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# AnEfficient Cluster Head Selection Algorithm for Wireless Sensor Networks Using Fuzzy Inference Systems

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**bstract**

An efficient cluster head selection algorithm in wireless sensor networks is proposed in this paper. The implementation of the proposed algorithm can improve energy which allows the structured representation of a network topology. According to the residual energy, number of the neighbors, and the centrality of each node, the algorithm uses Fuzzy Inference Systems to select cluster head. The algorithm not only balances the energy load of all nodes, but also provides a reliable selection of a new cluster head and optimality routing for the whole networks. Simulation results demonstrate that the proposed algorithm effectively increases the accuracy to select a cluster head and prolongs the network lifetime.

*Keywords:* Wireless Sensor Networks; Clustering; Energy; Fuzzy Inference Systems.



## 1. Introduction

Wireless sensor networks (WSN) have become a vibrant and exciting research area in recent years and can be used in many different applications, including battle-field surveillance, home security, smart spaces, environmental monitoring, target tracking, and so on [1], [2].

Sensor nodes in WSN are small battery powered devices with limited energy resources, and their batteries cannot be recharged once the sensor nodes are deployed [3]. Therefore, minimizing energy consumption and correct select cluster head is an important issue in the design of WSN protocols. The centrality cluster head is also the major consideration in designing the routing of the WSN so that it reduces power consumption of each node while sending packets to the network and increasing the network lifetime. Cluster routing is an effective solution in reducing energy consumption and achieving the network scalability [4]. Optimized consumption energy- efficient in clustering routing algorithms has been designed for WSN. LEACH [5] selects cluster heads with some probability. However, some cluster heads may be very close to each other and cannot be uniformly deployed in the networks by probability mechanism. Meanwhile, cluster head numbers are not always equal to the pre-established numbers. PEGASIS [6] organizes sensor nodes into a chain using a greedy algorithm so that each node only communicates with its neighbors. Nevertheless, PEGASIS requires the global knowledge of the network topology and the farther nodes will result in a bigger data delay. HEED [7] introduces a variable known as the cluster radius which is defined as the transmission power to be used for intracluster broadcast. But it is difficult to realize HEED in practical WSN.

In this paper, an efficient cluster head algorithm for wireless sensor networks (ECHA) is presented.

The implementation approach of this work is described as follows. Fuzzy System rules are mapped into Fuzzy Inference Systems for representation the chance of being cluster head for each node. Considering the residual energy, number of neighbors, and centrality of each node and using Fuzzy Inference Systems, cluster heads are selected.

## 2. A Kind of Fuzzy Inference Systems for Structure of a network Topology

Fuzzy sets theory provides a framework to materialize the fuzzy rule-based (or inference) systems which have been applied to many disciplines such as control systems, decision-making and pattern recognition [8]. The fuzzy rule-based system consists of a fuzzification interface, a rule base, a database, a decision-making unit, and finally a defuzzification interface [9]. These five functional blocks are depicted in Fig.1 where the rule base and the database are jointly referred to as the knowledge base.

The function of each block is as follow:

• A rule base containing a number of fuzzy IF-THEN rules.

• A database which defines the membership functions (MF) of the fuzzy sets.

• A fuzzification interface which transforms the input crisp values to input fuzzy values.

•A decision-
aking unit which performs the inference operation on the rules and producing the fuzzy results.

• A defuzzification interface which transforms the fuzzy results of the decision-making unit to the crisp output value.

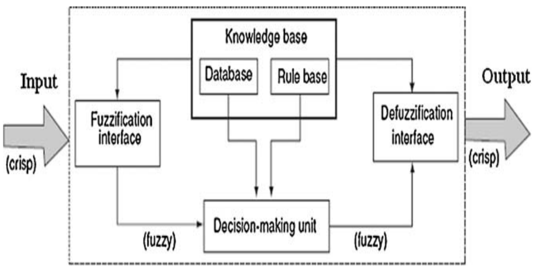


Fig.1. A typical fuzzy inference system (FIS).

