GAFO: Genetic Adaptive Fuzzy Hop Selection Scheme for Wireless Sensor Networks

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ABSTRACT
Throughput and energy efficiency are two important parameters to evaluate the performance of a Wireless Sensor Network (WSN). For WSNs involved in varying channel conditions, packet transmission reliability can be affected. This results in increased number of retransmissions and therefore energy consumption, with low throughput. Making optimal choices for robust packet transmission in this scenario is vital. For the purpose of this study, we propose a genetic adaptive fuzzy scheme that uses current network conditions in hop node selection. Signal to noise ratio (SNR) and outage probability (Pout) are chosen as input parameters for the proposed scheme, to decide in a distributed manner, the best hop for reliable packet forwarding. Simulation results show the proposed scheme does indeed provide advantages in improving on transmission reliability by 20% and energy efficiency performance by 15%, under different channel conditions.

Categories and Subject Descriptors
C.2.1 [**Network Architecture and Design**]: Wireless communications; C.2.2 [**Network Protocols**]

General Terms
Algorithms.

Keywords
Wireless sensor networks, Fuzzy logic, Genetic algorithms, Energy efficiency.

1. INTRODUCTION
Wireless Sensor Networks (WSNs) have recently become increasingly deployed for both military and civil applications such as threat identification, environmental control, habitat monitoring and patient care [1].

WSNs are distributed systems usually consisting of small and energy constrained sensor nodes. Each node is capable of sensing the data from their environment in a variety of modalities perform simple computations and transmit this wirelessly, often through multiple hops towards a command center or gateway. Nodes however have a limited sensing, computing and wireless communication capability, which is dictated by their energy levels.

The efficient use of energy is therefore crucial for extending the operational life of the overall sensor network. Sensor node energy is mainly consumed in three main activities: sensing, computation and communicating, with communication being the most expensive activity.

Within a static multi-hop WSN, varying channel conditions (sensor mobility) can make the existing point-to-point route invalid before another route must be chosen. The loss of nodes to link instability can cause significant topological changes and reorganization of the network.

Communicating to forward data within varying channel conditions therefore has implications for throughput and energy efficiency since:

- Data packets not received (lost) have to be retransmitted, increasing node energy consumption.
- Retransmissions limit useful data being sent and so decreases overall network throughput.

Making adaptive informed decisions within this scenario on next hop node selection for data forwarding therefore becomes an important issue. Existing proposed routing protocols for WSNs use fixed (crisp) metrics for making hop selection decisions [5][7][13]. This has the disadvantage of not being easily adaptive to changes in the network topology where routing paths (links) can change quite easily.

In this study we propose to apply a genetic adaptive fuzzy hop selection scheme (GAFO) for data forwarding, using both signal to noise ratio (SNR) and outage probability (Pout) as input parameters.

GAFO has the potential to deal with conflicting situations and uncertainty, using heuristic reasoning without needing complex mathematical modeling. The adoption of fuzzy genetic mechanisms [6][12][9] provides a suitable solution for dealing with imprecise input parameters, commonly found in WSN applications as well as for guiding the decision making process. Such a scheme can be applied to hop node selection in varying channel conditions.

From a communication perspective this can also be enhanced by using a cross-layer design approach. In this paper we aim to use information from the physical layer that is processed using our GAFO scheme and shared with the network layer.

Using GAFO in this way offers advantages in disruptive environments since:

- Only a reduced number of nodes (**those with good channel conditions**) will be competing for available bandwidth.
- Encourages opportunistic behavior among nodes.

- Increased chance that transmissions will be successful due to high channel quality. Less retransmission.
- **Energy Efficient**. Nodes with poor link quality can sleep more or not transmit.

By applying the GAFO scheme to the management of node selection, better energy efficiency and transmission reliability performance is expected.

The remainder of this paper is structured as follows. In section II we describe our system model. An overview to the GAFO scheme is given in section III. Simulation results are presented in section IV and section V concludes the paper.

