clustering algorithms motivates researchers to carry out more research work.

The current research fields of wireless sensor networks are very broad and WSN networks are becoming more extensive due to the expansion of their area of application

3. PROPOSED ALGORITHM

This section discusses the proposed ABCRF protocol in detail. ABCRF is a clustering algorithm creating unequal clusters; it performs cluster head selection and cluster radius calculation using local network information. The proposed algorithm optimizes the cluster radius twice. At the first level, each node calculates the cluster radius by utilizing the ABC-based index value. Algorithm 1 describes the protocol in more detail. Inputs of the algorithm are the number of nodes (n), range (R), initial energy, area, the position of the sink, probability (p), node_type, the maximum number of algorithm execution rounds ($r$max). The set of CHs and set of alive nodes are the outputs of Algorithm 1. Initially, each node calculates its distance from the other node in line 2. Algorithm 1 executes for $r$max rounds. In each round, parameter calculations accomplish in lines 4-8. Lines 9-16 present tentative cluster head selection. Each tentative cluster head node sends its ID, final competition range, and energy value to the other neighboring tentative CHs at line 17. ABCRF is a distributed clustering algorithm and uses messages to perform other necessary communications. Status of tentative cluster head node with less energy than other tentative CHs in communication range converts to a normal node in lines 18-27. The decision for final CHs takes place in lines 28-33. Clustering executes at line 34. The proposed protocol uses the Fuzzy chance to decide the tentative CHs. Mamdani system [42] defines fuzzy rules with a center of area method for defuzzification. After deploying nodes in the area, each node calculates its distance from other neighboring nodes based on some predefined range value. There are different methods for distance calculation. Initially, each node calculates its ABC-based index value by Eq. (5) given below:

$$A(S_i) = \left(\sum_{j\in E} \frac{1}{D(S_i)D(S_j)}\right) * C. \tag{5}$$

Where E, $D(S_i)$, $D(S_j)$, and C are set of neighbor nodes of S_i, degree of S_i, degree of S_j, and some constant respectively. The value of constant C(= 1000) is chosen in such a way to make the value of the initial range meaningful for all simulations. The higher the degree of a node the lower is the ABC-based index value of the node. A combined degree and high-order degrees are better than those of a node in discriminating nodes [43]. After the first round of the protocol, each node's range value is different and Eq. (6) calculates the initial competition range.

Initial range value of a node is

$$R_i(S_i) = (1 - e \times (\tfrac{\max(A)-A(S_i)}{\max(A)-\min(A)})) \times R. \tag{6}$$

Where e = some constant (0.2), R = range, max(A) = maximum value of A, min(A) = minimum value of A. The higher the ABC-based index value of a node, the higher is the initial range. Moreover, from Eqs. (5) and (6), the initial range is small for the node whose degree is large.

At the second level, the fuzzy rules in Table 1 produce each node's final competition range. Table 1 has a collection of 27 rules. Node's distance to BS, initial energy, and initial range value is the input parameters for the fuzzy system and the output of the fuzzy system gives the final range value. EAUCF calculates cluster head using distance to the base station and residual energy, but the proposed algorithm uses one more parameter. Rules of Table 1 calculate the final range of each node. The cluster radius is high for the distant nodes. The less is the amount of residual energy of a node, the smaller the competition radius will be. The final range increases for an increase in the initial radius. The initial range calculation uses the degree of the node and the degree of all neighbor nodes, so is more informative. ABC index helps to differentiate between two same degree nodes and also reduces the range for high degree nodes. The final range value in Table 1 has two different values for the two same degree nodes and small range for high degree nodes. Eq. (7) calculates the final range value of each node.

$$R_f(S_i) = fuzzy[dbs(S_i), E(S_i), R_i(S_i)] \tag{7}$$

Eq. (7) is a mathematical representation of Table 1. Figs. 1-3 show a representation of membership function for the three input variables, residual energy ($E_i(S_i)$), initial range ($R_i(S_i)$), and a distance of a node S_i from BS (dbs(S_i)) respectively. Fig. 5 describes the membership function for the final range. Energy has low, medium, and high as a linguistic variable. Distance from BS has close, medium, and far as the linguistic variable. The initial range has low, medium, and high as a linguistic variable. The output variable is the final range value and has linguistic variables as very small, small, rather small, medium small, medium, medium large, rather large, large, and very large. Boundary variables use the trapezoidal membership function and intermediate variables use the triangular membership function for all simulations. The value of linguistic variables (*e.g.* low, medium, high) is different for input/output parameters. The membership function of a parameter represents the value of corresponding linguistic variables. Consider the case of residual energy (Fig. 1);

Table 1. Fuzzy if-then mapping rules for final range calculation.

