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Research Article

Design and Development of Energy Efficient Routing Protocol for Wireless Sensor Networks using Fuzzy Logic

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Abstract: Wireless Sensor Networks (WSNs) is a emerging technology of real time embedded systems for a variety of applications. In general, WSNs has great challenges in the factor of limited computation, energy and memory resources. Clustering techniques play a vital role in WSNs to increase the network lifetime and also made energy efficiency. Existing clustering approaches like LEACH uses neighboring information of the nodes for selecting cluster heads and other nodes spent more energy for transmitting data to cluster head. It was not considered the expected residual energy for selecting a cluster head. In this study, Genetic Algorithm (GA) is used to form optimal clusters based on fitness parameters including Cluster Distance (CD), Direct Distance to Base Station (DDBS) and Energy of nodes. Also, fuzzy logic approach is applied to select optimal cluster head by using expected residual energy that increases the network lifetime. The aim of the study is providing a solution for unbalanced energy consumption problem in a WSN. The simulation results show that the proposed protocol performs well than other protocols like LEACH and LEACH_ERE.

Keywords: Cluster head, expected residual energy, fuzzy logic, genetic algorithm, wireless sensor networks

INTRODUCTION

WSNs consist of number of sensor nodes which are low-power and small in size (Akyildiz *et al*., 2002a). These sensor nodes can work as autonomous devices and be deployed in various types of environments. The sensor nodes observe the data (Akyildiz *et al*., 2002b) from environment that changes suddenly in the field and send the observed data to the sink node. The observed environment condition depends on continuous process in which the observed data have a certain correlation. WSNs are the promising technologies in the advances of Micro Electro Mechanical Systems technology in terms of battery power system and Radio Frequency (RF) designs. Smart sensor networks (Warneke *et al*., 2001) with wireless communication mainly used for monitoring health care, military, environment and other strategic applications. The critical application demands variety of equipment such as cameras, acoustic, infrared and measuring physical parameters (Chong and Kumar, 2003). A smart sensors network able to detect various threats that depends the energy efficiency (Bhargava and Zoltowski, 2003; Wood and Stankovic, 2002) of networks. A cooperative communication mechanism offers considerable energy efficiency in WSNs. Effective cooperative communication scheme based on the optimization of QoS provisioning described in Matamoros and Antón-Haro (2010). The objective of this study is developing energy efficient routing protocol by applying both genetic algorithm fuzyy logic. It optimizes the clustering schemes to increase the network life time of WSN.

LITERATURE REVIEW

Lee and Cheng (2012) proposed a fuzzy logic based clustering approach which follows the LEACH approach for increasing network lifetime. Expected or estimated remaining energy is used as a key parameter to select cluster head for evenly distributing the workload in wireless sensor networks. It used the fuzzy inference systems in each node for making computation. They are not considering optimal fuzzy set in clustering cycle including cluster formation phase and data communicating phase.

Anno *et al*. (2008) two fuzzy based systems for selecting cluster head in WSNs. They designed Fuzzy based CH Selection systems which considered three input linguistic parameters such as Remaining Battery Power, Degree of Neighbor Nodes and Distance from Cluster Centroid to found CHs. This system is not applicable for large scale WSNs.

Bagci and Yazici (2010) described a Fuzzy Unequal Clustering Algorithm (EAUCF) to increases

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the network lifetime. EAUCF adjusts the cluster head radius which considers the parameters including residual energy and distance to the base station for decreasing the intra cluster routing overhead. They used fuzzy logic for handling the uncertainties in cluster head radius estimation. EAUCF provides stable energy efficient clustering algorithm in real time WSNs applications.

Xie and Jia (2014) proposed the Compressive Sensing (CS) data transmissions for balancing the traffic load throughout networks. They introduced a clustering method that uses hybrid CS for sensor networks. And also they proposed an analytical model that studies the relationship between the size of clusters and number of transmissions in the hybrid CS method that aims to find the optimal size of clusters which assumed full knowledge of the network topology. Minimum spanning tree technique is used to compute the backbone tree that connects all CHs and the sink to find the optimal size of clusters that can lead to minimum number of transmissions.

