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Fuzzy Logic Based Clustering Algorithm for Network Lifetime Enhancement in Wireless Sensor Networks

K. Arthi, A. Vijayalakshmi and P. Vanaja Ranjan
Department of Electrical and Electronics Engineering, Anna University, Chennai, India

Abstract: Maximization of network lifetime is one of the most vital objective for any Wireless Sensor Network (WSN). The proper organization of nodes become a major technique to expand the lifetime of the network. In this study, Fuzzy Logic Based Clustering Algorithm (FBCA) is applied for producing energy aware cluster with optimal selection of cluster heads. The FBCA is performed within each node which makes it as a distributed approach. The selection criteria for the many existing cluster selection technique is generally based on the Residual Energy (RE). This study considers other parameter like Least Recently Selected (LRS), Number of Neighbours (NN) which has a major influence in network lifetime. The proposed protocol has shown 62% increase of network lifetime using static sink and 47% increase using mobile sink when comapred with few standard protocols taken for consideration. The performance evaluation of the proposed technique is compared with cluster based sensor network protocol. Extensive discussion is done for centralized and distributed sensor network.

Key words: Wireless Sensor Network (WSN), clustering algorithm, fuzzy reasoning, network lifetime, throughput, energy evaluation

INTRODUCTION

The Wireless Sensor Network (WSN) technology is a key component for ubiquitous computing. A WSN consists of a large number of sensor nodes. Each sensor node senses environmental conditions such as temperature, pressure and light and sends the sensed data to a Base Station (BS). Since, the sensor nodes are powered by limited power batteries in order to prolong the life time of the network, low energy consumption is important for sensor nodes. In general, radio communication consumes the most amount of energy which is proportional to the data size and proportional to the square or the fourth power of the distance. In order to reduce the energy consumption, a clustering and data aggregation approach has been extensively studied (Abbasi and Younis, 2007). In this approach, sensor nodes are divided into clusters and for each cluster, one representative node which called Cluster Head (CH), aggregates all the data within the cluster and sends the data to BS. Since, only CH nodes need long distance transmission, the other nodes save the energy consumption. In order to manage effectively clusters and CHs, distributed clustering methods have been proposed such as LEACH, HEED, ACE and ANTCLUST (Heinzelman *et al*., 2002).

One of the first and most influential cluster-based algorithms is LEACH (Low-Energy Adaptive Clustering Hierarchy) (Heinzelman *et al*., 2000) which uses a distributed probabilistic mechanism. Based on LEACH, most existing fuzzy clustering approaches (Bagci and Yazici, 2010; Ando *et al*., 2010; Kang and Nguyen, 2012; Gupta *et al*., 2005; AlShawi *et al*., 2012; Madan and Lall, 2006; Lee and Jeong, 2011; Swapna *et al*., 2011; Akyildiz *et al*., 2002; Malik and Qureshi, 2010) considered the residual energy of sensor nodes during the CH selection. However, the remaining energy after being selected as a CH and running a round has never been discussed. A fuzzy logic-based clustering approach with an extension to the energy predication has been proposed by Lee and Cheng (2012), Gupta *et al*. (2005), Kim *et al*. (2008), Anno *et al*. (2008) and Swapna *et al*. (2011) to prolong the lifetime of WSNs by evenly distributing the workload. However, in all the above discussion the density of cluster is not mainly considered as the selection criteria for a CH.

In this study, Fuzzy Logic Based Clustering Algorithm (FBCA) is proposed in which nodes are self selected to become CHs by considering different probabilities based on their Residual Energy (RE), Number of Neighbors (NN) and Least Recently Selected (LRS) criteria. Residual Energy (RE) is the remaining energy of a node. Number of Neighbors (NN) means the number of nodes present in the node's interference range which determines the density of the cluster. Least Recently Selected (LRS) is the count which indicates the interval of

Corresponding Author: K. Arthi, Department of Electrical and Electronics Engineering, Anna University, Chennai, India

a node being selected as Cluster Head (CH). By considering the above mentioned parameters for CH selection the energy consumption among the nodes in the network will be balanced. This study also discusses the change in cluster-head selection based on the criticality of the event.