Distance to BS	Residual energy	Initial range	Final range
Far	high	high	very large
Far	high	medium	large
Far	high	low	rather large
Far	medium	high	very large
Far	medium	medium	large
Far	medium	low	rather large
Far	low	high	very large
Far	low	medium	large
Far	low	low	rather large
Medium	high	high	medium large
Medium	high	medium	medium
Medium	high	low	medium small
Medium	medium	high	medium large
Medium	medium	medium	medium
Medium	medium	low	medium small
Medium	low	high	medium large
Medium	low	medium	medium
Medium	low	low	medium small
Close	high	high	rather small
Close	high	medium	small
Close	high	low	very small
Close	medium	high	rather small
Close	medium	medium	small
Close	medium	low	very small
Close	low	high	rather small
Close	low	medium	small
Close	low	low	very small

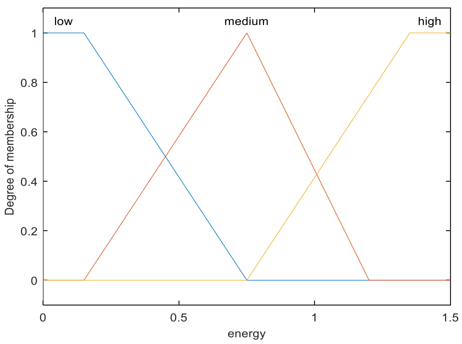


Fig. 1. Membership function for residual energy.

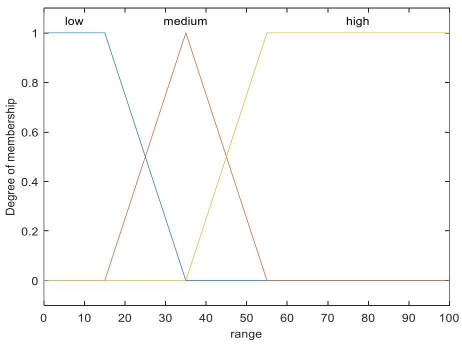
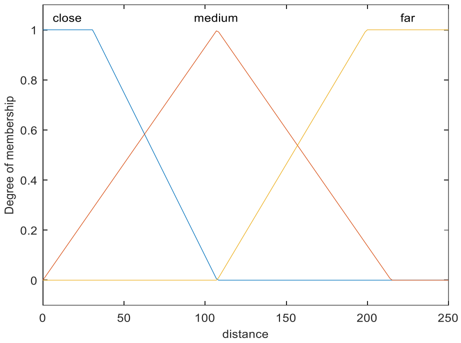


Fig. 2. Membership function for initial range.

it has three linguistic variables low, medium, and high. The range of values is 0-0.75, 0.12-1.2, and 0.75-1.5 for low, medium, and high respectively. Similarly, the membership function of other variables represents the value of their linguistic variables. The range of values of linguistic variables of a parameter is finalized by performing 10 simulation rounds and observing the performance of the algorithm. Existing work finalizes the linguistic variable's value by executing the algorithm for many rounds and considers the best case value.



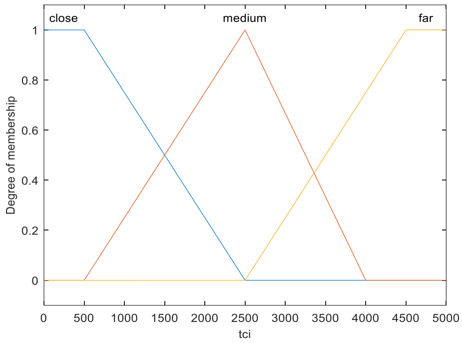


Fig. 3. Membership function for distance to BS. Fig. 4. Membership function for total coupling index.

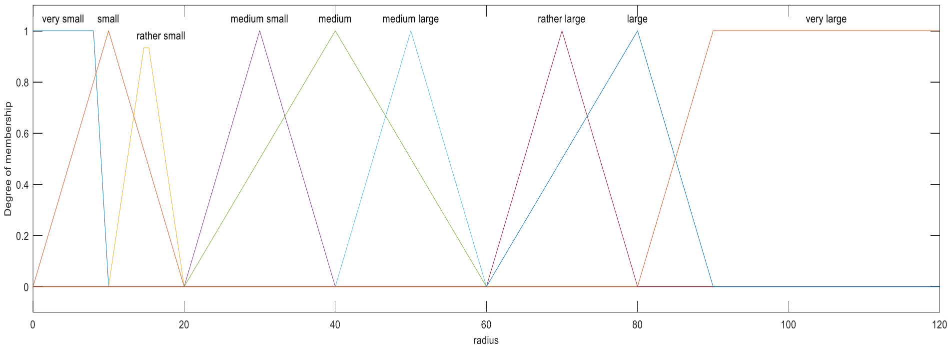


Fig. 5. Membership function for final range.

