Cluster-head Election using Fuzzy Logic for Wireless Sensor Networks

Indranil Gupta
Faculty of Computer Science
Dalhousie University
Canada, B3H 1W5
igupta@cs.dal.ca

Denis Riordan
Faculty of Computer Science
Dalhousie University
Canada, B3H 1W5
riordan@cs.dal.ca

Srinivas Sampalli
Faculty of Computer Science
Dalhousie University
Canada, B3H 1W5
srini@cs.dal.ca

Abstract

Wireless Sensor Networks (WSNs) present a new generation of real-time embedded systems with limited computation, energy and memory resources that are being used in a wide variety of applications where traditional networking infrastructure is practically infeasible. Appropriate cluster-head node election can drastically reduce the energy consumption and enhance the lifetime of the network. In this paper, a fuzzy logic approach to cluster-head election is proposed based on three descriptors - energy, concentration and centrality. Simulation shows that depending upon network configuration, a substantial increase in network lifetime can be accomplished as compared to probabilistically selecting the nodes as cluster-heads using only local information.

Index terms— Wireless Sensor Networks, Cluster-head, Fuzzy Logic.

1. Introduction

With the recent advances in Micro Electro-Mechanical Systems (MEMS) technology, low power digital circuitry and RF designs, WSNs are considered to be one of the potential emerging computing technologies, edging closer towards widespread feasibility [5]. Several useful and varied applications of WSNs include applications requiring information gathering in harsh, inhospitable environments, weather and climate monitoring, detection of chemical or biological agent threats, and healthcare monitoring. These applications demand the usage of various equipment including cameras, acoustic tools and sensors measuring different physical parameters [7].

WSNs consist of many inexpensive, portable wireless nodes, with limited power, memory and computational capabilities. The energy supply of the sensor nodes is one of the main constraints in the design of this type of network [6]. Since it is infeasible to replace batteries once WSNs are deployed, an important design issue in WSNs is to lessen the energy consumption with the use of energy conserving hardware, operating systems and communication protocols.

The energy consumption can be reduced by allowing only some nodes to communicate with the base station. These nodes called cluster-heads collect the data sent by each node in that cluster compressing it and then transmitting the aggregated data to the base station [1]. Appropriate cluster-head selection can significantly reduce energy consumption and enhance the lifetime of the WSN. In this paper, a fuzzy logic approach to cluster-head election is proposed based on three descriptors - energy, concentration and centrality. Simulation shows that depending upon network configuration a substantial increase in network lifetime can be accomplished as compared to probabilistically selecting the nodes as cluster-heads using only local information. For a cluster, the node elected by the base station is the node having the maximum chance to become the cluster-head using three fuzzy descriptors - node concentration, energy level in each node and node centrality with respect to the entire cluster, minimizing energy consumption for all nodes consequently increasing the lifetime of the network.

There are diverse applications of intelligent techniques in wireless networks [4]. Fuzzy logic control is capable of making real time decisions, even with incomplete information. Conventional control systems rely on an accurate representation of the environment, which generally does not exist in reality. Fuzzy logic systems, which can manipulate the linguistic rules in a natural way, are hence suitable in this respect. Moreover it can be used for context by blending different parameters - rules combined together to produce the suitable result.

We compare our approach to a previously proposed popular cluster-head selection technique called LEACH (Low Energy Adaptive Clustering Hierarchy) [1]. LEACH is based on a stochastic model and uses localized clustering. The nodes select themselves as cluster-heads without the base station processing. Other nodes in the vicinity join the closest cluster-heads and transmit data to them. Simulation results show that our approach increases the network lifetime considerably as compared to LEACH.

In the next section, we give an overview of related work and some shortcomings of stochastically selecting cluster-heads. In section 3 we describe our system model. Simulation results with the rule based fuzzy logic system and a comparison with LEACH is presented in section 4. Finally, section 5 concludes the paper.

2. Related Work

A typical WSN architecture is shown in Figure 1. The nodes send data to the respective cluster-heads, which in turn compresses the aggregated data and transmits it to the base station.

