CLUSTER-HEAD ELECTION USING FUZZY LOGIC FOR WIRELESS SENSOR NETWORKS

by

Indranil Gupta

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Dalhousie University

Faculty of Computer Science

The undersigned hereby certify that they have read and recommend to the Faculty of Computer Science for acceptance a thesis entitled “Cluster-Head Election Using Fuzzy Logic for Wireless Sensor Networks” by Indranil Gupta in partial fulfillment of the requirements for the degree of Master of Computer Science.

Dated: March 30, 2005

Supervisor: _________________________________

Dr. Srinivas Sampalli

Co-supervisor: _________________________________

Dr. Denis Riordan

Reader: _________________________________

Dr. Larry Hughes
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I dedicate this thesis to the memory of my uncle, late mathematician Dr. Radha G. Laha, who has been my source of inspiration in every detail of life.
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<td>Carrier Sense Multiple Access</td>
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<td>First Node Dies</td>
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<td>Minimum Transmission Energy</td>
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<td>NRC</td>
<td>National Research Council</td>
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<td>TDMA</td>
<td>Time Division Multiple Access</td>
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Abstract

Wireless Sensor Networks (WSNs) present a new generation of real-time embedded systems for a wide variety of applications. However WSNs have limited computation, energy, and memory resources. One of the approaches to minimize the energy consumption is to allow only some nodes in a cluster of sensor nodes, called cluster-heads, to communicate with the base station. Appropriate cluster-head election can drastically reduce the energy consumption and enhance the lifetime of the network.

In this thesis, a fuzzy logic approach to cluster-head election is proposed based on three descriptors - energy, concentration and centrality. After modeling the energy consumption for the WSN, we applied the algorithm to check for the quality of the network by measuring the time it takes for the first node to die in the cluster. We compare our algorithm with Low Energy Adaptive Clustering Hierarchy (LEACH), a previously proposed technique, by adjusting the cluster-head selection probabilities.
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Chapter 1

Introduction

1.1 Wireless Sensor Networks

With the recent advances in Micro Electro-Mechanical Systems (MEMS) technology, low power digital circuitry and RF designs, Wireless Sensor Networks (WSNs) are considered to be one of the potential emerging computing technologies, edging closer towards widespread feasibility [5]. Cheap and smart sensors networked through wireless communication with the Internet hold remarkable prospects for controlling and monitoring environment, homes, health care, military, and other strategic applications.

Several useful and varied applications of WSNs such as weather and climate monitoring, detection of chemical or biological agent threats, and healthcare monitoring require information gathering in harsh and inhospitable environments. These applications demand the use of various equipment including cameras, acoustic, infrared and seismic tools and sensors measuring different physical parameters [7]. A network of smart sensors can be deployed in a host of different environments, for example in military scenarios, to detect various threats. Thus these networks can gather intelligence in battlefields, track enemy lines, monitor potentially harmful chemical and nuclear materials using neutron based detectors, and detect viruses, toxins using bio-sensor chips coated with antibodies to attract specific biological agents [10] [14].

Figure 1.1 shows a typical cluster-based WSN architecture. The nodes sense the information and transmit it to the base station through an intermediate node called the cluster-head. The cluster-head aggregates the data, compresses it and then sends it to the
base station. The base station serves as a gateway to send the data to another network. The database connected to the base station provides the means to update and retrieve the data on demand.

![WSN Architecture Diagram](image)

**Figure 1.1: WSN architecture**

### 1.2 Design Issues

In general, wireless ad-hoc networks most closely resemble the sensor network abstraction [7]. Although wireless ad-hoc networks are similar to WSNs, wireless sensor networks have several additional design issues and constraints:

Firstly, sensor networks can contain thousand of nodes and thus scalability is one of the major issues for this type of network.
Secondly, sensor nodes in a WSN are severely constrained by power, memory and computational capabilities which although serves as a factor in Wireless Ad-hoc Networks, is not that severe. Power efficiency is a critical constraint for WSNs. Once deployed, sensor nodes with finite power sources and limited recharging capabilities should be able to sustain the operation for months at a stretch [24].

Thirdly, in the WSN only relevant data should be sent after compressing it as much as possible. This decision of condensing the data and sending it to the base station should be made at node levels, i.e., in the sensor nodes and cluster-heads. The said issue is not that critical for Ad-hoc networks [13].

Fourthly, in case of Ad-hoc networks, routing in general takes place between any pair of nodes whereas WSNs are meant for the purpose of sensing and gathering information and thus routing follows some distinct patterns [13] [18].

These patterns can be classified into -

- Many to one: Sensor nodes in each cluster send the sensed data to the cluster-heads, which in turn aggregates the data and transmits it to the base station.

- One to many: Base station or cluster-head multicasts (or broadcasts) different control and association signals to the sensor nodes.

- Local communication: In some topologies, this form of communication is desired for nodes to discover and co-ordinate with each other. Protocols like GAF (Geographical Adaptive Fidelity) [12] use this type of approach.
1.3 Sensors Types and Characteristics

There are different types of wireless smart sensors currently in use [10]. A more representative example is the sensor nodes of the smart dust project developed at UC Berkeley [5]. The sensor node is supported by Tiny OS, UC Berkeley's open source operating system for sensor networks. Each sensor node has limited resources, comprising of an 8 bit, 4 MHz CPU with 8K of Instruction flash memory, 512 bytes of RAM and 512 bytes of EEPROM with 10 Kbps communication and 433 MHz radio. Figure 1.2 shows a general hardware platform description [22].

![Diagram of sensor hardware platform]

Figure 1.2: Sensor hardware platform

Different characteristics of sensor nodes include size, battery consumption, power level, lifetime of operation, movement characteristics (indicating whether the nodes are stationary or mobile), position characteristics (indicating whether the nodes are embedded
into the system or independent of its surroundings), failure characteristics (indicating if
the sensor has failed, or is degrading slowly) [10].

1.4 WSN Topologies

As explained earlier, 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.