2. SYSTEM MODEL

As shown in figure 1, a sink based architecture offers advantages in that sense data can be aggregated before being sent to a remote command center. Using this setup also allows groups of nodes to be managed by the sink, with nodes having only one destination to forward data to. This can be reached via various routes through multi-hops over sensor nodes in the network.

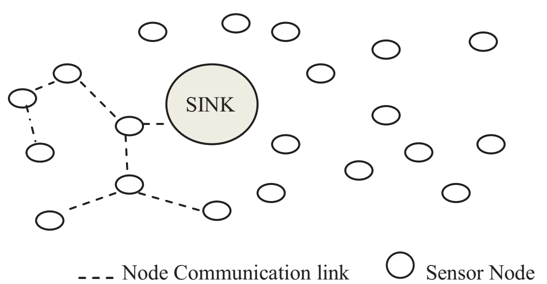

Figure 1. Sink Based Wireless Sensor Network

2.1. Route Discovery and Maintenance

The process of flooding forms the usual mechanism of route discovery and network initialization. The sink initiates the first flood message (FLOOD) by broadcasting to sensors within its communication range. Sensors within the range of the sink rebroadcast the flood message to other sensors within their neighborhood.

Flood messages broadcast by sensors are limited within the neighborhood, to prevent congestion. The sink initiates the flood process again after a certain interval.

Forward routes are maintained through nodes sending data packets (DATA) on a particular link. The reverse routes are maintained by the corresponding acknowledgement packet (ACK) sent from the data receiving node. Both mechanisms serve to reflect the changing state of the network and update the hop selection.

2.2 Wireless Channel

In this study we use the lognormal shadowing path loss model given by [10]:

$$PL\,(d) = PL(d_0) + 10n\log_{10}(d/d_0) + X_\sigma \qquad (1)$$

Where d is the transmitter-receiver distance, d_o a reference distance corresponding to a point in the far field of the antenna, n the path loss exponent (rate at which signal decays) and X_σ a zero mean Gaussian random variable (in dB) with standard deviation σ (shadowing effects).

Given a transmitter power Pt, the SNR at a distance d is:

$$SNR_{dB} = Pt_{dB} - PL(d)_{dB} - Pn_{dB} \qquad (2)$$

The noise floor power Pn_{dB} depends on both the radio and the environment.

Since the path loss model in (1) follows a normal distribution, the Q function maybe used to determine the probability that the received signal level will fall below a particular level. This can be calculated as:

$$Pout = 1 - Q(z) \qquad (3)$$

$$Where, Q(z) = {}^{1}\!/_{2} \times erfc\left(z/\sqrt{2}\right)$$

And z = Pmin – (Pt – PL (d_0) – 10nlog$_{10}$ (d / d_0)) / σ

Pmin is the minimum power level required for a packet to be adequately received, σ the value used in (1) and *erfc* defined as the complementary error function.

2.3 Energy Model

The same energy consumption model is used as in [4][14] for radio hardware dissipation. Energy required for transmitting a k-bit message to a distance d, where n is the path loss exponent is given by:

$$E_{TX}\,(\text{k, d}) = E_{elec} \times k + E_{amp} \times k \times d^n \qquad (4)$$

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

$$E_{RX}\,(k) = E_{elec} \times k \qquad (5)$$

Total energy consumed for a sensor node is (4) + (5). The electronics energy, E_{elec} depends on factors such as coding, modulation, pulse shaping and matched filtering. The amplifier energy, $E_{amp} \times k \times d^n$, depends on the distance to the receiver and the acceptable bit error rate.

3. GAFO ALGORITHM

Figure 2 shows the structure of our GAFO algorithm. Rules form the heart of the algorithm and are usually provided by experts or extracted from numerical data. Rules used in GAFO are expressed as a collection of IF-THEN statements, forming the rule base. The IF-part of a rule is its *antecedent* and the THEN-part of a rule is its *consequent*.

In our GAFO algorithm, rules are setup for adjusting hop node selection based on the following two antecedents:

1) **Antecedent 1**. SNR (A measure of channel condition / link quality).
2) **Antecedent 2**. Pout (Grade of service).

