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A FUZZY LOGIC BASED CLUSTER HEAD SELECTION ALGORITHM FOR WIRELESS HETEROGENEOUS SENSOR NETWORKS

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Abstract

Clustering is an important technique utilized to prolong the lifetime of a sensor network by reducing energy consumption. Homogeneous clustering techniques assume that all the sensor nodes are equipped with the same amount of energy and have the same capabilities. So, the developed cluster head selection algorithms cannot take sensor node heterogeneity into account. In this paper we propose a new fuzzy logic (FL) based cluster head selection algorithm for heterogeneous wireless sensor networks (HWSNs). The parameters, i.e., data rate, energy level and distance are considered as inputs of the developed FL unit. The proposed algorithm is compared with a FL based counterpart in the literature in terms of number of cluster head variations and energy consumption rate. The results show that the proposed FL based cluster head selection algorithm not only decreases cluster head variation dramatically but also reduces energy comsumption of heterogeneous sensor nodes between 5% and 75%.

Keywords: heterogeneous wireless sensor networks, clustering algorithm, fuzzy logic.

KABLOSUZ HETEROJEN ALGILAYICI AĞLAR IÇIN BULANIK MANTIK TABANLI BIR KÜME BAŞI SEÇME ALGORITMASI

Özet

Kümeleme, algılayıcı ağın yaşam süresini arttırmak için enerji tüketimini azaltan önemli bir tekniktir. Homojen kümeleme teknikleri tüm algılayıcı düğümlerin enerji miktarlarının ve özelliklerinin aynı olduğunu varsaymaktadır. Bu yüzden, geliştirilmiş küme başı seçme algoritmaları algılayıcı düğüm heterojenliğini dikkate almamaktadır. Bu çalışmada, heterojen algılayıcı ağlar için yeni bir bulanık mantık tabanlı küme başı seçme algoritması amaçlanmıştır. Veri oranı, enerji seviyesi ve mesafe parametreleri geliştirilen bulanık mantık biriminin girişleri olarak belirlenmiştir. Amaçlanan algoritma, küme başı değişim sayısı ve enerji tüketim oranı ölçütleri ile literatürdeki benzer bir bulanık mantık tabanlı algoritma ile karşılaştırılmıştır. Geliştirilen algoritma, sadece küme başı değişim sayısını azaltmakla kalmayıp enerji tüketim oranını da düğümlere göre %5 ile %75 arasında azaltmaktadır.

Anahtar Kelimeler: heterojen kablosuz algılayıcı ağlar, kümeleme algoritması, bulanık mantık

1. Introduction

Wireless Sensor Networks (WSNs) have become one of the most remarkable research area in recent years (Akyildiz, 2002). A sensor network is a frame composed of sensing, computing and communication components that assist administrators to observe and react to events in an environment (Sohraby et al, 2007). Nowadays, an increased interest in the potential use of WSNs is seen in various fields like military, health, industrial, agricultural, and etc. The sensor node lifetime is the most critical parameter in these WSNs' applications. Hence, the design of the energy efficient protocols comes into prominence to maximize the network

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lifetime due to the very limited power of sensor nodes and the difficulty of the battery renewal (Fang et al, 2011). Various energy efficient routing protocols implement cluster based technique for reducing the energy consumption of wireless sensor nodes (Heinzelman et al, 2000). The energy resources of the sensor nodes should be managed intelligently to prolong the lifetime of sensor nodes considering the characteristics of WSNs. Clustering of sensor nodes and selecting cluster leaders to aggregate the sensing data are considered a main way of saving energy and increasing the network lifetime (Abusaimeh et al, 2012).
The clustering algorithms have been proven to be an effective approach of forming a network into a connected hierarchy. In clustering techniques, several wireless sensor nodes are aggregated to form a group (Zhang et al, 2008). The cluster head (CH) is selected among the sensor nodes in the network using different CH selection methods. In the meanwhile, the CH node loses more energy than the other sensor nodes because it transfers all the collected data over long distance. Therefore, the sensor network must periodically cluster itself to distribute the network load uniformly among all the sensor nodes (Tuah et al, 2012). Thus, the sensor network achieves energy efficiency, reduces packet collisions and end-to-end delays, resulting in better network throughput under high load (Younis et al, 2004).
Several clustering algorithms have been especially aimed for WSNs to provide energy efficiency and scalability of the network. The sensor nodes are assumed that they are homogeneous in WSNs, but in practice, WSN applications often consist of heterogeneous sensor nodes (i.e., low-capacity nodes and high-capacity nodes). A low-capacity node (L-node), is a resource-constrained node that has low bandwidth, less memory, less computation power, and low battery power. A high-capacity node (H-node), has much more capabilities with more computation memory and power (Kumar et al, 2014). In this study, a HWSN is constructed with simple sensor nodes named L-nodes and H-nodes which are supported different data rates and equipped with FL-CH selection units. The heterogeneous sensor nodes employing the CH selection algorithm is simulated using OPNET Modeler (Riverbed Inc, 2014), in order to make a more realistic performance evaluation. Moreover, the FL-CH selection algorithm incorporated in H-nodes is implemented in MATLAB Software.
The contributions of this study can be summarized as follows:

