Cluster Head Selection using a Two-Level Fuzzy Logic in Wireless Sensor Networks

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***Abstract*—Due to resource limitations in wireless sensor networks, prolonging the network lifetime has been of a great interest. An efficient routing technique is known as hierarchical routing based on clustering, in which finding the optimum cluster heads and number of them has been a challenge. In this paper, a two-level fuzzy logic is utilized to evaluate the qualification of sensors to become a cluster head. In the first level (Local Level), the qualified nodes are selected based on their energy and number of neighbors of them. Then, in the second level (Global Level), nodes' overall cooperation is considered in the whole network with three fuzzy parameters. These parameters are centrality, proximity to base station and distance between cluster heads. Simulation results in five metrics show that the proposed approach consumes less energy and prolongs the network life time about 54 % compared with other algorithms.**

Keywords-energy aware routing; fuzzy logic; wireless sensor network

I. INTRODUCTION

A wireless sensor network (WSN) consists of a large number of sensor nodes and a base station (BS). These sensors collect data and send them to the BS via radio transmitter. They have limited power and computational capacity. WSNs can be used in many applications such as military, biomedical, and environmental applications. It is not easy to find the route and reserve it, because the limited amount of energy and sudden change in the position of the nodes creates unpredictable changes [1][2][3]. The energy is the major challenge for designing the routing protocol in WSNs. One of the most important routing algorithms is hierarchical or cluster-based routing. In a hierarchical architecture, higher energy nodes can be used to process and send the information while low energy nodes can be used to perform the sensing in the proximity of the target [2]. LEACH [4], PEGASIS [5], TEEN [2] and APTEEN [2] are some of hierarchical routing protocols.

Utilizing intelligent techniques improves the efficiency of wireless sensor network. In applications that require real time decision making, fuzzy logic is a powerful tool that can make decision even if there is insufficient data; while sufficient data (which is rare in real applications) is needed for making a decision in classic control. Recently, in some papers like [6] and [7], fuzzy logic is used for routing and improving network lifetime. We also used fuzzy logic as a mean to select cluster heads. In addition, due to the proved efficiency of clustering techniques in energy consumption, we utilized clustering in our proposed routing algorithm.

In this paper, we proposed a two-level fuzzy logic to evaluate the qualification of sensors to become a cluster head. In local level the qualified nodes are selected based on their energy and number of neighbors of them. Then, in the global level we seek for the best node cooperation regarding to the average energy consumption metric.

In the remainder of this paper, Section 2 discusses some related works and previous studies. Section 3 describes the system model and Section 4 discusses proposed scheme. Section 5 provides simulation results and discusses the efficiency of proposed algorithm. Finally, Section 6 gives concluding remarks.

II. RELATED WORK

One of the most popular cluster based routing protocol is Low Energy Adaptive Clustering Hierarchy protocol (LEACH) that is proposed in [4]. The operation of LEACH is divided into rounds and each round consists of setup phase and the steady state phase. In the setup phase, the clusters are organized and Cluster Heads (CHs) are selected. Each sensor n generates a random number between 0 and 1. If this number is less than T(n) defined by equation (1), then sensor n would be selected as a cluster head.

$$T(n)=\begin{cases}\dfrac{p}{1-p\times(r \bmod \frac{1}{p})} & if \;\; n\in G\\ 0 & if \;\; n\notin G\end{cases} \tag{1}$$

In this equation, p is the desired percentage of CHs, r specifies the current round and G is the set of nodes which have not been selected as cluster head in the past 1/P rounds. Optimal number of cluster heads is estimated to be 5% of the total number of nodes. After cluster head election, the CHs broadcast an advertisement message and other nodes select the closest CHs based on the received signal strength. Although LEACH [4] is able to increase the network lifetime, but it has two main weaknesses:

1) It is possible no or lots of CHs are selected.

2) It is possible that too many CHs are located in a specific area it means that CHs are not selected in a distributed manner.

