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CALAFL : Clustering Algorithm based on Learning Automata and Fuzzy Logic for wireless Sensor Networks

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Abstract: Wireless Sensor Networks (WSNs) consist of many low energy devices called Sensor Nodes (SNs) which sense and transfer the data to remote controller which is called Base Stations (BSs). They are typically deployed in abandoned environment and are limited in communication and computing power; it is not easy or economical to replace or charge the batteries. In order to operate independently, the sensor nodes should be capable of healing and equipping to a built-in intelligence. An area which has been studied greatly in this field is Energy efficient clustering which is a well-known optimization problem to extend the lifetime of wireless sensor networks (WSNs). In this paper, we propose a new Clustering Algorithm based on Learning Automata and Fuzzy Logic (CALAFL) scheme for WSNs which uses fuzzy logic to select appropriate cluster heads and learning automata to maintain appropriate cluster head. The performance of the proposed scheme is validated using the extensive simulation. The results indicate that the proposed scheme operates better than the existing schemes.

Keywords: Wireless Sensor Network, Clustering, Learning automata, Fuzzy logic.

1. Introduction

Wireless Sensor Networks (WSNs) are used in various applications: environment monitoring, military operations, target tracking and surveillance system, vehicle motion control, earthquake detection, patient monitoring systems, pollution control system, etc. The networks consist of SNs which can monitor and process data from a one geographical area and send the same data to a remote area which is called Base Station (BS). WSNs typically consist of small, economical, resource constrained devices that inter-communicate via a multi-hop wireless communication. Nodes in WSN, which are normally operated via battery, are called SNs, and comprise embedded processors, a sensor limited memory, and a low-power radio. Function of an SN is to sense a desired event locally and relay a remote event sensed by other SNs, thus the event will be reported to destination through BS. Due to energy limitations in them, authorities supposed to find optimum designs for applications and protocols of WSNs to optimize energy consumption and prolong network`s lifetime [1].

First, SNs collect the data, then transfer them in a hop which is carried out via hop manner to the remote locations where Base Station (BS) is deployed. Due to engaging in various communications between the nodes of the network, so much energy is wasted in such mechanisms. A novel mechanism can remove energy consumption issue in WSNs which can save energy through self-healing features. The main concern in WSNs is restrictions related to power demands including batteries. In many cases it is not practicable to replace sensor nodes when they end energy sources. Therefore, energy consumption for the sensor nodes is the most challenging issue for the long run operation of WSNs [2, 3].

Clustering of SNs has been widely used for performing various operations in WSNs in an efficient manner [4-7]. Regarding issues such as density, remaining energy, coverage and connectivity, we divided the area under investigation into various clusters. Between the nodes of the network, some of them may be selected as cluster heads (CHs) and the remaining represented as non CHs. The CHs monitor and transmit the data to BS in a specific region. The remaining non CHs nodes transmit the gathered information to their respective CH. This process will save a lot of energy as all the nodes need not to remain in contact with the BS all the time.

It has been found in literature that LA can be used to solve a wide variety of applications [8–12]. This is an optimization technique which utilizes the issue of learning according to the input parameters and creates an output, in other words, an adaptive learning technique with a decision making machine which can be improved by learning from its environment in order to choose the optimal action. The automaton is assumed to be deployed on CHs for capturing the information from the environment and then adaptively selects the operation to be performed. There is reward and penalty for actions taken by the automaton, automaton decides about coming action based on the inputs gathered from the environment. The automaton deployed on SNs, interconnect with each other and share their own prominent data. The automaton, after a few stages, converges into a particular value which is taken as the solution to a particular problem.

Fuzzy logic as a great problem solving control system methodologies, among the other clustering techniques inWSNs, provides a simple way to reach a definite conclusion with imprecise, non-numerical, noisy, or missing input information. Fuzzy logic uses heuristic knowledge and human reasoning to deal with contradictory situations and imprecise data.

Keeping in view of the above, in this paper we propose a new Clustering Algorithm based Learning Automata and Fuzzy Logic (CALAFL).

2. Related Work

A number of clustering algorithms [4-7] have been developed for WSN. LEACH [13] is a well-known clustering technique that forms clusters through distributed approach. However, this method has certain limitations First, a node with very low energy may be selected as a CH; second, the CHs use single-hop communication to send the data directly to the base station. As a result, they consume more energy. Therefore, a large number of improved algorithms have been developed over LEACH such as LEACH-G [14], DECHA [15], LEACH-SM [16], BSDCH [17], etc.

Abdellah et al. [18] proposed Advanced LEACH (A-LEACH) which is a heterogeneous-energy protocol. A-LEACH decreases the probability of failure of nodes and increase the stability period. In order to increase the life time of the network effectively, the selected CH transmits the received data from the CMs to the sink via gateways then reduces the energy consumption and failure probability of CHs. Chen et al. [14] proposed LEACH-G. This protocol originated from is LEACH protocol and its structural differences in the phase of clustering. Operation of the method is based on network congestion and it is necessary to select an appropriate cluster head, but there are fixed numbers of nodes as cluster heads in the basic protocol.