- To the best knowledge of authors, using data rate, energy level, and distance parameters for decision making of cluster head in order to optimize CH selection process in HWSNs is the first in literature.
- The proposed CH selection algorithm is compared with one of the last fuzzy based studies i.e. (Ben Alla et al, 2012) in terms of number of CH variations and energy consumption.
- Developed cluster head selection algorithm is modeled using MATLAB software. The network model employing the proposed algorithm is executed in OPNET Modeler. Both parts work concurrently during the simulation for more realistic estimation and substantiation.

The second section discusses related CH selection algorithms for HWSNs. In section 3, the proposed FL-CH selection system is explained. The results of the proposed algorithm are discussed in section 4. The proposed scheme and simulation results with final remarks are summarized in the last section.

2. Related works

There are many clustering algorithms in the literature used in WSNs. In this section, we review CH algorithms separately for homogeneous WSNs and heterogeneous WSNs. Weighted, hierarchal, and dynamic clustering algorithms have been proposed to organize sensor nodes as a cluster (Chatterjee et al, 2002; Banerjee et al, 2001; Chen et al, 2004) for homogeneous WSNs. One of the most used cluster based routing protocol is Low Energy Adaptive Clustering Hierarchy (LEACH) protocol (Heinzelman et al, 2000). LEACH algorithm is divided into rounds, and each round consists of a setup and a steady state phase. CH selection and cluster formation processes are occurred in the setup phase, and sensing and transmission processes are happened in the steady state phase. The LEACH algorithm has some restrictions i.e. it depends only a probability model, does not consider the energy level of sensor nodes, the CH may not be located at the center or near to the center. The other developed algorithm for CH selection is Gupta Fuzzy that uses FL approach (Gupta et al, 2005). Energy level, centrality, and concentration parameters are used in the Gupta Fuzzy algorithm. In (Ran, 2010) FL is adopted to the LEACH algorithm for improving LEACH algorithm. Energy level, distance, and node density parameters are utilized for CH selection.

Most of the clustering algorithms assume that all sensor nodes are equipped with the same quantity of links, computational resources and energy levels. Because of the heterogeneous sensor nodes' diverse characteristics, the clustering algorithms must be developed in details for constructing the heterogeneous sensor networks. A CH selection algorithm (GCHE-FL) is developed in (Ben Alla et al, 2012), efficiency and cluster distance parameters are combined in the fuzzy system for HWSNs. The authors say that simulation results show the GCHE-FL achieves better performance compared to LEACH, IB-LEACH and SEP in heterogeneous networks. Some of the clustering algorithms for HWSNs are only developed on energy parameter. The least energy consumed sensor node is selected as CH for prolonging the network lifetime. In Ref. (Kumar et al, 2009; Kumar et al, 2009), an energy efficient clustered scheme (EEHC) is proposed for HWSNs based on weighted election probabilities of each node to become CH and inspired from LEACH algorithm. The EEHC has extended the lifetime of the network by 10% as compared with LEACH. CHs are selected with a probability depending on the ratio between the remaining energy of sensor node and the average energy of network in (Duan et al, 2007). The high initial and remaining energy sensor nodes have more chances to be the CHs than the low energy sensor nodes. An energy-aware adaptive clustering protocol used in HWSNs in (Qing et al, 2006). CH is elected by a probability based on the ratio between the residual energy of each node and the average energy of the network. Several studies can be found in the literature and a number of surveys are written on the CH selection for HWSNs (Tuah et al, 2012; Katiyar et al, 2011).