In [6], Gupta used fuzzy logic to find cluster heads. In this algorithm three fuzzy variables is used for cluster head

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selection. Node's energy, node's concentration and node's centrality are these parameters. In this approach, the base station primarily collects the necessary information from all nodes and then selects a node as a cluster head according to the fuzzy rules. In this approach there is only one selected CH for each round, whereas more CHs are needed for balancing energy consumption and improving network lifetime.

In [7], Kim offers CHEF in which, the same as [6], the CHs are selected based on a fuzzy logic. The difference is that in this approach more than one cluster head is selected locally in each round. The fuzzy set includes nodes' energy and their local distances. CHEF [7] also generates a random number for each sensor and if it is less than a predefined threshold, P_{opt}, then the node's chance is determined. Thus, there may be some qualified nodes that lose their chance on a random manner.

In this paper, we used two-level fuzzy logic to determine CHs in each round for prolonging network lifetime to an acceptable limit.

III. SYSTEM MODEL

We make some assumptions about the sensor nodes and the underlying network model.

- There is a BS (i.e., data sink) located far away from the square sensing field.
- Sensors and the BS are all stationary after deployment.
- All nodes are homogeneous (i.e. the same energy resources).
- Cluster head selection is performed centrally at the base station.

IV. PROPOSED ALGORITHM

Initially the base station collects the necessary information from the nodes and cluster heads are selected in a centralized manner in each round that is discussed in the following. We assume number of cluster heads is equal to five percent (5%) of all sensors in each round.

Two levels of fuzzy decision making are considered in this approach. The reason is that the selected cluster heads must satisfy two general conditions:

1) CHs must be in the desired position with regard to the energy concerns. That provides the LOCAL Level of decision making.

2) Cluster head nodes cooperation while prolonging network lifetime. That provides the GLOBAL Level of decision making.

B. Local Level

In this level of decision making, the node's qualification for being a cluster head is evaluated according to its physical characteristics such as its internal energy and its neighbor nodes. We know that the traffic load is concentrated at most on CHs. Since on one hand, they must gather the data coming from the cluster member nodes, and on the other hand, they must forward the aggregated data to the sink. Therefore, CHs, must be powerful enough to be able for this job. In addition, more nodes in the neighborhood make the candidate CH more qualified. Hence, in the local level, these two parameters, i.e. energy and number of neighbors are defined as the inputs to the fuzzy system and sensor qualification parameter for becoming a CH is the output. The membership functions of these parameters are depicted in Figures 1 to 3. The fuzzy if-then rules in the local level are also shown in Table 1.

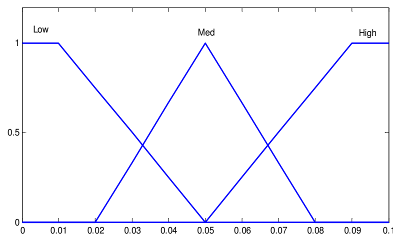


Figure 1. Membership functions of Energy

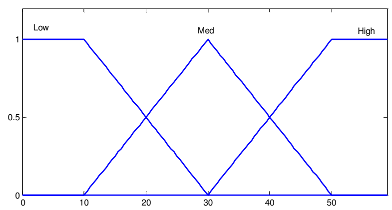


Figure 2. Membership functions of Number of Neighbors

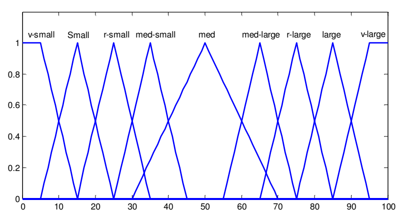


Figure 3. Membership functions of Qualification in Local Level

TABLE I. FUZZY IF-THEN RULES IN LOCAL LEVEL

Energy	Number of Neighbors	Qualification in Local Level
low	low	very small
low	medium	small
low	high	rather small
medium	low	medium small
medium	medium	medium
medium	high	medium large
high	low	rather large
high	medium	large
high	high	very large

C. Global Level

In the global level we seek for the best node cooperation regarding to the average energy consumption metric. At this level, we meet the following conditions:

1) CHs must locate at the center of their respective clusters. That is the centrality metric and makes the clusters more load balanced when adjacent nodes send their data to the CHs.