Although all of the above proposals have used various techniques for different levels of clustering to save energy, they lack any learning and self-healing mechanisms at SNs. Based on research findings, in order to find the optimal solution within the specified constraints, LA-based techniques work well and converge rapidly to solve various engineering applications [8–12]. Esnaashari et al. [8] have proposed a strategy which guides the movements of SNs within the area of the network without any sensor to get its position or its relative distance to other sensors. The same authors [9] have proposed LA-based scheduling algorithm to solve the network coverage problem in WSNs. The function of automaton in the proposed scheme is to learn the sleeping time of the node by knowing exactly the movement of the target points. Torkestani et al. [10], using LA, have described the mobility pattern of the nodes which can also be used in the construction of multicast tree. Also they have proposed LA-based sampling algorithm to solve the minimum spanning tree problem in stochastic graphs [11]. Kumar ea al. [12] proposed a clustering algorithm based on cellular learning automata, in which the study area is divided into cells including cluster heads and nodes. In this paper a solution is presented to cover the connection of nodes and cluster head selection.

In addition, there are some techniques that have used fuzzy logic for clustering in WSN. In [19] the fuzzy logic system is executed by the nodes locally for cluster head selection. In [20], the authors proposed a distributed dynamic clustering protocol that uses fuzzy logic technique to select root node. In this protocol, remaining energy is criteria for selection of tentative cluster heads with a non-probabilistic fashion and cluster head selections are performed sporadically. In [21], battery level, two parameters including node density and distance to base station are used by the base station to run fuzzy logic system. In [22], base station collects the data and runs fuzzy logic engine centrally to form clusters. In [23],cluster heads selected by fuzzy logic engine in a centralized way, clusters formed periodically without considering the requirement of cluster head selection.

3. Overview of Learning Automata

Alearning automaton is an adaptive decision-making unit. In order to improve its performance the unit should learn how to choose the optimal action from a finite set of allowed actions via repeated interactions with a random environment. The action is chosen randomly based on a probability distribution kept over the action-set and at each instant the given action is served as the input to the random environment. The environment responds to the taken action in turn with a reinforcement signal. In order to update the action probability vector, reinforcement feedback from the environment is utilized. The goal of a learning automaton is to find the optimal action from the action set meanwhile, the average penalty received from the environment is minimized [8–12].

Mathematically, LA is defined as _*Q, K, P, δ, ω*_, where $Q = \{q1, q2, \ldots, qn\}$ are the finite set of states of LA, $K = \{k1, k2, \ldots, kn\}$ are the finite set of actions performed by the LA, $P = \{p1, p2, \ldots, pn\}$ are the finite set of response received from the environment, and $\delta : Q \times P \rightarrow Q$ maps the current state and input from the environment to the next state of the automaton and ω is a function which maps the current state and response from the environment to the state of the automaton.

The environment in which the automaton operates can be defined as a triplet _*X, Y, ρ*_, where $X = (X1, X2, \ldots, Xn)$ are finite number of inputs, $Y = (Y1, Y2, \ldots, Yn)$ are values of reinforcement signal, and $\rho = (\rho1, \rho2, \ldots, \rho n)$ are penalty probability associated with each Xi, $1 \le i \le n$. The action of automaton will be either rewarded or penalized based on the actions taken by it, and its action probability vector is updated as follows [8–12]:

$$P_i(n+1) = P_i(n) + a[1 - P_i(n)]$$
$$P_j(n+1) = (1-a)P_j(n) \qquad \forall j \; j \neq i, \; Y = 1$$

$$P_i(n+1) = (1-b)\,P_i(n)$$
$$P_j(n+1) = \frac{b}{r-1} + (1-b)P_j(n) \qquad \forall j \; j \neq i,$$
$$0 < a, b < 1$$
$$, \; Y = 1 \qquad (1)$$

4. System Model

4.1.Network Model

We consider a model which is well suited for these sensor networks. It is based on the similar models used in [13].

(1) All sensor nodes are stationary and deployed randomly, each node has a unique ID.

(2) BS lies on the corner of the network and it is stationary.

(3) All sensor nodes are homogeneous. All nodes are synchronized in time.

(4) Each node has the ability to aggregate data; thus several data packets can be compressed as one packet.

(5) All nodes are of equal energy consumption with a uniform initial energy allocation.

4.2.Energy Model

In this paper we use a radio model for energy which is the same model as discussed by Heinzelman et al.[13]. In this model, regarding the distance between the transmitter and receiver, both the free space and multi-path fading channels are used. When the distance is less than a threshold value d_0, then the free space (fs) model is used, otherwise, the multipath (mp) model is used. Let E_{elec} , ε_{fs} and ε_{mp} be the energy required by the electronics circuit and by the amplifier in free space and multipath respectively. Then the energy required by the radio to transmit an l-bit message over a distance d is given as follows:

$$E_T(l,d) = \begin{cases} lE_{elec} + l\varepsilon_{fs} d^2 for d < d_0 \\ lE_{elec} + l\varepsilon_{mp} d^4 for d \geq d_0 \end{cases} \qquad (2)$$

The energy required by the radio to receive an l-bit message is given by

$$\mathrm{E_R}(l) = lE_{elec} \qquad (3)$$

Various factors including digital coding, modulation, filtering, and spreading of the signal, can affect E_{elec}, whereas the amplifier energy, $\varepsilon_{fs} d^2 / \varepsilon_{mp} d^4$, depends on the distance between the transmitter and the receiver and also on the acceptable bit-error rate. If a node spends energy E_{fusion} to aggregate one bit, then the energy utilized in aggregating m data packets to a single packet is:

$$E_f(m,k) = mkE_{fusion} \qquad (4)$$

5. Proposed Approach

This protocol is adapted from the classic LEACH protocol. The proposed approach focuses on three parameters: the density of the cluster, residual energy and distance to the sink node, in order to balance the energy consumption of network nodes, particularly cluster heads, and to postpone the death of the first network node as much as possible. Therefore, the proposed protocol has three stages which are established in two phases: clustering and steady state. Following stages carried out in proposed protocol orderly:

