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

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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, Fuzzified Clustering Algorithm (FCA) is applied for producing energy aware cluster with optimal selection of cluster heads. The FCA 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 52% increase of network lifetime using static sink and 36% 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; 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 discussion the density of cluster is not mainly considered as the selection criteria for a CH.

In this study, Fuzzified Clustering Algorithm (FCA) 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 a node being selected as Cluster Head (CH). By considering the above

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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 which considers only the residual energy of the node, the proposed algorithm with the earlier three constraints helps to select an efficient node as CH. In FCA 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 $p = k/N_n$ be the desired percentage of CHs. Let LRS(r) be the set of nodes that have not been CHs within the cluster including the current round r. In round r, node i (i = 1, 2,..., N) elects itself to become a CH with probability:

$$P_i(t) = \frac{p \times N_n}{N_n - \frac{p}{N_n}\left(r \times \mathrm{mod}\left(\frac{1}{p}\right)\right)} \quad (1)$$

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 distanced. The number of frames could be obtained by Eq. 2:

$$M_{frame} = \frac{p_t}{m \times s_t + CH_t} \quad (2)$$

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

$$E_T(l, d) = \begin{cases} l(E_e + \varepsilon_f d^2) & \text{if } d < \delta \\ l(E_e + \varepsilon_m d^4) & \text{if } d \geq \delta \end{cases} \quad (3)$$

where, E_t (J/bit) with represents the energy being dissipated to operate the circuitry per bit with ε_f (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 bit message is determined by:

$$E_R(l) = lE_e \quad (4)$$

Energy dissipation when a node listens for 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:

$$E_{cons} = M_{frame} \times E_T + m \times E_R \quad (5)$$

IMPLEMENTATION OF FUZZY APPROACH

Fuzzy logic was first introduced in the mid 1960s 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.

Figure 1 shows the membership function of the input variables. 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. 2.

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.

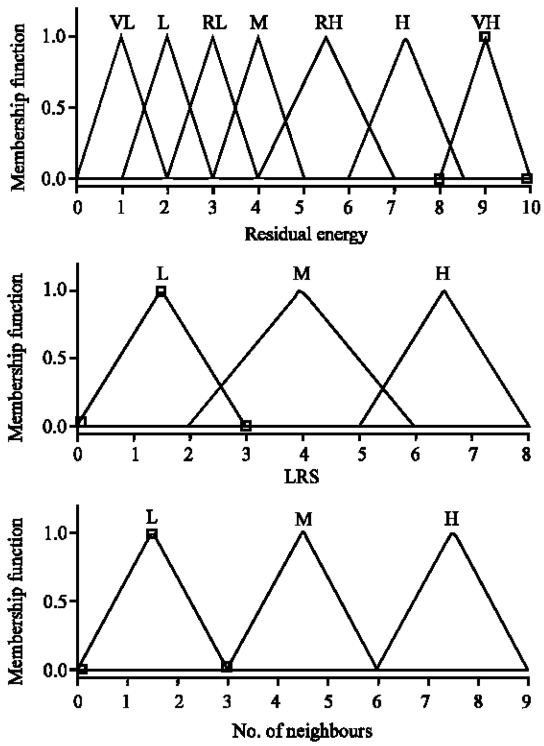

Fig. 1: Input membership function

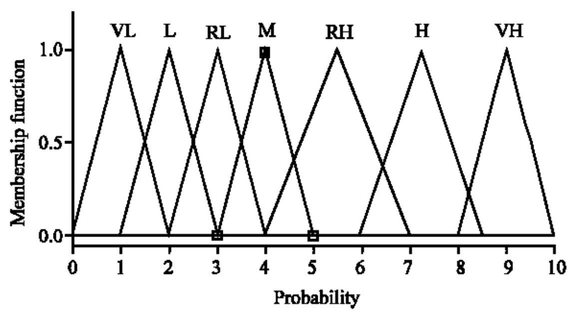

Fig. 2: Output membership function

Figure 3 shows the surface viewer for the probability of nodes being a cluster head based on FIS. 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.

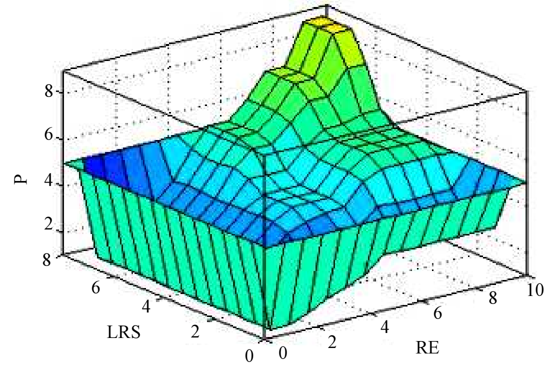

Fig. 3: Fuzzy set for output variable

Table 1: Fuzzy mapping rules

LRS	NN	RE	Probabilty
Low	Low	Low	Very low
Low	Medium	Medium	Low
Low	High	Rather high	Rather low
Medium	Low	Rather low	Low
Medium	Medium	Rather low	Rather low
Medium	High	Medium	Medium
High	Low	High	Ratherhigh
High	Medium	High	High
High	High	High	Very high

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 Fuzzified Clustering Algorithm (FCA). 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.