WSNs have one or more centralized control units called the base station. The base
station serves as a gateway for each sensor node to send data to another network
(Figure.1.1). Thus it can be an interface to interact with the network, to extract and
transfer information to the sensor nodes. Unlike sensor nodes, base stations are many
times more powerful and have an AC power supply, high communication bandwidth,
larger processing power and storage facilities [2].

The energy consumption in a WSN 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]. The model is suitable considering the amount of redundancy found in
WSNs; direct transmissions the base station will consume large amount of transmit power
from each node.

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.

For WSNs principal topologies includes tree-based and cluster-based networks.

1.4.1 Tree-based approach

In the tree-based approach, instead of sensor nodes sending the data to the cluster-heads directly, each node sends it to its parent. The base station selects some of the sensor nodes to be its children. The election criterion is based on factors like concentration of nodes in a given area and its closeness to immediate neighbors. Other nodes in the network associate with the child nodes, as selected by the base station, on the basis of the received signal strength.

Thus in this approach the number of long distance transmissions is reduced by having the nodes to send their data to their parent and in turn to the base station. This hierarchical approach with the base station as the root node (as shown in Figure 1.3) generates a spanning tree for the network. Only the immediate children of the base station are required to make the high energy transmission, after collecting and compressing the data received from its offspring.
1.4.2 Cluster-based approach

In the cluster-based approach, only some of the nodes in the network are allowed to transmit and receive information from the base station, which is located at a large distance from the sensor nodes [1]. The key issue here is that, this allows sensor nodes to sense and transmit the information to the cluster-heads directly, instead of routing it through its immediate neighbors. Also, since communication energy is proportional to the square of the distance (Eq. 3.1), having all nodes to transmit its sensed data individually
to the base station, exhausts the energy of each node drastically and hence the lifetime operation of the network gets significantly reduced. As a consequence it does not serve the purpose with which WSNs are designed for, namely network should be operational for a long period of time.

Figure 1.4 shows a typical cluster-based WSN. Cluster-heads collect the data sent by each node in that cluster, compressing it and then transmitting the aggregated data to the base station.
station for further processing. A review of the current cluster-head selection algorithms will be discussed in Chapter 2.

Comparative analyses of the performance of the two approaches have been made in [11]. A multi-hop tree based approach is considered inefficient for routing in WSN considering the global distribution of nodes as shown in [24].

1.5 Problem of cluster-head selection

Clustering helps the nodes to minimize the overall energy dissipation in the network by allowing only some nodes to take part in the transmission to the base station. Moreover it also helps to reuse the bandwidth and thus utilizes better resource allocation and improved power control. LEACH (Low Energy Adaptive Clustering Hierarchy) [1] is a popular current approach for cluster-head selection and has formed the basis for many other approaches [2] [9] [17]. Algorithms like LEACH use only the local information in the nodes to select cluster-heads stochastically. But this method of selecting cluster-heads using only local information has its own limitations. 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. Moreover, the node selected can be located near the edges of the network, in which the other nodes will expend more energy to transmit data to that cluster-head.

In fact considering only one factor, like energy, is not suitable to elect the cluster-head properly. This is because other conditions like centrality of the nodes with respect to the entire cluster, also gives a measure of the energy dissipation during transmission for all nodes. The more central the node is to a cluster, the more is the energy efficiency for
other nodes to transmit through that selected node. The concentration of the nodes in a
given region also affects in some way for proper cluster-head election. It is more
reasonable to select a cluster-head in a region, where the node concentration is high.

1.6 Motivation and Objective of thesis

The primary objective of this thesis is to present a fuzzy logic approach to cluster-head
election. This is being proposed based on three descriptors - energy, concentration and
centrality. Fuzzy logic systems can manipulate the linguistic rules in a natural way and
are capable of making real time decisions, even with incomplete information. 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 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.

We compare our approach with LEACH, which 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.
1.7 Outline

The rest of this thesis is organized as follows. In the next chapter, we give an overview of related work and some shortcomings of stochastically selecting cluster-heads. In Chapter 3 we describe our system model and a relevant application area for the algorithm in the field of biomedical sensors. Simulation results with the rule based fuzzy logic system and a comparison with LEACH are presented in Chapter 4. Finally, Chapter 5 concludes the thesis.
Chapter 2

Background and Related Work

In Chapter 1, it was mentioned that the energy supply to the WSNs are a major constraint to the design of this type of network. Selecting the appropriate cluster-head can significantly reduce the energy consumption of the sensor nodes and increase the network lifetime. This chapter provides a detailed background on the current work done in this topic. This chapter also surveys related literatures in this topic and studies different cluster-head selection algorithms that are effective on this type of network.

2.1 Clustering protocols

‘Power aware’ routing protocol [16] in wireless networks relies on utilizing routes that have high energy nodes in its path but are longer to reach the base station than the routes that have shorter paths and low energy nodes respectively. This is done to minimize the overall energy of the network.

Another early approach involves selecting the MTE (minimum transmission energy) routing [15], where the nodes are chosen for routing such that the total transmit energy is minimized. We assume $d^2$ power loss for the total transmitting energy of $E_{TX}(d)$ (Eq. 3.1). Thus for three nodes A, B and C, A transmits to node C through B if and only if

$$E_{TX}(d = d_{AB}) + E_{TX}(d = d_{BC}) < E_{TX}(d = d_{AC}) \tag{2.1}$$

or $d_{AB}^2 + d_{BC}^2 < d_{AC}^2$. 

The drawback of this approach is that, although the transmitting distance is being taken into consideration, the energy present at the nodes are not, it might not generate the lowest energy routes.

2.1.1 LEACH

LEACH is a popular and significant communication protocol that helps the nodes to minimize the overall energy dissipation in the network using clustering [1]. It is the first significant protocol for the minimization of the overall energy in this type of network. LEACH organizes nodes into clusters with one or multiple nodes from each cluster acting as a cluster-head.

The aim of the protocol is to randomize the cluster-head election in each round so that the energy among the sensor nodes becomes evenly distributed. In this approach, the base station is assumed to be fixed and all the nodes are assumed to be energy constrained in nature.