2) More network lifetime is achieved when the overall CHs' energy consumption is less. This parameter is directly related to the CH's proximity to BS.

3) To balance the energy consumption, there must be a suitable distribution of CHs in the network. In other words, there must be sufficient distance among CHs.

Thus, after evaluating the qualifications of CHs in the local level, those sensors whose qualifications are more than α, will be reevaluated in the global level based on three mentioned parameters: centrality, proximity to BS and distance between CHs. A threshold α is defined as the minimum qualification requirement to become a cluster head that we assumed α =0.5(max qualification of sensors in current round).

In other word, in this level, the comparison is made among different sets of sensor nodes to select a set with maximum qualification as final CHs in the current round. The centrality parameter is measured by total distances from cluster members to the cluster heads. Proximity to BS parameter is also measured by total distance from cluster heads to the BS. In addition, the BS is capable of measuring the distances among all CHs. In the global level these three parameters are considered as the inputs to the fuzzy system and sensors' qualification parameter for becoming a CH are considered as the output. The membership functions and the fuzzy rules of these parameters are depicted in Figures 4 to 7 and Table 2 respectively.

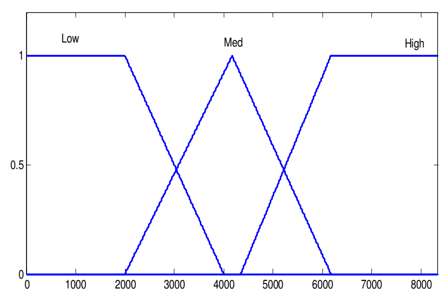


Figure 4. Membership functions of Centrality

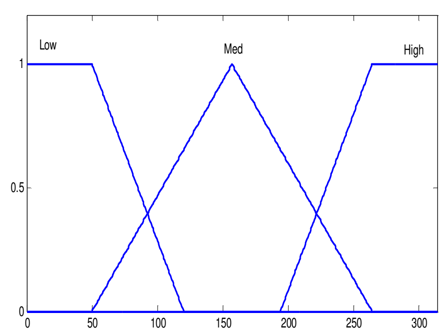


Figure 5. Membership functions of Proximity to Base station

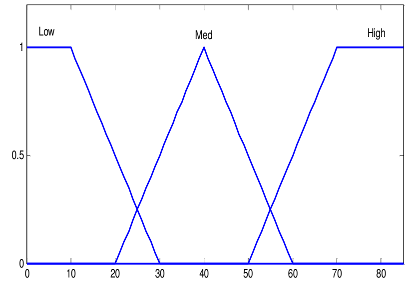


Figure 6. Membership functions of Distance Between CHs

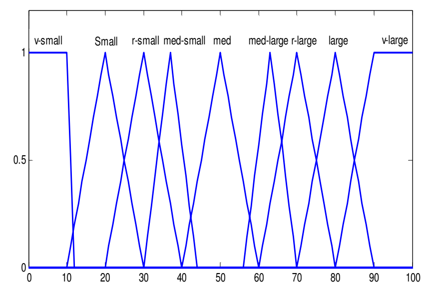


Figure 7. Membership functions of Qualification in Global Level

TABLE II. FUZZY IF-THEN RULES IN GLOBAL LEVEL

Centrality	**Proximity to BS**	**Distance between CHs**	**Qualification in Global Level**
Low	low	low	large
Low	low	medium	very large
Low	low	high	very large
Low	medium	low	rather large
Low	medium	medium	large
Low	medium	high	large
Low	high	low	medium large
Low	high	medium	rather large
Low	high	high	rather large
Medium	low	low	medium
Medium	low	medium	medium large
Medium	low	high	medium large
Medium	medium	low	medium small
Medium	medium	medium	medium
Medium	medium	high	medium
Medium	high	low	rather small
Medium	high	medium	medium small
Medium	high	high	medium small
High	low	low	small
High	low	medium	rather small
High	low	high	rather small
High	medium	low	very small
High	medium	medium	small
High	medium	high	small
High	high	low	very small