Eq. (8) calculates total coupling index of each node and is as follows:

$$T(S_i) = D(S_i) + CC(S_i) + EC(S_i). \tag{8}$$

Where $D(S_i)$, is the degree of node S_i. Eq. (9) defines the common coupling $CC(S_i)$ of different nodes.

$$CC(S_i) = \text{Number of nodes whose range } S_i \text{ belongs to} \tag{9}$$

Eq. (10) describes the external coupling value of a node S_i.

$$EC(S_i) = \sum_{j=1}^{n} \begin{array}{l}\text{Number of nodes in the range of } S_j \text{ who are} \\ \text{also in the range of } S_i\end{array}. \tag{10}$$

External coupling is a parameter to measure a neighbor node's participation in the other nodes in the area. Table 2 describes the corresponding fuzzy rules for chance value calculation. In the first round of Algorithm 1, the input range helps calculate each node's degree. Second round onwards, line 4 of Algorithm 1 uses the final range's crisp value to calculate the degree of each node. A higher value of chance increases the probability of a node being CH. We use degree, common coupling, and external coupling to calculate the total coupling index by Eq. (8). Chance value calculation takes place using the total coupling index as defined in Table 2.

Table 3 shows different cases of chance value calculation. Each row of Table 3 demonstrates chance value calculation by utilizing the total coupling index ($T(S_i)$) and residual energy (E). Second, the third and fourth column represents degree, context coupling, and external coupling of sensor nodes. The higher the energy is, the higher the chance for CH. Smaller is the value of $T(S_i)$, lesser is the chance for CH. Examples 6 and 7 have the same degree and same energy value, but different, $T(S_i)$, so a higher $T(S_i)$ node gets a higher chance value. So the common coupling, the external coupling, and each node's degree are important in deciding the chance value for the node. MCFL algorithm considers degree and energy at one stage, distance to the CH, and energy at another stage but the ABCRF algorithm considers two additional parameters (common coupling and external coupling) for chance value calculation.

Algorithm 1: Algorithm of ABCRF clustering protocol

```
Input: n, range, energy, area, sink, p, node_type, rmax
Output: X = {CHs, alive nodes}
Sensor node deployment in a rectangular area;
Calculate distance (Si Sj) by using Eq. (8);
for r = 1 to rmax
Calculate degree (Si) i.e. number of nodes in range of Si;
Calculate ABC index by using Eq. (9);
Calculate initial range Ri(Si) by using Eq. (10);
Calculate final range Rf(Si) by using Eq. (11);
Calculate total coupling index T(Si) by using Eq. (12);
    for i = 1 to n
            if (Si.energy <= 0)
                  alive = alive-1;
            end if
            for i = 1 to n
            Select p nodes with largest chance and assign Si.type = TCH;
            end for
    end for
  Send CH_MESSAGE (ID, Rf, Sensor_Energy) to the neighbor nodes
            for i = 1 to n
            for j = 1 to n
                  if ((Si, Sj).type= TCH && d(Si, Sj) <= Rf(Si))
                        if (Si.energy < Sj.energy)
                              Si.type = normal;
Advertise QUIT_FROM_ELECTION_MESSAGE(ID)
                        end if
                  end if
            end for
            end for
            for i = 1 to n
                        if(Si.energy>0 && Si.type=TCH)
Advertise CH_MESSAGE(ID)
                              Si.type=CH;
                        end if
            end for
Cluster members will join the nearest CH by sending the JOIN_TO_CH_MESSAGE(ID)
end for
Return X
```

Further, a node's chance to become CH based on the total coupling index is defined in Eq. (11). Eq. (11) is a mathematical representation of Table 2. The fuzzy inference system calculates the chance value using the rules defined in Table 2.

Chance of a node for CH is calculated by

$$C(S_i) = fuzzy[T(S_i), E(S_i)]. \tag{11}$$

The two input variables; total coupling index ($T(S_i)$) and residual energy ($E(S_i)$) are shown in Figs. 4 and 1 respectively. The fuzzy output variable, chance ($C(S_i)$) is described in Fig. 6.

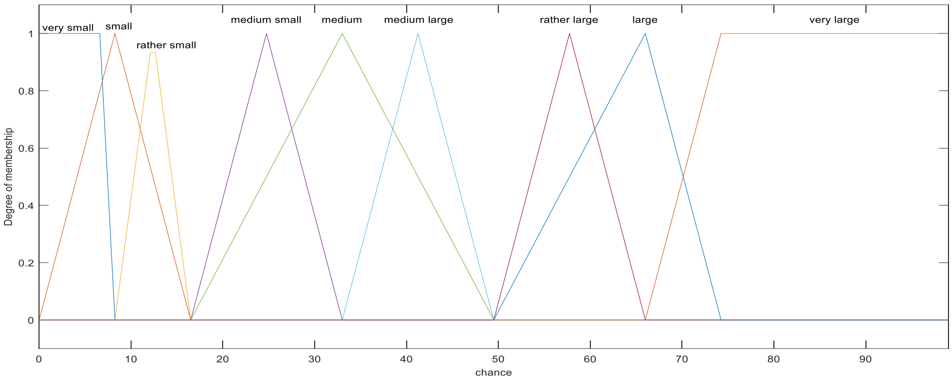


Fig. 6. Membership function for chance.