In order to perform the inference operation in the fuzzy rule based system, the crisp inputs are firstly converted to the fuzzy values by comparing the input crisp values with the database membership functions. Then IF-THEN fuzzy rules are applied on the input fuzzy values to make consequence of each rule, as the output fuzzy values. The outputs obtained for each rule are aggregated into a single output fuzzy value, using a fuzzy aggregation operator. Finally, defuzzification is utilized to convert the output fuzzy value to the real world value as the output.

Mamdani type is one the most commonly used fuzzy inference method which is employed in this study as well [9]. In this method, Ri as ith IF-THEN linguistic rules is defined by:

$R_i$: IF $x_1$ is $A_{i1}$ and...and $x_r$ is $A_{ir}$ THEN $y$ is $C_i$ ,where $x_j$ ($j$=1,2,...,$r$) are the input variables, $y$ is the output variable, and $A_{ij}$ and $C_i$ are fuzzy sets for $x_j$ and $y$ respectively. Given input of the form: $x_1$ is $A'_1$, $x_2$ is $A'_2$, ..., $x_r$ is $A'_r$. Where $A'_1$, $A'_2$, ..., $A'_r$ are fuzzy subsets of $U_1$, $U_2$, ..., $U_r$, the contribution of rule $R_i$ to Mamdani model's output is a fuzzy set whose membership function is

$$\mu_{C'_i}(y) = (\alpha_{i1} \wedge \alpha_{i2} \wedge ... \wedge \alpha_{in}) \wedge \mu_{C_i}(y) \quad (1)$$

Where $\alpha_i$ is the matching degree of rule $R_i$, and where $\alpha_{ij}$ is the matching degree between $x_j$ and $R_i$'s condition on $x_j$.

$$\alpha_{ij} = \sup(\mu_{A'_j}(x_j) \wedge \mu_{A_{ij}}(x_j)) \quad (2)$$

where ∧ and sup denote the "min" and "supremum" operators, respectively.

The final output of the model is the aggregation of outputs from all rules using the "max" operator as:

$$\mu_C(y) = \max\{\mu_{C'_1}(y), \mu_{C'_2}(y), ..., \mu_{C'_L}(y)\} \quad (3)$$

where L is the number of MF's.

The output $C$ is a fuzzy set. The fuzzy results generated cannot be applied as such, therefore; it is necessary to convert the fuzzy quantities in to crisp quantities for further steps. This can be achieved using defuzzification process. Defuzzification reduces the collection of membership values to a single-valued quantity.

## 3. ECHA: An Efficient Cluster Head selection Algorithm for Wireless Sensor Networks Using FIS

ECHA, like LEACH, constructs clusters at each round to balance all the nodes of energy consumption. Three fuzzy sets and different fuzzy production rules for knowledge representation are considered to get a cluster head election chance. The fuzzy variables that are used in the fuzzy production rules are defined as follows.

1) Residual Energy – the remained energy of each node. The amount of residual energy determines the data that is processed and transmitted, and the node lifetime.

2) Number of Neighbors – number of neighbor nodes of each node. The number of neighbor nodes affects the election of proper cluster head. It is more sensible to select a cluster head in a region where the node has more neighbors.

3) Centrality – the sum of distances

between the node and the nodes which is within its communication range, which represents how central the node is to the cluster. The more central the node is to a cluster head, the more is the energy efficiency for it to transmit the data through that cluster head.

The number of neighbor nodes that a node has is the number of nodes within its communication range. The node centrality is the sum of the squared distances between a node and its neighbor nodes [10]. The above fuzzy linguistic variables are input fuzzy variables for the fuzzy production rules, and the output variable is the node's cluster head election chance. They are defined as follows.