The differences of our study can be summarized as; (i) to the best knowledge of the authors, using data rate, energy level, and distance parameters for CH selection for HWSNs is the first in the literature, (ii) simulation results of the developed algorithm have been compared with a FL based approach in terms of number of CH variations and energy consumption rate (iii) OPNET and MATLAB tools have been worked together for more realistic performance evaluation.

3. The proposed fuzzy logic based cluster head selection algorithm

In Homogeneous Wireless Sensor Networks, a CH selection process is generally based on energy level and distance of the sensor nodes to the center of the cluster because of all the sensor nodes have the same characteristics. However, the sensor nodes may have high-bandwidth, long-distance transceiver, more powerful, and etc. Contrast to homogenous WSNs, in heterogeneous WSNs, just energy level and distance parameters individually are not sufficient for the CH selection process since the diverse sensor nodes construct a sensor network. Other metrics related to the heterogeneity of WSNs, application requirements, and sensor node characteristics should be considered in the CH selection decision. When these requirements are considered, one can easily infer that in order to apply an efficient CH selection method, more intelligent approaches are required.

In WSNs, sophisticated cluster head selection algorithms should consider more than one criteria and a methodology to combine and process them. Diverse CH selection algorithms have been proposed in the literature for HWSN as mentioned earlier. Due to their non-linearity and generalization capability for pattern classifiers, artificial intelligence based systems for example FL and neural networks are good approaches (Onel et al, 2004; Sun, 2007). And FL is an efficient multi-attribute decision method since it corresponds human expert reasoning. Therefore, in the proposed CH selection system a FL-based approach has been adopted. FL based CH selection algorithm should initialize selection process considering available sensor nodes (link capacity, power consumption, remaining battery, cost, QoS parameters, and so on). Accordingly, in this study, we propose a FL-based CH selection algorithm which considers the parameters; data rate, energy level, and distance as inputs in order to handle any CH selection process.

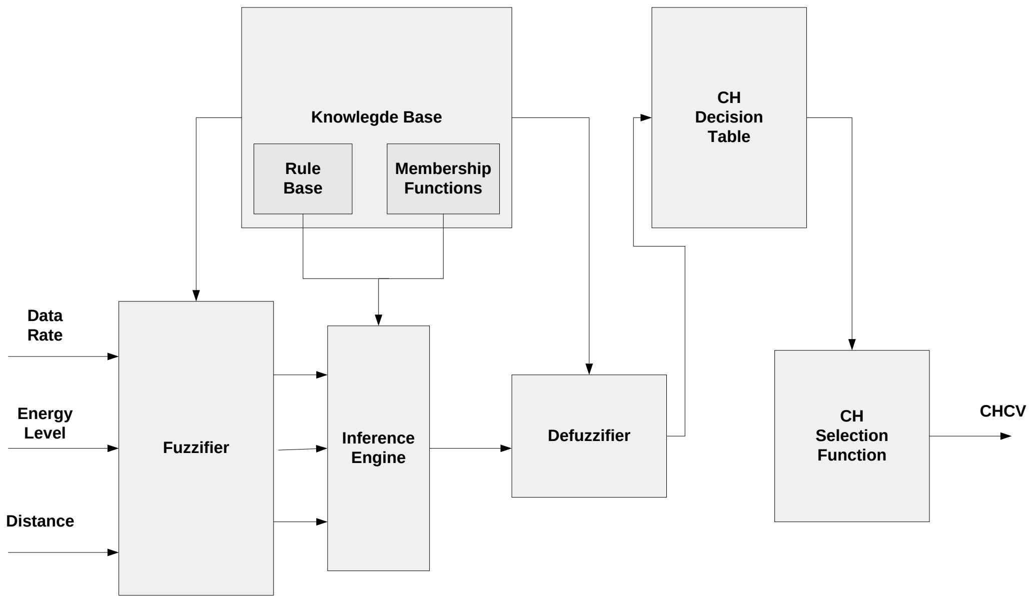

Fig. 1: The proposed FL-based CH selection system scheme.

Fig. 1 shows the essential modules of the FL-based CH selection structure. As can be seen in Fig. 1, the FL system consists of three main parts named fuzzifier, fuzzy inference engine, and defuzzifier. Fuzzifier transforms a crisp input into a fuzzy variable where physical quantities are represented by linguistic variables with suitable membership functions. The linguistic variables are then utilized in rule base of fuzzy inference engine. For example, if the energy level is considered in crisp set, it can be represented as low, medium or high in the corresponding fuzzy set. The membership values, i.e. μ, are obtained by mapping the values obtained for a particular parameter into a membership function. Defuzzifier is responsible for converting this fuzzy engine output into a number called Cluster Head Candidacy Value (CHCV). Finally, the calculated CHCV is used for selecting the best CH.

