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Research paper

Distributed fuzzy logic based cluster head election scheme (DFLCHES) for prolonging the lifetime of the wireless sensor network

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Abstract

Wireless sensor networks (WSNs) is considered as the predominant technology due to their high suitability and adaptability that makes it possible to be deployed in wide range of applications like civil and military domain. But energy-constraint is the significant feature that needs to be addressed for sensor networks since energy drain of sensor nodes affects network lifetime, stability and co-operation of sensor nodes in the event of enforce reliable data dissemination. Cluster head election has to been performed periodically in order to handle energy balance for facilitating reliable packet delivery. Most of the cluster head election schemes of the literature elect a node as cluster head either randomly or by elucidating their stochastic probabilities. Hence a Distributed Fuzzy Logic based Cluster Head Election Scheme (DFLCHES) that discriminates and discards packets from the sensor nodes that has the least probability of being elected as cluster head is proposed. DFLCHES utilizes five significant parameters such as trust, energy, node density, hop count and centrality measure for quantifying the probability of cluster head election. This DFLCHES is run on each neighbor nodes of the cluster members to facilitate the action of discrimination. DFLCHES also balances the energy consumption of the cluster members during transmission as it discards packets from ineligible nodes. Further the action of cluster head election has to be optimized periodically for reducing and balancing energy consumption for prolonging the network lifetime. In DFLCHES, the process of optimizing cluster head depends on the incorporation of the concept of Genetic algorithms for enabling and ensuring reliable routing.

Keywords: *Fuzzy logic, wireless sensor network, cluster head election, fuzzy clustering.*

1. Introduction

In wireless sensor network, the network lifecycle plays an important role [2015]. The identification of topology of the network and it also facilitates in analyzing the quality of the network [2014]. The network lifetime can be assessed by analyzing dead nodes and nodes are in the status to reach dead state due to energy depletion. In such cases, the topology control concept plays a vital role in the wireless sensor network. The concept topology control plays a significant role in enhancing the lifetime of the network by reducing the communication intrusion factors. Most commonly used topology control algorithms are Hierarchical topology control algorithm which is implemented using clustering of the sensor nodes for organized communication. In Hierarchical topology control algorithm, the selection of cluster head is considered to be the most challenging task and has high level of impact in improving the lifetime of the network [2008].
The clusters formed in the network can be further divided into sub-clusters by defining its size based on the number of sensor nodes [2000]. Cluster formation based on the transmission between the sensor node (source node/ base station) and sink node (base station) via cluster head [2015]. The cluster head nodes are selected in such a way that the node possesses high level of energy resource. Cluster head selection algorithms play a vital role in the transmission of the network.

2. Existing Work

Vamsi and Neha et al. presented a novel of clustering in a hierarchical way. This hierarchical way of clustering suggests that any number of parameters can be taken for consideration in order to predict the behavior of the node. The approach reduces the number of dead nodes present in the network, decreases the utilization of energy resource of a node by limiting the formation of new clusters which in turn enhances the lifetime of the network. Each node from the cluster is calculated for its weight function which aids in the selection of cluster head. Fuzzy inference engine is designed to perform Hierarchical Routing. In this work, the cluster head selection happens based on the threshold period set during each and every cluster selection process.
Hemavathi et al., [2014] presented an efficient approach which is termed as fuzzy predictive method based cluster head selection. In this approach, four more parameters are considered for predicting the node behavior apart from the traditional parameters the rate of transmission in that particular node. The additional parameters which are considered for prediction are the power left out in the battery source of the nodes, the number of neighboring nodes present in that particular zone, calculating the node distance from base station and mobility factor of the sensor node. The nodes' transmission history is also considered to forecast the behavior of the node and analysis is carried out with respect to its suitability towards cluster head.

Akshay Kumar et al., [2014] introduced a fuzzy based dynamic cluster head selection algorithm on cloud based implementation in a wireless sensor networks. In this work, every node's parameter is analyzed for potential value which aids selecting cluster head in the network. The main advantage of this work, cluster overlapping is reduced by means of its spatial distribution and malicious nodes are not allowed to participate in the routing process.
Vipin Pal et al. [2015] presented a novel approach for selecting and shifting the cluster head role among the nodes that participate in the transmission process. The work presents the cluster head selection based on genetic algorithm.
Abbas Karimiet al. [2013] presented a hybrid methodology which combines fuzzy logic and chaotic based genetic algorithms to enhance the life time of the sensor network. They used three parameters such as energy, density and centrality are considered to manipulate with fuzzy logic in order to choose efficient node as the cluster head. The number places the cluster is deployed are determined by means of the genetic algorithms. The implementations of the genetic algorithms are done based on chaotic manner.