Clustering algorithms like K-means and FCM to achieve a better formation of clusters with more uniform distribution of sensor nodes have also been introduced in Hoang *et al*. (2010). Fair CH selection algorithm (Wang *et al*., 2010) takes into account the distances from sensors to a base station that optimally balances the energy consumption among the sensors.

Hoang *et al*. (2014) used harmony search algorithm and Meta heuristic optimization method for selecting CH in real time WSNs. It minimizes the intra cluster distances to optimize the energy distribution. It is suitable to indoor ambient temperature environment. The sensor nodes of clusters perceive the ambient temperature then send the measurement to their CHs. The CHs also performs aggregation then transmit the aggregated data packets to base station.

Wu *et al*. (2012) proposed cooperative communication scheme to balance between the QoS provisioning and the energy efficiency to a clustered WSNs. They characterized the tradeoff by using multi variable optimization problem for improving the network lifetime. An optimal algorithm is applied for making dynamic coalition formation that depends on the best reply with trial opportunity. Works in Kang and Thinh (2012) described a distributed CH selection algorithm that taken distances from sensors to a base station as a metric for balancing the energy consumption optimally. Liao *et al*. (2013) proposed a load balanced clustering algorithm that consider the metrics including sensor's distance and density distribution. It formed stable cluster structure to improve the network life time.

Lindsey and Raghavendra (2002) proposed the PEGASIS clustering protocol, which was an extension of the LEACH approach. The advantage of PEGASIS is in the robustness of node failure compared to LEACH. Hussain *et al*. (2007) used genetic algorithm for obtaining optimum cluster heads and cluster members.

The proposed fitness function uses the parameters including Cluster distance, Distance to Base Station and node's energy. Then fuzzy logic approach is applied to select optimal cluster head by using expected residual energy.

PROPOSED METHODOLOGY

Cluster formation: A Genetic Algorithm methodology is implemented in WSNs. We considered Distance and energy consumption metrics for developing the fitness function because making large numbers of clusters shortens the distance between the sensor member nodes. The genetic algorithm optimizes the clustering schemes that extends the life time of the network through distributed clustering. This algorithm makes a trade of between energy consumption and distance parameter.

Fitness parameters: In WSNs, to transmit a k-bit packet from node i to node j, the weight assignment is performed as follows:

$$w_{ij}(k) = \min\left\lfloor E_i - T_{ij}(k), E_j - R_j(k) \right\rfloor \tag{1}$$

where, E_i is the current energy of node i and T_{ij} (k) is the energy required to transmit a k bit packet from node i to node j. The term R_j (k) denotes energy consumed to receive a k bit packet for node j. Both T_{ij} (k) and R_j (k).

The fitness of a chromosome represents its qualifications on the bases of energy consumption minimization and coverage maximization. Some important fitness parameters are described below.

Direct Distance to Base Station (DDBS): Total direct distance between the all sensor nodes and the base station, denoted by d_i is calculated as below:

$$DDBS = \sum_{i=1}^{m} d_i \tag{2}$$

where, 'm' is the number of nodes. As can be seen from the above formula, energy consumption logically depends on the number of nodes, such that it will be extreme for large WSN. On the other hand, DDBS will be acceptable for smaller networks with a few closely located nodes.

Cluster based Distance (CD): CD is the sum of the distances between CHs and base station, added to the sum of the distances between associated members and their CHs:

$$CD = \left(\sum_{i=1}^{n} \left(\sum_{j-1}^{m} d_{ij} \right) + D_{is} \right) \tag{3}$$

where, 'n' and 'm' are the number of clusters and the corresponding members, respectively. 'd_{ij}' is the distance between a node and its CH and 'D_{is}' is the distance between the CH and the base station. This solution is appropriate for networks with a large number of widely spaced nodes. The cluster distance will be higher, which results in higher energy consumption. The CD should not be too large in order to minimize the energy consumption. Using this measurement, the density of the clusters will be controlled, where density is the number of nodes per cluster. In the following, μ computes the average of the cluster distances, which will be our standard SD formula for computing cluster distance variation:

$$\mu = \frac{\sum_{i=1}^{n} d_c}{n} \quad (4)$$

$$SD = \sqrt{\sum_{i=1}^{n} (\mu - d_c)^2} \quad (5)$$

Fitness function: The fitness parameters are evaluated for a chromosome c_i and a fitness score f_i, then it is calculated as follows:

$$f_i = w_1 \text{ x CD} + w_2 \text{ x DDBS} + w_3 \text{ x SD} \quad (6)$$

where, w_1, w_2 and w_3 are weight factors and are updated as follows:

$$w_c = \frac{w_p + |f_c - f_p|}{i + e^{-f_p}} \quad (7)$$

In Eq. (7) w_c is the current weights and w_p is the previous weights. f_c is the fitness values of the current chromosomes and f_p is the fitness values of previous chromosomes. Each chromosome is calculated by using given fitness criteria. GA based algorithm create clusters at the BS. Each cluster operates based on a TDMA schedule for ensuring activate the sensor's radios when they transmitting a packet of data otherwise they keep their radios off. The next phase Cluster Head election phase which is formed by applying fuzzy logic approach.

Cluster head selection: We proposed optimum fuzzy set approach to elect the cluster head based on three fuzzy descriptors namely expected energy, residual energy and centrality of cluster for making optimum decisions even with uncertainty. We considers the energy dissipated radio model for transmitter or receiver is Eelec = 50 nJ/bit, the energy dissipation of the transmission amplifier is amp = 100 pJ/bit/m^2. The energy spent during transmission and reception for a k-bit message to a distance d is given by:

$$ET_x (k, d) = E_{elec} * k + \varepsilon_{amp} * k * d \quad (8)$$

$$ER_x (k) = E_{elec} * k \quad (9)$$

where, ε is the path loss exponent and ε≥2.

In this study, we uses the fuzzy controller consists of four elements such as rule-base, inference mechanism, fuzzification interface and defuzzification interface. A rule-base is a set of If-Then rules contains a fuzzy logic quantification to achieve good control. An inference mechanism emulates the expert's decision making in interpreting and applying knowledge about the best to control the plant. A fuzzification interface converts the controller inputs into information to activate and apply rules. A defuzzification interface converts the conclusions of the inference mechanism into actual inputs for the process.

Algorithm: Optimum fuzzy set.

```
Function optimumfuzzyset (E_residualEnergy, E_expectedEnery);
Initialization:
Linguistic variables: highval, midval, lowval
Membership functions: trapezoidal, triangular
Rule base: set of If-Then rules
Fuzzification:
//Convert crisp input data to fuzzy values
If TH = E_residualEnergy
Input = E_residualEnergy
else
input = EexpectedEnergy
Midlow = midval-lowval;
Highmid = highval-midval;
if (input < = lowval) || (input = highval)
        CH_chance = 0;
else
         if (input>midval)
           CH_chance = (highval - input) /highmid;
         else
              if (input == midval)
                CH_chance =1.0;
         else
              CH_chance = (input - lowval) /midlow;
return CH_chance;
Inference:
   Evaluate the rules from rule base
   Combine the outputs of each rule
Defuzzification:
  Convert the output data into non fuzzification values
End Function
```

This member function gives the relative membership of an input with a maximum of 1.0. In this study, we considers three linguistic variables for fuzzy set including high, medium and low. The input variables like residual energy $EE_{residual}$ and the expected residual energy $ER_{expResidual}$ shown in Fig. 1. Figure 2a and b describes two membership functions namely trapezoidal membership function and triangular