Table 2. Fuzzy if-then rules for chance value calculation.

Total coupling index	Residual energy	Chance
Far	high	very large
Medium	high	large
Close	high	rather large
Far	medium	medium large
Medium	medium	medium
Close	medium	medium small
Far	low	rather small
Medium	low	small
Close	low	very small

Table 3. Example of chance value calculation.

Example No.	Degree	$CC(S_i)$	$EC(S_i)$	$T(S_i)$	E	Chance
1	4	4	376	384	0.487	17.297
2	4	3	377	384	0.477	17.145
3	4	4	376	384	0.485	17.246
4	7	7	647	661	1	42.258
5	8	8	738	754	1	42.917
6	10	10	903	923	1	43.705
7	10	10	821	841	1	43.355

The following points explain the reason for selecting rules of Tables 1 and 2:

– Rules of Table 1 decrease the final competition range of a node that is very near to the BS. It will minimize the hot spot issue and will increase the performance.

– The competition radius of a node should be small if the energy of the node is less. The rules of Table 1 reduce the competition range for a node with lower residual energy.
– Past research reveals that the competition radius should decrease when the degree of a node increases. Rules of Table 1 decrease the competition radius when the node degree increases and hence improves the lifetime.
– The energy of tentative CHs should be high because final CHs are selected from the tentative CHs. Rules of Table 2 select the tentative CHs with high residual energy and hence final CHs have more residual energy.
– Common coupling and External coupling maintain the uniform node distribution among clusters and also prevents closeness between CHs because there are fewer common neighbors between nodes in sparse networks.

The chance value calculated by Eq. (11) is normalized as $NC(S_i)$ for further use.

The desired number of nodes with the largest chance value is declared as a tentative cluster head. Further, a tentative cluster head whose energy is higher than all other tentative cluster head nodes in its competition range is declared as the final cluster head. The status of those nodes who could not qualify for final CH changes to a normal node. The cluster formation process permits member nodes to join the nearest CH node. Each cluster head node aggregates data and sends it to the BS via the multi-hoping technique.

4. OVERVIEW OF NEURO-FUZZY OPTIMIZATION MODEL AND CRYPTOGRAPHY TECHNIQUE

This section explains the neuro-fuzzy optimization model and security mechanism (cryptography technique). We carry out the performance evaluation of the proposed algorithm by incorporating the artificial intelligence approach and secure data aggregation method.

4.1 Neuro-Fuzzy Optimization Model

We propose the neuro-fuzzy optimization model mechanism for implementation with the proposed protocol. We evaluate the Adaptive Neuro-Fuzzy Inference System (ANFIS) estimator to monitor the status of different sensor nodes in a cluster. Fuzzy rules help to fix the status of each sensor node. There are three input parameters in the fuzzy logic to calculate the node status. The input parameters are FC (Fault Count-number of rounds a node is faulty), successful packets (ratio of successful packets to total packets), and residual energy. We mention the different rules in Table 4. Lastly, the ANFIS estimator calculates the crisp value using the centroid method of defuzzification. The value of node status may be healthy or unhealthy. We use the status of a node to create a matrix (Cluster Health Matrix (CHM)) for each cluster and further define Cluster Unhealthy Index (CUI) as below:

$$CUI = \frac{Count\ of\ \ unhealthy\ nodes}{Total\ \ node\ \ count} \times 100. \tag{12}$$

The cluster having the CUI value higher than the pre-defined threshold value works as unhealthy cluster and will not participate for data aggregation.

Table 4. Fuzzy if-then rules for node status calculation.

FC	Successful packets	Residual energy	Status
high	very poor	high	unhealthy
medium	poor	high	unhealthy
low	good	high	healthy
low	average	medium	healthy
medium	very poor	medium	unhealthy
medium	poor	medium	unhealthy
high	very poor	low	unhealthy
medium	very poor	low	unhealthy
high	poor	low	unhealthy

4.2 Cryptographic Technique

We use Gorti's Enhanced Homomorphic Cryptosystem (EHC) technique [50] to encrypt and decrypt the data. The method guarantees end-to-end data confidentiality and does not share the key with the intermediate node. It uses public and private keys of the base station for computations like direct addition or multiplication for encrypting data. We mainly use multiplicative homomorphic and additive homomorphic techniques.