5.1.Clustering Phase

5.2.Steady-State Phase

5.1.1 The Proposed Clustering Mechanism

In clustering phase, based on LEACH protocol at the beginning, the appropriate cluster head and the number of optimal clusters were calculated:

$$K_{opt} = \sqrt{\frac{N}{2\pi}} \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp} d^4_{toBS} - E_{elec}}} \qquad (5)$$

5 cluster heads assigned based on the above formula appropriately, for 100 sensor nodes in a simulation environment, and the energy model used in LEACH standard. Now, according to the following formula:

$$Member_{opt} = \frac{N}{K} \qquad (6)$$

N represents the number of network nodes, *K* represents the optimal number of cluster heads and $Member_{opt}$ represents the number of optimized cluster members. For these values, $\frac{N}{K} - 1$ corresponds to 19 members, each sensor node introduced as a cluster head.

First, 10 cluster head nodes were assigned after random distribution of the network, contrary to LEACH protocol then, the cluster head node propagation began and each cluster formed its cluster head candidates. At the end of this step, 5 high-density nodes candidates are chosen rather than broadcasting timing phase. Then, clustering phase was carried out for selected candidates of nodes.

The advantage of this method is filtering the cluster head`s node and it may be in appropriate in arandom selection of cluster members. Meanwhile, it prevents aggregation of cluster heads in an area as much as possible. Random selection of cluster heads creates either very crowded or solitary nodes. Hence, the first step is to select 10 cluster head node and then select 5 appropriate cluster head out of them to accomplish filtration operation and prevents heterogeneous clusters as much as possible. We have not selected more than 10 cluster heads since clustering phase and network nodes propagation message are costly, and overall process of the protocol creates a reverse result by increasing the number of candidates, the overall process of protocol, i.e. waste rather than saving energy. The diagram of above process is shown in figure 1.

5.1.2. Selection of the Next Cluster Head

At this stage, a mechanism proposed, based on automata learning, to promote and maintain appropriate cluster head. In this section, an energy-aware protocol called CALAFL, is proposed that utilizes learning algorithm to be maintained as cluster head and used a fuzzy logic to select appropriate cluster head. This results in balancing energy consumption among nodes and increases the overall lifetime of wireless sensor network. In this protocol, after the clustering phase of the first stage described in section 5.1.1, next step is using the proposed formula as automata evaluation function, giving achance to the node to bere-selected as cluster head. Since the phase of cluster heads selection consumes energy at most, our protocol will introduce the best state after the first and second phase. That

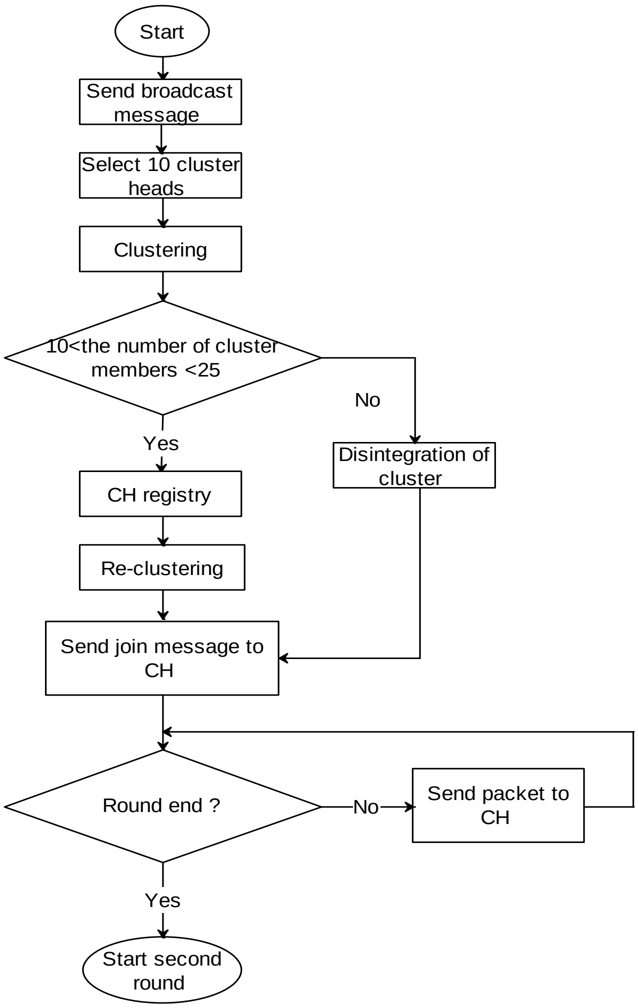

Figure 1: Diagram of Selection Cluster Head.

is, the node will be rewarded if the node`s energy consumption is less than the average of that in the network and again it has a chance to be selected as cluster head. It will be penalized, if the node`s energy consumption is more than the average of it in the network. It means that, penalized node, selected as cluster head once in the cycle, has no other chance.

5.1.2.1. Using LA to Maintain Appropriate Cluster Heads

In this method, based on learning automata, we use a system of automata with fixed operators. A clustering and energy-aware based protocol, called CALAFL, introduced to select appropriate cluster heads and to balance load distribution between the sensor nodes and to balance the energy consumption among nodes and consequently increasing the network lifetime. The performance of this protocol is capability of scheduling technique that uses local data aggregation. The scheduling is accomplished in MAC layer.

