# A Fuzzy Approach to Energy Optimized Routing for Wireless Sensor Networks

Tarique Haider[1] and Mariam Yusuf[2]
[1] Hamdard Institute of Information Technology, Hamdard University Karachi, Pakistan
[2] Departments of Telecommunication and Computer Engineering, Pakistan

**Abstract:** *In recent years, many approaches and techniques have been explored for the optimization of energy usage in wireless sensor networks. Routing is one of these areas in which attempts for efficient utilization of energy have been made. These attempts use fixed (crisp) metrics for making energy-aware routing decisions. In this paper, we present a generalized fuzzy logic based approach for energy-aware routing in wireless sensor networks. This generalized approach is soft and tunable and hence it can accommodate sensor networks comprising of different types of sensor nodes having different energy metrics.*

**Keywords:** *Wireless sensor networks, fuzzy logic, routing.*

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## 1. Introduction

Wireless Sensor Networks (WSNs) can be safely identified as one of the most important technologies of recent times. Developments in the areas of VLSI, WSNs storage and power management all have contributed to this exciting area. WSNs have become increasingly popular for both military and civil applications such as target tracking, space exploration, environmental control, habitat monitoring and patient care [9, 2].

A wireless sensor network consists of a large number of unattended, usually self-organized micro sensors, of size of the order of a cubic centimeter, scattered in an area for a specific application. Each micro sensor is capable of sensing data from the environment, performing simple computations and transmitting this data over wireless medium either directly to command centre or through some cluster head, commonly known as gateway. WSNs although have some similarities with ad-hoc networks but they differ from ad-hoc networks mainly due to their more severe energy constraints, much larger density of sensor nodes, lower cost and usually static nature of nodes. Moreover, WSNs are designed for information gathering, rather than distributed computing.

Sensors nodes are battery operated and once deployed are unattended and expected to operate for a long period of time, usually from a few months to years. Thus, energy is a scarce resource in a wireless sensor network and hence its efficient usage is crucial for extending the life of the whole sensor network. A sensor's energy is mainly consumed in the three main activities: sensing, computing and communicating.

Various approaches for optimizing the energy usage in wireless sensor networks have been proposed [2, 7, 20]. These include physical-level design decisions such as modulation scaling, voltage scaling etc. to energy-aware routing and energy-aware MAC protocols [18, 23, 25].

In this paper, we present a fuzzy model for energy-aware routing in wireless sensor networks. Existing proposed routing protocols for WSNs use fixed (crisp) metrics for making energy-aware routing decisions [1, 24]. This has the disadvantage of not being easily adaptive to changes in sensor types because energy metrics vary widely with the type of sensor node implementation platform [15]. Moreover, some of the factors for calculating routing metric are conflicting. For example, short multiple-hops reduces transmission power but results in greater number of hops thereby reducing the energy of a larger number of nodes involved in relaying. Fuzzy logic, on the other hand, has potential for dealing with conflicting situations and imprecision in data using heuristic human reasoning without needing complex mathematical modelling. The potential of fuzzy logic is being fully explored in the fields of signal processing, speech recognition, aerospace, robotics, embedded controllers, networking, business and marketing [6]. In this work, we present a soft, tuneable parameter based approach to energy-optimized routing using fuzzy variables and rule base. This results in soft accommodating way of routing in WSNs capable of handling a wide range of energy metrics of different sensor implementation platform.

We have assumed a cluster-based architecture for WSN, where a group of nodes is managed by a gateway. Various criteria for cluster-formulation have been proposed but in this paper our focus is on routing within a cluster. The gateway is responsible for the management of nodes in its cluster, communicating with other gateways, processing of data received from sensor nodes and transmitting the processed data to the command center. We have assumed that the gateway is much powerful as compared to sensor nodes and has no energy limitation. Moreover, the routing is centralized, i.e., the gateway sets routes for sensor nodes. All sensor nodes have one destination namely the gateway, reachable via various routes through multiple-hops over sensor nodes.

The remaining of this paper is structured as follows. Section 2 summarizes the related work. In section 3 we describe our system model. We present our fuzzy model in section 4. Simulation results are presented in section 5. Section 6 concludes our paper.