The motivation for this approach came from the MIT’s μ-AMPS project - the fact that communication energy between sensor nodes and base station is expensive and thus it is infeasible for the sensor nodes to sense and gather data and send them to the base stations individually in a single hop, which is a high power operation. Moreover, if cluster-head selection is static, the nodes selected as cluster-heads will quickly drain out its limited power and die quickly. Apart from selecting the cluster-head, priorities were given to data aggregation and data fusion methodologies. Data fusion combines different data measurements and then reduces the uncorrelated noise to provide a more accurate signal. The randomized rotation of nodes that is necessary to be cluster-heads, for even
distribution of energy consumption over all nodes in the network is the main characteristic of this algorithm.

LEACH operation is broken into rounds, having a set-up phase and a steady-state phase. In the beginning of the set-up phase, each node probabilistically decides whether or not to be a cluster head.

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:

\[
T(n) = \begin{cases} 
  \frac{P}{1 - P \times (r \mod \frac{1}{P})} & \text{if } n \in G \\
  0 & \text{otherwise}
\end{cases}
\]

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. Thus, after \( 1/P -1 \) rounds, \( T(n) = 1 \) for all nodes that have not been a cluster-head.

After electing itself as a cluster-head, the node broadcasts an advertisement message announcing its intention to the rest of the nodes, using CSMA-MAC (Carrier Sense Multiple Access- Medium Access Control) protocol [25]; all the cluster-heads broadcast using the same transmit energy. Each non cluster-head node thus receives advertisements from the cluster-heads and selects the cluster to join based on the largest received signal strength of the advertisement. This implies that minimum amount of transmission energy is needed for communication with the selected cluster-head. Nodes inform the cluster-head of the cluster they intend to join, using the CSMA-MAC protocol. Each cluster-head then assigns a TDMA (Time Division Multiple Access) schedule for the nodes in the
cluster, for sending sensed data. The TDMA slots are being calculated based on the number of nodes present in the cluster and are then broadcasted back to the cluster nodes.

In the steady-state phase, each cluster-head waits to receive data from all nodes in its cluster and then sends the aggregated result back to the base station.

Figure 2.1: Cluster-head nodes (marked in •) in two rounds of operation. Nodes with the same symbols are the nodes in the same cluster [1]

Simulation proved that LEACH reduces the communication energy as much as 8x times as compared to direct transmission. Figure 2.1 shows cluster-heads selected at two different time intervals.

2.1.2 LEACH-C

Motivated by the previous approach, Heinzelman et al. proposed a centralized clustering algorithm having the steady state phase operation similar to LEACH, called LEACH-C [2]. The protocol offers a way out to the shortcoming in the earlier protocol. LEACH offers no assurance about the placement of the cluster-head nodes in the cluster. Thus
other nodes in that cluster may expend more energy transmitting through the selected node located far from the cluster centroid. Figure 2.2 shows one of the scenarios, where cluster-heads are located at the network edges and the adjacent nodes are cluster-heads.

![Figure 2.2: Cluster-head nodes (marked by squares) in two consecutive rounds of operation [9]](image)

Moreover there is no guarantee about the number of cluster-head nodes selected per round. Since nodes become cluster-head when the random number it generates is less than the threshold, it might happen at times that more than the desired percentage of nodes becomes cluster-head.

Consequently LEACH-C uses a centralized algorithm and provides another approach to form clusters, as well as selecting the cluster-heads using the simulated annealing technique. Centralized control algorithm approach produces better cluster-heads by dispersing the cluster-heads throughout the network. During the setup phase, the nodes send the location co-ordinate information and the energy level to the base station. The base station computes the average node energy in each round. Thus, in addition to determining good clusters, this approach eliminates the nodes to become the cluster-heads.
whose energy falls below the average energy of the network. It then forms the clusters based on the remaining nodes as cluster-heads, using the simulated annealing technique.

A relevant contribution to our work comes from the fact that the algorithm tries to minimize the amount of energy required by non cluster-head nodes to transmit their data thorough the cluster-head, by minimizing the total sum of the squared distances between all the non cluster-head nodes and the possible cluster-head. After the clusters and the cluster-heads have been calculated at the base station, the base station broadcasts cluster-head ID for each node. If a match occurs between the node ID and the cluster-head ID, the node is a cluster-head. Otherwise the nodes find out the TDMA time slots for transmitting the data to the cluster-head. The steady state phase is identical to the steady state phase of LEACH.

2.1.3 Deterministic Model of LEACH

Handy et al. [9] proposed an algorithm for reducing the power consumption of the wireless sensor network. The stochastic method of selecting cluster-heads in the LEACH approach was extended by adding a deterministic component. They propose to make it energy efficient by multiplying the factor $\frac{E_{n_{-\text{current}}}}{E_{n_{-\text{max}}}}$ in Eq. (2.2). Where, $E_{n_{-\text{current}}}$ is the current energy and $E_{n_{-\text{max}}}$ the initial energy of the node. Hence the new threshold is

$$T(n) = \frac{P}{1 - P \times \left( r \mod \frac{1}{P} \right)} \frac{E_{n_{-\text{current}}}}{E_{n_{-\text{max}}}}$$

(2.3)
Now since the ratio $\frac{E_{n\_current}}{E_{n\_max}}$ is less than one, from the second round onwards, the total number of cluster-heads generated in each round reduces, by multiplication of a factor less than one. This can significantly impact the average energy dissipated per round as demonstrated in [2].

2.1.4 Other Approaches

In [3] each node calculates its distance from the area centroid in the specified cluster. Performance issues for biased distribution of nodes are one of the drawbacks of this algorithm. The single nodes that are strategically placed close to the area centroid will be more often selected as cluster-heads. Consequently it leads to overall high energy consumption in the network for other nodes to transmit data through the selected node located relatively far from the cluster.

Recently, Voigt et al. [17] propose a new approach to utilize solar power in WSNs and extended LEACH to become solar-aware. They propose a handover scheme that allows changes of cluster-heads during the steady state phase of the LEACH protocol, proving that making LEACH solar aware increases the lifetime of the network substantially.

