

Hybridized Fuzzy Based Clustering For Wireless Sensor Networks Based On Cognitive Internet Of Things



S.Suganthi Devi

Abstract- *Wireless sensor network explosive growth has increased demand for radio spectrum and has created problems with spectrum shortage since different wireless services and technologies have already been assigned the full range of wireless sensor networks. Cognitive radio has become a promising solution for resource-controlled wireless sensor network to access the reserved under-used frequency bands resourcefully. Artificial intelligence algorithms allow sensor nodes to avoid crowded congested bands by detecting under utilized licensed bands and to decide to adapt their transmission parameters. However, clusters are based on fixed spectrum distribution and cannot deal with the dynamic spectrum allocation required for future generation networks. Clusters are used to reduce power usage and support scalability of sensor networks. This article proposes an Hybridized Fuzzy Clustering (HFC), which groups adjacent nodes with comparable sets of idle channels and optimally forming power-efficient clusters based on three fuzzy energy parameters, proximity to the base station, and the level of the node to determine the possibility of each node being a cluster head.*

Keywords- *Wireless Sensor Network, Artificial Intelligence Algorithms.*

I. INTRODUCTION

A number of distributed sensor devices are included in the wireless Sensor Network (WSN), which collect environmental or physical data for monitoring the environment in several ways. The sensor nodes in WSN are subject to certain energy supply, bandwidth and computer capacity constraints [1,2]. The constraint of energy supply makes it vital to maintain energy in the sensor nodes to increase network durability. Energy minimisation is, therefore, one of the most important problems in WSN analysis in extending the life of the network [3,4]. The energy consumption of the sensor network can be classified in terms of useful and residual energy [5]. Data transmission and receipt, query processing as well as transmission of inquiries / data to neighboring nodes can contribute to a good energy usage.

Due to overhearing, media idleness, packet collision transmission and control packages generation / processing, leakage power can occur [6,7].

In the WSN direct communication the sensor nodes communicate their information directly to the Base Station (BS) while the entire network split into individual clusters in the cluster-based WSN.

Each node communicates the aggregate information to the desirable BS with its cluster head (CH). WSN clusters can be categorized as a centralized and distributed protocol [8].