## 2. Related Work

As wireless sensor networks differ from ad-hoc networks in many aspects, separate routing protocols for WSN have been proposed [14, 21, 5]. A survey of recent routing protocols for WSNs and their classification is given in [1].

Among the various approaches that have been proposed in literature for minimizing the energy usage in wireless sensor networks, energy-aware routing attempts to extend the life of a WSN at network layer. Energy-efficient routes can be computed using either the minimum energy path, maximum residual energy path, path with minimum number of hops to sink *etc.* [2]. Chang et al [4] have argued that always selecting the route with minimum energy will quickly deplete the energy of sensor nodes on the minimum energy path, thereby decreasing the life of WSN. Rahul *et al.* [17] have presented an energy aware routing protocol that keeps a set of minimal energy paths and randomly selects one of these sub-optimal paths, thereby significantly increasing the network lifetime. In [4], the problem of maximizing network lifetime by energy-aware routing has been formulated as integer-programming problem, whereas in [11] convex non-linear optimization techniques have been used. Jain *et al* [9] have presented an energy-aware multi-path routing approach that attempts to spread the traffic over the nodes lying on different possible paths connecting the source to the sink, in proportion to their residual energy. In [24], an energy-aware routing algorithm for cluster-based wireless sensor networks have been proposed in which a cost function is defined between two sensor nodes in terms of energy conservation, delay optimization and other performance metrics.

The above approaches make use of fixed (crisp) metrics and mathematical modelling for finding energy-aware routing metrics. In this paper, we present a novel approach for calculating the cost of link between any two sensors nodes, using fuzzy logic. Fuzzy logic has been successfully applied in various areas including communications and has shown promising results [6, 13]. However, the potentials of fuzzy logic in wireless sensor networks still need to be explored. Optimization of wireless sensor networks involve various tradeoffs, for example, lower transmission power vs. longer transmission duration, multi-hop vs. direct communication, computation vs. communication *etc.* Fuzzy logic is well suited for applications having conflicting requirements. Moreover, in WSN, as the energy metrics vary widely with the type of sensor node implementation platform, using fuzzy logic has the advantage of being easily adaptable to such changes. We, therefore, present our fuzzy logic based approach for energy-optimized routing in WSNs and compare our solution with conventional crisp approaches.

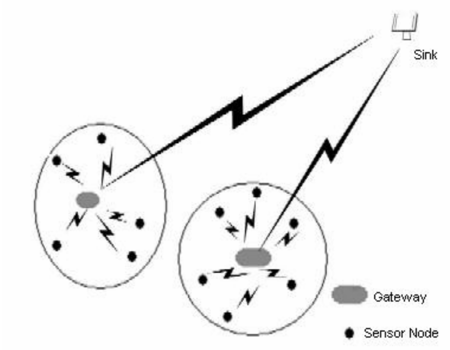

Figure 1. Cluster-based wireless sensor network.

## 3. System Model

Cluster-based routing has been shown to be quite effective in wireless sensor networks [8]. The main advantage of using this approach is that as the data gathered by sensors in the close vicinity is usually redundant, the gateway can perform the task of data aggregation before sending it to the remote command node (sink). Moreover, as WSN is usually formed for a specific application, gateways can be chosen to be much powerful as compared to the sensor nodes. This relieves the energy-constrained sensor nodes of communicating directly with the remote sink.

In this paper, we have assumed a cluster-based architecture for WSN, where a group of nodes is managed by a gateway. The gateway can communicate directly with all the sensor nodes and can retrieve their status. All sensor nodes have one destination namely the gateway to which they send their sensed data. Sensors can communicate directly with the gateway but this will be very costly for those sensor nodes which are not close to the gateway. Therefore, the gateway is also reachable via various routes through multiple-hops over sensor nodes in the network.