High	high	medium	very small
High	high	high	small

We used Mamdani method for fuzzy inference technique and center averaging for defuzzification. The maximum range of membership functions are determined by maximum values of input parameters. These values can be derived as bellow:

$$Max\, number\, of\,\, neighbors = n - 1 \quad (2)$$

$$Max\,\, centrality\,\, = (n-1)\sqrt{x_m^2 + y_m^2} \quad (3)$$

$$Max\,\, proximity\,\, to\,\, BS\,\, = (0.05 \times n)\sqrt{x_{BS}^{\;2} + y_{BS}^{\;2}} \quad (4)$$

$$Max\,\, dis\tan ce\,\, between\, CHs\,\, = (0.05 \times n - 1)\sqrt{x_m^{\;2} + y_m^{\;2}} \quad (5)$$

Where n is the number of sensors, (x_m, y_m) is size of network and (x_{BS}, y_{BS}) is the position of BS.

The most qualified nodes are selected as CHs for the current round. Once they advertise themselves across the network, other nodes will choose the closest one and clusters are formed similar to [4].

V. Simulation and Evaluation

In this section, we evaluate the performance of our proposed algorithm in MATLAB. In four different scenarios, 30 and 60 nodes are randomly distributed in a 60×60 and 120×120 m^2 network. The initial energy of the sensors is 0.1J. Simulation was performed for 200 rounds. We use a simplified model proposed in [8] for the radio hardware energy dissipation. We compare our proposed algorithm to LEACH [4], Gupta [6] and CHEF [7] in Lifetime, Network's residual energy, variance of energy and CH's distribution.

A. *Network's lifetime*

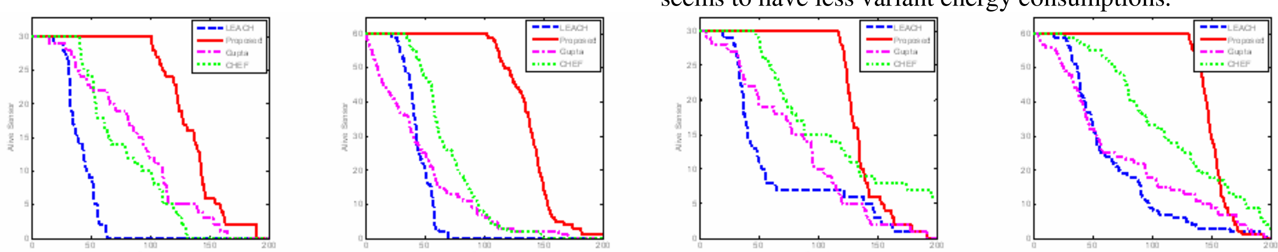
Although various definitions has been proposed in the literature, in this paper lifetime is considered as the time when the first node dies. Figure 8 shows the number of alive nodes with respect to the operation of the network in 200 rounds for different scenarios. It is easy to find out that the proposed algorithm prolongs the death time of the first and last sensors compared with other algorithms. Our proposed algorithm improves the overall network lifetime about 54 %.

B. *Residual energy of network*

Residual energy of network in each round can be a good metric to measure the energy efficiency of the algorithms. The less steep the figure is the more clearness of balance energy utilization and fairer distribution of energy on the nodes would be. Figure 9 shows the comparison of energy consumption rate of the four algorithms. In the proposed algorithm the residual energy of network is much more than others.