3. Proposed work

The proposed DFLCHES facilitates the process of optimal cluster election based on four steps such as i) Fuzzy clustering based Initialization process, ii) Estimation for number of clusters, iii) design of objective function, iv) Genetic Algorithm(GA) based cluster head election. Genetic algorithms are mainly used as it is one of the potential meta-heuristic optimization schemes that aids in dynamic optimization. In this paper, GA is used for selecting the cluster head form the estimated candidate solution of cluster heads achieved through the design of fitness objective function. The fitness function is computed based five potential factors that relate to energy, trust, node density, Maximum mean distance of a cluster member to Cluster head and Maximum mean distance of Cluster head to the base station.

Background for Fuzzy clustering based Initialization process

In general, clusters in WSN are determined based on the proximity in the location of the sensor nodes as cluster members can be suitably allocated to the closest cluster heads as the energy consumption of the network can be effectively minimized. In DFLCHES, Fuzzy clustering based Initialization process is used for clustering the entire set of sensor nodes into several categories of initial fuzzy subsets before the start of communication. Hence, each node of the network is associated to any of the initial fuzzy subsets based on a quantified probabilistic value. Then the cluster members of each fuzzy subsets associates with each other and they parallelly select their cluster heads for disseminating the data to the base station for drastically reducing the time and size of computation.
In case of classical deterministic clustering [19], the primitive set is partitioned into a number of disjoint subsets that possess a same degree of similarity. In this paper, we propose a method of initialization based on fuzzy clustering model [21].In this fuzzy clustering model, 'n' number of sensor nodes represented through $P = p_1, p_2, ..., p_n$ are clustered into 'k' number of clusters denoted through $C_1, C_2, ..., C_k$. Thus the clustering state of DFLCHES can be expressed through a matrix of size' $m \times n$ ' with the degree of mapping ' M_{ij} 'that quantifies the degree of association established between the cluster members and the cluster heads. This fuzzy clustering also infers that decrease in the distance between the position between the cluster member and cluster center ensures the degree of mapping of node ' p_i ' to cluster ' C_j '.In DFLCHES, the fuzzy clustering model used in[22] is considered for computing the degree of mapping ' $Degree(M_{ij})$ 'through equation (1) as

$$Degree(M_{ij}) = \frac{1}{dist(p_i, C_j)^2} \tag{1}$$

Then the degree of mapping is normalized based on equation (2) as

$$M_{ij} = \frac{\dfrac{1}{dist(p_i, C_j)^2}}{\sum_{i=1}^{k} \dfrac{1}{dist(p_i, C_j)^2}} \tag{2}$$

Finally, the process of clustering is achieved based on equation (3) through

$$C_j = \frac{\sum_{i=1}^{n} M_{ij} \bullet p_i}{\sum_{i=1}^{n} M_{ij}} \tag{3}$$

This clustering process is also called as soft clustering as each sensor node can act as cluster member to any number of clusters.

Estimation for number of clusters in DFLCHES

Fuzzy clustering necessitates the determination of accurate number of clusters in the network for controlling the clustering granularity and to maintain a reliable balance between precision and compressibility. Hence DFLCHES determines the appropriate number of clusters based on the parameter called Sum of Squared Error (SSE) through (4) using

$$C_j^{SSE} = \sum_{i=1}^{n} W_{ij}^{pf} dst(p_i, C_l)^2 \tag{4}$$

Where' p_i 'and ' C_j 'defines the position of each cluster member and cluster group to which each cluster member is assigned respectively.
Further SSE can be used for estimating the possibility of data fitting through equation (5) as

$$C_j^{SSE}(k) = \sum_{i=1}^{n} \sum_{j=1}^{k} W_{ij}^{pf} dst(p_i, C_l)^2 \tag{5}$$

In DFLCHES, Elbow method [16] is used for determine the number of clusters as increase in the number of cluster reduces the degree of SSE with each cluster. This is because, more number of clusters is potential enough in elucidating the characteristic features of each cluster formed. Moreover, the similarity measures in each object of the cluster are highly correlated. When Elbow method is used, the number of clusters depends on the calculation of SSE and inflection point determined by drawing the curve using the computed SSE achieved for 'k' clusters.

Fuzzy clustering based Initialization process for DFLCHES

Once the optimum numbers of clusters are estimated using Elbow method, matrix ' M_{ij} 'is calculated based on fuzzy clustering. The matrix ' M_{ij} ' is mainly for identifying the degree of mapping that maps each object to a specific cluster before the commencement of each rounds and it also plays a vital role in partitioning the entire sensor network into 'k' clusters. In specific, each node ' p_i ' is mapped onto cluster ' C_j 'when it satisfies the constraints given in (6) as

$$\sum_{b_1=1_1}^{j-1} M_{ib_{1_1}} \le N_r \prec \sum_{b_2=1}^{j-1} M_{ib_2} \tag{6}$$

Where' N_r 'refers to the random number which is uniformly distributed and it ranges between 0 and 1.Finally, genetic algorithm is incorporated for selecting the cluster heads in each subset of clusters in a parallel manner and further the massages are forwarded to the base station.