Let us consider the different notations as below:

EN for encryption, *DE* for decryption, + for addition operation, $*$ for multiplication operation, $A1$ for the private key, $A2$ for the public key, and R for data set.
The condition for additively homomorphic is

$$p + q = DE_{A1}(EN_{A2}(p) + EN_{A2}(q)) \qquad p, q \in R, \tag{13}$$

The condition for multiplicatively homomorphic is

$$p * q = DE_{A1}(EN_{A2}(p) * EN_{A2}(q)) \qquad p, q \in R, \tag{14}$$

The CHs share the secret key with the BS. Each cluster uses the above technique to secure the network.

5. COMPARATIVE ANALYSIS OF RESULT AND SIMULATION WORK

Here we simulate our work (ABCRF protocol) and compare performance with LEACH, EEUC, EAUCF, MCFL, and FBUCA protocols by using the matlab tool. We deploy a sufficient number of nodes in the area of interest. There are three parts to our experiments. The first part is for a small area network, the second part is for a large area network, and the third part is for the dynamic network, mobile sink, and secure artificial intelligence. The simulation and analysis of results take place into 3 different categories as follows:

– Small area networks: We carry out experiments in 4 different scenarios to evaluate the ABCRF protocol. The deployment area is the same for each scenario. We consider the different combinations of (base station location, sensor node count, and initial energy) for each scenario. The detail about simulation parameters is shown in Table 5.

Table 5. Simulation parameter details of different scenario.

Parameters	Value scenario 1	Value scenario 2	Value scenario 3	Value scenario 4
Field area of WSN	200∗200 m^2	200∗200 m^2	200∗200 m^2	200∗200 m^2
BS location	(100, 100)	(100, 100)	(100, 100)	(200, 200)
Sensor node count	100	200	100	100
Initial energy	1 J	1 J	0.5-1.5J	0.5-1.5J
Initial radius of cluster	70 m	70 m	70 m	70 m
E_{elec}	50 nJ/bit	50 nJ/bit	50 nJ/bit	50 nJ/bit
E_{fs}	100 pJ/bit/m^2	100 pJ/bit/m^2	100 pJ/bit/m^2	100 pJ/bit/m^2
E_{mp}	0.0013 pJ/bit/m^4	0.0013 pJ/bit/m^4	0.0013 pJ/bit/m^4	0.0013 pJ/bit/m^4
E_{da}	5 nJ/bit/message	5 nJ/bit/message	5 nJ/bit/message	5 nJ/bit/message

– Large area networks: We consider static network and fixed sink scenarios for large area networks. We assume that nodes and sink are not movable. The proposed protocol shows its superiority in all scenarios for small area networks, but a fair comparison with other protocol’s performance is also analyzed for large area networks. The area for the large network is 500∗500 and 300 nodes are deployed with BS at (500, 500). The initial energy of each node is 5 J as each node spends a large amount of energy in each round.
– Dynamic network, mobile sink, and secure artificial intelligence: We consider dynamic network, sink mobility, and secure artificial intelligence separately and perform a comparison with ABCRF protocol.

[A] Small area networks – We run each experiment 20 times and calculate the average for each scenario; it illustrates the proper analysis of the results. Simulation outcome shows that the ABCRF performs better than LEACH, EEUC, EAUCF, MCFL, and FBUCA in all scenarios. The first node death (FND), half node death (HND), residual energy of network after 500 rounds (RE_500), and residual energy of network after 1000 rounds (RE_1000) are parameters to compare the performance of protocols. We do not consider the last node death since network energy is mostly exhausted after 50% of the node death and the network becomes almost functionally inefficient. To better analyze the algorithm, we consider 4 different network scenarios. The first and second scenarios are homogeneous with 100 and 200 nodes respectively. The third and fourth scenarios are heterogeneous with BS at (100, 100) and (200, 200) respectively. The proposed algorithm shows better performance for all the scenarios. Each algorithm execution round decides the members after the finalization of CHs. Each member node transmits 4000 data bits to its CHs. For all scenarios, the cluster’s initial radius is analogous to R (range) used in Eq. (6). The energy model of [36] defines E_{elec}, E_{fs}, E_{mp} and its value is the same in all scenarios. E_{da} denotes data aggregation energy. Table 5 contains all the parameters of a different scenario.