The main mechanism of the protocol is defined as determining threshold sensitive energy based on optimum input selection and learning automata. Thus, here we use an energy consumption threshold in order to avoid the burden imposed on a few number of network nodes and to prevent cluster heads to consume energy at once. Also, we try to select cluster heads as learning ones and not to perform clustering phase periodically since it consumes the most energy of nodes. In this protocol, cluster head selection is vital to compute the nodes residual energy. If the node is selected according to the criterion and thresholds for the cluster head, the cluster head is rewarded by LA and no other cluster enters this phase, thus the node remains in the cluster head, unless the automata penalize the desired node and the penalty in this protocol is defined as switching into clustering phase and running LEACH protocol routine.

In the beginning of LA activity, the functions possibility is the same and equals $\frac{1}{r}$(r represents the number of automata actions). The environment, shown with triple E = {α, β, C} of which α represents the inputs of the environment set, β represents outputs and C represents penalty. The environment output (response) to any actionr, is determined by $\beta_i . \beta_{i(n)} = 0$, As unfavorable response or failure, and $\beta_{i(n)} = 1$, intended as a favorable response or success. Here, because our environment is fixed, the amount of penalty and reward probability is constant. In this environment, we use automata to select the best input only. Automata evaluate the environment by its input then selects one of the operations, this process continues until the efficiency is rising and we receive an unfavorable response in next step. As a result automata select an input with respect to the number of inputs.

Our input is as followingα:

$$\alpha = (10 - CH_{UsedEnergy}), \qquad or\ CH_{CurrentEnergy}$$

$$Threshold = (N_{AverageUsedEnergy} = \frac{N_{TotalUsedEnergy}}{Number of Node}) \tag{7}$$

The equation (7) means that, if the average energy consumption of the network exceeds consumption energy of cluster head, the node given will be awarded for being cluster head again. The first stage, input is applied at the environment when the node has been selected as cluster head in a round, and now we check whether it has jurisdiction to be cluster heads again. If it compiles them, once again it becomes cluster heads and clustering phase is not implemented, consequently it improves energy consumption.

Equations (8) and (9) used to determine reward or penalty of selected action. That is, *a* and *b* represent coefficients of reward and penalty respectively. When the action take rewarded, LA update action probability vector using the learning algorithm to the following relations:

- favorable response of the environment ($\beta_{i(n)} = 1$):

$$P_i(n+1) = P_i(n) + a[1 - P_i(n)]$$
$$P_j(n+1) = (1-a)P_j(n)$$
$$\forall j \ j \neq i \quad (8)$$

- unfavorable response of the environment ($\beta_{i(n)} = 0$):

$$P_i(n+1) = (1-b)\ P_i(n)$$
$$P_j(n+1) = \frac{b}{r-1} + (1-b)\ P_j(n)$$
$$\forall j \ j \neq i, a = b = 0.1 \quad (9)$$

We will receive two responses from environment since the selected automata is absolute. $\beta i_{(n)} = 0$ and $\beta i_{(n)} = 1$ represents unfavorable/failure and favorable/success responses respectively.

According to the proposed algorithm, if we receive unfavorable response from the environment, the process of entering the fuzzy function (which is intended as penalty here) will run to select the appropriate cluster heads. If we receive favorable response of the environment, LA function rewards the current cluster head and according to the proposed algorithm it has a chance to be selected as cluster head in next round. The diagram of above process is described in Figure 2.

5.1.2.2. The Proposed Fuzzy System

In next step, second inner-round, fuzzy system is proposed to select the appropriate cluster head if the requirements of the automata are not established (as shown in Figure 2). The goal of fuzzy system is to select an appropriate cluster head with the highest residual energy and the minimum distance to the sink node, considered as inputs of fuzzy system. Proposed fuzzy system is used to calculate the cost of the node (NC represents node cost) that is same output. Distance from the sink is calculated by the equation (10) :

$$\Delta_x = \frac{V}{\Delta_t} \quad (10)$$

In equation (10), Δ_x represents distance of the node n to sink, V is a constant parameter represents the signal speed which is light same. But Δ_t parameter equals the difference of the time of sending package and that of received package. In this way, the more Δ_t , the more the distance between transmitter and receiver will be.

Thus, each node in the network will be a particular situation any time originated from two parameters, the remaining energy and distance to the sink. These two parameters will be calculated via equation 11, after logging into proposed fuzzy system and fuzzy operation and compliance with the rules transforming into a fuzzy system output which is regarded as the cost of the node $NC_{(n)}$ as follow:

$$NC(n) = \frac{\sum_{i=1}^{n} U_i \times C_i}{\sum_{i=1}^{n} U_i} \qquad (11)$$

Finally, asensor node will be selected that has the highest amount of NC and it is as the best candidate to assume the role of cluster head node in current inner round. The proposed fuzzy system is designed according to the following figure 3:

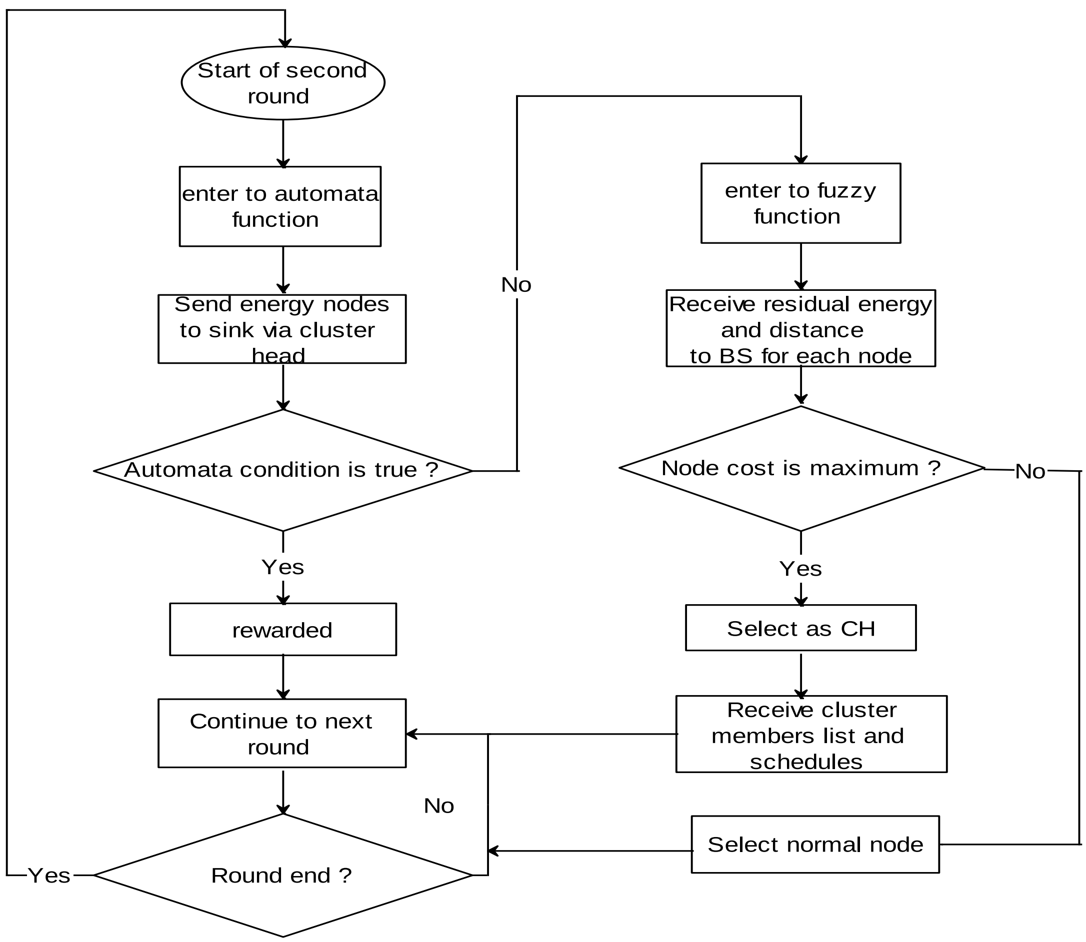

Figure 2: Diagramof the proposed.

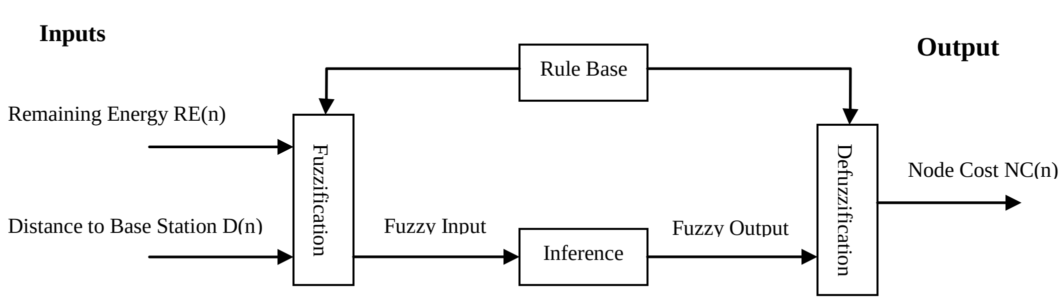

Figure 3:A snapshot of the proposed fuzzy system with two inputs (residual energyand

distance to thesink) and one output (node cost) is designed.

According to proposed fuzzy logic and triangular model, the input parameters of the fuzzy system include a diagram of the triangulation. Regarding the specified same triangles, one can assign a value for a parameter`s behavior on variables of x-axis and a value on y-axis.

In figure 4, initial amount of energy of each node in the network assigned 10 jule. This energy can be placed on five levels. : Very High, High, Medium, Low and Very Low. The remaining energy of each sensor node can be placed in one of the levels or in two consecutive levels. The more residual energy is, the higher the selection chance will be as head cluster in next round.

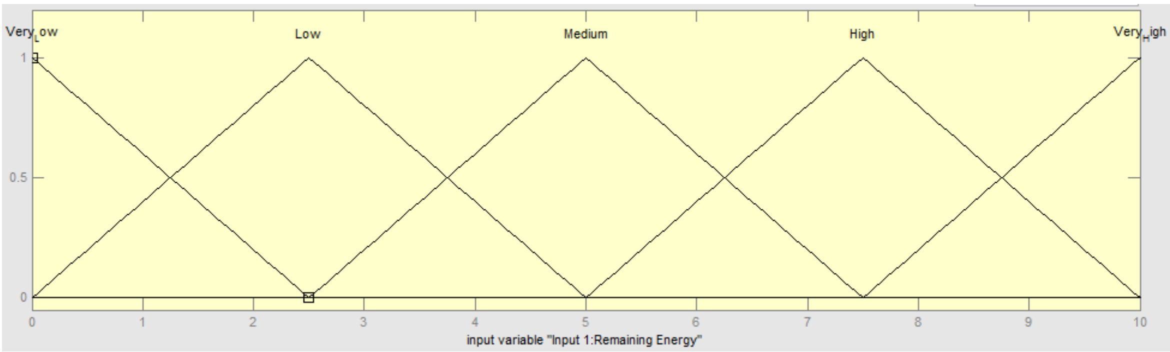

Figure 4: Fuzzy Diagram of the Remaining Energy of Nodes at Different Levels

The second input of proposed fuzzy system is the distance of a sensor node to sink. Due to the static characteristics of the network nodes, this distance assumed constant. For example, in the proposed network, sum of sides` square of network is considered as the maximum distance. Thus, if we implement the network in an environment with of 100 × 100 m, the maximum distance of a node in the network will be diameter of the environment. $\mathrm{Max}_{(D)} = \sqrt{a^2 + b^2}$ , *a* and *b* represent sides of network`s environment. In this network amount of $Max_{(D)}$equals 141.43 meters. At this point we create a proportion distances in order to locate the nodes in 10 units of the x-axis in figure 5. The more the distance of a node to sink is , the low selection priority as cluster head will be in future round.