The rule base relates the received current network condition values (input fuzzy variables) with the consequents (output fuzzy variables) using linguistic variables each of which is described by a fuzzy set and fuzzy implication operator AND, OR etc.

The linguistic variables used to represent both SNR and Pout are divided into three levels: *low*, *moderate* and *high*. The consequent, the possibility of this node will be selected for data forwarding is divided into 5 levels, *Very High*, *High*, *Medium*, *Low* and *Very Low*.

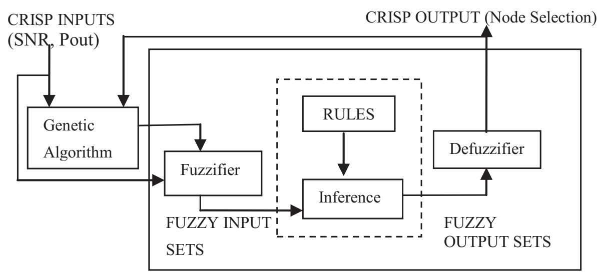

Figure 2. Proposed GAFO Algorithm Structure

We design such rules as:

IF SNR is *high* and Pout is *low*, THEN the possibility for this node being selected is _____.

A desired node to be selected for data forwarding should have a high SNR and low outage probability.
Table 1 summarizes the rules and consequents used in our GAFO algorithm. All the rules are processed in a parallel manner by the inference engine. Any rule that fires contributes to the final crisp output .The nature of the rule base determines how and which consequents are copied to the final crisp output.

Table 1. The Rules and Consequents for Data Forwarding Hop Node Selection

SNR	Pout	Consequent
Low	High	Very Low
Low	Moderate	Low
Low	Low	Medium
Moderate	High	Low
Moderate	Moderate	Medium
Moderate	Low	High
High	High	Medium
High	Moderate	High
High	Low	Very High

The crisp output (weighted average), through *singleton defuzzification* [2] is calculated as follows:

$$\frac{\sum_{i=1}^{n} \mu(k_i) \times k_i}{\sum_{i=1}^{n} \mu(k_i)} \qquad (6)$$

Where n = Number of rules activated, $\mu\ (k_i\ )$ the maximum assigned value of input fuzzy variable activated and k_i the activated singleton rule consequent value.

The crisp output reflects the current status of the network and is shared with the network layer for hop selection purposes.

3.1 Genetic Adaptability

Received current network condition values (SNR, Pout) are made fuzzy by the fuzzification process. We use a common fuzzification process namely *singleton fuzzification* [2]. Fuzziness reflects the degree of uncertainty within our received network condition values. This uncertainty is essentially characterized by the *membership functions* (MFs) shown in figure 3(a) and 3(b). Trapezoidal MFs are used to represent *low* and *high* and triangle MFs to represent *moderate*.

Since the input MFs serve as a representation of the channel dynamics for our inference engine, to improve performance for our GAFO scheme a genetic algorithm is employed to tune the input MF shapes used in the fuzzifier, shown in figure 2, to current received network conditions.

Tuning of MFs can be performed by either using linguistic hedges or adjusting the parameters defining them [10]. GAFO focuses on tuning the parameters defining each MF, thus varying their shape to reflect current received network characteristics and such influencing system performance.

Genetic algorithms themselves are self-tuning search procedures based on the mechanism of natural selection and genetics and don't rely on the characteristics of the considered system. The flow chart describing the genetic algorithm process used in GAFO is shown in figure 4.

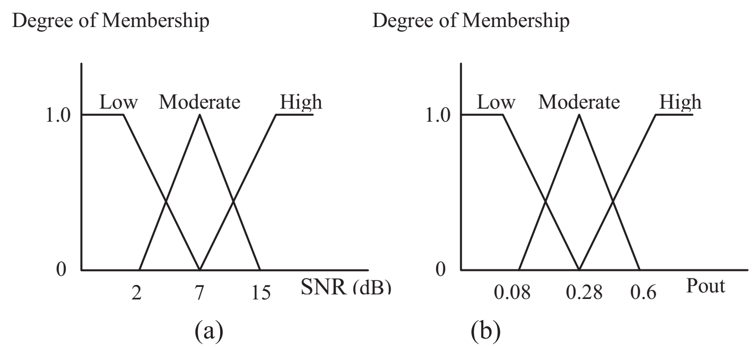

Figure 3. (a) MF for SNR (b) MF for Pout

4. PERFORMANCE EVALUATION

The OMNeT++ network modeler tool was used as our simulation platform.