Scenario 1: The total number of nodes deployed is 100 in this scenario. BS is located in the center of the area. Due to the homogeneous network, each node is having the same initial energy of 1 joule. Before the protocol starts execution, the total network energy is 100 joule. As shown in Table 6, ABCRF performs better than LEACH, EEUC, EAUCF, MCFL, and FBUCA for FND, HND, RE_500, and RE_1000. For FND, EEUC and EAUCF perform better by 14.7% and 29.9% respectively than LEACH protocol. EAUCF is 13.2% more efficient than the EEUC protocol for FND. LEACH performs the worst among all protocols for FND. ABCRF performs 47% better than LEACH, 28.2% better than EEUC, 13.1% better than EAUCF, 9.6% better than MCFL, and 12.4% better than the FBUCA algorithm for FND. For HND, ABCRF performs 50.2% better than LEACH, 22.5% better than EEUC, 15.1% better than EAUCF, 12.1% better than MCFL, and 13.4% better than FBUCA. The performance of the ABCRF algorithm is higher because it considers double range optimization and chance value calculation based on the total coupling index, while LEACH, EEUC, EAUCF, MCFL, and FBUCA do not consider it. The probabilistic method itself is not sufficient for suitable CH selection. Fuzzy logic gives flexibility for proper value selection in a case of uncertainty. EAUCF tries to combine range with sensor node energy to decide CH node but the range calculation based on the distance parameter does not guarantee better performance.

Table 6. Performance of scenario 1.

Algorithm	FND	HND	RE_500	RE_1000
LEACH	381	635	28.4	4.9
EEUC	437	779	36.96	5.9
EAUCF	495	829	41.3	6.17
MCFL	511	851	43.6	7.01
FBUCA	498	841	42.9	6.35
ABCRF	560	954	47.8	7.17

Table 7. Performance of scenario 2.

Algorithm	FND	HND	RE_500	RE_1000
LEACH	451	881	91.2	22.35
EEUC	466	895	92.3	23.15
EAUCF	475	901	94.35	25.36
MCFL	471	911	97.1	26.3
FBUCA	461	916	98.3	25.1
ABCRF	525	998	106.79	32.23

Scenario 2: The total number of nodes for deployment is 200 in scenario 2 with 1 joule of the initial energy of each node. Total network energy is 200 joule. The BS station location is in the center of the area as in scenario 1. The other parameters are listed in Table 5. As shown in Table 7, ABCRF performs better than LEACH, EEUC, EAUCF, MCFL, and FBUCA for FND, HND, RE_500, and RE_1000. The performance of ABCRF is 16.4% better than LEACH, 12.7% better than EEUC, 10.5% better than EAUCF, 11.4% better than MCFL, and 13.9% better than FBUCA for FND. The performance of ABCRF is 13.3% better than LEACH, 11.5% better than EEUC, 10.8% better than EAUCF, 9.6% better than MCFL, and 9% better than FBUCA for HND. The EAUCF algorithm performs 0.67% better than EEUC for HND. The last two columns of Table 7 show the residual energy of the network after 500 rounds and 1000 rounds of algorithm execution. After 500 rounds the residual energy of ABCRF is 17.1% better than LEACH, 15.7% better than EEUC, 13.2% better than EAUCF, 10% better than MCFL, and 8.6% better than FBUCA. The residual energy of the network after 1000 rounds for ABCRF improves 44.2% over LEACH, 39.2% over EEUC, 27.1% over EAUCF, 22.5% over MCFL, and 28.4% over FBUCA. It clearly shows that ABCRF also performs better for dense network environments.

Scenario 3: In this scenario, nodes are having different initial energy. The nodes are randomly initialized with initial energy between 0.5 and 1.5. The BS location is in the center of the area. The total number of nodes for this scenario is 100. Table 5 illustrates the parameters of scenario 3. Due to heterogeneity, we execute the algorithm 20 times and then take the average for further calculation. Table 8 shows the final results. ABCRF performs better than other algorithms for all the parameters considered. FND parameter is 39.9% better than LEACH, 32.9% better than EEUC, 8.9% better than EAUCF, 13.1% better than MCFL, and 25.9% better than FBUCA, while HND parameters perform 18.2% better than

LEACH, 11% better than EEUC, 8.6% better than EAUCF, 4.6% better than MCFL, and 4.1% better than FBUCA. The third and fourth column of Table 8 clearly shows that ABCRF has more residual energy than other protocols considered after 500 rounds and 1000 rounds. After 1000 rounds ABCRF still has approximately double energy than LEACH protocol. The residual energy of the network for ABCRF is 29.4% more than LEACH, 22.1% more than EEUC, 14.3% more than EAUCF, 16.7% better than MCFL, 20.2% better than FBUCA for 500 rounds. The residual energy of the network for ABCRF is much better than other algorithms for 1000 rounds. After 1000 rounds, ABCRF improves the residual energy of the network by 69.2% over LEACH, 52.6% over EEUC, 25.2% over EAUCF, 23.65% over MCFL, and 23.3% over FBUCA.

Scenario 4: In this scenario, 100 heterogeneous nodes work in the 200∗200 area. This scenario is different than other scenarios for the BS location. BS is located at (200, 200), which is distant from most of the nodes in the area.