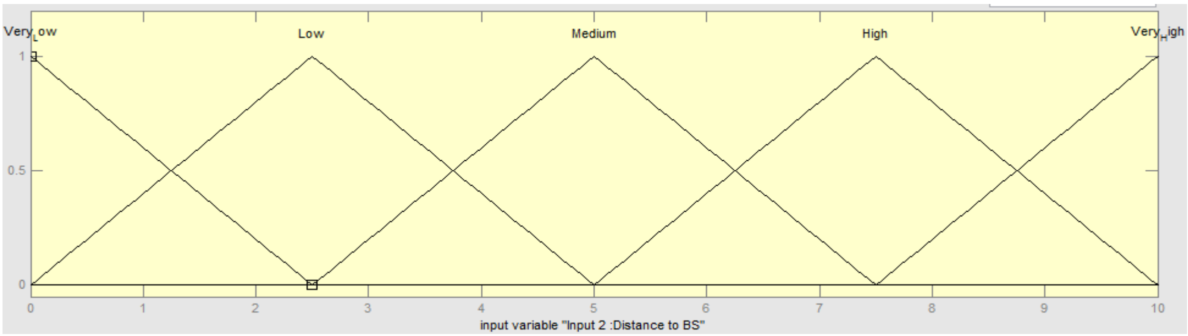

Figure 5: Distance Fuzzy Diagram Nodes at Different Levels

As indicated in relation (11), the input of fuzzy system was integrated in the fuzzy diagram format, then the cost of each sensor node was calculated. In Figure 6 the cost of each sensor node is in the interval [0, 1]. The higher the cost is, the higher selection priority of node will be. Fuzzy system operates for calculating NC (n) acts according to equation (12):

$$NC = \frac{\sum Rule_i \times C_i(NC)}{\sum Rule_i} \quad (12)$$

Cost diagram indicates that, based on fuzzy rules` table, the value obtained of NC (n) is considered in the cost function coefficient. This value will be achieved through the diagram 3. For example, a node with a High fuzzy rule, impact coefficient C_i equals 0.75.

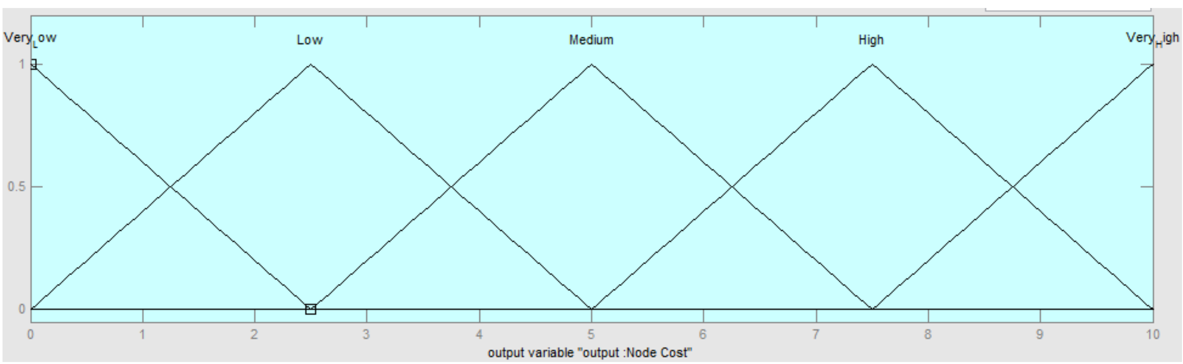

Figure 6: Fuzzy Diagram of Cost Coefficient for Each Sensor Node

We use fuzzy rules in Table1 in the proposed fuzzy system. Total rules are as IF-THEN ones and the relationship betweenthe fuzzy input variables and output variables is described using linguistic variables of them by the fuzzy sets and fuzzy operator concepts. Corresponding table presents the rules that used by $5^2 = 25$ mode, and indicates the fuzzy rule base. These cases are carried out by AND rules. For example, if $RE_{(n)}$ equals Very High and $D_{(n)}$ equals Very Low then the $NC_{(n)}$ equals Very High.

5.2. Steady-State Phase

Table1: The relevant rules to proposed fuzzy Systems.

No	Antecedent		Consequent
	Remaining Energy $RE_{(n)}$	Distance to BS $D_{(n)}$	Node Cost $NC_{(n)}$
1	Very Low	Very Low	Low
2	Very Low	Low	Very Low
3	Very Low	Medium	Very Low
4	Very Low	High	Very Low
5	Very Low	Very High	Very Low
6	Low	Very Low	Medium
7	Low	Low	Medium
8	Low	Medium	Low
9	Low	High	Low
10	Low	Very High	Very Low
11	Medium	Very Low	High
12	Medium	Low	Medium
13	Medium	Medium	Medium
14	Medium	High	Low
15	Medium	Very High	Low
16	High	Very Low	Very High
17	High	Low	High
18	High	Medium	High
19	High	High	Medium
20	High	Very High	Medium
21	Very High	Very Low	Very High
22	Very High	Low	Very High
23	Very High	Medium	Very High
24	Very High	High	High
25	Very High	Very High	High

At steady-state phase, the member nodes collect data and send information to the CH in the scheduled transmission time, and then turn off the radio. Based on the received signal strength of the CH advertisement and the assumption of the symmetrical radio channel, the transmission can use a minimum amount of energy. The CH must keep a working state to receive the information coming from its members. When a frame of data from all the members is received, the CH applies data fusion to aggregate the received data into a single packet. Then the CH sends the aggregated data to the BS directly.