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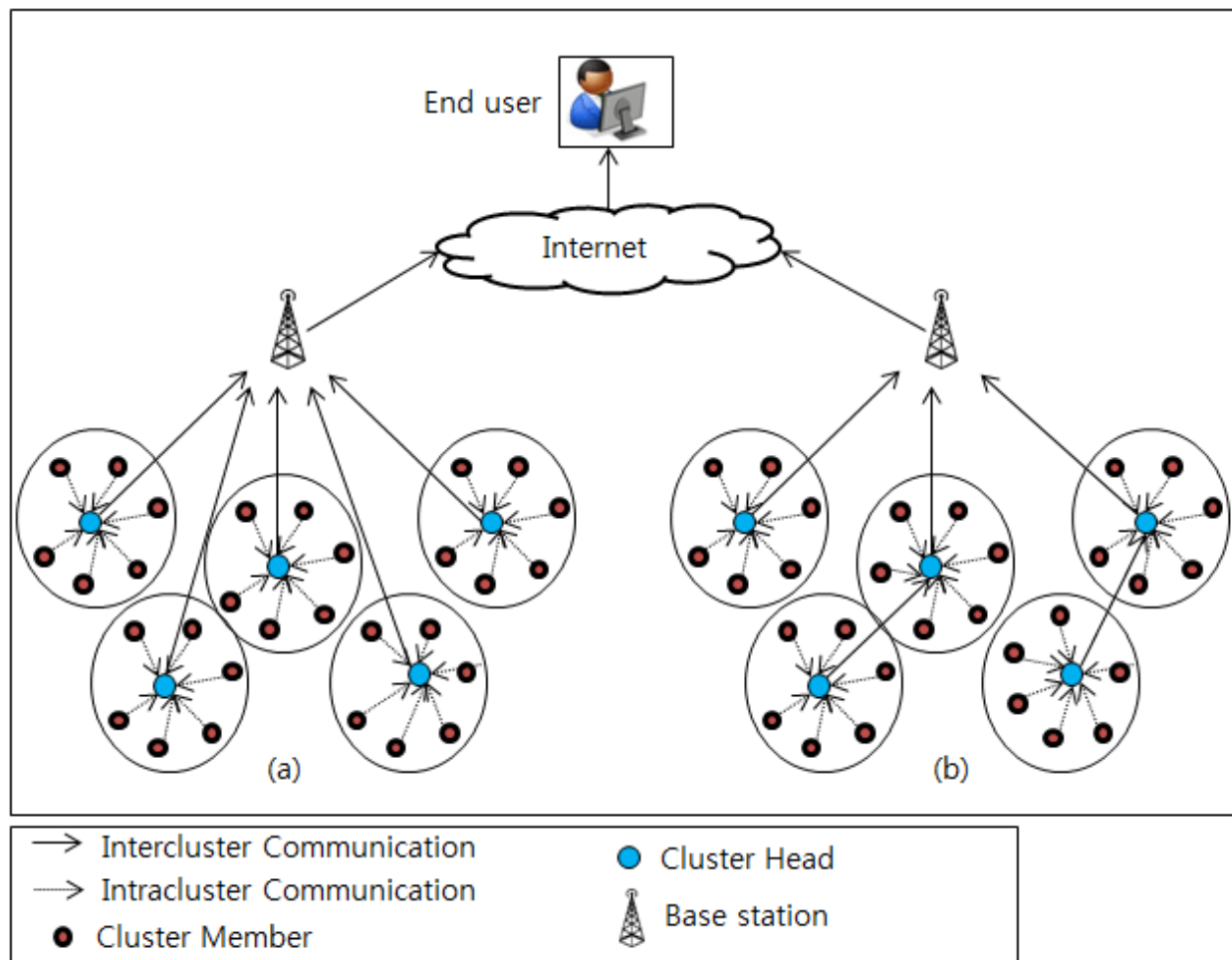


Figure 1. Wireless Sensor Network (WSN) with cluster-based data communication

Centralized methods for large sensor networks are less effective than spread, as all information on a key BS needs energy and time [9-12]. However, a sensor node is a CH or a class member of the clustering algorithm in the distribution method. Clusters are formed permanently during static clustering, while operations are carried out in dynamic protol, clusters are formed for one round and are reformed in the next round in general. Static and dynamic are also classified as clusters. The typical dynamic clustering protocol is the LEACH Protocol, a protocol where the random rotation [13] of the CH takes place to evenly distribute energy dissipation through the network. The most important characteristic is that LEACH is distributed completely and extends the life of the network [14]. It has some disadvantages, too. One of the major LEACH weaknesses is load imbalance, i.e. because the CHs are randomly selected, certain nodes can be selected as close to each other. This states that CHs are not evenly distributed over the network, which limits maximum energy efficiency.

II. LITERATURE SURVEY

One of the most important technologies of wireless sensor networks (WSN) [15] has a wide range of applications, such as health monitoring, smart phones, military devices, disaster management and other surveillance systems. Sensor nodes are often deployed independently in large numbers in harsh environments. These wireless nodes are grouped into energy-efficient communication clusters due to constrained resources, generally battery power. In order to minimize

energy consumption [16], the hierarchical systems of clusters have attained huge interest. Hierarchical plans are usually divided into Cluster-Based and Grid-Based Methods (CBM & GBM). In cluster-based methods, nodes are grouped into clusters where a resourceful sensor node is designated for cluster head (CH), while the network is separated into confined virtual grids normally performed out by base station in a grid-based strategy. This paper shows and discusses the difficulties for the design and classification of cluster-based systems, significant parameters of clustering formation. In addition, existing cluster and grid based techniques are evaluated with a view to selecting appropriate techniques using certain parameters [17].