The simulation region was specified as 400 x 400 meters. 15 sensor nodes were used in the simulation model and randomly placed within the simulation region. A basic non-persistent CSMA technique was used for channel access. Radios are assumed to be in a constant receive state at each node.

The simulation is run for a length of time, in order for results to converge.

Initial results are ignored when the network is in initial stages. Table 2 lists the simulation parameters used for GAFO performance evaluation.

The number of FLOOD broadcast messages, permitted within a sensor neighborhood is set as 4.

Data to be transmitted is generated at the application layer of each node using a Bernoulli trial, with constant probability of success (p) at each trial (data to be sent) set at 0.4.

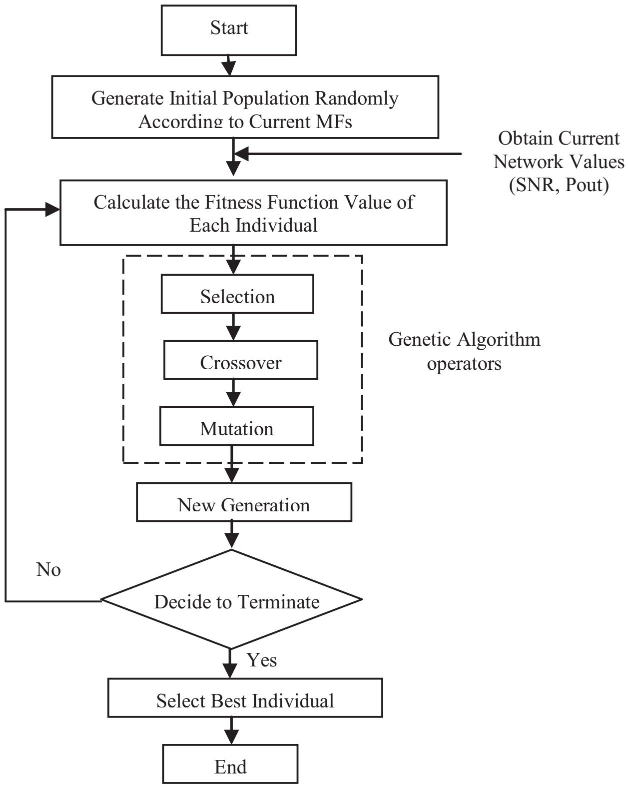

Figure 4. Genetic Algorithm for Searching Optimal Input MF Parameters for GAFO

We define transmission reliability as a success probability calculated as, the total number of data packets received correctly at each node through a corresponding acknowledgement packet, divided by the total number of data packets sent from each node within an interval period.

The total energy consumption of the sensor nodes (equations (4) + (5)) in the network is used to determine whether the FGS scheme is more energy efficient or not.

For each path loss exponent value (Table 2), an average SNR value was calculated for all nodes in the network, within a complete simulation time. This served to give an indication of overall network channel quality. SNR values were computed using equation (2). The same procedure above was also applied for both transmission reliability and total network energy consumption.

The fitness function used for the genetic algorithm (GA) in figure 4, is the well known mean square error (MSE) defined below in (7), where N = number of rules, F (x^l) being the output obtained from the GAFO rule base when the l-th rule is considered and y^l being the known desired output.

$$MSE = \frac{1}{2.N} * \sum_{l=1}^{N} (F(x^l) - y^l)^2 \qquad (7)$$

Parameters adopted for the GA operation have been set as population size of 100, crossover rate of 0.6 and a mutation rate of 0.01. Decision to terminate is based on the number of generations, set at 60. A fitness-proportionate selection method is also adopted.