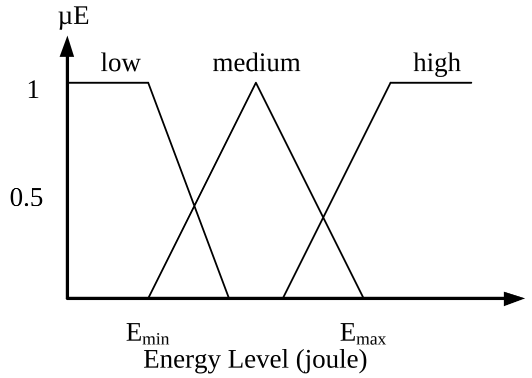

Fig. 2: Membership functions of energy level (E).

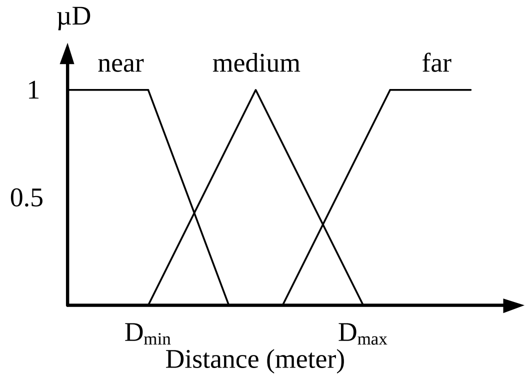

Fig. 3: Membership functions of distance (D).

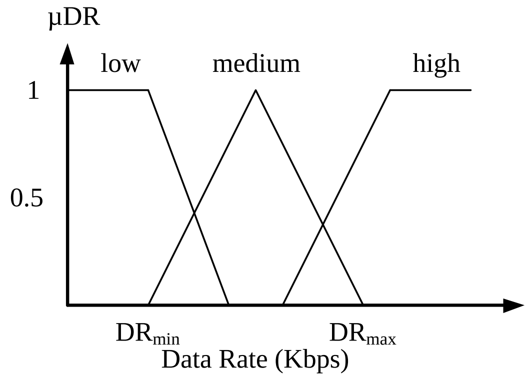

Fig. 4: Membership functions of data rate (DR).

Membership functions of the FL system inputs are shown in Fig.s 2, 3, and 4, respectively. Trim and trapezoid are preferred as the fuzzy membership functions owing to their capability of achieving better performance for especially real time applications (Ceken et al, 2009; Wang, 1994). Our FL system has totally 27 fuzzy rules and some of developed fuzzy rules are shown in Table 1.

Table 1: Example fuzzy rules.

IF (Energy is Low) & (Distance is Far) & (DataRate is Low) then (CHCV is 0.1)
IF (Energy is medium) & (Distance is Far) & (DataRate is Medium) then (CHCV is 0.5)
IF (Energy is High) & (Distance is Far) & (DataRate is Medium) then (CHCV is 0.6)
IF (Energy is High) & (Distance is Near) & (DataRate is Medium) then (CHCV is 0.8)
IF (Energy is High) & (Distance is Near) & (DataRate is High) then (CHCV is 1)

The CHCV varies between zero and one where zero indicates the weakest, whereas one represents the strongest candidacy level of CH. For example, if a sensor node is able to support a data rate of 100 Kbps, has an energy level of 8000 joules and a distance to the center of the network of 10 m then the CH candidacy level of this sensor node is calculated as 0.92. The calculated CHCV is utilized for selecting the best candidate CH.

The analytic model of the fuzzy inference system is as follows. Three dimensional pattern vectors (input of the fuzzifier) for candidate access points is:

$$PV_C = [E_C; D_C; DR_C] \tag{1}$$

where E is energy, D is distance, and DR is the data rate value of vehicle. Three -dimensional fuzzy pattern vectors (output of fuzzifier and input of inference engine) for candidate cluster head is:

$$PV_F = [PF_1; PF_2; PF_3] \tag{2}$$

Since the product inference rule is utilized in the fuzzy inference engine, then, for a new pattern vector, the contribution of each rule in the fuzzy rule base is computed by:

$$C_r = \prod_{i=1}^{3} \mu_{F_i}(P_i) \tag{3}$$

Since we have 27 rules and a center average defuzzifier is utilized, the output of the defuzzifier is:

$$M_a = \frac{\sum_{l=1}^{27} y^l \left(\prod_{i=1}^{3} \mu_{F_i}(P_i)\right)}{\sum_{l=1}^{27} \left(\prod_{i=1}^{3} \mu_{F_i}(P_i)\right)} \tag{4}$$

where, yl is the output of the rule l.