The clustering of Wireless Sensor Networks (WSNs), is one of the most significant methods for expanding network life [18]. It includes the grouping of sensor nodes and the selection of cluster heads. CHs collect and communicate information for aggregation from the cluster nodes to the core station. In WSNs, selecting suitable cluster headers is a significant challenge. In this article, when selecting heads for clusters [19], we present a fuzzy decision-making approach. In choosing the cluster heads in this paper we present a fuzzy decision-making strategy. Fuzzy's approach for decision-making multiple attributes (MADM) uses three criteria to choose CH's including remaining power, quarter and base station node distance [20].

The simulation findings indicate that this strategy is more efficient when prolonging the life of the network than the distributed Hierarchical Clustering (DHAC) protocol.

Hybridized fuzzy based clustering for wireless sensor networks based on cognitive internet of things

This section presents the proposed hybridized fuzzy based clustering model used for CH selection and a cluster method based on the proposed hybridized fuzzy based clustering model in order to achieve optimal clustering within WSN.

Therefore, they should be combined appropriately for the best decisions. Hybridized fuzzy based clustering is an reliability mechanism in this field. It allows the combination

of all input parameters so as to reflect their effectiveness in choosing CH. Different factors influence CH's choosing in WSN.

For the maximum benefits of fuzzy logic to be achieved for CH elections, factors that affect Choice must be explored, efficient means of evaluating each of these factors used and an effective fuzzy model should be developed that is featured in an effective combination of fuzzy rules and appropriate designs for fuzzy sets. The results should be identified.