For a WSN we make the following assumptions:

- The base station is located far from the sensor nodes and is immobile.
- All nodes in the network are homogeneous and energy constrained.
- Symmetric propagation channel.
- Base station performs the cluster-head election.
- Nodes have location information that they send to the base station with respective energy levels during set up phase.
- Nodes have little or no mobility.

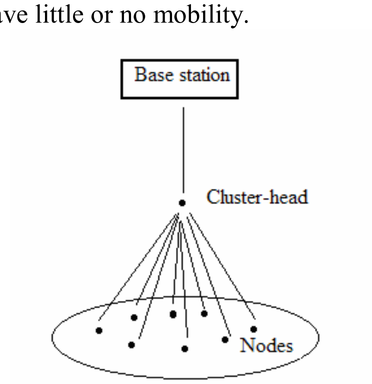


Figure 1. WSN architecture

Many proposals have been made to select cluster-heads. In the case of LEACH [1], to become a cluster-head, each node n chooses a random number between 0 and 1. If the number is less than the threshold T(n), the node becomes the cluster-head for the current round. The Threshold is set at:

$$T(n) = \frac{P}{1 - P \times \left(r \bmod \frac{1}{P} \right)} \quad \text{if } n \in G$$

$$T(n) = 0 \quad \text{otherwise} \tag{1}$$

where, P is the cluster-head probability, r the number of the current round and G the set of nodes that have not been cluster-heads in the last 1/P rounds.

Several disadvantages are there for selecting the cluster-head using only the local information in the nodes. Firstly, since each node probabilistically decides whether or not to become the cluster-head, there might be cases when two cluster-heads are selected in close vicinity of each other increasing the overall energy depleted in the network. Secondly, the number of cluster-head nodes generated is not fixed so in some rounds it may be more or less than the preferred value. Thirdly, the node selected can be located near the edges of the network; wherein the other nodes will expend more energy to transmit data to that cluster-head. Fourthly, each node has to calculate the threshold and generate the random numbers in each round, consuming CPU cycles.

LEACH-C [2] uses a centralized algorithm and provides another approach to form clusters as well as selecting the cluster-heads using the simulated annealing technique.

In [3] each node calculates its distance to the area centroid which will recommend nodes close to the area centroid and not the nodes that is central to a particular cluster, cluster centroid. Thus it leads to overall high energy consumption in the network for other nodes to transmit data through the selected node.

3. System Model

In this paper the cluster-heads are elected by the base station in each round by calculating the chance each node has to become the cluster-head by considering three fuzzy descriptors - node concentration, energy level in each node and its centrality with respect to the entire cluster.

In our opinion a central control algorithm in the base station will produce better cluster-heads since the base station has the global knowledge about the network. Moreover, base stations are many times more powerful than the sensor nodes, having sufficient memory, power and storage. In this approach energy is spent to transmit the location information of all the nodes to the base station (possibly using a GPS receiver). Considering WSNs are meant to be deployed over a geographical area with the main purpose of sensing and gathering information, we assume that nodes have minimal mobility, thus sending the location information during the initial setup phase is sufficient.

The cluster-head collects n number of k bit messages from n nodes that joins it and compresses it to cn k bit messages with c $\leq$ 1 as the compression coefficient. The operation of this fuzzy cluster-head election scheme is divided into two rounds each consisting of a setup and steady state phase similar to LEACH. During the setup phase the cluster-heads are determined by using fuzzy knowledge processing and then the cluster is organized. In the steady state phase the cluster-heads collect the aggregated data and performs signal processing functions to compress the data into a single signal. This composite signal is then sent to the base station.

The radio model we have used is similar to [1] with E_{elec} = 50 nJ/bit as the energy dissipated by the radio to run the transmitter or receiver circuitry and ε_{amp} = 100 pJ/bit/m2 as the energy dissipation of the transmission amplifier.