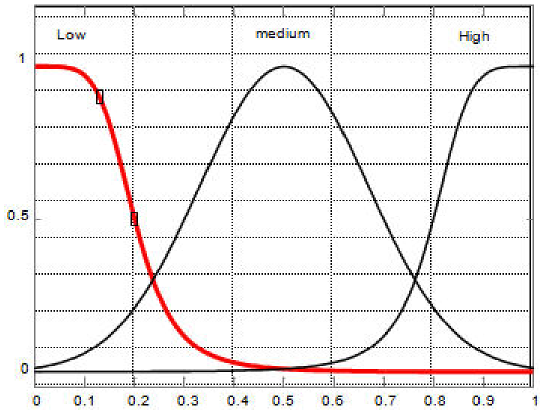

Fig.2. Membership function of the fuzzy input variable "residual energy".

–The fuzzy variable "residual energy" has three fuzzy sets high, medium and low; and its membership function is shown in Fig.2.

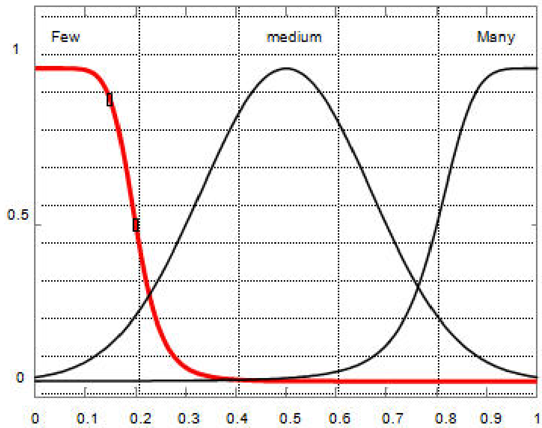

Fig.3. Membership function of the fuzzy variable "number of neighbors".

–The fuzzy variable "number of neighbors" has three fuzzy sets many, medium and few. The possible range of fuzzy quantization is [0.1, 1] for the number of neighbors. The membership function is shown in Fig.3.

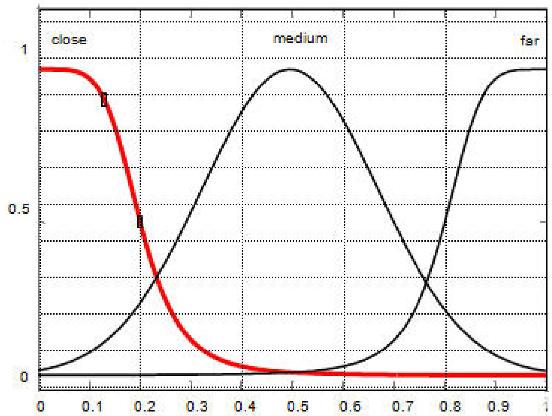

Fig.4. Membership function of the fuzzy input variable "Centrality".

–The fuzzy variable "centrality" has three fuzzy sets far, medium and close; and its membership function is shown in Fig.4.

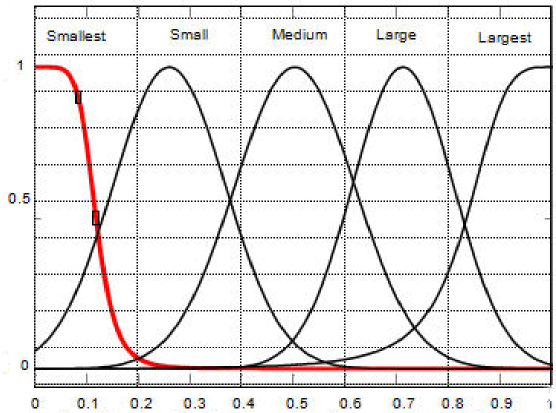

Fig.5. Membership function of the fuzzy output variable "chance".

–The outcome of the node's cluster head election chance has five fuzzy sets -smallest, small, medium, large, and largest; and its membership function is represented in Fig.5.