Algorithm: fuzzified 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}

$$FBC(n_i)=\frac{E_{TRA}(n_i(t))}{\sum_j^k E_{REC}(n_j(t))}\times P(n_i)$$

If (FBC(n_i) ==
max (FBC(n_j) |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
If
(Cost($n_{(i)}$) = min cost($n_{(j)}$) && ((CH))$_{(MAX)}$== CH(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 and 90 m) in the case of static sink and sink travelling diagonally across the specified dimension in the case of mobile sink.

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 in details.

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 Joule
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)

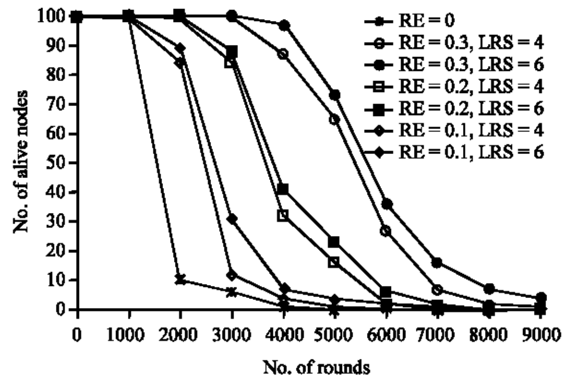

Fig. 4: Number of Alive nodes with static sink for LRS = 4 and LRS = 6

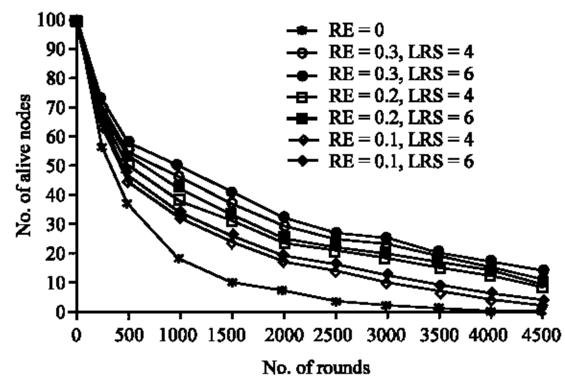

Fig. 5: Number of alive nodes with mobile sink for LRS = 4 and LRS = 6

The number of alive nodes as a function of rounds 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. 4 and 5, respectively.

It can be seen that the proposed method outperforms the standard clustering protocol (RE = 0). Moreover, in Fig. 4 and 5, it can be seen that the number of alive nodes of the proposed method is always higher.

Network lifetime is the time recorded when the first node of the network completely drains out of battery resource. The proposed technique is simulated for various values of RE (0.1-0.3 J) and compared with the standard clustering protocol.

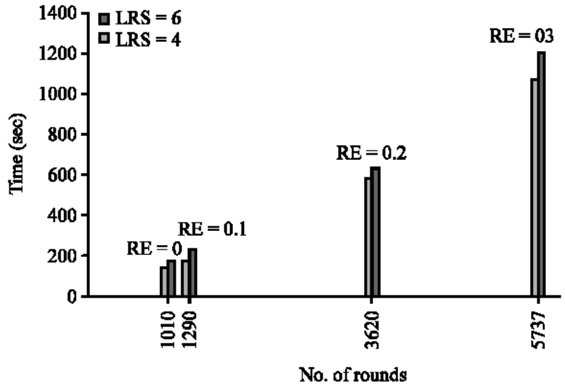

Fig. 6: Network lifetime with static sink for LRS = 4 and LRS = 6

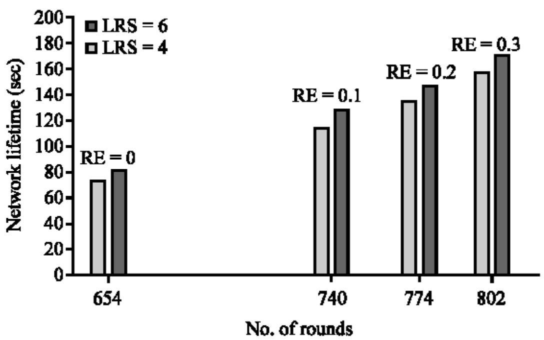

Fig. 7: Network lifetime with mobile sink for LRS = 4 and LRS = 6

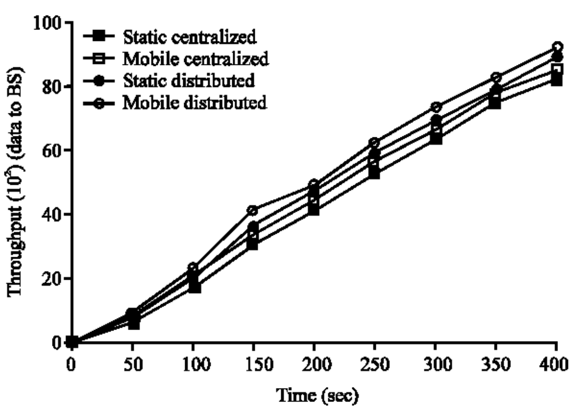

Fig. 8: Throughput for centralized and distributed network

The network lifetime achieved by the proposed method using a static sink is increased by nearly 52% than that can be obtained by the standard algorithm and also increased by nearly 36% when using a mobile sink as shown in Fig. 6 and 7, respectively.