The energy expended during transmission and reception for a k bit message to a distance d between transmitter and receiver node is given by:

$$E_{Tx}(k, d) = E_{elec} * k + \varepsilon_{amp} * k * d^{\lambda} \quad (2)$$

$$E_{Rx}(k) = E_{elec} * k \quad (3)$$

where, λ is the path loss exponent and $\lambda \geq 2$.

3.1. Fuzzy Logic Control

The model of fuzzy logic control consists of a fuzzifier, fuzzy rules, fuzzy inference engine, and a defuzzifier. We have used the most commonly used fuzzy inference technique called Mamdani Method [8] due to its simplicity. The process is performed in four steps:

- Fuzzification of the input variables energy, concentration and centrality - taking the crisp inputs from each of these and determining the degree to which these inputs belong to each of the appropriate fuzzy sets.
- Rule evaluation - taking the fuzzified inputs, and applying them to the antecedents of the fuzzy rules. It is then applied to the consequent membership function (Table 1).
- Aggregation of the rule outputs - the process of unification of the outputs of all rules.
- Defuzzification - the input for the defuzzification process is the aggregate output fuzzy set *chance* and the output is a single crisp number.

During defuzzification, it finds the point where a vertical line would slice the aggregate set *chance* into two equal masses. In practice, the COG (Center of Gravity) is calculated and estimated over a sample of points on the aggregate output membership function, using the following formula:

$$COG = \left(\sum \mu_A(x) * x\right) / \sum \mu_A(x) \quad (4)$$

where, $\mu_A(x)$ is the membership function of set A.

3.2. Expert Knowledge Representation

Expert knowledge is represented based on the following three descriptors:

- Node Energy - energy level available in each node, designated by the fuzzy variable *energy*,
- Node Concentration - number of nodes present in the vicinity, designated by the fuzzy variable *concentration,*
- Node Centrality - a value which classifies the nodes based on how central the node is to the cluster, designated by the fuzzy variable *centrality*.

To find the node centrality, the base station selects each node and calculates the sum of the squared distances of other nodes from the selected node. Since transmission energy is proportional to d^2 (2), the lower the value of the centrality, the lower the amount of energy required by the other nodes to transmit the data through that node as cluster-head.

The linguistic variables used to represent the node energy and node concentration, are divided into three levels: *low*, *medium* and *high,* respectively, and there are three levels to represent the node centrality: *close*, *adequate* and *far,* respectively. The outcome to represent the node cluster-head election chance was divided into seven levels: *very small*, *small*, *rather small*, *medium*, *rather large*, *large*, and *very large*. The fuzzy rule base currently includes rules like the following: if the *energy* is *high* and the *concentration* is *high* and the *centrality* is *close* then the node's cluster-head election *chance* is *very large*.

Thus we used 3^3 = 27 rules for the fuzzy rule base. We used triangle membership functions to represent the fuzzy sets *medium* and *adequate* and trapezoid membership functions to represent *low*, *high*, *close* and *far* fuzzy sets. The membership functions developed and their corresponding linguistic states are represented in Table 1 and Figures 2 through 5.