The chance of a node as a cluster head can be calculated using fuzzy rules; the rules to elect cluster head based on the input of fuzzy system can usually be considered as follows:

1. If (residua_energy is low) and (neighbors # is few) and (centrality is far) then (chance is the smallest)

2. If (residua_energy is medium) and (neighbors # is few) and (centrality is far) then (chance is the smallest)
3. If (residua_energy is high) and (neighbors # is many) and (centrality is close) then (chance is the largest)

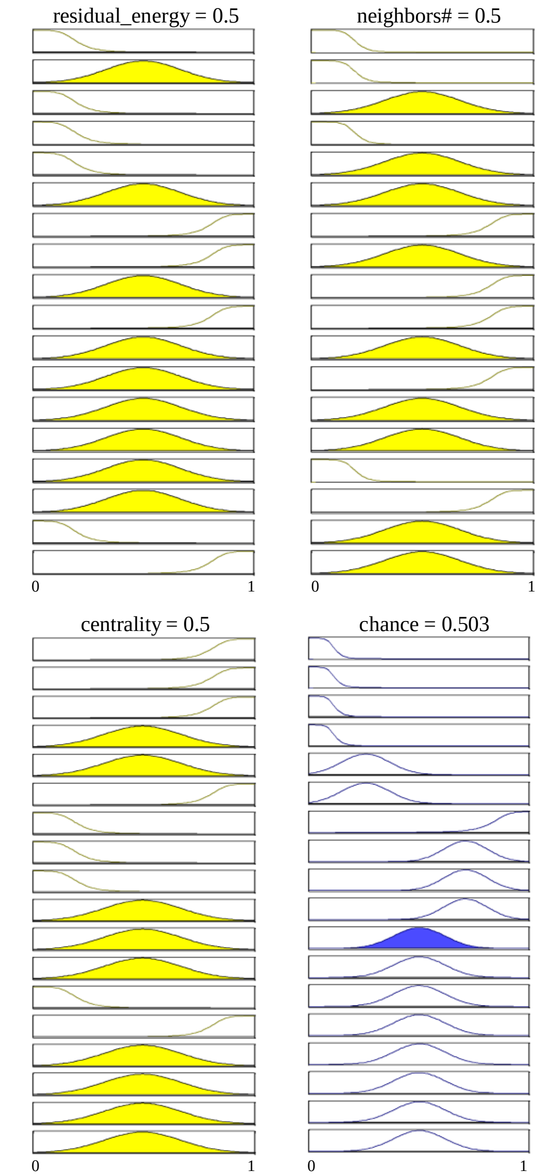


Fig.6. Membership the process of change FIS

The major variables, each with three specific inputs, are fuzzy inference system, using fuzzy rules that can be further defined by rule 27. The processes of a change Inference System to Production chance are shown in Fig.6. The how of change in the input process fuzzy system is characterized by the cluster head. Since the number of neighbors varies between 0.1 and 1 to be considered as accurate, there may be no neighbors. Therefore, we use the following approach for the accurate chance:

In order to identify the nearest neighbors node, we can make use of ($h_s(r) = 2\lambda\pi\, r e^{-\lambda\pi r}$ ($r \geq 0$)). We denote $R$ as critical transmitting range of the node when it's the nearest neighbors node got. We can deduce the probability distribution function of the nearest neighbor's node distance [14].

$$P(r \leq R_{1st}) = \int_0^{R_{1st}} h_1(r)dr = \int_0^{R_{1st}} 2\lambda\pi r e^{-\lambda\pi r^2}\, dr = 1 - e^{-\lambda\pi R_{1st}^2}$$

## 4. Simulation Results

### *A. Network Models*

In this paper, we assume $N$ sensor nodes to be uniformly distributed in an $M \times M\ field$, with the following properties:

1) All the sensor nodes are stationary after the sensors are deployed.
2) A fixed base station is located far away from the sensor nodes.
3) All the sensor nodes are homogeneous and power limited, and they have exclusive identification.
4) All the sensor nodes are equipped with power control capabilities to vary their transmitted power, and they are time synchronous.
5) The communication link is symmetrical. The nodes can estimate the distance between the transmitter and receiver by the received signal strength indication (RSSI) [3].