Objective Function design for DFLCHES

The core objective for controlling the topology is mainly to reduce the net energy consumption rates that are incurred due to the establishment of communication among the nodes. In DFLCHES, five significant parameters pertaining to energy, trust, node density, Maximum mean distance of a cluster member to Cluster head and Maximum mean distance of Cluster head to the base station are used for designing the objective function.

1) Net energy consumptions of the network

In the data cycle, the net energy consumption is defined through equation (7) during each round as

$$E_{net-sum} = \sum_{i=1}^{K} (E_{REQ-CLUST} + \sum_{J=1}^{N_i} E_{CLUST-MEMB}^{ij}) \tag{7}$$

2) Trust factor of the network

The trust factor of the network is the cumulative trust estimated through the weighted sum of trust elucidated from node based on direct observation and neighbour based observation using (8) as

$$TF = \beta_1 T_s + \beta_2 T_p \tag{8}$$

3) Estimated node density

The node density of the network is calculated through the ratio of number of neighbours interacting with each cluster member to the entire number of nodes deployed in the network as defined in [17] through(9) as

$$N_{density(f(i))} = \frac{N_{neigbours(i)} - 1}{N_{Entire-network}} \tag{9}$$

4) Maximum mean distance of a cluster member to Cluster head

The maximum mean distance between the clusters member to the cluster head is estimated using (10) as

$$M_{mean-dist(1)} = Max\{\frac{dist(CLUST_{memb(ij)}, CLUST_{mem(i)})}{N_i}\} \tag{10}$$

5) Maximum mean distance of Cluster head to the base station

The maximum mean distance between the cluster head to the base station is estimated using (11) as

$$M_{mean-dist(2)} = Max\{dist(CLUST_{head}, BS_i)\} \tag{11}$$

Where 'i' varies between 1 to K and ' K' refers to the number of cluster head nodes.

The aforementioned five parameters must be integrated as the elucidated factors vary in magnitude and dimension and hence a normalized function portrayed in equation (12) is used for transforming the data into a threshold level [18].

$$NFun = \frac{2}{\pi} \tanh(x) \tag{12}$$

Then the objective function is formulated based on equation (13) as

$$OBJ_{func} = \alpha E_{net-sum} + \beta TF + \gamma N_{density(f(i))} + \varphi M_{mean-dist(1)} + \chi M_{mean-dist(2)} \tag{13}$$

Where $\alpha, \beta, \gamma, \varphi, \chi$ refers to the positive priority factor based on the condition that the sum of priority factor sum to the value of 1.All the priority factors are initially set to 0.2 at the initial point of time.

Genetic algorithm based cluster head election for DFLCHES

Once the objective function is formulated, it is used as input by the Genetic Algorithm (GA) based on fitness computation, selection. The topology control is ensured in this approach for selecting 'K' number of cluster head nodes that are selected from the eligible nodes that compete for cluster head election. This competition among the cluster heads can be formulated as an optimization problem. The main goal of this optimization problem is the lifespan of the network since it is considered as the major evaluation index used for avoid the emerge of death nodes in the network. The possibility of dead node can be mitigated by proper allocation energy proportionally and uniformly to each and every node of the network. Moreover, the energy possessed by the cluster heads must be greater than their cluster members. In DFLCHES, energy residual energy possessed by each cluster head is compared with the residual energy of cluster members of the network and if it is found to be greater than the mean degree then that specific cluster head is elected[20] and added to the candidate set of cluster head solution possible in that network. Then the optimal cluster head from the determined candidate solution is facilitated through the incorporation of GA for reducing the objective function phenomenally. Similarly, the clustering process in WSN necessitates the computation of number of cluster head nodes. This determination of identifying the number of cluster head nodes are estimated based on (14) through

$$K_C = \frac{A\sqrt{n.\varepsilon_{amplify}}}{\sqrt{2\pi(n..E_S + \varepsilon_{amplify}.dist_{mean}^2}} \tag{14}$$

Where 'A' is the WSN area under detection with'n' number of sensor nodes under signal amplification factor ' $\varepsilon_{amplify}$ ', energy incurred for transmitting a single bit of data' E_S 'and mean cluster head possessed coverage region' $dist_{mean}$ '. Then the steps of GA such reproduction, mutation and crossover operation are performed for cluster head selection form the identified cluster head based candidate solution.