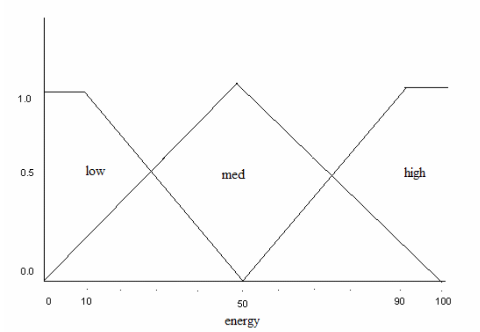


Figure 2. Fuzzy set for fuzzy variable *energy*

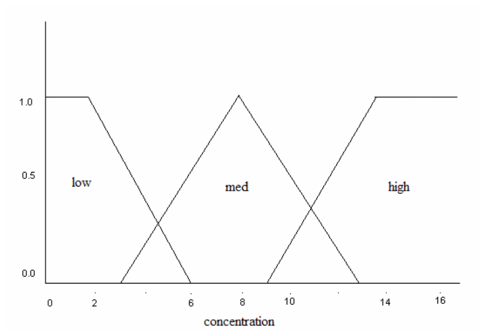


Figure 3. Fuzzy set for fuzzy variable *concentration*

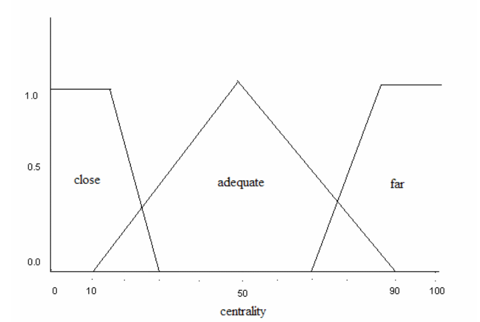


Figure 4. Fuzzy set for fuzzy variable *centrality*

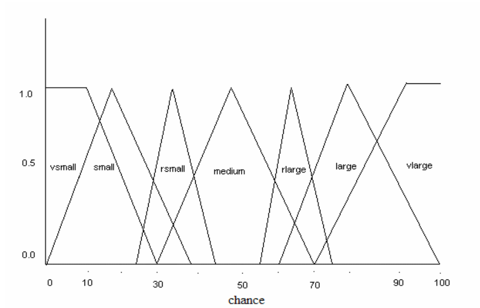


Figure 5. Fuzzy set for fuzzy variable *chance*

Table 1. Fuzzy rule base

	energy	concentration	centrality	chance
1	low	low	close	small
2	low	low	adeq	small
3	low	low	far	vsmall
4	low	med	close	small
5	low	med	adeq	small
6	low	med	far	small
7	low	high	close	rsmall
8	low	high	adeq	small
9	low	high	far	vsmall
10	med	low	close	rlarge
11	med	low	adeq	med
12	med	low	far	small
13	med	med	close	large
14	med	med	adeq	med
15	med	med	far	rsmall
16	med	high	close	large
17	med	high	adeq	rlarge
18	med	high	far	rsmall
19	high	low	close	rlarge
20	high	low	adeq	med
21	high	low	far	rsmall
22	high	med	close	large
23	high	med	adeq	rlarge
24	high	med	far	med
25	high	high	close	vlarge
26	high	high	adeq	rlarge
27	high	high	far	med

Legend: *adeq=adequate, med=medium, vsmall=very small, rsmall=rather small, vlarge=very large, rlarge=rather large.*

All the nodes are compared on the basis of chances and the node with the maximum chance is then elected as the cluster-head. Each node in the cluster associates itself to the cluster-head and starts transmitting data. The data transmission phase is similar to the LEACH steady-state phase.

4. Results

To test and analyze the algorithm, experimental studies were performed. The simulator was programmed using Java Foundation Classes and the NRC fuzzy Java Expert System Shell (JESS) toolkit. We modeled the energy consumption in WSN as given in (2, 3). To define the lifetime of the sensor network we used the metric First Node Dies (FND) [9], meant to provide an estimate for the quality of the network.

4.1. Sample network 1

The reference network consists of 150 nodes randomly distributed over an area of 100X100 meters. The base station is located at 200, 50. In the first phase of the simulation each node has a random energy between 0 and 100. The base station computes the concentration for each node by calculating the number of other nodes within the area of 20X20 meters, with that node in the center. The values are then fuzzified and passed to the fuzzy rule base for rule evaluation. After this, defuzzification gives the cluster-head election chance. Figure 6b shows the defuzzified output and the aggregate set *chance* for a specific node.

The best nodes in terms of fuzzy overall, centrality and energy are shown in Figures 6a and 6c. Illustrating the results we can see that the best energy node has a very high centrality of 41 implying the overall energy spent by other nodes to transmit through node 62 will be high and hence a low cluster-head election chance. Similarly, although the central node has a very low centrality value but it also has a very low energy which does not make it suitable for being elected. The best node 108 on the other hand has all the three descriptors suitable for being elected as the cluster-head with a maximum chance of 75 for the current scenario.