The gateway is responsible for setting up of routes for sensor nodes and for the maintenance of the centralized routing table that indicates the next hop for each sensor node. Gateway periodically invokes the fuzzy routine to determine the cost of link between any two sensor nodes. Once the costs of all possible links to the single destination (gateway) are computed using fuzzy logic, the route can then be determined using any shortest path algorithm. We have used Dijkstra's algorithm for our simulation. Routing table entries are periodically refreshed to reflect the updated state of the network. We have further assumed that the gateway is much powerful as compared to sensor nodes and has no energy limitation. In this paper, we have not considered the issues of cluster formation, routing between gateways and energy optimization of gateways as our main focus is on effective energy-optimized routing within the cluster. We have used Heinzelman's energy model for sensor networks [7]. Energy required for transmitting a *k*-bit message to a distance *d* is given by:

$$E_{Tx}(k,d) = E_{elec} \times k + E_{amp} \times k \times d^2 \quad (1)$$

Energy consumed in receiving a *k*-bit message is given by:

$$E_{Rx}(k) = E_{elec} \times k \quad (2)$$

where $E_{elec}$ = 50nJ/bit and $E_{amp}$ = 100pJ/bit/m$^2$ energy consumed in sensing one bit has been taken to be approximately equal to the energy dissipated in receiving one bit. Computation energy has been taken as the random summation of energies spent in various computational algorithms as mentioned in [7].

# 4. Fuzzy Model

## 4.1. Overview of Fuzzy Logic

Fuzzy Logic [3] is used in this work as main implementation of perceptive reasoning. Fuzzy logic imitates the logic of human thought, which is much less rigid than the calculations computers generally perform. Fuzzy Logic offers several unique features that make it a particularly good alternative for many control problems. It is inherently robust since it does not require precise, noise-free inputs and can be programmed to fail safely. The output control is a smooth control function despite a wide range of input variations. Since the FL controller processes user-defined rules governing the target control system, it can be modified and tweaked easily to improve or drastically alter system performance.

Fuzzy Logic deals with the analysis of information by using fuzzy sets, each of which may represent a linguistic term like "Warm", "High" *etc*. Fuzzy sets are described by the range of real values over which the set is mapped, called domain, and the membership function. A membership function

Assigns a truth value between 0 and 1 to each point in the fuzzy set's domain. Depending upon the shape of the membership function, various types of fuzzy sets can be used such as triangular, beta, PI, Gaussian, sigmoid *etc*.

A Fuzzy system basically consists of three parts: fuzzifier, inference engine, and defuzzifier. The fuzzifier maps each crisp input value to the corresponding fuzzy sets and thus assigns it a truth value or degree of membership for each fuzzy set.

Table 1. Fuzzy rule base.

| S# | A | B | C | D | E | F | O |
|---|---|---|---|---|---|---|---|
| **1** | low | high | low | small | small | large | VL |
| **2** | low | high | medium | small | small | large | VL |
| **3** | low | high | medium | small | large | large | L |
| **4** | low | high | low | small | large | large | L |
| **5** | low | high | low | large | large | large | LM |
| **6** | low | medium | high | small | small | large | LM |
| **7** | low | medium | medium | large | small | small | HM |
| **8** | high | medium | low | small | small | small | HM |
| **9** | high | medium | medium | large | small | small | H |
| **10** | high | medium | medium | large | large | large | H |
| **11** | high | low | low | small | small | large | VH |
| **12** | high | low | medium | small | large | small | VH |

The fuzzified values are processed by the inference engine, which consists of a rule base and various methods for inferring the rules. The rule base is simply a series of IF-THEN rules that relate the input fuzzy variables with the output fuzzy variables using linguistic variables, each of which is described by a fuzzy set, and fuzzy implication operators AND, OR *etc*. The part of a fuzzy rule before THEN is called predicate or antecedent, while the part following THEN is referred to as consequent. The combined truth of the predicate is determined by implication rules such as MIN-MAX (Zadeh) and bounded arithmetic sums. All the rules in the rule-base are processed in a parallel manner by the fuzzy inference engine. Any rule that fires contributes to the final fuzzy solution space. The inference rules govern the manner in which the consequent fuzzy sets are copied to the final fuzzy solution space. Example, techniques are MIN-MAX and fuzzy adaptive method. The defuzzifier performs defuzzification on the fuzzy solution space. That is, it finds a single crisp output value from the solution fuzzy space. Common defuzzification techniques are centroid, composite maximum, composite mass, *etc.* Details of the theoretical and practical aspects of fuzzy logic can be found in [3, 12].