Algorithm 1 depicts the steps involved in GA-based Fuzzy clustering that enables the sensor nodes to be classified into a multiple number of clusters. In DFLCHES, the algorithm for expectation maximization is applied for facilitating fuzzy clustering that aids in generating various number of clusters 'k'.

Algorithm 1: Initialization process of Fuzzy clustering for DFLCHES

Function GA_FUZZY_CLUSTER_PROCESS(n, k)
For j=1 to k do
Initially $C_j = Random(1, n)$
End For
Repeat
For i=1 to n do
For j=1 to k do

$$M_{ij} = \frac{\frac{1}{dist(p_i, C_j)^2}}{\sum_{i=1}^{k} \frac{1}{dist(p_i, C_j)^2}}$$

End For
End For
For j=1 to k do

12. $C_j = \frac{\sum_{i=1}^{n} M_{ij} \bullet p_i}{\sum_{i=1}^{n} M_{ij}}$
13. End For
14. Until C_j is constant for
15. For j=1 to k do
16. Return M_{ij}
17. End Function

Algorithm 1 aims in identifying the degree of association of sensor nodes to each of the clusters. Initially, each and every sensor nodes are deployed in a random manner. Then the concept of expectation maximization is used for generating various size and number of clusters on which the cluster head election process is facilitated Through GA.

Algorithm 2 portrays the steps involved in the election of cluster heads in GA-based DFLCHES.

Algorithm 2: GA-based DFLCHES Cluster Head Election Algorithm

1. Using Elbow method, estimate the number of clusters'k'
2. M_{ij} = GA_FUZZY_CLUSTER_PROCESS(n, k)
3. Repeat
4. Locate each node ' C_j' to a specific cluster 'k'
5. For j=1 to k do
6. Initialize the population with defined number of sensor nodes
7. Use Fitness function for evaluating the population using objective function.
8. Implement Elitism selection method for selecting optimal sensor nodes
9. Apply single point crossover and evaluate fitness.
10. Apply bitwise mutation and evaluate their fitness.
11. Repeat optimum number of clusters is formed
12. Until Iterations =Max iterations
13. Sensor is in its normal co-operative behaviour
14. End for
15. Until the lifetime of the network expires

Algorithm 2 initially identifies the number of clusters based on elbow method, then the degree of association of each sensor nodes are identified and set as fitness objective function Once the fitness objective function is evaluated, the population size is initialized and three operations of GA namely, Roulette wheel, single point crossover and bitwise function is computed. This computation of GA is carried until maximum number of eligible clusters are formed and until normal operation of the sensor network sustains and the process gets terminated when the life of the network expires.

4. Performance evaluation and analysis

In this section, the performance evaluation of DFLCHES is carried out using ns-2.25. A maximum of 100 sensor nodes were simulated in this environment with an area of 100 * 100 m. Packet size was considered as 500 bytes. IEEE 802.11 was used as MAC protocol. The simulation was carried over a period of 300 s. The results are compared with the baseline cluster head election mechanisms like KBPSO and LEACH. Generally, the reliability in data transfer of the sensor network solely depends on the cluster head of each cluster group formed through local clustering. Hence, the technique used for cluster head election may decrease the packet delivery and throughput. But it may increase the total energy consumption and packet drop rate. Hence, DFLCHES is evaluated based on the following performance metrics.

The following table 1 illustrates the simulation parameters that are set for our study.

Table 1: Simulation Parameters of Dflches

Parameter	Value
NS 2 Version	2.35
Number of sensor nodes	100
Simulation area	100x100 metres
Mac Layer	802.11
Simulation Time	300 seconds
Initial energy	2J
Energy for election Packet size	50×10^{-9} J/bit
Size of broadcast message	100 bytes
Size of sensed information transmitted	500 bytes

The performance investigation of DFLCHES is achieved by carrying out three experiments viz.,

a) Experiment 1-Performance evaluation based on Node mortality

b) Experiment 2-Performance evaluation based on number of alive nodes.

c) Experiment 3-Performance evaluation based on varying number of sensor nodes.

a) Experiment 1-Performance evaluation based on Node mortality

In experiment1, the performance of DFLCHES is analyzed based on two situations. In the first scenario, the initial energy of sensor nodes is set to 1J and in the second scenario, the energy of the sensor nodes are gradually varied from 0.4J to 0.8J respectively. Besides, the performance DFLCHES is analyzed by varying the location of base station. Figure 1 represents the performance of DFLCHES with equal energy at the base station location of (200,200). Similarly, Figure 2 and 3 represents the performance of DFLCHES investigated with location varied from (200,200), (500,500) with unequal energy. This experiment is mainly performed by varying the mortality rate that could be possible in the considered number of rounds of operation.