6.Simulation

In order to evaluate the performance of the proposed protocol, we have performed simulation using the ns-2. We compared the performance of the proposed protocol with that of LEACH [13] and LEACH-G [14]. The simulation parameters used in our experiments are shown in Table 2. We have run 25 experiments and result is average of them.

6.1. Simulation Result

In this section, we evaluate the results with Baseline algorithms. The parameters, considered and discussed here, are all dependent on the network energy and we tried to balance the pressure on the cluster head nodes which have a high value, thus, prolonging the death of the first node delay. This parameter, in turn, is directly enhances the lifetime of the sensor network.

Parameter	Value
Electronics energy (E_{elec})	50 nj/bit
Energy for data aggregation (E_{DA})	5 nJ/bit/signal
Communication energy (ε_{fs})	10 pJ/bit/m2
Communication energy (ε_{mp})	0.0013 pJ/bit/m4
Number of nodes (N)	100
Environment dimensions ($M \times M$)	100×100
Initial energy	10 j
Simulation time	100 s
Sink position (X,Y)	(0 , 0)
Number ofcluster heads	5

Table 2: Simulation Parameters.

6.1.1. Network Residual Energy

The remaining energy of network is an appropriate criterion to evaluate the lifetime of the network. However, this parameter depends on the number of packets exchanged on the network. This means that saving energy is acceptable by taking the appropriate number of streams in the network. One can see that, considering other routing tests and further number of routing packets, the network`s energy cost is appropriate in the proposed algorithm (see figure 7).

6.1.2. Death Time of First Node

Figure 8 shows the death time of the first network node. Obviously, the later the death of first node in the network happens, the better the network energy improves. This figure represents the influence of appropriate selection and maintaining of cluster head and the death time delay Of the first node, if it is necessary to replace the cluster head node with the valuable node.

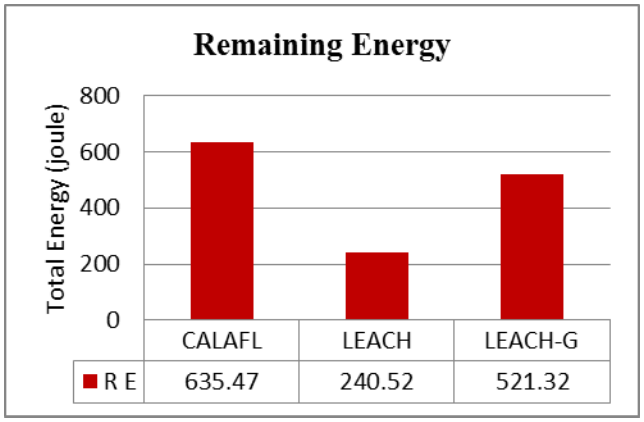

Figure 7: Remaining Energy in the Network

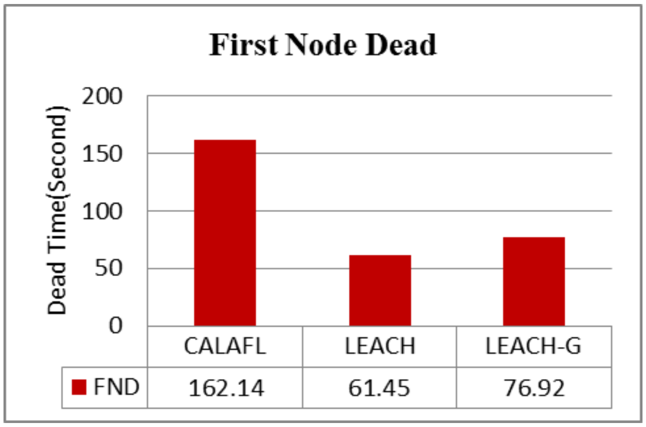

Figure 8: The First Node Dead Time

6.1.3. Number of Alive Nodes

In this test it is seen (see figure 9) that after 100 seconds of simulation time in the proposed algorithm, all network nodes are alive. The first network node dies in 165 seconds. The number of alive nodes in LEACH algorithm after the simulation equals 83 and in LEACH-G equals 92. The proposed algorithm has the same100-node network.

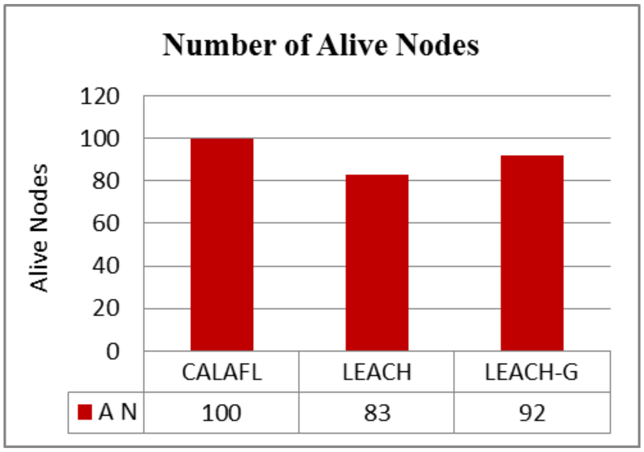

Figure 9: Number of Network Alive Nodes

7. Conclusion

In this paper, we used learning automata and fuzzy logic to reduce energy consumption in wireless sensor network based on clustering. We proposed, an energy-aware cluster head protocol called CALAFL that operates in combination of an innovative approach, learning automata and fuzzy logic to maintain and select the cluster heads in the network. In the proposed method following parameters including: density and population the cluster, maintaining appropriate cluster head and selecting cluster head based on residual energy and distance to the sink were our criterion. Simulation results show that the proposed method operates better than the existing protocols.