ENERGY MODEL

Evaluation of energy prediction: Cluster formation comprises of two phases: Set-up phase and steady state phase. In the setup phase the nodes estimates its eligibility before advertising itself as cluster head. In the proposed algorithm the estimation is done based on three criteria Residual Energy (RE), Number of Neighbors (NN) and the count which give the number of times the nodes has been cluster head (Least Recently Selected-LRS). However, the earlier standard cluster formation protocols such has LEACH (Xia and Wang, 2012) which considers only the residual energy of the node, the proposed algorithm with the above three constraints helps to select an efficient node as CH. In FBCA algorithm, time is divided into rounds (r = 0, 1, 2,...). The number of CHs in each round is a random variable with expectation k which is a pre-calculated value as a system parameter. Let p be the desired percentage of CHs. Let $LRS_i(r)$ be the notation to indicate that the node i has not been CHs within the cluster including the current round r. In Eq. 1, $P_i(n)$ is the probability of a node i being elected as CH. In round r if the corresponding $LRS_i(r)$ is >0. Otherwise $P_i(n)$ tends to be zero:

$$P_i(n) = \frac{p}{1-p(r\bmod(1/p))} \quad \text{if } LRS_i(r)>0 \tag{1}$$

After the cluster formation, the steady-state operation is broken into frames where nodes send their data to the CH at most once per frame during their allocated transmission slot. In a frame, suppose a CH has m cluster members, it would receive m messages from all the members and then transmit one combined message to the base station at a distance d. The number of frames could be obtained by Heinzelman *et al*. (2002).

$$M_{frame} = \frac{p_t}{m\times s_t + CH_t} \tag{2}$$

A node transmitting l bit message over a distance d (meter) will dissipate an energy amount E_T (l, d):

$$E_T(l,d) = \begin{cases} l\,(E_e+\varepsilon_f d^2 & \text{if } d<\delta \\ l\,(E_e+\varepsilon_m d^4 & \text{if } d\geq\delta \end{cases}$$

where, E_t(J/bit) represents the energy being dissipated to operate the circuitry per bit ε_m(J/bit/m^2) and ε_m(J/bit/m^4) denote the factors in Friss Free Space Model and the typical multi-path model, respectively and:

$$\delta = \sqrt{\frac{\varepsilon_f}{\varepsilon_m}}$$

The energy dissipation for receiving l bit message is determined by:

$$E_R(l) = lE_e \tag{4}$$

Energy dissipation when a node listens for t sec is tE_L where energy dissipation per unit time E_L(J/sec) is assumed to be constant. Then, the energy consumed by a node CH after a steady-state phase could be obtained by:

$$E_{cons} = M_{frame}\times E_T + m\times E_R \tag{5}$$

IMPLEMENTATION OF FUZZY APPROACH

Fuzzy logic was first introduced in the mid 1960s by Lotfi-Zadeh by Zadeh (1994). Since then, its applications have rapidly expanded in adaptive control systems and system identification. It has the advantages of easy implementation, robustness and ability to approximate to any nonlinear mapping (Kulkarni *et al*., 2011).

The goal of the fuzzy part of the proposed protocol is to determine the probability of the node to become the Cluster Head (CH) that depends on the residual energy RE(n), NN(n) and LRS(n) of node n.

A triangular membership function for the input variable RE(n) is given by very high, high, rather high, medium, rather low, low and very low. A triangular membership function is used for the other two input variable LRS(n) and NN(n) are high, medium and low. The only fuzzy output variable is the probability of a CH candidate. The fuzzy set for the probability output variable is demonstrated in Fig. 1.

A triangular membership function for the output variable P(n) is given by variables are very high, high, rather high, medium, rather low, low and very low. The higher the probability shows that more chance for the node to be a CH.

In order to see the entire output surface of system, i.e., the entire span of the output set based on the entire span of the input set, the surface viewer is generated. Figuer 2 shows the surface viewer for the probability of nodes being a cluster head based on FIS.