### *B. Simulation and Analysis*

A wireless sensor network is considered with N=100 nodes randomly and uniformly distributed in a $100m \times 100m$ area.

According to changes in the distance and number of neighbors, the constant radius r is obtained in accordance with Section 3. Consequently, the implementation of our proposed algorithm, to explore cluster heads in two phases by changing the radius and implementation 1500 round, for the cluster heads in two-dimensional space reliable and efficient results will be gained. (See Figures 7, 8 & 9).

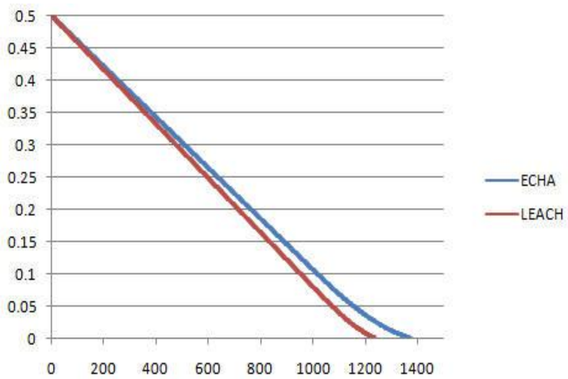

Fig.7. Membership function of the fuzzy variable “residual energy”.

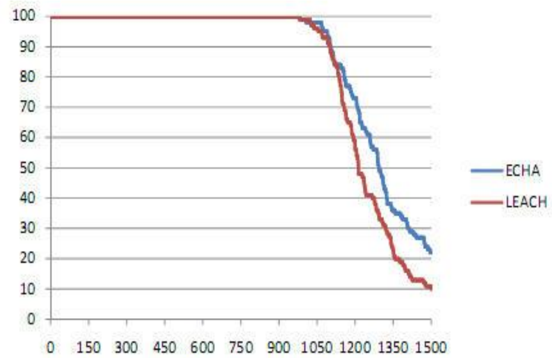


Fig.8. Number of nodes alive over time of ECHA

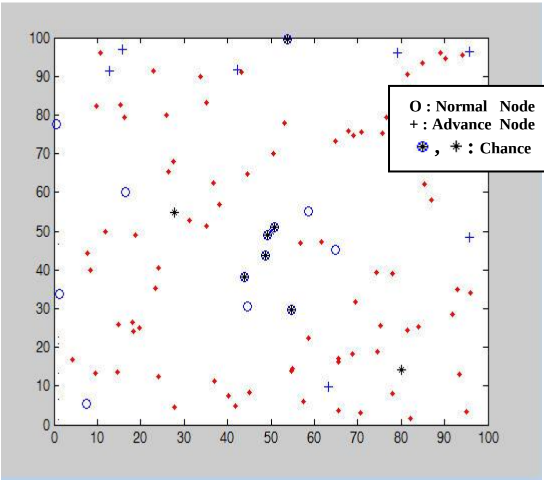


Fig.9. Simulation in progress

As it is indicated in Fig.7, during the ECHA algorithms reduce both the energy consumption by 20% and the residual energy in the nodes. On the other hand, they increase the network lifetime. The proposed algorithm can be seen in Fig.8, in which live nodes are 22% more than the algorithm LEACH which demonstrates a 12% improvement. By selecting a suitable cluster head at runtime and during the simulation we can increase the lifetime of network and reduce the energy consumption. So the reliability of the proposed algorithm is perspicuous.

## 5. Conclusion

In this paper, an Efficient Cluster Head selection Algorithm has been proposed as one of the effective solutions to enhance energy efficiency and scalability of wireless sensor networks. The algorithm employs Fuzzy Inference systems to select cluster heads by the multi-criteria including residual energy, number of neighbors, and centrality. Simulation results show that the algorithm can effectively increase the accurate selection of a cluster head and can prolong the network lifetime. Furthermore, the simulation results confirm that the proposed algorithm reduces the energy consumption of nodes and prolongs the network lifetime.

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