For solar-aware distributed LEACH, they modify the LEACH equation (Eq. 2.1) to incorporate two different constraints. Firstly, they suggest that the solar powered nodes must become cluster-heads with a higher probability than a non solar powered node. Secondly, a node that has been solar powered while it is a cluster-head should have the provision to become a cluster-head even during next 1/P rounds.

The new threshold equation is -
\[ T(n) = sf(n) \times \frac{P}{1 - \left( \frac{cHeads}{numNodes} \right)} \] (2.4)

Where, \( sf(n) \) the scaling factor, is greater than one for solar powered nodes and less than one for battery powered nodes. \( cHeads \) gives the number of cluster-heads since the start of the last metaround. They define each metaround to consist of \( 1/P \) rounds of LEACH, in which every node becomes cluster-head. Each node knows the value of \( cHeads \). Thus when \( cHeads \) equals the \( numNodes \) (number of nodes) the current metaround gets finished and \( cHeads \) is reset back to zero.

### 2.2 Review of Fuzzy Systems

Fuzzy logic is based on the idea that all things admit of degrees. It attempts to model our sense of words, our decision making and our common sense.

In 1965 Lotfi Zadeh, extended the work on possibility theory into a formal system of mathematical logic with the application of natural language terms to create ‘Fuzzy Logic’. Unlike Boolean logic having two values, fuzzy logic is multi-valued and uses continuum of logical values or degrees of membership between 0 and 1 [8].

#### 2.2.1 Crisp and Fuzzy Sets

The basic idea of the fuzzy set theory is that an element belongs to a fuzzy set with a certain degree of membership [23]. This degree is usually taken as a real number in the interval \([0,1]\). For a given fuzzy set, the x-axis represents the universe of discourse - the range of all possible values applicable to a chosen variable and the y-axis represents the membership value of the fuzzy set [8].
The characteristic function of a crisp set $A$, can be defined as $f_A(x)$, where $X$ is the universe of discourse with its elements denoted as $x$

$$f_A(x) = \begin{cases} 
1, & \text{if } x \in A \\
0, & \text{if } x \notin A 
\end{cases} \quad (2.5)$$

$$f_A(x) : X \rightarrow \{0, 1\},$$

Hence, for any element $x$ of universe $X$, characteristic function $f_A(x)$ is equal to 1 if $x$ is an element of set $A$, and is equal to 0 if $x$ is not an element of $A$.

In fuzzy logic, fuzzy set $A$ of universe $X$ is defined by the membership function $\mu_A(x)$ of set $A$. For any element $x$ of universe $X$, membership function $\mu_A(x)$ equals the degree to which $x$ belongs to set $A$. The degree of membership value ranges between 0 and 1 (Figure 2.3).

$$\mu_A(x) : X \rightarrow [0, 1], \text{ where } \mu_A(x) = 1 \text{ if } x \text{ is totally in } A$$

$$\mu_A(x) = 0 \text{ if } x \text{ is not in } A$$

$$0 < \mu_A(x) < 1 \text{ if } x \text{ is partly in } A. \quad (2.6)$$

Sigmoid, gaussian and other linear functions can be used to represent the fuzzy sets. Implementing non linear functions increases the computational complexity for the algorithm.
2.2.2 Operations on Fuzzy Sets

Complement, containment, intersection and union are the four major operations on fuzzy sets. Figure 2.4 shows the different operations done on fuzzy sets schematically.

**Complement:** The complement of the fuzzy set is the opposite of the given set. Fuzzy complement for fuzzy set A, on universe of discourse X is given by equation,

\[ \mu_{\sim A}(x) = 1 - \mu_A(x) \], where \( x \in X \)  \hspace{1cm} (2.7)

**Containment:** Containment or subset is a set which can contain other sets or which is a part (partial or full) of another set. It is important to note fuzzy subset elements have lower or equal membership values than the set it is part of.

**Intersection:** An intersection between two sets contains the common elements of the two sets. In fuzzy sets, an element can partly belong to both sets with different memberships. Thus we choose the minimum of the two membership values to find the fuzzy intersection. The fuzzy intersection of two fuzzy sets A and B on universe of discourse X is given by,
\( \mu_{A \cap B}(x) = \min \{ \mu_A(x), \mu_B(x) \} = \mu_A(x) \cap \mu_B(x) , \text{ where } x \in X \)  \hspace{1cm} (2.8)

**Union:** The union is the opposite of the intersection. As a consequence, the union is the largest membership value of the element in either set.

The fuzzy union of two fuzzy sets A and B on universe of discourse X is given by,

\( \mu_{A \cup B}(x) = \max \{ \mu_A(x), \mu_B(x) \} = \mu_A(x) \cup \mu_B(x) , \text{ where } x \in X \)  \hspace{1cm} (2.9)

![Diagram of fuzzy set operations](image)

*Figure 2.4: Fuzzy Set Operations [8]*

### 2.2.3 Linguistic variables and hedges

A linguistic variable is a fuzzy variable [8]. For example, “concentration is high” implies that the linguistic variable concentration takes the linguistic value high.
Hedges are fuzzy set qualifiers for a linguistic variable (Figure 2.7). These are terms that modify the shape of fuzzy sets and includes adverb like very, somewhat, quite, more or less and slightly [8]. From the figure below it is clear how the fuzzy set gets modified with various mathematical curves for different type of fuzzy set qualifiers or hedges used.

<table>
<thead>
<tr>
<th>Hedge</th>
<th>Mathematical Expression</th>
<th>Graphical Representation</th>
</tr>
</thead>
<tbody>
<tr>
<td>A little</td>
<td>$[\mu_A(x)]^{1.3}$</td>
<td></td>
</tr>
<tr>
<td>Slightly</td>
<td>$[\mu_A(x)]^{1.7}$</td>
<td></td>
</tr>
<tr>
<td>Very</td>
<td>$[\mu_A(x)]^2$</td>
<td></td>
</tr>
<tr>
<td>Extremely</td>
<td>$[\mu_A(x)]^3$</td>
<td></td>
</tr>
</tbody>
</table>

Figure 2.5: Hedges [8]

### 2.2.4 Fuzzy Rules and Fuzzy Sets

A conditional statement based on two linguistic values A and B on universe of discourse X and Y with linguistic variables x and y of the form

IF x is A THEN y is B, defines a fuzzy rule.