Throughput is the amount of data collected by a node at a particular time. In Fig. 8, the throughput at the base station is compared between static and mobile sink in a centralized and distributed network. From the graph, it has been found that the mobile sink with network distributed out performs the other three combination network.

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 FCA 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 FCA 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.

REFERENCES

Abbasi, A.A. and M. Younis, 2007. A survey on clustering algorithms for wireless sensor networks. Comput. Commun., 30: 2826-2841.

Akyildiz, I.F., W. Su, Y. Sankarasubramaniam and E. Cayirci, 2002. A survey on sensor networks. IEEE Commun. Mag., 40: 102-114.

AlShawi, I.S., L. Yan, W. Pan and B. Luo, 2012. Lifetime enhancement in wireless sensor networks using fuzzy approach and a-star algorithm. Sensors J., 12: 3010-3018.

Ando, H., L. Barolli, A. Durresi, F. Xhafa and A. Koyama, 2010. An intelligent fuzzy-basedcluster head selection system for wireless sensor networks and its performance evaluation. Proceedings of the International Conference on Network-Based Information Systems, September 14-16, 2010, Takayama, pp: 55-61.

Anno, J., L. Barolli, A. Durresi, F. Xhafa and A. Koyama, 2008. Performance evaluation of two fuzzy-based cluster head selection systems for wireless sensor networks. Mobile Inform. Syst., 4: 297-312.

Bagci, H. and A. Yazici, 2010. An energy aware fuzzy unequal clustering algorithm for wireless sensor networks. Proceedings of the IEEE International Conference on Fuzzy Systems, July 18-23, 2010, Barcelona, pp. 1-8.

Gupta, I., D. Riordan and S. Sampalli, 2005. Cluster-head election using fuzzy logic for wireless sensor networks. Proceedings of the 3rd Annual Communication Networks and Services Research Conference, May 16-18, 2005, IEEE., pp: 255-260.

Heinzelman, W.B., A.P. Chandrakasan and H. Balakrishnan, 2002. An application specific protocol architecture for wireless microsensor networks. IEEE Trans. Wireless Commun., 1: 660-670.

Heinzelman, W.R., A. Chandrakasan and H. Balakrishnan, 2000. Energy-efficient communication protocol for wireless microsensor networks. Proceedings of the 33rd Annual Hawaii International Conference on System Sciences, January 4-7, 2000, Cambridge, MA., USA., pp: 10-16.

Kang, S.H. and T. Nguyen, 2012. Distance based thresholds for cluster head selection in wireless sensor networks. IEEE Commun. Lett., 16: 1396-1399.

Kim, J.M., S.H. Park, Y.J. Han and T.M. Chung, 2008. CHEF: Cluster head election mechanism using fuzzy logic in wireless sensor networks. Proceedings of the 10th International Conference on Advanced Communication Technology, Feberuary 17-20, 2008, Gangwon-Do, pp: 654-659.

Kulkarni, R.V., A. Forster and G.K. Venayagamoorth, 2011. Computational intelligence in wireless sensor networks: A survey. IEEE Commun. Surv. Tutor., 13: 68-96.

Lee, C. and T. Jeong, 2011. FRCA: A fuzzy relevance-based cluster head selection algorithm for wireless mobile ad-hoc sensor networks. Sensors, 11: 5383-5401.

Lee, J.S. and W.L. Cheng, 2012. Fuzzy-logic-based clustering approach for wireless sensor networks using energy predication. IEEE Sens. J., 12: 2891-2897.

Madan, R. and S. Lall, 2006. Distributed algorithms for maximum lifetime routing in wireless sensor networks. IEEE Trans. Wireless Commun., 5: 2185-2193.

Malik, A.S. and S.A. Qureshi, 2010. Analyzing the factors affecting network lifetime for cluster-based wireless sensor networks. Pak. J. Engine. Appl. Sci., 6: 9-16.

Runkler, T.A., 1997. Selection of appropriate defuzzification methods using application specific properties. IEEE Trans. Fuzzy Syst., 5: 72-79.

Swapna, K.S., K.M. Nanda and V.S. Sheeba, 2011. Fuzzy logic based energy efficient hierarchical clustering in wireless sensor networks. Int. J. Res. Rev. Wirel. Sens. Netw., 1: 53-57.

Zadeh, L.A., 1994. Soft computing and fuzzy logic. IEEE Software, 11: 48-56.