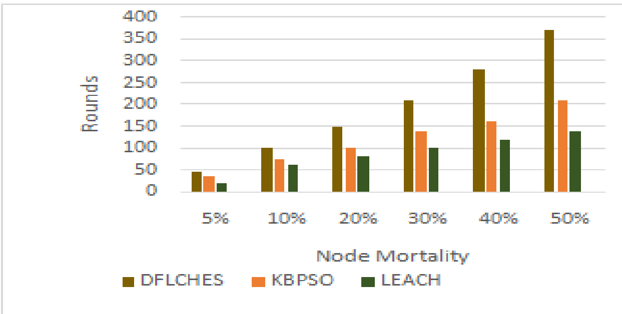

Fig. 1. Performance of DFLCHES based on equal energy at BS location of (200,200)

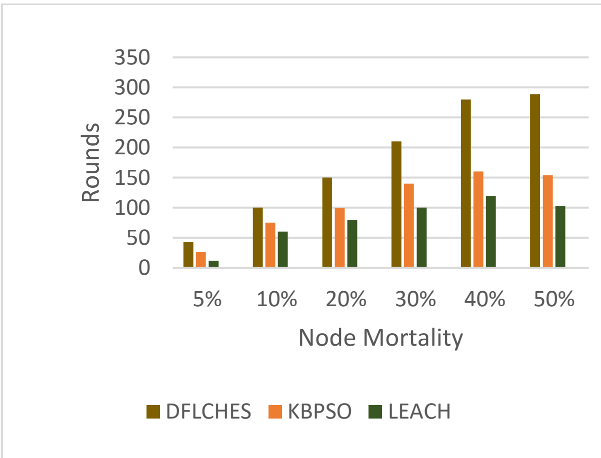

Fig. 2. Performance of DFLCHES based on unequal energy at BS location of (200,200)

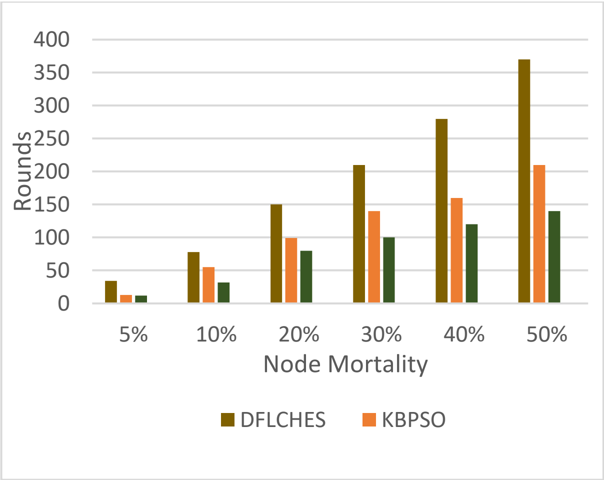

Fig. 3. Performance of DFLCHES based on unequal energy at BS location of (500,500)

Figure 1 and 2 infers that the death time of the network is maximum prolonged with DFLCHES even the initial energy of the node is not equal in both cases but the location of BS is same. This significant improvement of DFLCHES is due to the impactful election of cluster head nodes through the concept of GA as it reduces the degree of energy consumption to a potential degree. Thus DFLCHES enables the node with maximum residual energy to play the role of optimal cluster head for prolonging the lifetime of the network. It is also identified that the performance of DFLCHES in an average significant enough of about 23% superior to KBPSO and 28% greater than LEACH in terms of mortality rate. Figure 3 infers the performance of DFLCHES is superior when the base stations are located in the center of the cluster but when the base stations move towards the edge proximity, the scenario inverses but in this case, it exhibits an improvement of 16% over KBPSO and 19% over LEACH.

b) Experiment 2-Performance evaluation based on number of alive nodes

In experiment2, the performance of DFLCHES is also analyzed based on two situations similar to previous experiment. Figure 4 represents the performance of DFLCHES with equal energy at the base station location of (200,200) with respect to number of alive nodes. Similarly, Figure 5 and 6 represents the performance of DFLCHES investigated with location varied from (200,200), (500,500) with unequal energy based on varying number of alive nodes that could be realized in specific number of rounds.