## 4.2. Description

The objective of our fuzzy routine is to determine the value of cost for a link between two sensor nodes such that the life of a sensor network is maximized. The lifetime of wireless sensor networks is generally defined as the time when the energy level of the first sensor node becomes zero. The fuzzy rule base has been tuned so as to not only extend the life time of the sensor network but also to balance the routing load among sensor nodes effectively so that a maximum number of nodes have sufficient energy to continue performing their own sensing tasks.

Figure 2 displays our fuzzy model. The input fuzzy variables are: transmission energy, remaining energy, rate of energy consumption, queue size, distance from gateway and weight. The rule base therefore consists of 2^4 x3^2 =144 rules. There is a single output fuzzy variable, namely cost, the defuzzified value of which determines the cost of link between two sensor nodes.

Figure 3 gives details of the input fuzzy variables. In determining the cost of link from node *i* to node *j*, "transmission energy" represents the energy needed to transmit a data packet from node *i* to *j*. Lower value of transmission energy leads to lower link cost. "Remaining energy" indicates the energy level of node *j*. Nodes with less value of remaining energy should be avoided in being selected as next-hop. Consequently, its lower value results in a higher link cost. "Energy consumption rate" of node *j* is another important parameter.

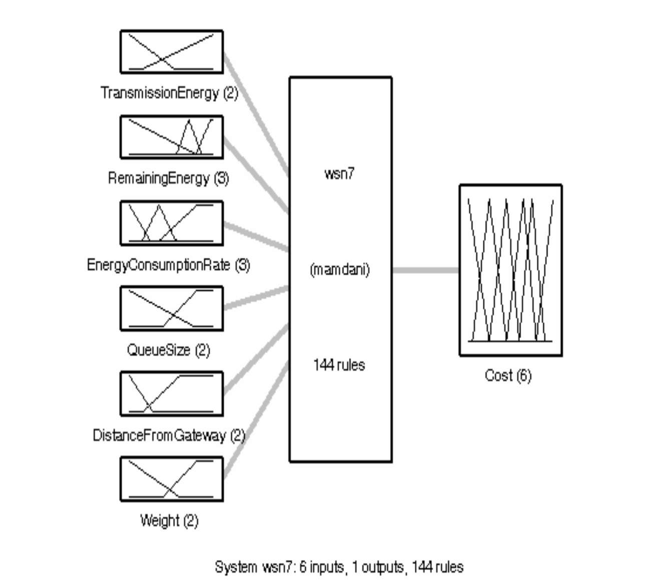

Figure 2. Fuzzy system model.

It is possible to have a node with a high value of initial energy, resulting in a higher value of remaining energy in spite of its high rate of energy consumption. Nodes with high rate of energy consumption are, therefore, assigned higher link costs. The fuzzy input variable "Distance from the gateway" enables selection of routes with minimum hops. Nodes nearer to the gateway are thus assigned lower link cost. Each sensor node is assigned a dynamic weight depending upon its current status. An in-active node that is neither sensing nor relaying is assigned a highest value whereas a node that is performing both these tasks is as signed a least weight. This parameter helps in selecting nodes which are either inactive or are only in the sensing state. Thus, a high value of weight makes the node favourable for next-hop, resulting in a lower value of link cost. The input fuzzy variable "queue size" indicates the buffer capacity at node *j*. This parameter helps avoid packet drops due to congestion at the receiver.

The output fuzzy variable, as shown in Figure 4, consists of six membership functions. A cost between 0 and 100 is assigned to each link.