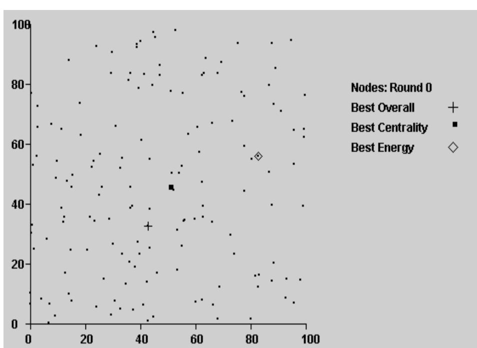


Figure 6a. Network cluster showing the best nodes

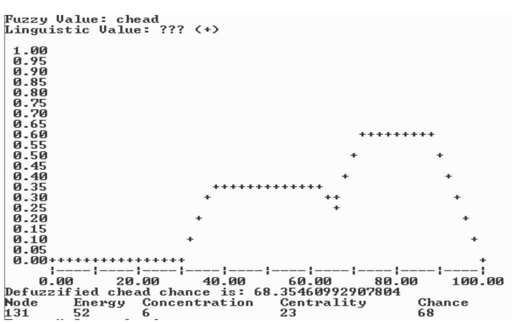
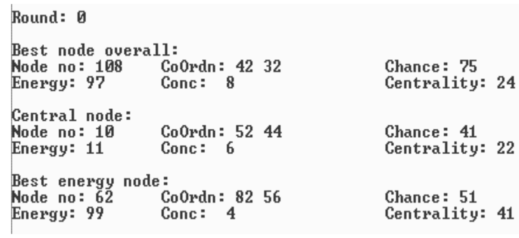


Figure 6b. Output fuzzy set for fuzzy variable *chance*



Round: 0

Best node overall:
Node no: 108 CoOrdn: 42 32 Chance: 75
Energy: 97 Conc: 8 Centrality: 24

Central node:
Node no: 10 CoOrdn: 52 44 Chance: 41
Energy: 11 Conc: 6 Centrality: 22

Best energy node:
Node no: 62 CoOrdn: 82 56 Chance: 51
Energy: 99 Conc: 4 Centrality: 41

Figure 6c. Different node parameters

4.2. Sample network 2

In this case each node is supplied with an energy of 1J at the beginning of the simulation. The *energy* fuzzy set is scaled accordingly, other parameters remaining unaltered. Each node transmits a 200 bit message, per round, to the elected cluster-head. The path loss exponent λ is set at 2 for intra-cluster communication and 2.5 for base station transmission. Cluster-head compresses the collected data to 5% of its original size. Figure 7a shows a snapshot of the simulation run for round number 44 with fuzzy elected cluster-head nodes. Figure 7b shows parameters for elected cluster-heads during two consecutive rounds 43 and 44. It takes about 2500 rounds for the FND in the network.

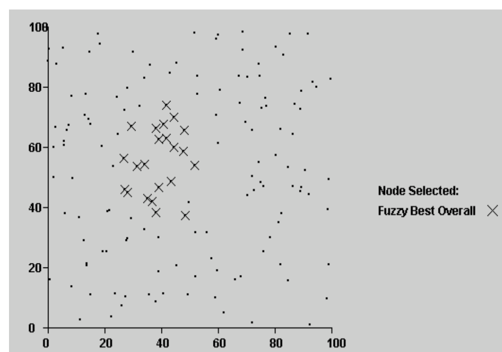
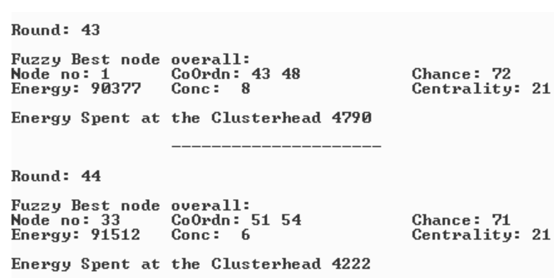