4. Simulation results

In this section, we evaluate the performance of our proposed CH selection algorithm using OPNET and MATLAB. The HWSN model has been implemented using OPNET MODELER simulation tool. Furthermore, the newly proposed FL based CH selection algorithm which is incorporated into the H-nodes have been modeled using MATLAB software.

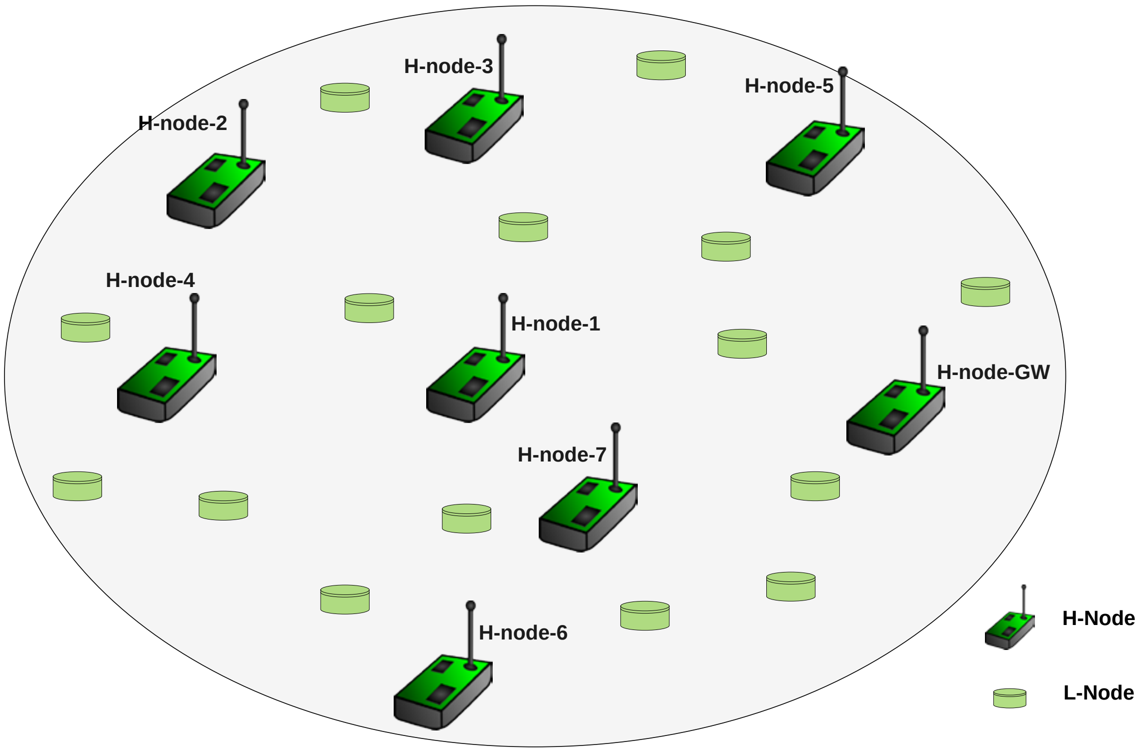

Fig. 5: Example cluster head selection scenario.

The simulation scenario is modeled using OPNET and illustrated in Fig. 5, there are several L-nodes and eight H-nodes in a cluster; i.e., H-node-1, H-node-2,…, and H-node-GW. H-node properties are given in Table 2. Both L-nodes and H-nodes are randomly distrubited in the field, and only H-nodes can be selected as a cluster head in HWSN.

Table 2: SN parameters.

	Data Rate	Initial Energy Level	Distance to CH
H-node-1	100 Kbps	8640 joule	0 m
H-node-2	100 Kbps	8640 joule	49.5 m
H-node-3	80 Kbps	8640 joule	38 m
H-node-4	50 Kbps	8640 joule	38.6 m
H-node-5	40 Kbps	8640 joule	59.2 m
H-node-6	20 Kbps	8640 joule	44.7 m
H-node-7	10 Kbps	8640 joule	26.7 m

Each of H-node in HWSN has supported a specific data rate as can be seen from Table 2. We assume that the H-nodes have an AA battery with 8640 joule. All the H-nodes have same initial energy level at the beginning of the scenario and different distances to CH. Each sensor node (L-nodes and H-nodes) sends the sensed data to the CH. The CH aggregates the collected data and transmits the aggregated data to the gateway (H-node-GW).