In fuzzy expert systems, linguistic variables are used in fuzzy rules which relates to fuzzy sets. For example:

IF energy is high

THEN cluster-head chance is high
The range of possible values of a linguistic variable represents the universe of discourse of that variable. To site an example, the universe of discourse of the linguistic variable energy may have the scaled range between 0 and 100, and can include fuzzy sets as low, medium, and high. All rules fire to some extent, depending upon the degree of membership to which the antecedent relates with the consequent. A simple example may be,

IF the energy is low and
IF the concentration is low and
IF the centrality is far
THEN the node’s cluster-head election chance is very small.

2.2.5 Fuzzy inference

Up to this point we have provided the details of the fuzzy sets, fuzzy rules and the working of different operators like union and intersection. In this section, a commonly used fuzzy inference technique called the Mamdani method is reviewed. It requires us to find the centroid of a two-dimensional shape by integrating across a continuously varying function. From the computational point of view this method is not so efficient. Another inference technique, called Sugeno fuzzy inference proposes the use of a single spike, called singleton, as a membership function of the rule consequent [8]. But since the popular Mamdani technique allows us to describe the expert knowledge in a more intuitive manner, we have used it in our system.

To explain how the complete steps work, we take a basic example:

Here we consider two basic fuzzy rules,

IF energy is medium THEN cluster-head chance is medium and
IF energy is high THEN cluster-head chance is high

These are the steps that the system would undertake to carry out the fuzzy inference:

1. Input of crisp value and fuzzification,
2. Rule evaluation,
3. Aggregation of the rule outputs,
4. Defuzzification.

![Figure 2.6: Steps in fuzzy inference](image-url)
Step 1: Input of crisp value and fuzzification

This is rather straightforward. Our input is a crisp value, energy level, as shown in Figure 2.6 with a single point of reference. Based on the crisp number, we determine our input values from the fuzzy sets. It is seen that the crisp input energy value of 60 intersects the input fuzzy sets with a membership value of 0.3 and 0.5 from the first and second rules respectively.

Step 2: Rule Evaluation

Based on the fuzzification values of 0.3 and 0.5 obtained earlier, we deduce these values to the output rules to determine our new fuzzy output set. For a given fuzzy rule having multiple antecedents, the fuzzy operator (AND or OR) is used to obtain a single number that represents the result of the antecedent evaluation. This number (the truth value) is then applied to the consequent membership function.

Step 3: Aggregation of the rule outputs

For the crisp value of energy (= 60) both the defined rules apply. Aggregation is the process of unification of the outputs of all rules. Based on two fuzzy sets, a new fuzzy output set is created (Figure 2.6). Aggregation is an OR logic because we are looking at the aggregation of both rules, thus we use the fuzzy logical operator OR to create the new aggregate fuzzy set.

Step 4: Defuzzification

This is the last step where we determine our final fuzzy system crisp output. We produce a single crisp number from the output fuzzy set. We have used the Mamdani technique to calculate the inference value in the later part of the thesis. Centroid defuzzification method [8] finds a point representing the centre of gravity of the fuzzy set. The center of
gravity is a weighted average calculation that takes each subdivided area's center and averages according to the weight that that area contributes to the whole. Therefore after defuzzification it gives a value of 55 as the cluster-head election chance (Figure 2.6).

2.3 Fuzzy Systems in Wireless Networks

There are varied applications of intelligent techniques in wireless networks [4]. Halgamuge et al. presents an energy efficient cluster formation for WSNs using subtractive and fuzzy C-mean clustering approach [21]. The increase in the growth of wireless application demands for the wireless network to have the capability to trace the locations of mobile users. Location updating scheme using fuzzy logic controls have been proposed in [20] that adaptively adjusts size of the location area for each user.

Different approaches in improving the reliability and accuracy of measurement information from the sensor networks have been described in [19]. It offers a way of integrating sensor measurement results with association information, available or a priori, derived at aggregating nodes by using some optimization algorithm. They have considered both neuro-fuzzy and probabilistic models for sensor results and association information. The models carry out classification of the information sources, available in sensor systems.

2.4 Summary

This chapter has examined two different concepts for WSNs: the different clustering protocol in use and various applications of fuzzy systems. We observe that, although approaches like minimum transmission energy routing and power aware routing protocols
are meant to minimize the power consumption, each has its own limitations. Yet clustering approaches like LEACH, attempted to minimize the energy consumption by stochastically rotating the cluster-heads. LEACH-C fixed the shortcomings of this approach by suggesting a centralized control algorithm to form clusters. Several other proposals regarding energy minimization like the solar-aware distributed LEACH have also been discussed. A review of fuzzy logic systems and fuzzy set theory has been done. Applications of intelligent systems in wireless networks have also been discussed in the end.
Chapter 3

Fuzzy logic Approach to Cluster-head Election

3.1 Objective

In this chapter we describe our fuzzy based system model for the WSN. 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. An analysis to the disadvantages of local information processing to select the nodes and the advantages to use a base station control algorithm are also discussed in this chapter.

3.2 Motivation for our approach

3.2.1 Disadvantages of local information processing

Several disadvantages are there for selecting the cluster-head using only the local information in the nodes as in the case of LEACH:

- 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.
- The number of cluster-head nodes generated is not fixed so in some rounds it may be more or less than the preferred value.
- 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.
- Each node has to calculate the threshold and generate the random numbers in each round, consuming CPU cycles.
3.2.2 Advantages of base station control algorithm

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.

3.2.3 Advantages of using fuzzy logic in our system

We have chosen a fuzzy based control algorithm in the base station for electing the cluster-heads. Several reasons support our use of fuzzy control in this regard:

- Representing the problem in mathematical (or probabilistic) model domain involves dealing with several variables and parameters at a time. Moreover these variables are to be defined separately for each scenario, in order to provide a collective output on the basis of the multiple input variables. Problem arises as the number of these variables increases. The mathematical model becomes too complex to handle so many parameters at a time, limited by the effective combination of different parameters together. Fuzzy logic systems on the other hand have got an inherent ability to integrate numeric (‘fuzzy’) and symbolic (‘logic’) aspects of reasoning. Therefore different parameters like concentration,
energy, and centrality can be combined easily to give the desired result by defuzzifying the output fuzzy set.