Figure 7a. Simulation in progress



Round: 43

Fuzzy Best node overall:
Node no: 1 CoOrdn: 43 48 Chance: 72
Energy: 90377 Conc: 8 Centrality: 21

Energy Spent at the Clusterhead 4790

Round: 44

Fuzzy Best node overall:
Node no: 33 CoOrdn: 51 54 Chance: 71
Energy: 91512 Conc: 6 Centrality: 21

Energy Spent at the Clusterhead 4222

Figure 7b. Elected Cluster-heads for two consecutive rounds

4.3. Sample network 3

We compare the LEACH algorithm with our design in the final simulation. Although LEACH does local information processing to select the cluster-head nodes, it offers a comparison platform to check for improvements. To compare with LEACH, we select the reference network consisting of 20 randomly generated nodes over an area of 100X100 meters with the cluster-head probability of 0.05. Therefore about 1 node per round becomes cluster-head, making it suitable for us to compare easily. The *concentration* fuzzy set is scaled accordingly, with the other parameters remaining the same as sample network 2. Both algorithms optimize the intra-cluster energy consumption and thus do not influence the energy required to transmit to the base station. Table 2 shows four simulation runs to calculate the number of rounds taken by LEACH and the fuzzy cluster-head election algorithm for FND.

Table 2. Summary table

	Run 1	Run 2	Run 3	Run 4
LEACH	1597	1577	1627	1558
Our Approach	2716	3118	3094	2976

5. Conclusion

This paper has discussed a novel approach for cluster-head election for WSNs. Cluster-heads were elected by the base station in each round by calculating the chance each node has to become the cluster-head using three fuzzy descriptors. Our approach is more suitable for electing cluster-heads for medium sized clusters. With this system model a substantial increase in the network lifetime is accomplished as compared to LEACH. By modifying the shape of each fuzzy set accurately, a further improvement in the network lifetime and energy consumption can be achieved.

Since centrality, calculated on the basis of the sum of the squared distances of other nodes from the given node, is one of the descriptors for electing suitable cluster-head, a network with biased distribution of nodes can be tested in the future with further experiments.

References

[1] W. Heinzelman, A. Chandrakasan and H. Balakrishnan, "Energy-efficient communication protocol for wireless microsensor networks," in *Proc. of the 33rd Annual Hawaii International Conference on System Sciences (HICSS)*, Maui, HI, Jan. 2000, pp. 3005 – 3014.

[2] W. Heinzelman, A. Chandrakasan and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks," in *IEEE Transactions on Wireless Communications*, Oct. 2002, pp. 660 - 670.

[3] Q. Liang, "Clusterhead election for mobile ad hoc wireless network," in *Proc. 14th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, (PIMRC)*, Sept. 2003, pp. 1623 - 1628.

[4] S. Hammadi and C. Tahon, "Special issue on intelligent techniques in flexible manufacturing systems," in *IEEE Transactions on Systems, Man and Cybernetics*, May 2003, pp. 157 - 158.

[5] B. Warneke, M. Last, B. Liebowitz and K.S.J. Pister, "Smart Dust: communicating with a cubic-millimeter computer," *IEEE Computer*, Jan. 2001, pp. 44 - 51.

[6] E. Cayirci, "Data aggregation and dilution by modulus addressing in wireless sensor networks," *IEEE Communications Letters*, Aug. 2003, pp. 355 – 357.

[7] C. Chee-Yee and S.P. Kumar, "Sensor networks: evolution, opportunities, and challenges," in *Proc of the IEEE,* Aug. 2003, pp.1247 - 1256.

[8] M. Negnevitsky, *Artificial intelligence: A guide to intelligent systems*, Addison-Wesley, Reading, MA, 2001.

[9] M.J. Handy, M. Haase and D. Timmermann, "Low energy adaptive clustering hierarchy with deterministic cluster-head selection," in *Proc. 4th International Workshop on Mobile and Wireless Communications Network*, Sept. 2002, pp. 368 - 372.