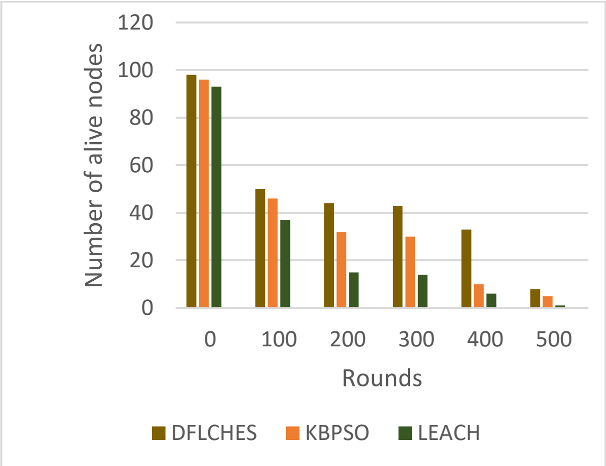

Fig. 4. Performance-DFLCHES-Number of alive nodes with equal energy at BS location of (200,200)

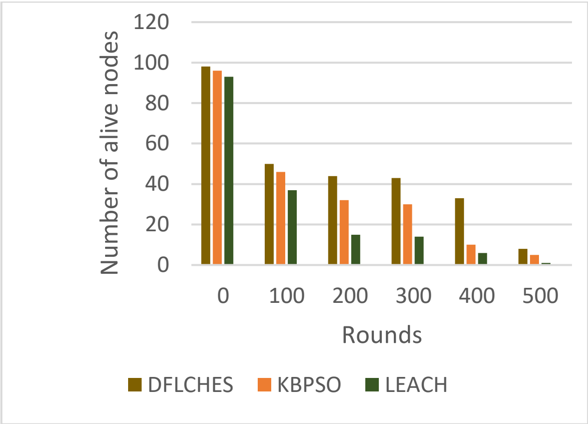

Fig. 5. Performance-DFLCHES-Number of alive nodes with unequal energy at BS location of (200,200)

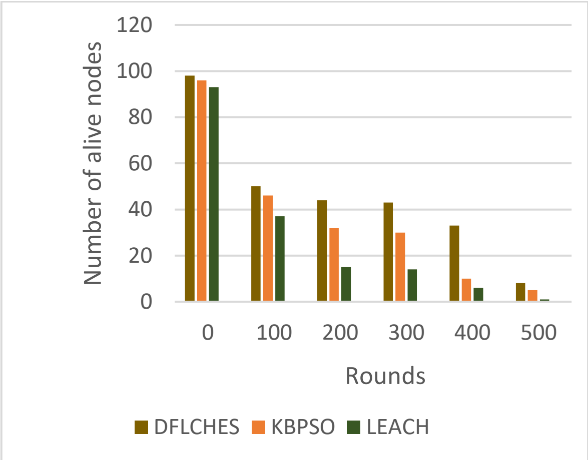

Fig. 6. Performance-DFLCHES-Number of alive nodes with unequal energy at BS location of (200,200)

The analysis on number of alive nodes identified over several rounds of analysis is realized through Figure 5, 6 and 7 respectively. The dying process of nodes are found to be relatively stable than KBPSO and LEACH. This is due to the utilization of five significant parameters that emphasis node density, energy consumption, trust and distance between cluster head and cluster member and distance between cluster head and the base station. Hence the net energy consumptions is dramatically decreased so as to ensure that not even a single node will be in the lack of energy in the early situation for lengthening the lifetime of the network.

c) Experiment 3-Performance evaluation based on varying number of sensor nodes

In experiment 3, the performance of DFLCHES is analyzed based on packet delivery ratio, throughput, energy consumptions, packet drop rate and average delay by varying the number of sensor nodes of the network. The following Figure 7 and Figure 8 highlights the superior performance of DFLCHES with respect to the packet delivery ratio and throughput investigated by considering the existing cluster head selection approaches like DFLCHES, KBPSO and LEACH. DFLCHES exhibits an improvement of 15% to 18% higher than KBPSO and 25% to 28% superior to LEACH in terms of packet delivery ratio. Similarly, DFLCHES shows an improvement in throughput of 17% to 24% higher than KBPSO and 26% to 28% than LEACH.