According to the available H-nodes' parameters, the FL inference system produces an output (CHCV) which describes the candidacy level of H-nodes and varies from 0 to 1. At the beginning of the simulation, the SNs send their data over the H-node-1 to H-node-GW since it has a sufficient data rate, extremely near to center of HWSN with fully charged battery as a cluster head. So, it has a better CHCV, which indicates that it is the best candidate cluster head, as shown in Fig. 6.

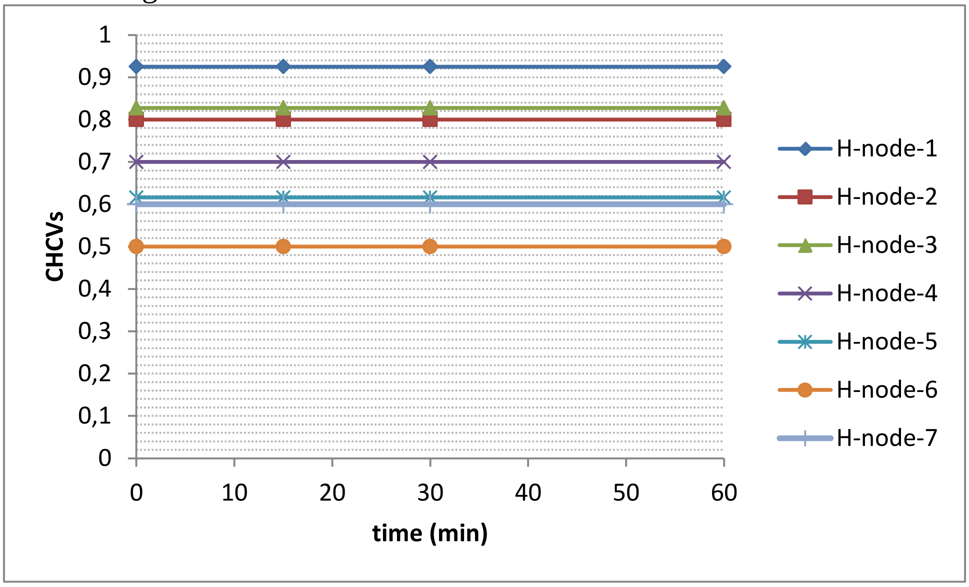

Fig. 6: CHCV output of the developed CH selection algorithm.

In Fig. 6, the results are taken for an hour. To point out the CH selection process with the FL CH selection algorithm, the simulation time is extended to several hours. As can be seen in Fig. 7, for avoiding the long end to end delays, the developed FL based CH selection algorithm selects the most appropriate H-node for serving as CH. H-nodes named H-node-1, H-node-3, and H-node-2 are selected as CH respectively according to supported data rate, distance to center of HWSN, and energy level.

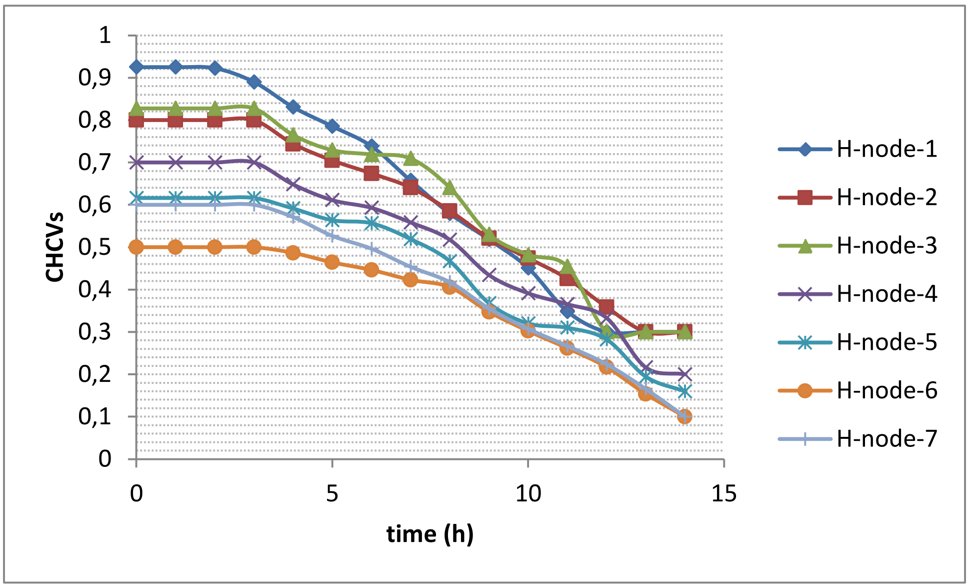

Fig. 7: CHCV output of the developed CH selection algorithm.