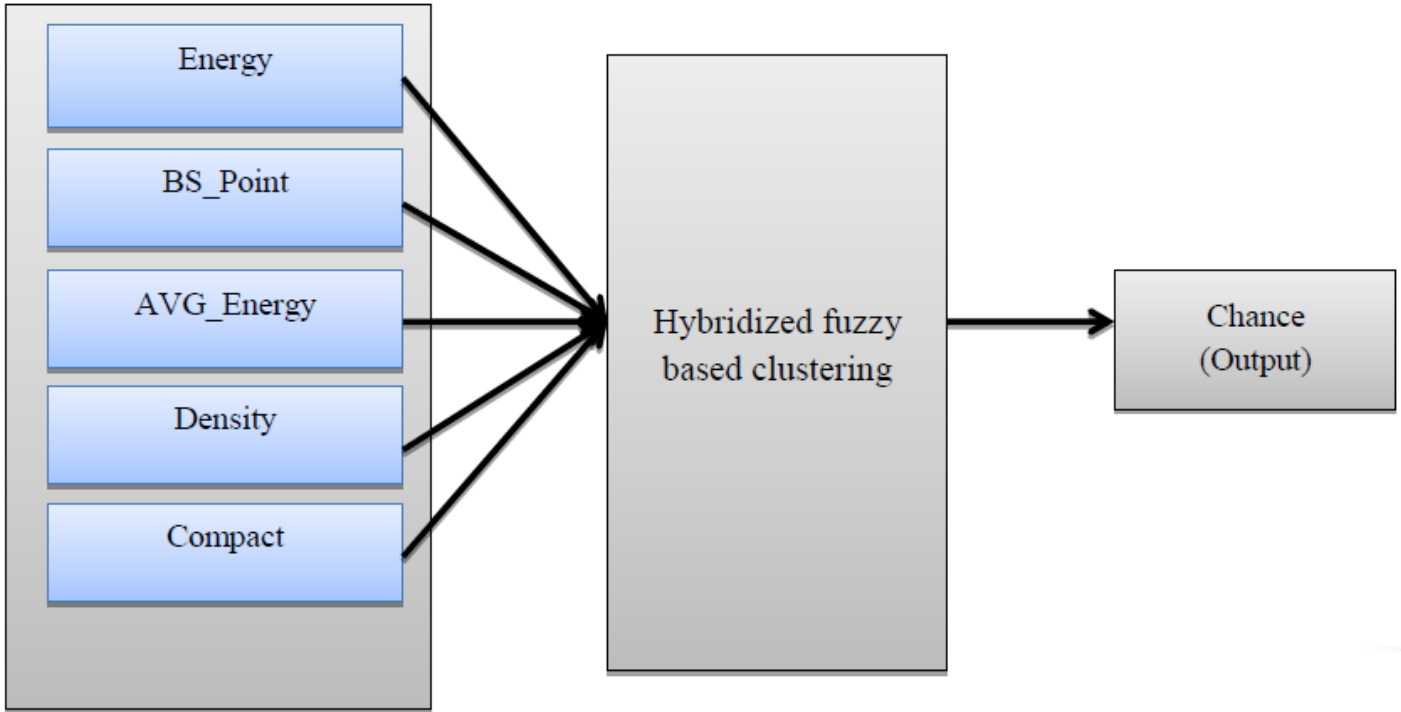


Figure 2. Hybridized fuzzy based clustering model

In this proposed section cloud based client server technology is implemented by using Cognitive Internet of things. Fuzzy based clustering systems for Cloud Internet of Things is described in each and every node pick points and it is randomly determined in the manner 0 to 1. Based on this the threshold equation is given as

$$P(q) = \begin{cases} \frac{s}{1-sy(w \bmod \frac{1}{v})} & \text{if } q \in U \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

The desired node percentage is described as the following $s = \frac{v}{Q}$, here s in the round current given in the equation and U is the nodes that have not been appeared.

After each and every nodes has been broadcasted the desired channels and the nodes have joined together to form a cluster based network. And here the spectrum part is added to every part of the equation and described as

$$A_j(p) = \min \left(V \cdot \frac{d_j}{\sum_{j=1}^m d_j} \right) \quad (2)$$

Here V denotes the each and every cluster heads in the network and the channels of each and every network is determined as d_j and it is noted by j.

The command line characteristic d_j starts as cluster centers, which are meant to mark the area of every cluster. The initial guess for these cluster facilities is most likely wrong. Additionally, d_j assigns each records point a club grade for each cluster.

Suppose when cluster heads does not entering to the probability function the equation is determined as $A_j(p)$

$$A_j(p) = \min \left(\frac{d_j * x_j}{X_p * X_p}, 1 \right) \quad (3)$$

d_j It represents the channels that are entered in the node j and here V represents the cluster in every round. And each and every node are multiplied to the summation part

$$A_j(p) = \min \left(V * Y \frac{d_j * x_j}{X_p * X_p}, 1 \right) \quad (4)$$

Y represents the number of nodes and the nodes that are subjected to higher number of channels that is equal to V. By iteratively updating the cluster facilities and the membership grades for each data point, $A_j(p)$ actions the cluster facilities to the right region within a facts set.

The spectrum equation is determined as

$$BC = \frac{d_j}{n} \quad (5)$$

The numbers of idle channels are represented as d_j and here n denotes the number of total channels and when this equation is entered in to the parameters of the fuzzy based model the radius of the equation is determined as

$$H = \sqrt{\frac{E.F}{\pi.m.a}} \quad (6)$$

This iteration is based on minimizing a goal characteristic that represents the distance from any given information point factor to a cluster center weighted by the way of information factors club grade.

And the dimension of the network is denoted by e and f , m is the number of nodes that are located to the boundary level near to radius H .

$$KL = \frac{\sum_{j=1}^{\#} \sqrt{y_j - \bar{y}} - (x_j - \bar{x})^2}{\# \text{ of neighbouring vector}} \quad (7)$$

KL denotes the lower energy that is consumed by the cluster value and by the intermediate cluster equations and the coordinates are denoted as x_j and y_j and for each and every level it is transmitted to three sets of energy levels.

The energy consumption equation can be determined as

$$[AB(s)]_{db} = [AB(s_0)]_{db} + \beta \log\left(\frac{s}{s_0}\right) + [y_\sigma]_{db} \quad (8)$$

Here the energy consumption is denoted in the values of decibels and it is denoted as in the function of reality and lognormal functions $AB(s_0)$ referred as the loss path at a distance reference to s_0 and the path loss exponent is denoted as β . Gaussian random variable at zero level is denoted as y_σ .