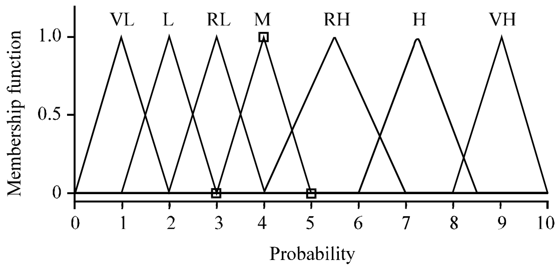

Fig. 1: Output membership function

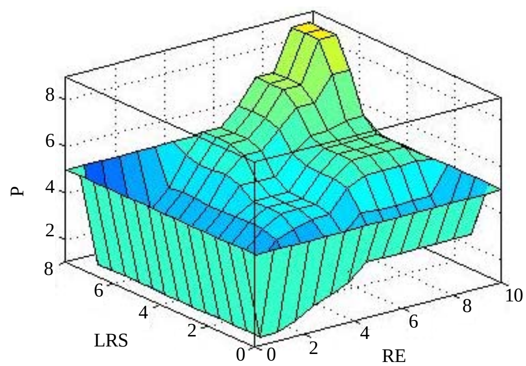

Fig. 2: Fuzzy set for output variable

Table 1: Fuzzy mapping rules

LRS	Event	RE	Probabilty
Low	Critical	Low	Medium
Low	Critical	Very high	Very high
High	Critical	Medium	High
Medium	Critical	Rather low	Rather high
Medium	Critical	Medium	High
Medium	Very critical	Medium	Medium
Low	Very critical	High	Rather low
Medium	Very critical	Medium	Medium
High	Very critical	Low	Low
High	Very critical	Medium	Medium
High	Very critical	High	Very high

For the fuzzy approach, the fuzzified values are processed by the inference engine which consists of a rule base and various methods to inference the rules. The rule base is simply a series of IF-THEN rules that relate the input fuzzy variables and the output variable using linguistic variables each of which s described by fuzzy set and fuzzy implication operator AND. Table 1 shows the IF-THEN rules used in the proposed method with a total number of 63 fuzzy rule base.

Any rule that fires contributes to the final fuzzy solution space. At the end, the defuzzification finds a single crisp output value from the solution fuzzy space. This value represents the node's probability. Practice defuzzification is done using centre of gravity method (Runkler, 1997) given by:

$$\text{Probability} = \frac{\sum_{i=1}^{n} U_i \times c_i}{\sum_{i=1}^{n} U_i} \qquad (6)$$

Where:
U_i = The output of rule base i
c_i = The centre of the output membership function

PROPOSED ALGORITHM

The pseudo code of the proposed clustering method is described as Fuzzy Logic Based Clustering Algorithm (FBCA). In every clustering round (lines 4-13), each sensor node generates a random number between 0 and 1. If the random number for a particular node is bigger than a predefined threshold T which is the percentage of the desired tentative CHs, the node becomes a CH candidate. Then, the node calculates the probability using the fuzzy inference system which is mentioned above and broadcasts a Candidate-Message with the probability. This message means that the sensor node is a candidate for CH with the value of probability. Once a node advertises a Candidate-Message, the node waits Candidate-Messages from other nodes. If the probability of itself is bigger than every probability values from other nodes, the sensor node broadcasts a CH-Message which means that the sensor node itself is elected as the CH.

Fuzzy Logic Based Clustering Algorithm:
Input:
N-Network
T-Threshold value to become a cluster head
n-Node
Cost (n)-Probability of a node being a cluster head
C-Number of clusters
CH_{MAX}-Maximum number of times a node n has a chance of being a CH
Output: CH node

Begin
if (rand(0, 1)>T)
Broadcast energy of a node n_i, E_{TRA},
Receive signal with energy E_{REC}

$$FBCA(n_i) = \frac{E_{TRA}(n_i(t))}{\sum_{j=1}^{k} E_{REC}(n_j(t))} \times \varphi(n_i)$$

If (FBCA(n_i) ==
max (FBCA(n_i)|j = 1, 2, ... n))) then begin
Broadcast CH_ADV (i)
Receive REQ_JOIN (i, j)
CH(i) = CH(i) U {j}
CH(i)_count+ = 1
Calculate available power
Cost(n_i) = RE(n_i) + LRS(n_i)
If
((Cost(n_i) =
minCost(n_i)) & & (CH_{MAX} ==
CH(n_i)_count))
Send NOT_CH
End
Else
Goto step 5
End
End
End

If a node which is not a CH receives the CH-Message, the node selects the closest cluster head as its CH and sends a JOIN-REQ request to the head.