Handoff can be described as a process of transferring a sensed data session from one CH to another in HWSNs. The number of handoffs is shown in Fig. 8 and there are two handoffs happened in the second simulation scenario. If the CHCV is greater than the one current CH has, then the handoff process is intialized.

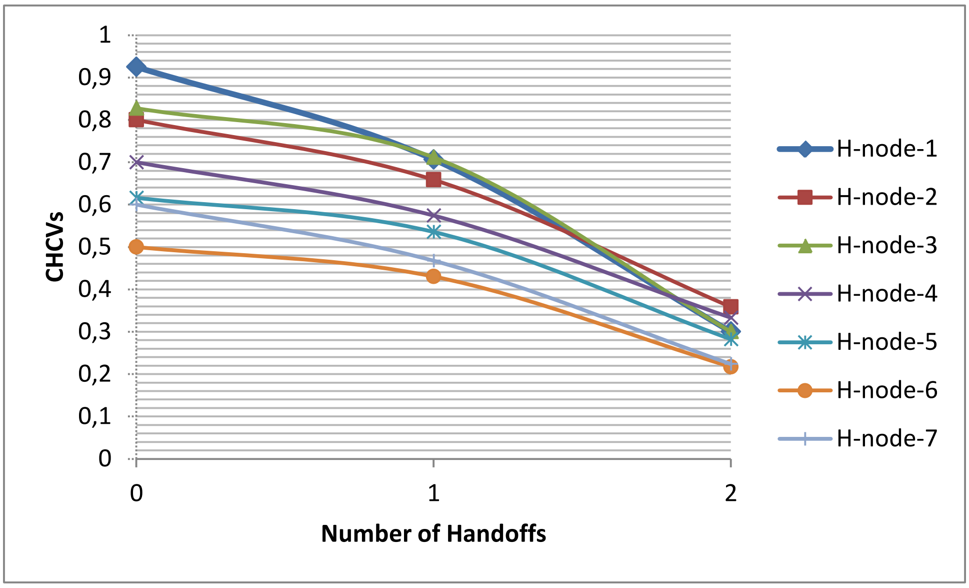

Fig. 8: Number of handoffs according to developed fuzzy based CH algorithm.

Performance of proposed FL based CH algorithm is compared with an energy level and distance based CH selection algorithm in (Ben Alla et al, 2012). All the H-nodes may be selected as CH and also some of them have not supported enough data rate, and therefore, the end to end delays of the network are increased dramatically when only energy and distance based CH selection algorithm is used in HWSNs.