The domains of input fuzzy variables have been selected according to our simulation environment, but they can be easily modified to make them general purpose. MIN-MAX inference technique has been used in the fuzzy controller. To find a crisp output value from a solution fuzzy region, the controller uses Centroid Defuzzification method. Centroid defuzzification finds the balance point of the solution fuzzy region by calculating the weighted mean of the fuzzy region. Mathematically, the crisp output domain value R, from solution fuzzy region *A*, is given by:

$$R = \sum_{i=0}^{n} W_i \mu_A(W_i) \Big/ \sum_{i=0}^{n} \mu_A(W_i) \qquad (3)$$

where $W_i$ is the domain value corresponding to rule $i$, $n$ is the number of rules triggered in the fuzzy inference engine and $\mu_A\ (W_i\ )$ is the predicate truth for that domain value.

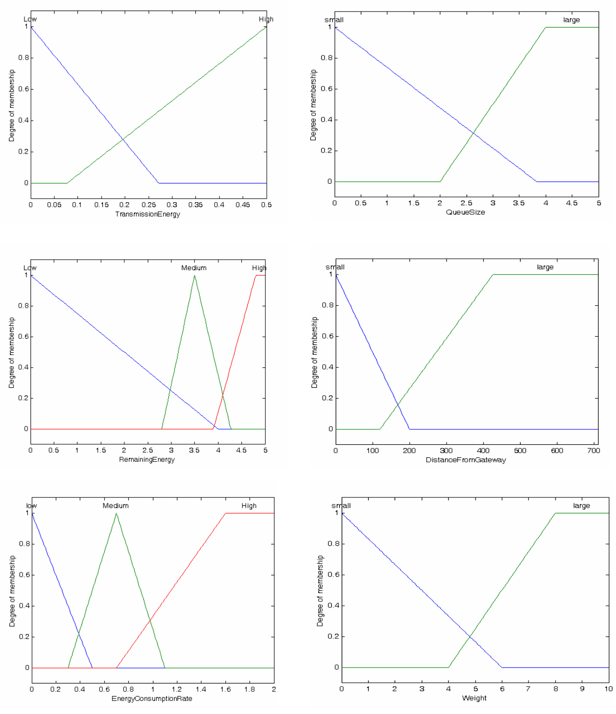

Figure 3. Input fuzzy variables.

Our rule base consists of 144 rules. A few rules are given in Table 1. The rules have been formulated according to the criteria described above.

In Table 1, the input fuzzy variables have been denoted by A, B, C, D, E and F. These represent the input fuzzy variables viz., transmission energy, remaining energy, rate of energy consumption, queue size, distance from gateway and weight respectively. The last column contains the output fuzzy variable i.e., the cost denoted by O.

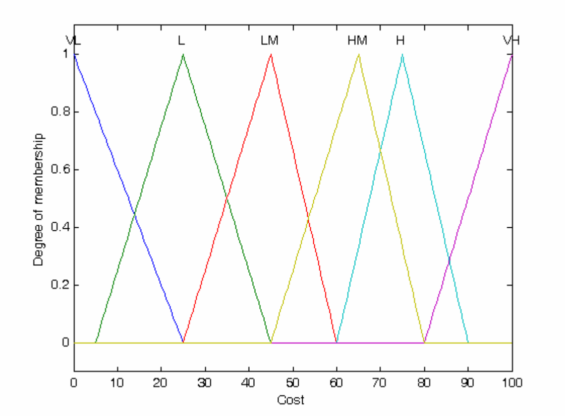

Figure 4. Output fuzzy variable.

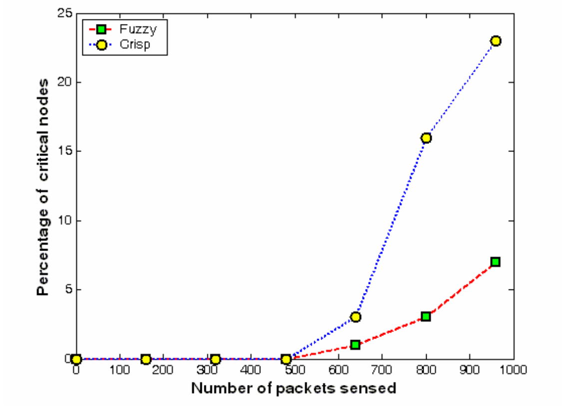

Figure 5. Network lifetime.