PERFORMANCE EVALUATION

The simulations are carried out in MATLAB. The 100 sensor nodes are randomly deployed in a topographical of dimension 300×300 m. The topographical area has the sensed transmission limit of 30 m. There is only one data sink which located at (90, 90 m) in the case of static sink and sink travelling diagonally across the specified dimension in the case of mobile sink.

Figure 3 shows the surface view output for higher critical value (c = 9). From the result, it is shown that the probability of a nodes acting as cluster heads is more when there is an occurrence of a critical event. Figure 4 shows the surface view output for less critical value (c = 1). The output infers that there is less probability for a node to act as cluster head when there is less critical event.

All sensor nodes have the same initial energy of 0.5 J. The proposed method uses the Friss free space radio model for its simulation. Simulations are done using the values 50 nJ/bit and 100 pJ/bit/m^2 for ε_f and E_e, respectively. Table 2 presents the systems parameters.

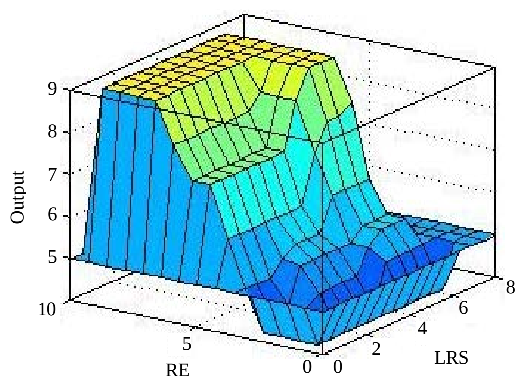

Fig. 3: Critical event based on high criticality value = 9

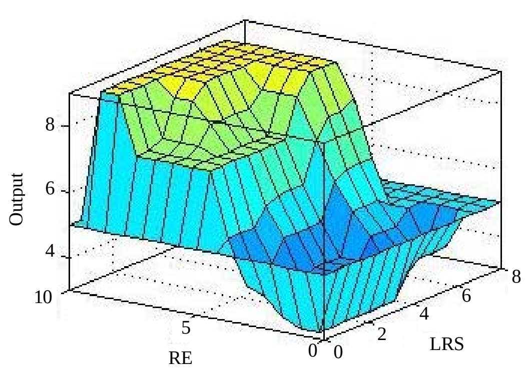

Fig. 4: Critical event based on less criticality value = 1

The energy consumption rate can directly influence the life-time of the sensor nodes as the depletion of battery resources will eventually cause failure of the nodes. The number of alive nodes vs. function of rounds is analyzed by changing the value of RE between 0.1-0.3 J and the value of LRS to be 4 and 6 with the constant value of NN (fixed as 5) as shown in Fig. 5. Both the proposed protocol and LEACH protocol are based on a hierarchical structure in which all the nodes rotate to take responsibility for being the cluster-head and hence no particular sensor is unfairly exploited in battery consumption. From the results, it can be seen that in leach protocol the number of nodes that are alive is almost equals 100 till 890th round but in other proposed scheme it is found that 1900th, 3000th and 3500th round for RE = 0.1, 0.2, 0.3 J with static sink. Moreover, in Fig. 5, it can be seen that the number of alive nodes of the proposed method is always higher.

Energy is the most important issue in WSN and the most important standard for measuring WSN is network life time. Figure 6 shows the comparison of simulation results of network lifetime of the proposed protocol with the standard LEACH protocol. From the arrived results,

Table 2: Simulation parameter

Parameters	Values
Topographical area (m)	300×300
Sink location (m)	90×90
Number of nodes	100
Transmission range	40 m (133 ft)
Packet size	500 bytes
Initial battery level	0.5 J
Energy for data aggregation	5 nJ/bit/signal
E_e	50 nJ/bit
ε_f	100 pJ/bit/m^2
MAC protocol	IEEE 802.15.4