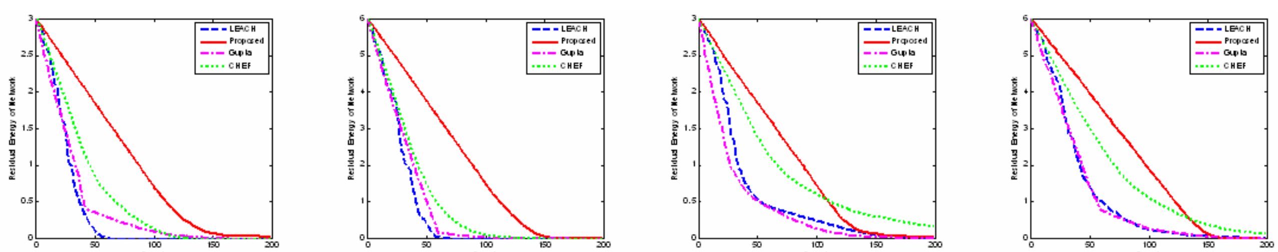
C. *Variance of energy in each round*

The fairness of energy consumption can be well observed by measuring the variance of the residual energy of all nodes in each round. The less variant residual energy in each consequent round is the reason of the fairer energy consumption. Contrary, more variance in energy consumption shows that the network's load is on some sets of nodes. Once again, the more straight line demonstrates the less variant energy consumption, which is due to the better energy balancing. Figure 10 shows the variance of energy in different scenarios. In this case, our proposed algorithm seems to have less variant energy consumptions.



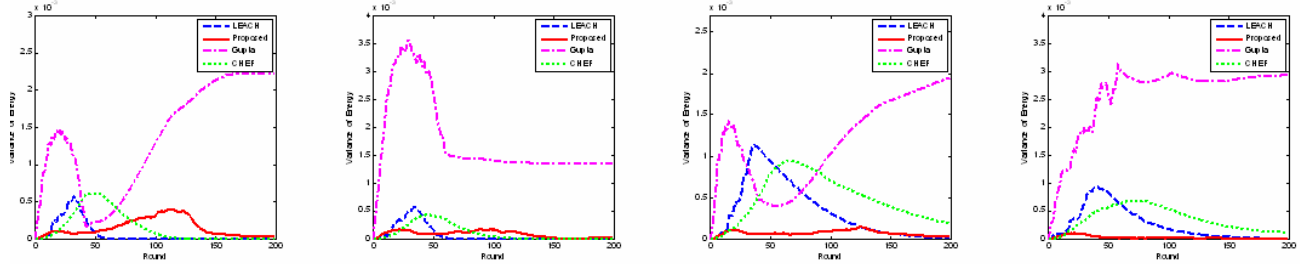
(a) Number of Sensors= 30 Network size= 60×60
(b) Number of Sensors= 60 Network size= 60×60
(c) Number of Sensors= 30 Network size= 120×120
(d) Number of Sensors= 60 Network size= 120×120

Figure 8. Network life time



(a) Number of Sensors= 30 Network size= 60×60
(b) Number of Sensors= 60 Network size= 60×60
(c) Number of Sensors= 30 Network size= 120×120
(d) Number of Sensors= 60 Network size= 120×120

Figure 9. Residual energy of network



(a) Number of sensors= 30
Network size= 60×60

(b) Number of sensors= 60
Network size= 60×60

(c) Number of Sensors= 30
Network size= 120×120

(d) Number of Sensors= 60
Network size= 120×120

Figure 10. Variance of energy

D. Distance among CHs

One of the important parameters in clustering is the distance among CHs, which is directly related to the distribution of CHs. Suitable distribution of CHs results in more balanced the load to be on the nodes. In this paper, we achieved a well distribution of CHs by counting this parameter in the global level of our fuzzy system. From Figure 11, it can be observed that the distances among CHs are more than other algorithms that implies better distribution of CHs in the network.

E. Scalability

The scalability of the proposed scheme was also tested by considering four different scenarios. The proposed scheme proved to have considerable efficiency in different scenarios.

VI. CONCLUSION

An efficient routing technique is known as hierarchical routing based on clustering that prolongs the network lifetime.

In this paper, the most qualified cluster heads were selected via a two-level fuzzy logic. In the local level the qualified nodes were selected based on their energy and number of neighbors. Then, in the global level, nodes' overall cooperation is considered according to centrality, proximity to BS and distance between CHs in the whole network. The proposed algorithm was compared with three similar approaches LEACH [4], Gupta [6] and CHEF [7] in lifetime, energy consumption, distance between CHs, variance of energy and scalability. The performance of the algorithm was evaluated by a simulation and the results showed that in this approach, nodes consume less energy and live longer. Moreover, a fair load distribution and hence fewer variance of energy consumption demonstrate the efficiency of the proposed algorithm.

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