## 5. Simulation Results

We have simulated our fuzzy model using Matlab by randomly deploying sensors in an area of 1000m x 1000m. The gateway was positioned at the center. Initial energy and buffer capacity of each sensor node have been taken as 5 joules and 5 packets respectively. Eighty percent of the sensor nodes have been taken to be initially in the sensing state. A node has been assumed to stop sensing when its energy level drops to zero. Simulation was run for 960 sensed packets, the size of each packet being 10k bits.

For comparison with the crisp approach, the same scenario was simulated using non-fuzzy/crisp variables. The link cost is again determined on the basis of percentage of remaining energy of each node. Consequently, the routes are selected so as to avoid nodes with low remaining energy, thereby extending the lifetime of the sensor network. Figures 5, 6 and 7 show simulation results. We have considered a node to be in critical state if its remaining energy becomes less than 40% of its initial energy. In Figure 5, it can be seen that fuzzy performs better than the crisp approach as the percentage of critical nodes is significantly lower as compared to the crisp approach.

Another metric that we have taken is the least energy that remains with a sensor node. Figure 6 compares the performance of fuzzy vs. crisp approach in terms of the minimum remaining energy at any sensor node against the total packets sensed by the network. Referring Figure 6, the lifetime of an individual node is slightly lesser in the fuzzy approach as compared to the crisp one. This decrease in an individual node's lifetime has been traded off with a much longer network lifetime as shown in Figure 5.

Packet drop percentage is shown in Figure 7. Packets are dropped either due to insufficient buffer capacity at the receiver or because of the lack of energy needed to transmit the packet. Percentage of packets dropped is significantly lower for our fuzzy approach resulting in greater reliability.

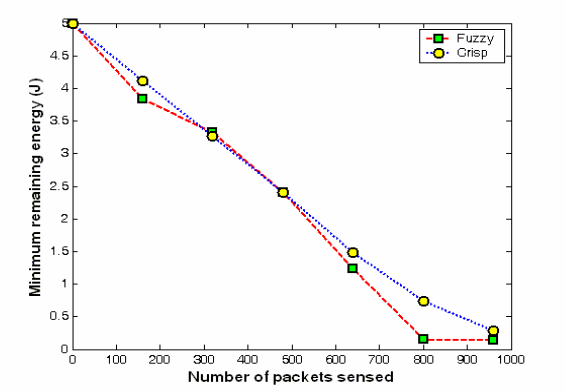

Figure 6. Sensor node lifetime.

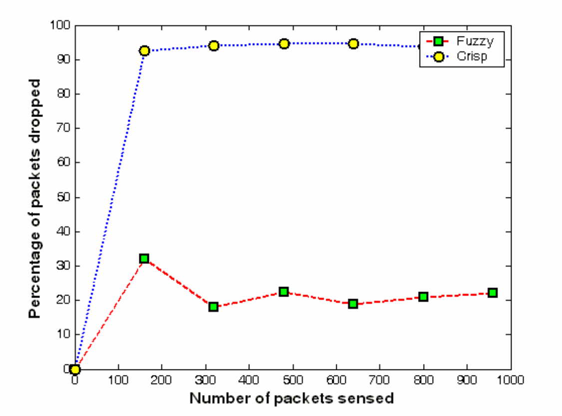

Figure 7. Percentage of packets dropped.

## 6. Conclusions

We have presented a novel fuzzy model for energy-optimized routing in wireless sensor networks. Our simulation results have demonstrated the reliability and efficiency of this approach. Moreover, as fuzzy approach is soft it can be easily tuned for different network and node conditions simply by changing shapes of the fuzzy sets.

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**Tarique Haider** did his BE in electrical engineering from NED University of Engineering and Technology, Karachi, Pakistan and MSc from Illinois Institute of Technology, Chicago, USA in 1991. Since then, he has remained associated with academia and industry.

**Mariam Yusuf** got the BE in computer systems from NED University of Engineering and Technology, Karachi, Pakistan, and MSc in computer engineering from Centre for Advanced Studies in Engineering, Islamabad. She has been associated with the academia and industry for the past ten years.