- Fuzzy logic 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. In addition, it can be used for context by blending different parameters - rules combined together to produce the suitable result.

- Fuzzy logic offers a full range of operators to combine uncertain information in a better way than any other systems. Fuzzy logic control techniques can be used to design individual behavior units. Fuzzy controllers incorporate heuristic control knowledge in the form of if-then rules. They have also demonstrated a good degree of robustness in face of large variability and uncertainty in the parameters.

In fact considering only one parameter like energy is not suitable to elect the cluster-head properly. This is because other conditions like centrality of the nodes with respect to the entire cluster, too gives a measure of the energy dissipation during transmission for all nodes. The more central the node is to a cluster the more is the energy efficiency for other nodes to transmit through that selected node. The concentration of the nodes in a given region too affects in some way for the cluster-head election. It is more feasible to select a cluster-head in a region, where the node concentration is high.
3.3 Model Description

The cluster-head collects $n$ number of $k$-bit messages from $n$ nodes in the cluster 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 rounds consisting of a setup and steady state phase.

3.3.1 Setup phase

During the setup phase the cluster-heads are determined by using fuzzy knowledge processing and then the cluster is organized.

After the cluster-heads have been calculated at the base station, base station broadcasts cluster-head ID for each node in the cluster. If a match occurs between the node ID and the cluster-head ID the node is a cluster-head. Otherwise the nodes obtain the TDMA time slots for transmitting the data to the cluster-head.

3.3.2 Steady state phase

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 similar to the steady state phase of LEACH. This composite signal is then sent to the base station.

The radio model we have used is similar to [1] with $E_{\text{elec}} = 50$ nJ/bit as the energy dissipated by the radio to run the transmitter or receiver circuitry and $e_{\text{amp}} = 100$ pJ/bit/m$^2$ 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:

$$E_{\text{TX}}(k, d) = E_{\text{elec}} * k + e_{\text{amp}} * k * d^4$$  \hspace{1cm} (3.1)
\( E_{RX}(k) = E_{elec} \ast k \)  \hspace{1cm} (3.2)

where, \( \lambda \) is the path loss exponent and \( \lambda \geq 2 \).

### 3.4 Fuzzy Logic Control

The model of fuzzy logic control consists of a fuzzifier, fuzzy rules, fuzzy inference engine, and a defuzzifier. As mentioned in section 2.2.6 we have used the most commonly used fuzzy inference technique called Mamdani method 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 3.1).

- **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 \textit{chance} and the output is a single crisp number.

During defuzzification, it finds the point where a vertical line would slice the aggregate set \textit{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:

\[
COG = (\sum \mu_A(x) \ast x) / \sum \mu_A(x) \hspace{1cm} (3.3)
\]

where, \( \mu_A(x) \) is the membership function of set A.
3.5 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*, the energy value is scaled while representing in the fuzzy set,
- 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*. The centrality value is scaled while representing in the fuzzy set.

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 $d^2$ (Eq. 3.1), 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 3.1 and Figures 3.1 through 3.4.

Figure 3.1: Fuzzy set for fuzzy variable energy

Figure 3.2: Fuzzy set for fuzzy variable concentration
Figure 3.3: Fuzzy set for fuzzy variable *centrality*

Figure 3.4: Fuzzy set for fuzzy variable *chance*

Table 3.1: Fuzzy rule base

<table>
<thead>
<tr>
<th></th>
<th>energy</th>
<th>concentration</th>
<th>centrality</th>
<th>chance</th>
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<td>1</td>
<td>low</td>
<td>low</td>
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<td>small</td>
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<td>low</td>
<td>far</td>
<td>vsmall</td>
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<td>high</td>
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<td>med</td>
</tr>
<tr>
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<td>high</td>
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<td>vlarge</td>
</tr>
<tr>
<td>26</td>
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<td>high</td>
<td>adeq</td>
<td>rlarge</td>
</tr>
<tr>
<td>27</td>
<td>high</td>
<td>high</td>
<td>far</td>
<td>med</td>
</tr>
</tbody>
</table>

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. If there are multiple nodes having maximum chance, then the node having more energy is selected. 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.
3.6 Application Case Study: Health care system

3.6.1 Description

The confluence of wireless sensor networks, soft computing techniques, and MEMS technology has opened a new arena for designing remote autonomous health monitoring systems. This will shift the point of health care from the health-care providers like clinics and hospitals to individual residences. Vital resources can therefore be freed up with the continuous monitoring and management of diseases [10].

As this is a multidisciplinary area, a lot of active research is being carried out in various fields to build the components for these complex systems. [24] describes some smart sensors and related issues, focusing on the artificial retina, glucose level monitors and other general health monitors.

3.6.2 System model and design

This section gives the description of the architecture of our model and an algorithm involved in the design of such systems. The intent of the system is to model a ‘diagnostic control loop’, so that continuous feedback is available to guide the bio-controller to adjust its output continuously.

Figure 3.5 shows the overall system architecture consisting of following the system components

- Wireless Sensor Networks - representing the system in form of a sensor hierarchy.

  Individual biomedical sensors are organized into clusters based on the physiological measurement being made. Each cluster has a cluster-head that acts as a gateway for all communications between the cluster and the base station. The cluster-head is nominated by the base station. Individual sensors do not
communicate with each other. Cluster-heads do not have any enhanced features as compared to other nodes.

Figure 3.5: Overall system architecture

- Base Station and Bio Controller(s) - the cluster-heads collects the data form the sensors and transmits it to the base station. The base station is responsible for maintaining the communication within the WSN. It then feeds the data to the bio-
controller. The processing in the bio-controller can be based on many soft computing approaches - like neuro-fuzzy or case based reasoning techniques.

- **Actuator** - can be conceptualized as those which are involved in the actual delivery of drugs into the individuals. Bio-controllers take the decision regarding the action the actuators need to take.