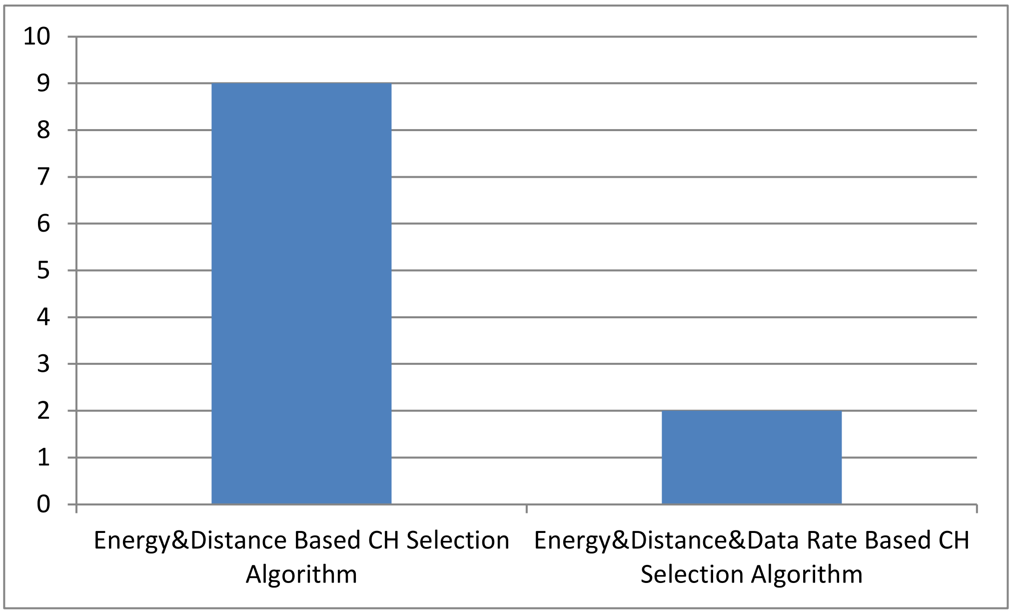

Fig. 9: Number of CH variations.

The results show that developed FL based CH selection algorithm dramatically reduces the number of CH variations and end to end delays with selecting most appropriate H-node as CH. As can be shown in Fig. 9, the proposed fuzzy based algorithm decides CH variation only two times as expected result while energy level and distance based algorithm triggers handoff nine times. Also, the supported data rates of H-nodes are very important in HWSNs. For example, if an H-node is selected as CH that supports 20 Kbps, then, when the other H-node which has 100 Kbps data rate sends its data packet to CH, the CH sends that packet in five seconds to H-node-GW. So, the end to end delays and overhead are increased dramatically. And also, this situation decreases the energy level of H-nodes. We also compared our proposed algorithm with the aforementioned energy and distance based algorithm in terms of energy-saving rate. In Fig. 10, the energy saving rates of H-nodes in HWSNs are shown. The proposed CH selection algorithm selects the optimum H-node as CH with considering supported data rates of H-nodes. Therefore, by selecting optimum H-node as CH, the end to end delay and energy consumption rate are decreased. The proposed CH selection algorithm increases the energy-saving rates of H-nodes significantly as shown in Fig. 10.

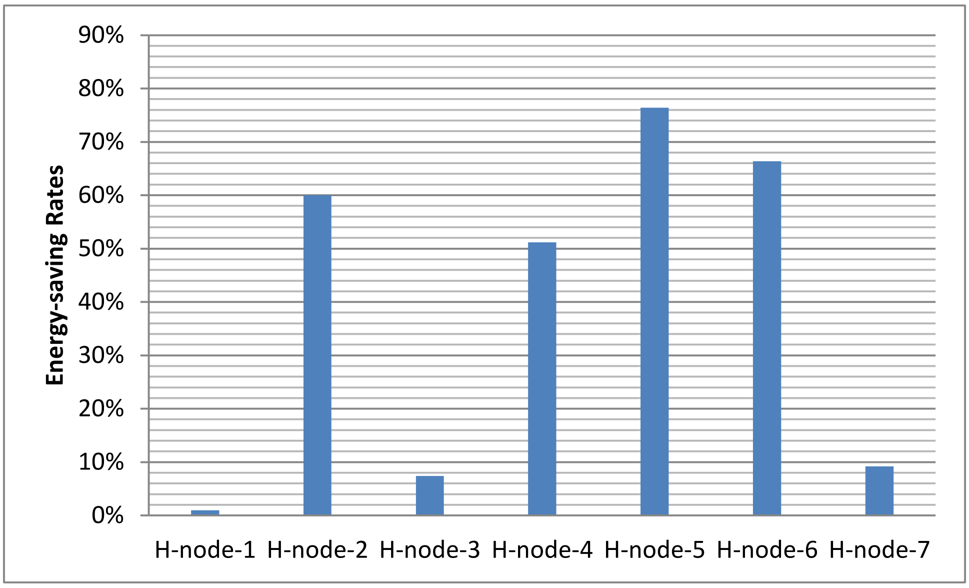

Fig. 10: Energy-saving rates of H-nodes.

5. Conclusions

In this paper, we propose a fuzzy logic based cluster head selection algorithm for wireless heterogeneous sensor networks by taking three important parameters, i.e., data rate, energy level, and distance into account. The simulation results show that the proposed method is able to determine the most appropriate wireless sensor node as cluster head. The simulation results of the proposed fuzzy based algorithm are also compared with energy level and distance based counterpart. It is also observed that, developed algorithm noticeably reduces the number of handoff, energy consumption rates of sensor nodes and end to end delays without shortening the network lifetime compared with the energy level and distance based algorithm.

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