References

[1] S. Tyagi, N. Kumar. A systematic review on clustering and routing techniques based upon LEACH protocol for wireless sensor networks. Journal of Network and Computer Applications 36 (2013) 623–645.

[2] A. Giuseppe, C. Marco, D.F. Mario, P. Andera et al., Energy conservation in wireless sensor networks: a survey, Ad Hoc Networks 7 (2009) 537–568.

[3] L. Emanuele, R. Edoardo, A. Andera, B. Alessandro, Energetic sustainability of routing algorithms for energy-harvesting wireless sensor networks, Computer Communication 30 (2007) 2976–2986.

[4] Fuad, B.,&Awan, I. (2011). Adaptive decentralized re-clustering algorithm for wireless sensor networks. Journal of Computer and System Sciences, 77(2), 282–292.

[5] Zhang, Y., Li, K., Gu, H., & Yang, D. Adaptive split and merge clustering algorithm for wireless sensor networks. Procedia Engineering, 29(2012)., 3547–3551.

[6] Khalil, E. A., &Attea, B. A.. Energy aware evolutionary algorithm for dynamic clustering of wireless sensor networks. Swarm and Evolutionary Computation, 1(4)(2011), 195–203.

[7] Lin, C.,Wu, G., Xia, F., Li, M., Yao, L., & Pei, Z.. Energy efficient ant colony algorithms for data aggregation in wireless sensor networks. Journal of Computer and System Sciences, 78(6)(2012), 1686–1702.

[8] Esnaashari, M., & Meybodi, M. R.. A cellular learning automata based deployment strategy for mobile wireless sensor networks. Journal of Parallel and Distributed Computing, 71(7)(2011), 988–1001.

[9] Esnaashari,M., &Meybodi,M. R.. A learning automata based scheduling solution to the dynamic point coverage problem in wireless sensor networks. Computer Networks, 54(14)(2010), 2410–2438.

[10] Torkestani, A. J., &Meybodi, R. M.. Mobility-based multicast routing algorithm for

wireless mobile ad-hoc networks: A learning automata approach. Computer Communication, 33(6)(2010), 721–735.

[11] Torkestani, A. J., &Meybodi, R. M.. Learning automata based algorithms for solving stochastic minimum spanning tree problem. Applied Soft Computing, 11(6)(2011), 4064–4077.

[12] Neeraj Kumar · Jongsung Kim. .ELACCA: Efficient Learning Automata Based Cell Clustering Algorithm for Wireless Sensor Networks. Wireless PersCommun (2013) 73:1495–1512.

[13] Heinzelman, et al., Application specific protocol architecture for wireless microsensor networks, IEEE Transactions on Wireless Communications 1 (4) (2002) 660–670.

[14] Chen, H., Zhang, C., Zong, X., & Wang, C.. LEACH-G: an Optimal Cluster-heads Selection Algorithm based on LEACH. Journal of Software,8(10)(2013), 2660-2667.

[15] Xu, Z., Yin, Y., Wang, J., & Kim, J. U. (2014). A Density-based Energy-efficient Clustering Heterogeneous Algorithm for Wireless Sensor Networks. 4th International Workshop on (pp. 368-372). IEEE.

[16] Bakr, B. A., &Lilien, L. (2011, May). LEACH-SM: A protocol for extending wireless sensor network lifetime by management of spare nodes. In Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks (WiOpt), 2011 International Symposium on (pp. 375-375). IEEE.

[17] Khoshtarash, A., &Noori, M.. BSDCH: New Chain Routing Protocol with Best Selection Double Cluster Head in Wireless Sensor Networks. Wireless Sensor Network, 5(2)(2013).

[18] E. A., S. B., A. B. H., M. Hasnaoui, Advanced low energy adaptive clustering hierarchy, International Journal on Computer Science and Engineering 2 (7) (2010) 2491–2497.

[19] Kim JM, Park SH, Han YJ, Chung TM. CHEF: cluster head election mechanism using fuzzy logic in wireless sensor networks. In: ICACT; 2008. p. 654–9.

[20] Taheri H, Neamatollahi P, Younis OM, Naghibzadeh S, Yaghmaee MH. An energy-aware distributed clustering protocol in wireless sensor networks using fuzzy logic. Ad Hoc Netw 2012;10(7):1469–81.

[21] Kumar SS, Kumar MN, Sheeba VS. Fuzzy logic based energy efficient hierarchical clustering in wireless sensor networks. Int J Res Rev Wirel Sensor Netw 2011;1(4):53–7.

[22] Ando H, Kulla E, Barolli L, Durresi A, Xhafa F, Koyama A (2011). A new fuzzy-based cluster-head selection system for WSNs. In: International conference on complex, intelligent, and software intensive systems.

[23] Taheri M, Kavian YS. Energy efficient clustering algorithm for wireless sensor networks using fuzzy logic. Int J Comp Appl (0975 - 8887) (2014);89(14).