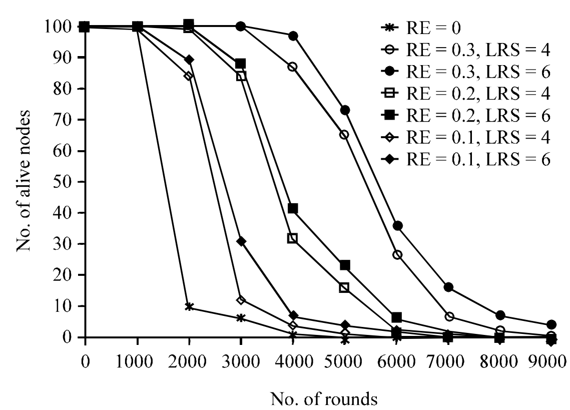

Fig. 5: Number of alive nodes with static sink for LRS = 4 and LRS = 6

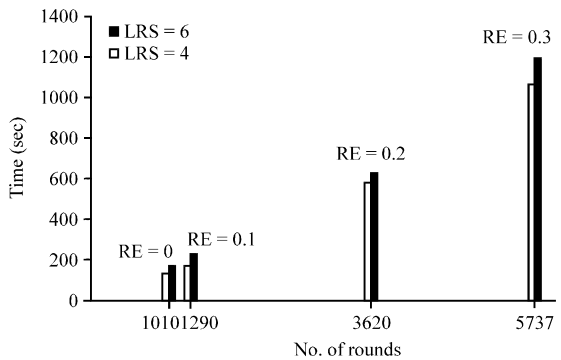

Fig. 6: Network lifetime with static sink for LRS = 4 and LRS = 6

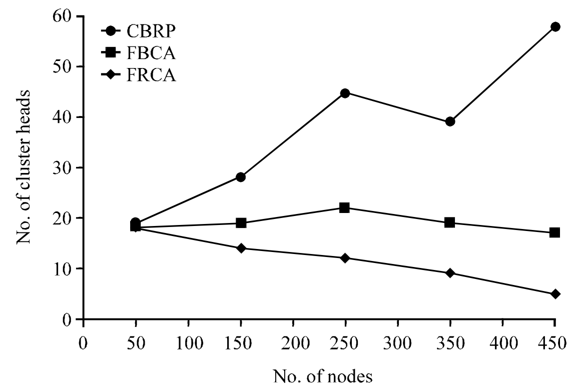

Fig. 7: Number of cluster heads vs. number of nodes

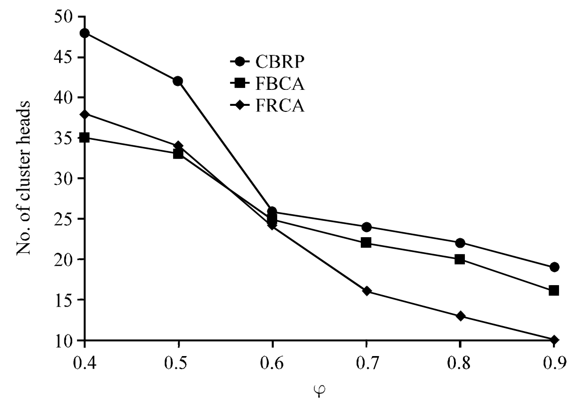

Fig. 8: Number of cluster heads for variable values of φ

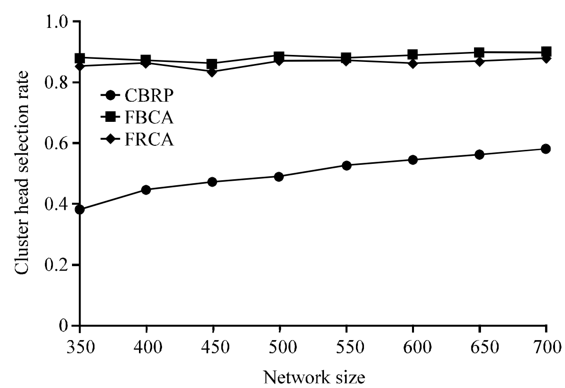

Fig. 9: Cluster head selection ratio

the death of the first node is earlier in LEACH protocol than the proposed protocol with RE = 0.3 J using static sink. The time of death of the first node in proposed protocol occurred at 1195 sec whereas in LEACH it occurs nearly 1026 sec earlier. Therefore, proposed protocol extend the network life time than LEACH.