### 3.6.3 Incorporating our fuzzy cluster-head election algorithm

Biomedical WSN has certain features distinct [24] from general type of WSN or to be more precise, they have more preset features than conventional WSN:

- The sensor nodes are considered to be immobile, and relatively stationary. This fits into our assumption regarding sensor networks as we have described in section 1.3. These fixed placements of nodes can lead to more efficient network management.

- There is no need for self-organization protocols [1] [9] to form the clusters based on stochastic models. Determining the proximity and the concentration of the neighbors by the individual nodes consumes valuable energy and CPU cycles of each node.

- There is no need to develop routing protocols to send the data to the base stations through different sensor paths. Thus the power expenses to develop the network topology can be avoided.

Self organizing clusters and determining various routing paths via the sensor nodes are imperative for WSNs deployed to gather information over a vast region; for example, to gather intelligence in battle field conditions. In these cases, the WSNs are formed by
simply ejecting a large number of sensor nodes by means of some mass deployment scheme, for example: from an aircraft.

But this issue does not arise in biomedical sensor applications, since in this case, the nodes are surgically implanted and the total numbers of nodes required at a given area with their positions are known beforehand. Hence taking the advantage of the design by encoding this information in the sensors, optimized communication strategies can be implemented. Our approach of selecting the cluster-head by the base station processing follows the same model. Overall energy consumption can be reduced by following the cluster-based approach as proven in [24].

**Basic overall operation algorithm**

The overall operational algorithm can be described as follows. Cluster heads are ascertained by the base station which knows the data transfer rates of the sensors:

begin

1. while (t < T_{BS}) /* T_{BS} = Base station period of operation */

2. base station selects cluster-head using fuzzy knowledge processing (as described in section 3.3)

3. base station broadcasts cluster-head ID and cluster-head polling times (T_{int}) in the TDMA schedule in each cluster

4. if a match occurs between the node ID and the cluster-head ID the node is a cluster-head

5. base station assigns TDMA slots for the nodes in the cluster, to transmit data to the cluster-head
6. nodes transmit sensed data to the cluster-head using TDMA
7. cluster-head aggregate data received from nodes for a given time period
8. cluster-head compress and transmit the data to the base station
9. base station feeds controller
10. base station updates history database only on change
11. end while
end

3.7 Summary

This chapter has described our fuzzy based system model for the WSN. An analysis to the disadvantages of local information processing to select the nodes and the advantages to use a base station control algorithm with fuzzy logic has also been discussed. The radio model was used to represent the energy dissipation during transmission and reception. Detailed looks at the model with the descriptions of different fuzzy sets and variables have been made. Finally, we have developed a system model and framework that can be used for autonomous health monitoring systems by using our fuzzy based cluster-head election scheme. The system architecture consisted of biomedical sensor nodes, base station with bio-controller and actuators.
Chapter 4

Experimental Results

To test and analyze the algorithm, experimental studies were performed. The simulator programmed using Java Foundation Classes and NRC fuzzy Java Expert System Shell (JESS) toolkit. We modeled the energy consumption in WSN as given in Eqs. (3.1, 3.2). 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.

One important aspect is that the nodes should remain in operation for a long period of time. The network quality declines as soon as a node dies in the network. This parameter measured by FND, gives an estimated value of the overall network lifetime. Other metrics like HNA (Half Node Alive) and LND (Last Node Dies) can also be taken into account to test for the lifetime of the WSN; although LND does not serve the purpose since for cluster-based approach it requires more than one node to participate in the cluster. The metric FND, the number of rounds it takes until the first node dies thus indicates the duration for which the sensor network remains fully functional. HNA metric is application dependent. When the application requires the sensors to be placed in the proximity of each other, adjacent sensors could witness related or identical data. Thus loss of a few sensor nodes will not automatically lead to a diminished quality of service of the network, since active half of the total nodes can still send the relevant information. Considering our cluster-based approach can be used in scenarios such as bio-medical sensing and fire detection where it is necessary for all nodes to stay alive as long as possible, we chose the metric FND for our comparisons.
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 the coordinate 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. Figures 4.1, shows the concentration calculation for the network with a random distribution of nodes.

Figure 4.1: Calculation of concentration for the network cluster
Figure 4.2 shows a snapshot of the sensor nodes and their corresponding node concentrations.

In addition, the base station selects each node and calculates the sum of the squared distances of other nodes from the selected node, which gives a value for the centrality. Thus the higher the value of centrality, the more is the energy expended by other nodes to transmit the data to the cluster-head.

Figure 4.3 shows an illustration of centrality calculation for a particular node, in this regard. The centrality value is scaled before it is applied for fuzzification. Figure 4.4 illustrates typical node centralities for this sample network after scaling.
Figure 4.3: Centrality calculation

Figure 4.4: Some typical node centralities
All the three values are then fuzzified and passed to the fuzzy rule base for rule evaluation. After this, defuzzification gives the cluster-head election chance. Figure 4.6 shows the defuzzified output and the aggregate set chance for a specific node after simulation run.

The best nodes in terms of fuzzy overall, centrality and energy are shown in Figures 4.5 and 4.7. 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. It has an energy value of 97, node concentration and centrality value of 8 and 24 respectively.

![Figure 4.5: Network cluster showing the best nodes](image-url)
In this case each node is supplied with an energy of 1 Joule 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 $\lambda$ is set at 2 for intra-cluster communication and 2.5 for base

<table>
<thead>
<tr>
<th>Node no.</th>
<th>CoOrd:</th>
<th>Energy</th>
<th>Conc:</th>
<th>Centrality</th>
</tr>
</thead>
<tbody>
<tr>
<td>108</td>
<td>42 32</td>
<td>97</td>
<td>8</td>
<td>24</td>
</tr>
<tr>
<td>10</td>
<td>52 44</td>
<td>11</td>
<td>6</td>
<td>22</td>
</tr>
<tr>
<td>62</td>
<td>82 56</td>
<td>99</td>
<td>4</td>
<td>41</td>
</tr>
</tbody>
</table>

Figure 4.6: Output fuzzy set for fuzzy variable chance

Figure 4.7: Different node parameters

4.2 Sample network 2

In this case each node is supplied with an energy of 1 Joule 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 $\lambda$ is set at 2 for intra-cluster communication and 2.5 for base
station transmission. The cluster-head compresses the collected data to 5% of its original size.