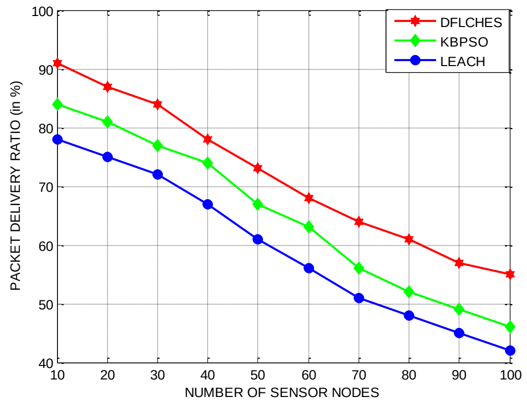

Fig. 7. DFLCHES-packet delivery ratio with varying number of sensor nodes

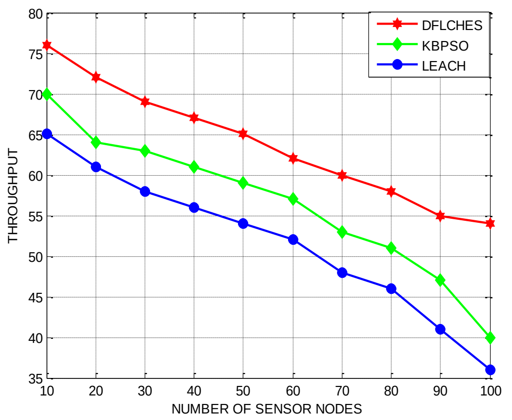

Fig. 8. DFLCHES-throughput with varying number of sensor nodes

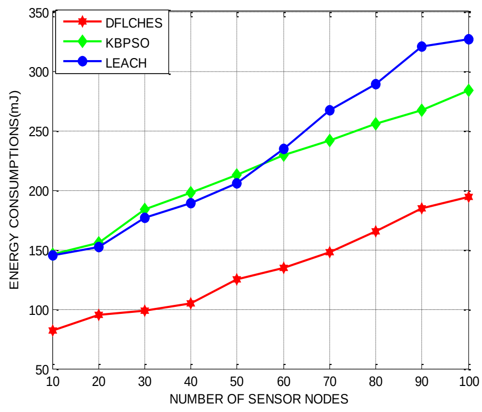

Fig. 9. DFLCHES-energy consumptions with varying number of sensor nodes

It is inferred from the comparative analysis that DFLCHES is a reliable cluster election scheme in improving the packet delivery ratio and throughput of the network as it uses fuzzy clustering model and GA for cluster head reliability and selection. Thus DFLCHES in an average it increases the packet delivery rate and throughput to a maximum extent of 25% and 32% respectively.
Likewise, Figure 9 and Figure 10 present the performance of DFLCHES in comparison with KBPSO and LEACH analyzed in terms of total energy consumption and packet drop rate. DFLCHES decreases the total energy consumption rate and packet drop rate as it elects a reliable and optimal cluster head by considering each nodes packet forwarding rate and available energy.

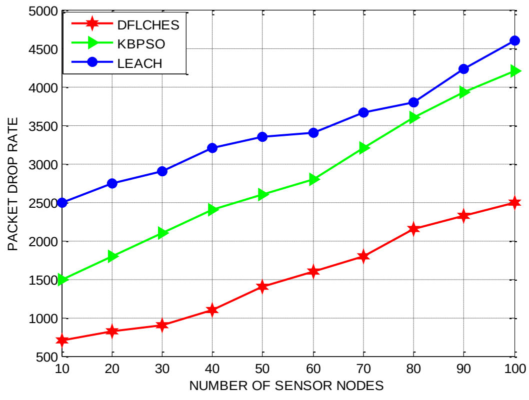

Fig. 10. DFLCHES-packet drop rate with varying number of sensor nodes

Thus DFLCHES reduces the total energy consumption to a maximum extent of 18% to 21% higher than KBPSO and 27% to 33% superior to LEACH. DFLCHES also minimizes the packet drop to a considerable level of 16% to 18% superior to KBPSO and 25% to 31% greater than LEACH. It is also inferred that effective and efficient enough in reducing the total energy consumption and packet drop rate in an average by 25% and 27% respectively. In addition, Figure 11 portrays the performance of DFLCHES based on average delay. DFLCHES also minimizes the average delay to a considerable level of 9% to 12% superior to KBPSO and 18% to 21% greater than LEACH. It is also inferred that DFLCHES is effective and efficient enough in reducing the average delay in an average by 18%.

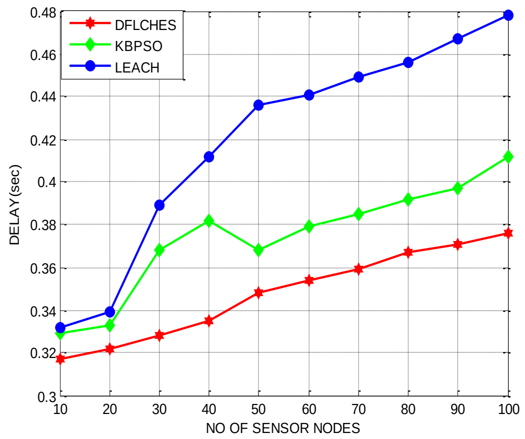

Fig. 11. DFLCHES-average delay with varying number of sensor nodes

The fuzzy tool box diagram depicting membership grade function is estimated based on residual energy (E_{res}). The residual energy function of membership is classified into six predominant sections such Vey Low, Low, Medium Secondary, Medium Primary, High and Very High. This linguistic fuzzy variable depends on the residual energy possessed by the sensor nodes under communication. If the residual energy is less than 5% of the mean residual energy, it belongs to the category of Very Low and in contrast if the value of residual energy is found to be greater than 5% of the mean residual energy, it belongs to the category of Very High. Depending on the degree of association, the Cluster heads are elected such that cluster heads need not be low energy sensor node. Similarly, investigation is performed based on membership function through cluster size, Similar to residual energy, cluster size function is also categorized into the same six thresholds. The probability of enabling maximum number of CHs depends radius of influence of each sensor nodes.