The EEUC algorithm performs better than the EAUCF algorithm for HND, RE_500, and RE_1000. ABCRF performs better than all other algorithms under comparison. ABCRF improves 13.9% over MCFL, 16.9% over FBUCA, 19% over EAUCF, 23.5% over EEUC, and 91% over LEACH for FND. HND parameter of ABCRF is 35.9% more than LEACH, 5.22% more than EEUC, 22.1% more than EAUCF, 78.1% more than MCFL, and 81.2% more than FBUCA. The residual energy after the 1000th round of ABCRF algorithm is significantly better than all other algorithms. We achieve maximum improvement in the network's residual energy of ABCRF supported network than LEACH after 1000 rounds. The last column clearly shows that ABCRF has 3.78-joule residual energy after the 1000th round, which is much better than LEACH, EEUC, EAUCF, MCFL, and FBUCA algorithm. Fig. 7 shows the energy spent per round by the protocols for different scenarios. ABCRF protocol requires minimum energy among protocols considered in each scenario.

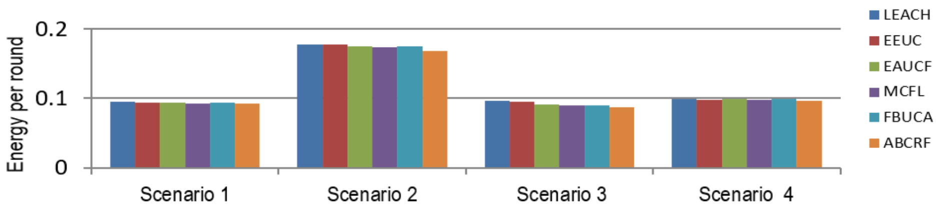


Fig. 7. Average energy spent per round for 1000 rounds in different scenario.

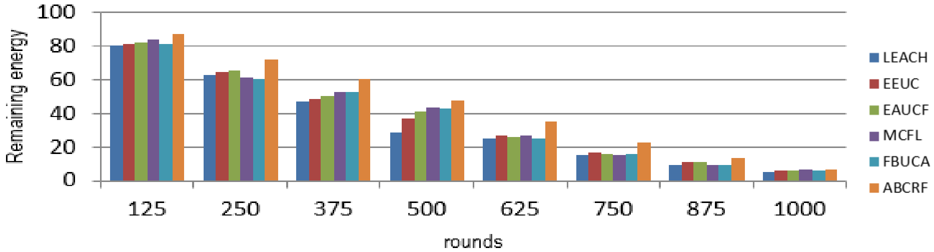


Fig. 8. Remaining energy vs. rounds in scenario 1.

Table 8. Performance of scenario 3.

Algorithm	FND	HND	RE_500	RE_1000
LEACH	271	766	40.31	7.91
EEUC	285	815	42.72	8.77
EAUCF	348	833	45.65	10.69
MCFL	335	865	44.7	10.82
FBUCA	301	869	43.4	10.85
ABCRF	379	905	52.18	13.38

Table 9. Performance of scenario 4.

Algorithm	FND	HND	RE_500	RE_1000
LEACH	137	460	13.76	1.32
EEUC	213	594	20.71	1.91
EAUCF	221	512	18.25	1.51
MCFL	231	351	19.3	1.85
FBUCA	225	345	19.1	1.75
ABCRF	263	625	23.6	3.78

The remaining energy vs. rounds of protocols is shown in Figs. 8-11 for Scenarios 1-4 4 respectively. The remaining energy of the ABCRF protocol is higher than other protocols considered in each scenario.

[B] Large area network – The algorithms execute 200 rounds and the results are shown in Figs. 12-14. FND, HND, packets transmitted to BS, cluster overhead are the parameters taken for simulation of a large network scenario. The ratio of energy required during the setup phase and total dissipated energy calculates the cluster overhead. Throughput is a measure of packets transmitted to BS. Due to the large size of the network, most of the nodes die early so we consider that the algorithms execute only for 200 rounds. ABCRF performs significantly better for all the parameters as compared to LEACH, EEUC, EAUCF, MCFL, and FBUCA.

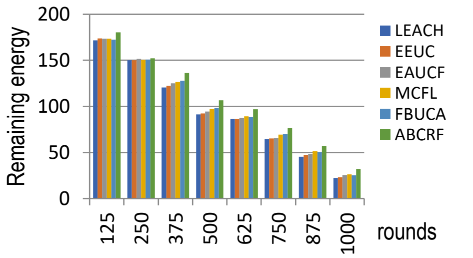


Fig. 9. Remaining energy vs. rounds in scenario 2.

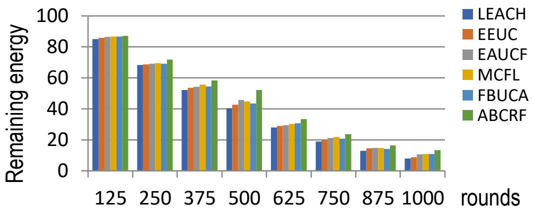


Fig. 10. Remaining energy vs. rounds in scenario 3.