Algorithm for the fuzzy based cluster systems

- 1) Initially get all the inputs from the cluster heads.
- 2) And the process and execute it by using if and else if conditions which will be very helpful to store the data's in the cluster heads.
- 3) Here $d_1 d_2 d_3 d_4 d_5$ be the cluster head data's.
- 4) Check the availability as CH is true or not
- 5) If it is true then CH =0, and the cluster heads will be appeared.
- 6) Else if CH =1 the cluster heads will enter to the probability type.
- 7) If it is a false condition then check for the availability of cluster.
- 8) Then just move for the operation and then goto step 4.
- 9) Else continue to move the operations.

III. RESULTS AND DISCUSSIONS

1. Packet Loss

Packet loss in a Communication varies from the number of generated packets to the number of received packets. Packet Loss is calculated using the AWK script that processes the trace file and results in a graph indicating the amount of loss of the packet at a number of rounds. The graph is plotted on the basis of the trace file. Packet loss may be caused primarily by slow web or bandwidth, simultaneous data recovery, inconsistent jitter which cause packet spacing, or

hardware / software failure. The proposed Hybridized Fuzzy Clustering (HFC) model which have minimum packet loss in comparison with traditional methods such as CBM and GBM, MADM and DHAC. Figure 3 shows the Packet loss of HFC model.

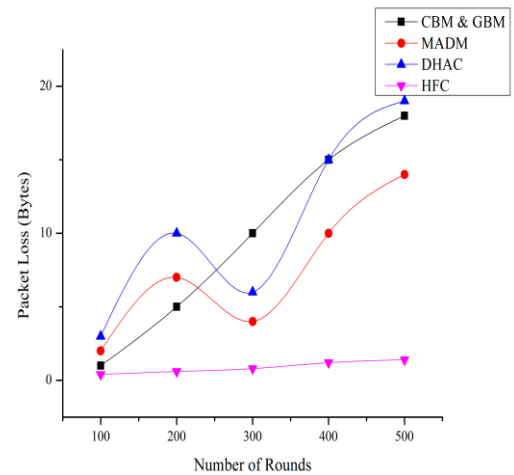


Figure 3. Packet Loss of HFC model

2. Network Lifetime

Routing algorithms create small sized packets called routing packets to stay on the latest data on network routes. Packets are one case and are used to verify if the neighboring node is active. Packets routing does not convey any application content other than what packets do. The proposed Hybridized Fuzzy Clustering (HFC) model which have high network life time in comparison with traditional methods such as CBM and GBM, MADM and DHAC. Figure 4 shows the network life time of HFC model.

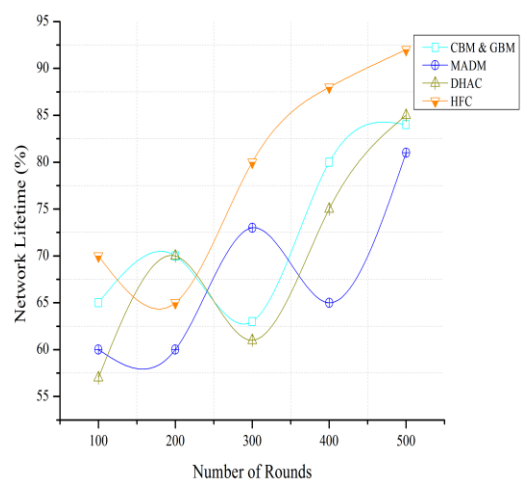


Figure 4. Network Life time of HFC model

3. Energy Consumption

Clustering is one of the techniques used to efficiently utilize network energy. HFC model has proven to be the most efficient hierarchy routing protocol in conventional routing protocols, such as direct transmission, static heretics, etc. HFC model is an organizing protocol for the dynamic clustering, randomization for even distribution of energy across the network.