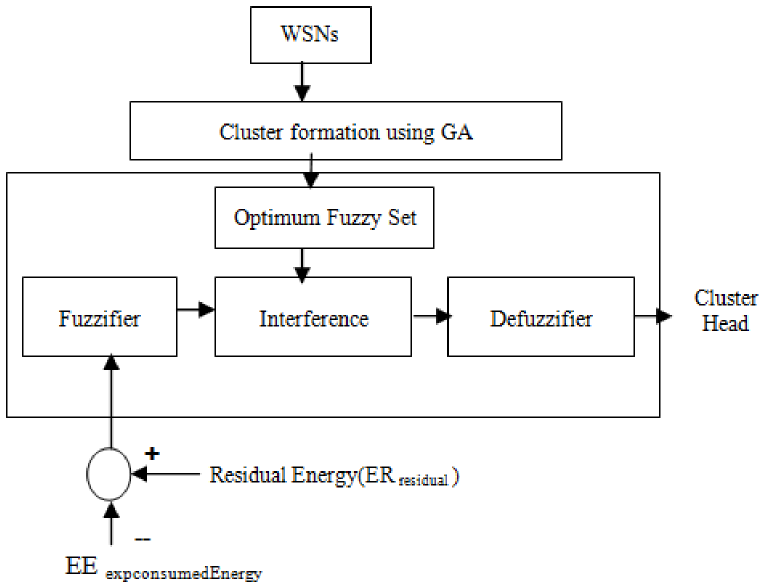

Fig. 1: Block diagram of cluster head selection using fuzzy approach

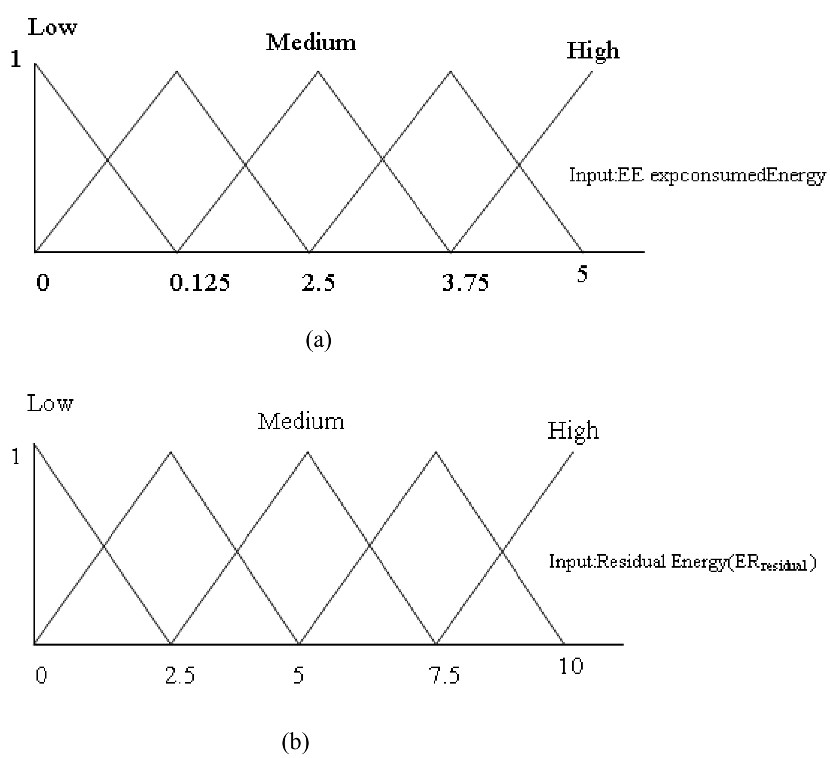

Fig. 2: (a) Residual energy (b) expected residual energy

membership function. It used to describe linguistic variables like high, low and medium respectively. Linguistic variables provide optimum set and also it reduce the computation time. The fuzzy mapping rules are shown in Table 1.

The fuzzy based cluster head election approach consists of a setup and maintains phases. Cluster-heads are elected in setup phase by using optimum fuzzy set processing and then the cluster is formed by group of nodes. After the cluster-heads have been elected, it broadcast its cluster head ID for each node in the cluster. In maintain phase, the cluster heads collect the aggregated information and then sends it to the base station. The node with the maximum chance is elected as cluster head. The node with most energy is selected among multiple nodes with maximum chance.

Table 1: Fuzzy mapping rules

Residual energy $ER_{Residual}$	Expected residual energy $EE_{expResidual}$	CH_chance
High	High	High
High	Medium	High
High	Low	Medium
Medium	High	Medium
Medium	Medium	Medium
Medium	Low	Low
Low	High	Medium
Low	Medium	Medium
Low	Low	Low

Table 2: Simulation parameters

Parameter	Value
Number of Nodes (N)	50, 150, 300
Area	200×200 m
Source location	175 m, 175 m
Sink location	20 m, 20 m
Pause time	300 msec
Constant bit rate	1 packet/sec
Packet frame size	30 bytes
Initial energy	2 joules

The CH calculation is evaluated by using fuzzy if-then mapping rules to handle uncertainty. Table 1 shown the 11 fuzzy mapping rules based on the two fuzzy input variables. We are getting the fuzzy variable chance from the fuzzy rules and transformed it into a single crisp number. The center of area method is used for defuzzification to get a CH chance. A node with higher residual energy obtained to become a CH.