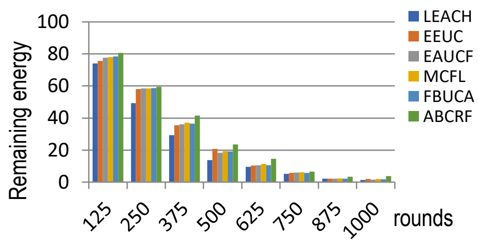


Fig. 11. Remaining energy vs. rounds in scenario 4.

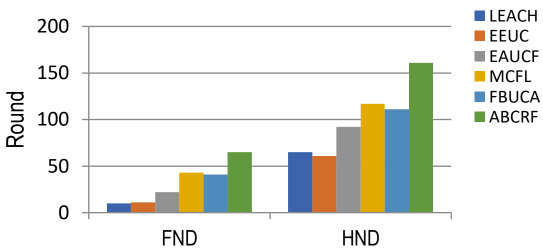


Fig. 12. FND and HND for large scale network.

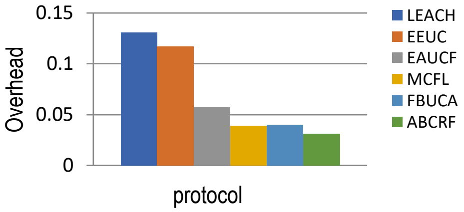


Fig. 13. Cluster overhead for large scale network.

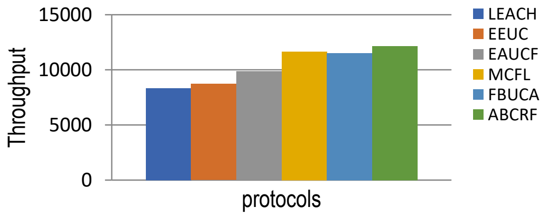


Fig. 14. Throughput for large scale network.

[C] Dynamic network, mobile sink, and secure artificial intelligence – We perform the simulations for the dynamic network (ABCRF-DN), sink mobility (ABCRF-SM), and secure artificial intelligence (ABCRF-SAI) separately and perform a comparison with ABCRF protocol. We consider FND and HND parameters for the simulation. The value of FND for ABCRF, ABCRF-DN, ABCRF-SM, and ABCRF-SAI protocols are 65, 131, 188, 195 respectively. The value of HND for ABCRF, ABCRF-DN, ABCRF-SM, and ABCRF-SAI protocols are 161, 191, 502, 521 respectively. Here we assume that nodes and sink are mobile and the rest of the simulation parameters are the same as the static network and fixed sink scenario of a large area network. Fig. 15 shows a comparison of ABCRF protocol with ABCRF-DN, ABCRF-SM, and ABCRF-SAI for FND and HND. ABCRF-SAI performs better than ABCRF, ABCRF-DN, and ABCRF-SM for FND and HND.

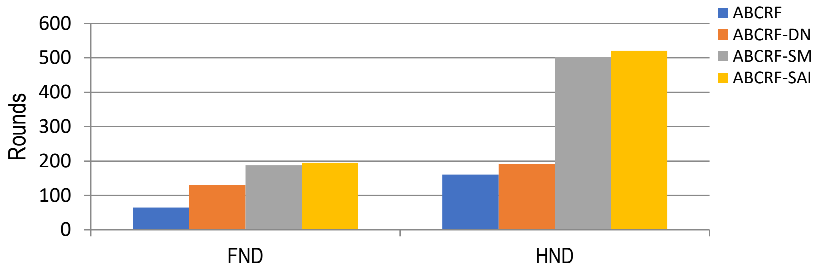


Fig. 15. Performance for sink mobility, dynamic network and secure artificial intelligence.

We perform the simulation of the proposed protocol using the neuro-fuzzy optimization model and Gorti’s Enhanced Homomorphic Cryptosystem (EHC) technique for the FND and HND.

The above simulation work proves that the ABCRF algorithm is better than other algorithms. The proposed algorithm shows better performance due to the use of energy and total coupling index for cluster head chance value calculation. The total coupling index performs better CH distribution in the network and extends network lifetime. Range calculation of ABCRF algorithm considers more informative parameters and proves its usefulness by extending the network lifetime.

6. CONCLUSIONS

Nodes closer to BS die quickly due to heavy traffic in multi-hop WSN and create hot spot issues. The proposed ABCRF protocol handles the hot spot issue properly and increases network stability by combining the fuzzy inference feature with the unequal clustering method. Double range optimization ensures a suitable range value for each node and helps to lower the intra-cluster cost of a cluster. ABCRF algorithm uses an atomic bond connectivity index to calculate the initial range value, which is further used with other network features like energy and distance from BS to calculate the final range value. ABCRF performs better than in comparison to LEACH, EEUC, EAUCF, MCFL, and FBUCA in each scenario.

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