The proposed Hybridized Fuzzy Clustering (HFC) model which have minimum energy consumption in comparison with traditional methods such as CBM and GBM, MADM and DHAC. Figure 5 shows the minimum energy consumption of HFC model.

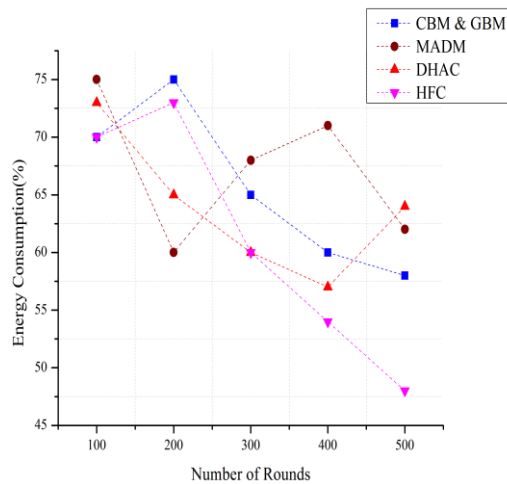


Figure 5. Energy consumption of HFC model

4. Dead nodes

The figure clearly shows the number of dead nodes over time, which is very different from each other, to show the duration of the stability period [21]. It is noted that the proposed procedure clearly offers a longer stability period compared to the others [22]. The proposed Hybridized Fuzzy Clustering (HFC) model which have less number of dead nodes in comparison with traditional methods such as CBM and GBM, MADM and DHAC. Figure 6 shows the number of dead nodes of HFC model.

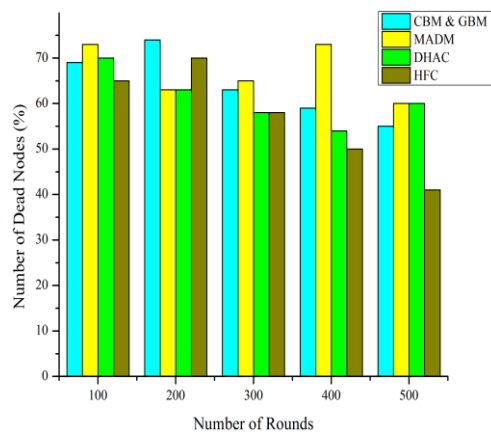


Figure 6. Number of dead nodes of HFC model

5. Alive Nodes

A protocol that performs well and extends the network life and succeeds in providing the most data for the base station, as all criteria have been taken for the optimal choice of CHs [23]. The proposed Hybridized Fuzzy Clustering (HFC) model which have high number of alive nodes in comparison with traditional methods such as CBM and GBM, MADM and DHAC. Figure 7 shows the number of alive nodes of HFC model.

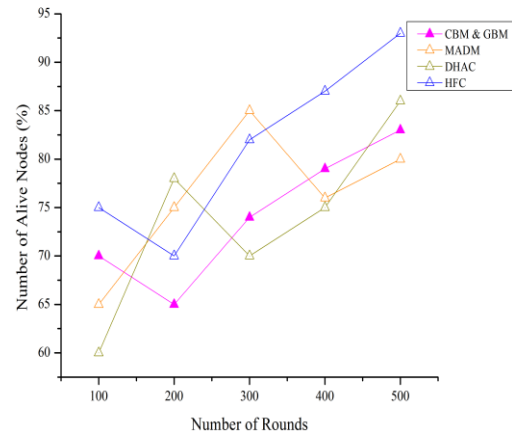


Figure 7. Number of alive nodes of HFC model

IV. CONCLUSION

The results showed clearly that the proposed protocol improved network life on other protocols and also extended network stability, with a substantial improvement in the number of databases delivered to the base station. The proposed protocol further improved efficiency by taking into account several parameters to choose CHs optimally based on three fuzzy parameters: residual energy, node levels and proximity to BS to distribute nodes in clusters equally so as to make energy consumption across the network more diverse. The results indicate that the proposed fuzzy protocol reduced the energy consumption successfully and increased network life. This has made the network's energy optimally balanced and increased the network's stability and life time.

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