Table 2. Simulation Parameters Used for GAFO Performance Evaluation

Parameter	Value
Path loss exponents (n)	2, 2.5, 3, 3.5, 4
X_σ (Equation 1)	6-10dB
Receiver noise floor (Equation 2)	-75dBm
Pt (Equation 2)	13dBm
Pmin (Equation 3)	0dBm
E_{elec} (Equation 4 and 5)	50nJ / bit
Message Size	Data (1kbit), FLOOD (200bit) and ACK (200bit)
K_i (Equation 6)	Very High (90) , High (70), Medium (50), Low (30), Very Low (10)

4.1 Performance Comparison

For comparison purposes the GAFO approach is measured against two alternative mechanisms for hop node selection. Firstly a crisp approach using the same network scenario is simulated using non-fuzzy/crisp input SNR values as a mechanism for updating hop node selection. Secondly a non-GA (non-optimized) fuzzy logic system (FLS) is used for hop node selection, applying the same mechanisms and rules described in section 3. Results of this comparison are shown in figures 5 and 6.

From each of figures 5 and 6, using our proposed GAFO scheme approach for determining hop node selection, greatly improves both network energy consumption and transmission reliability performance.

In low SNR channel conditions (-12 to 0 dB) results indicate the GAFO algorithm improves, on average by 6% for transmission reliability and 5% for total energy consumption, when compared with the FLS mechanism.

However in the same conditions the GAFO algorithm outperforms the crisp approach on average by 20% for transmission reliability and 15% for total energy consumption.

Our proposed scheme clearly makes an improvement to network performance at low SNR channel conditions. When channel conditions are good (SNR is high) results indicate that the GAFO algorithm, FLS and crisp schemes are comparable in performance.

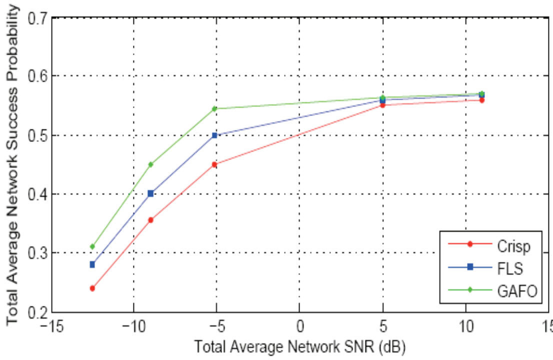

Figure 5. Total Average Network Success Probability

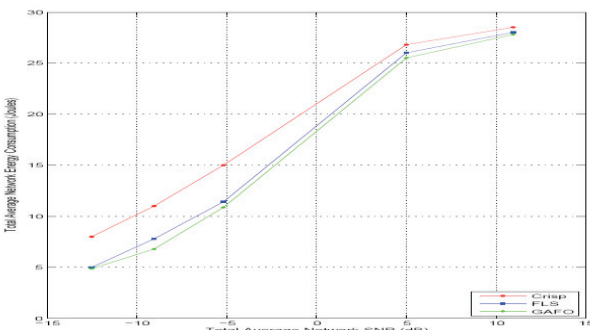

Figure 6. Total Average Network Energy Consumption

5. CONCLUSIONS

In WSNs, channel quality can greatly affect packet transmission. If the SNR is low, the chances of packets being lost increases. For WSNs involved in varying channel conditions packet transmission reliability can be affected. Making optimal choices for robust packet transmission in this scenario is vital.

This paper has proposed a genetic adaptive fuzzy scheme to hop node selection (GAFO).

Simulation results show that this scheme compared to using a crisp and standard non-optimized fuzzy logic approach, can improve a nodes decision making capability and adaptability within a varying channel environment. This improves both transmission reliability and energy efficiency performance.

Our scheme is a fully distributed approach where each sensor only needs to know its network quality state values (SNR and Pout) and apply the GAFO algorithm, for hop node selection.

Future work is still required as to the performance of our scheme in Rican or Raleigh type fading channels. In the future a routing protocol will also be investigated using this scheme or integrated into existing routing protocols, such as content based routing, for improved transmission reliability and performance within varying channel conditions.

6. ACKNOWLEDGEMENTS

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