RESULTS AND DISCUSSION

Simulation shows that prolong network lifetime in network can be accomplished as selected node as cluster head. We compare our approach with LEACH and LEACH-ERE which shows better solution than the previous approaches. The parameters setting for WSNs are shown in Table 2.

Remaining energy level of network: Figure 3 shows the Remaining energy level of network as a simulation time. As the time an increase, the proposed protocol named as Energy Efficient Routing Protocol for wireless sensor networks using Fuzzy logic (EERP_FUZZY) performs better than both LEACH and LEACH-ERE because genetic approach and fuzzy logic approach is applied to select optimal cluster head by using the expected residual energy. EERP_FUZZY protocol consumed minimal energy for routing and clustering phases. This shows efficient energy balance is achieved by the proposed method that increases the network lifetime.

Packet delivery ratio: The Packet Delivery Ratio of three different approaches is shown in Fig. 4. It shows the proposed method has the minimum delay than other two approaches like LEACH and LEACH-ERE which indicates both energy efficiency and efficient packet transmission. Packets are routed by using multipath routing to avoid network congestion and increases the network lifetime. Figure 5 shows that proposed method has achieved maximum received packets at base station compare to the other two.

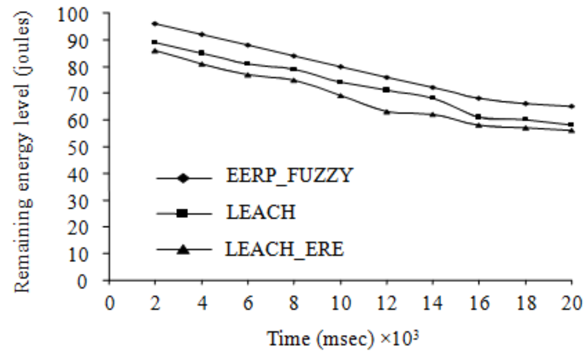

Fig. 3: Remaining energy level of network

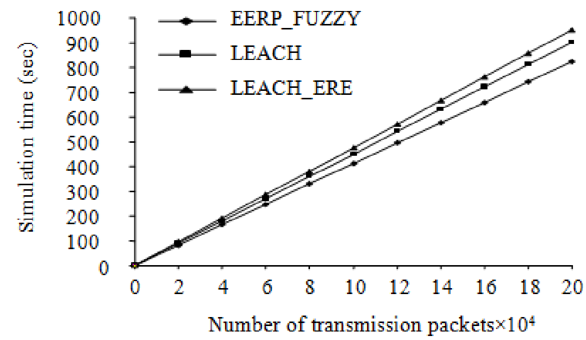

Fig. 4: Packet delivery ratio

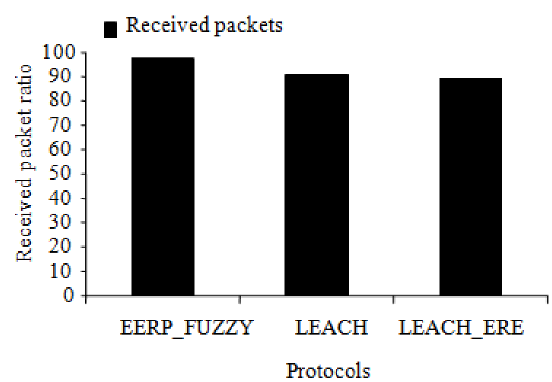

Fig. 5: Received packet ratio

CONCLUSION

We proposed a new algorithm which combined both Fuzzy logic and genetic algorithm for providing a solution for unbalanced energy consumption problem in a WSN. EERP_FUZZY able to select optimal clusters that has highest remaining energy for making efficient route among multiple paths. It rotates the cluster head on the basis of the defuzzified CH chance value for balancing the node's energy. The performance of the EERP_FUZZY is evaluated and compared with the other two protocols including LEACH and LEACH-ERE. Simulation results expressed the efficiency of the EERP_FUZZY for enhancing the lifetime of WSNs.

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