The network lifetime achieved by the proposed method using a static sink is increased by nearly 52% than that can be obtained by the LEACH algorithm. This shows that the use of proposed algorithm can improve energy efficiency and prolong the life of the network.

Figure 7 shows the number of cluster heads formed in a WSN by varying the number of nodes in the network against the standard cluster based protocols such as CBRP and FRCA. It has been observed that the proposed algorithm creates optimal number of cluster heads compared to other algorithms, thereby showing the compromise between reductions in the hop count to the cluster head by a sensor node and the energy utilization by more number of nodes acting as cluster heads.

Figure 8 shows the number of cluster heads formed in a WSN as a function of the probability of CH selection for the proposed algorithm against the standard cluster based protocols such as (Cluster Based Routing Protocol) CBRP and (Fuzzy Relevance based Clustering Algorithm) FRCA. The simulation is done using 350 nodes for different values of φ. From the graph, it is understood that as the probability increases the number of CH gradually decreases in all the three methods. In CBRP the formation of CH is more compared to FRCA and the proposed FBC algorithms which results in increased overhead traffic between clusters. On the other hand the FRCA shows very minimal clusters formation which ends up in large clusters with heavy overload for the CH to maintain the cluster. The proposed FBC protocol shows optimal number of clusters for various values of φ ranging from $0.4 \leq \varphi \leq 0.9$.

Figure 9 shows the performance of the proposed FBCA algorithm for various network sizes. As shown in Fig. 9, the proposed FBC achieves better CH Selection Rate (CHSR) than FRCA that is known for its good performance. Better CHSR of the proposed FBC is due to the selection criteria such as LRS, number of nodes and the residual energy of the node. Thus, the performance of the proposed FBC does not degrade with the increase of network size. CHSR is influenced by nodes with <0.8 that

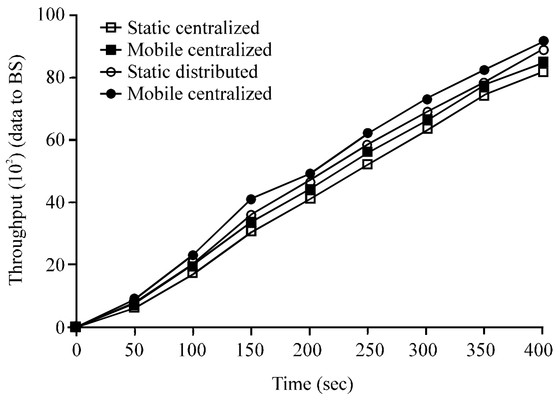

Fig. 10: Network lifetime with mobile sink for LRS = 4 and LRS = 6

means low signal intensity and low battery power. Therefore, the simulation is performed with $\varphi \geq 0.9$. The CHSR of the proposed method is compared with the standard protocols such as CBRP and FRCA Methods.

Throughput is the amount of data collected by a node at a particular time. The proposed algorithm is implemented for both centralized and distributed networks. In both these networks the analysis is done using static sink and mobile sink. As shown in Fig. 10 in case of network using static sink, the base station itself acts as the sink. On the other hand, for the network using mobile sink, the base station is located near the observation area. The mobile sink is responsible to collect the data to the base station. In this graph, the throughput of the proposed algorithm is compared between the four combinations of networks at various level of time. From the graph, it has been found that the mobile sink with distributed network out performs the other three networks with a small difference.

CONCLUSION

In this study, a novel cluster head selection technique was framed considering three essential parameters like RE, LRS and NN. It has been shown that the FBCA algorithm efficiently performs with the threshold of 0.3 J residual energy when compared with 0.1 and 0.2 J for network having static sink and network having mobile sink. The FBCA algorithm was also applied for centralized and distibuted networks and its throughput was analysed for both static sink and mobile sink. The proposed algorithm is capable to adapt the selection criteria for cluster head selection dynamically based on the criticality of the event in the network. Simulation results demonstrate the effectiveness of the new approach with regards to enhancement of the lifetime of wireless sensor networks with randomly scattered nodes.

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