Figure 4.8 shows sample defuzzification for a particular node, during simulation in progress. We have used centroid defuzzification formula (Eq. 3.3) that finds the point where a vertical line would slice the aggregate set chance into two equal masses, giving a crisp value of 60.53.

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**Figure 4.8: Sample defuzzification**

**Figure 4.9: Simulation in progress**
Figure 4.9 shows a snapshot of the simulation run for round number 44 with fuzzy elected cluster-head nodes. A typical observation from the experiment is that during initial rounds, the cluster-head selected are more central to the cluster and with progressing iterations they tend to move outward. This can be attributed by the fact that since node centrality is a descriptor in the fuzzy set, nodes with lower value of centrality has more chance of getting selected.

Figure 4.10 shows parameters for elected cluster-heads during two consecutive rounds 43 and 44. In round 43, node 1 becomes the cluster-head on the basis of the overall election chance. The cluster-head node dissipates much energy as compared to the other nodes, thus in the next round, round 44, the best node overall becomes node 33. It takes about 2500 rounds for the FND in the network.

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. Comparison with LEACH enables us to
determine how the centralized control algorithm at the base station can improve the
cluster-head election by incorporating the global knowledge about the network. LEACH-
C, another centralized algorithm uses simulated annealing to solve the NP-hard problem
of finding \( k \) optimal clusters in a given network such that it minimizes the overall energy
consumption. This is somewhat different to our approach wherein we are trying to find
the best possible cluster-head in a given cluster. Moreover the authors do not present the
detailed algorithm the base station uses to choose \( k \) clusters. Thus we have not considered
it for comparison with our algorithm.

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. Figure 4.11 shows the nodes
selected by the fuzzy algorithm and LEACH in the first round. It can be seen from Figure
4.12, that the node selected by LEACH, near the edge, dissipates more energy as cluster-
head than our fuzzy based algorithm.
Both algorithms optimize the intra-cluster energy consumption and thus do not influence the energy required to transmit to the base station. Table 4.1 shows four simulation runs...
to calculate the number of rounds taken by LEACH and the fuzzy cluster-head election algorithm for FND.

Table 4.1: Iterations for FND for Sample network 3 simulations

<table>
<thead>
<tr>
<th></th>
<th>Run 1</th>
<th>Run 2</th>
<th>Run 3</th>
<th>Run 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>LEACH</td>
<td>1597</td>
<td>1577</td>
<td>1627</td>
<td>1558</td>
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<tr>
<td>Our Approach</td>
<td>2716</td>
<td>3118</td>
<td>3094</td>
<td>2976</td>
</tr>
</tbody>
</table>

4.4 Summary

A computer simulation has been designed to test and analyze the algorithm we developed in Chapter 3. After modeling the energy consumption for the WSN we applied the algorithm to check for the quality of the network. The algorithm performs very well, finding the best node by combining three parameters - energy, concentration and centrality of the nodes. To check for improvements, we compared our algorithm with LEACH by adjusting the cluster-head election probabilities and the results were reasonable.
Chapter 5

Conclusion

This thesis has discussed a novel approach for cluster-head election for WSNs. The objective of this thesis were to develop an approach for electing the cluster-head in a given cluster for a WSN and to provide means to incorporate different parameters like energy, centrality that significantly affect the cluster-head election chance.

Our algorithm offered several advantages as listed below:

Since the cluster-head is the node responsible for the high energy transmissions to the base station, selecting a single static cluster-head would have drained out the power drastically; our approach is to rotate the cluster-head on the basis of the defuzzified chance value. Thus, all the nodes are compared on the basis of chances and the node with the maximum chance is then elected as the cluster-head. The primary idea throughout the thesis was to find means as how to incorporate different parameters that affects the node election criterion with the provision for rotating the cluster-head to conserve energy.

Secondly, we used a central control algorithm in the base station, which has sufficient power, memory and storage capacity and thus we overcame the limitations of resource constrained processing at each node, as in local node based clustering.

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. Thus the drawbacks of selecting the cluster-head using only the local information in the nodes have been removed too. In addition it is not necessary to calculate the threshold using local information in the nodes, utilizing the node CPU cycles. Also, representing the problem
in fuzzy logic domain reduced the complicacy to integrate these variables in some stochastic or mathematical model. Thus by using three different descriptors and blending the fuzzy rules together, the fuzzy logic system produced an appropriate result.

Fourthly, use of a single descriptor, like energy, was not suitable to elect the cluster-head as other conditions like cluster centrality of the node and node concentration, too gave a measure of the energy dissipated. As we have found in the experimental results, the more central the node is to a cluster, the more is the energy efficiency for other nodes to transmit through that selected node. On the contrary, the node can have a very low energy value making it unsuitable for being elected as a cluster-head.

For distinctly separable clusters, the approach performs the cluster-head election appropriately. Hence this can be applied to WSN where the total numbers of sensor nodes required at a given area with their positions are known beforehand. Our approach is more suitable for electing cluster-head for medium sized clusters.

Some extensions of this approach can be to minimize the overall high energy expense for large clusters, by breaking them into multiple clusters and then apply the algorithm. An approach to dynamically form the cluster that each node should join, by checking the concentration of the nodes in a given area and by placing the degree of node association in a particular cluster as a fuzzy variable, can be taken for large clusters. Nodes join the cluster that has the maximum degree of association. An analysis with this type of network configuration will be useful.

By modifying the shape of each fuzzy set accurately, a further improvement in the network lifetime and energy consumption can be achieved. Future work in this area will
also include experiments with mobile sensors, where degree of mobility for the nodes varies.

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.
The research work reported in this thesis has been accepted for presentation at the *Third Annual Conference on Communication Networks and Services Research (CNSR2005)* as ‘Cluster-head Election using Fuzzy Logic for Wireless Sensor Networks’, authors: Indranil Gupta, Denis Riordan and Srinivas Sampalli.
Bibliography