Finally, the performance of DFLCHES is also compared with the predominant cluster head mechanisms like KBPSO and LEACH as portrayed in Table2.

Table 2: Performance Evaluation of Dflches, Kbpso and Leach

Cluster Head Election Schemes	Increase in PDR	Increase in throughput	Decrease in packet latency	Decrease in packet drop rate
DFLCHES	16%	21%	19%	34%
KBPSO	11%	17%	13%	28%
LEACH	8%	13%	11%	24%

5. Conclusion

In this paper, DFLCHES has been proposed for effective cluster head election in order to improve the lifetime of network. DFCHES used the benfits of fuzzy clustering and GA for effective cluster head selection ensuring the improvemnt in the lifetime of the network. Simulation results of DFLCHES portray that the average delay is minimized to a considerable level of 9% to 12% superior to KBPSO, 14% to 17% than LEACH. DFLCHES reduces the total energy consumption to a maximum extent of 13% to 16% higher than KBPSO and 23% to 26% superior to LEACH. KBPSO is also effective and efficient enough in reducing the total energy consumption and packet drop rate in an average by 22% and 15% respectively.In the near future, it is palnned to employ another impotant meta-heiuristic approach like Grenade explosion based clsuter head selection with the aid of cauchy operator.

References

[1] Kemal Akkaya and Mohamed Younis. A survey on routing protocols for wireless sensor networks. Ad hoc networks, 3(3):325–349, 2015.

[2] Wendi B Heinzelman, Anantha P Chandrakasan, and Hari Balakrishnan. An application-specific protocol architecture for wireless microsensor networks. IEEE Transactions on Wireless Communications, 1(4):660–670, 2002.

[3] Tadahiko Murata and HisaoIshibuchi.Performance evaluation of genetic algorithms for flowshop scheduling problems. In Proceedings of the IEEE World Congress on Computational Intelligence (WCCI), pages 812–817. IEEE, 1994.

[4] Shokri Z Selim and K1 Alsultan. A simulated annealing algorithm for the clustering problem. Pattern recognition, 24(10):1003–1008, 1991.

[5] Yamille Del Valle, Ganesh K Venayagamoorthy, Salman Mohagheghi, J-C Hernandez, and Ronald G Harley. Particle swarm optimization: basic concepts, variants and applications in power systems. IEEE Transactions on Evolutionary Computation, 12(2):171– 195, 2008.

[6] Wendi Rabiner Heinzelman, Anantha Chandrakasan, and Hari Balakrishnan. Energy-efficient communication protocol for wireless micro sensor networks. In Proceedings of the 33rd Annual Hawaii International Conference on System Sciences.IEEE, 2000.

[7] G S M Vamsi, Neha Choubey, "A Fuzzy Based Approach of Energy Efficient Hierarchical Clustering Method in Wireless Sensor Networks", International Journal of Science and Research (IJSR), Vol. 4 Iss. 6, pp. 3000 - 3006, June 2015.

[8] Hemavathi Natarajan , Sudha Selvaraj, "A Fuzzy Based Predictive Cluster Head Selection Scheme for Wireless Sensor Networks", Proceedings of the 8th International Conference on Sensing Technology, Sep. 2-4, 2014, Liverpool, UK.

[9] Akshay Kumar Payal Pahwa, Deepali Virmani, Sahil, Vikas Rathi, Sunil Swami, "Dynamic Cluster Head Selection Using Fuzzy Logic on Cloud in Wireless Sensor Networks", International Conference on Intelligent Computing, Communication & Convergence (ICCC-2014), in proc., Computer Science 48 (2015) 497 – 502.

[10] Vipin Pal,Yogita, Girdhari Singh, R.P. Yadav, "Cluster Head Selection Optimization Based on Genetic Algorithm to Prolong Lifetime of Wireless Sensor Networks", International Conference on Recent Trends in Computing 2015 (ICRTC-2015), in Proc., Vol. 57, 2015, pp. 1417–1423.

[11] Abbas Karimi, S. M. Abedini1 , Faraneh Zarafshan1, S.A.R Al-Haddad, "Cluster Head Selection Using Fuzzy Logic and Chaotic Based Genetic Algorithm in Wireless Sensor Network", Journal Basic Applied Science Research vol. 3(4) pp. 694-703, 2013.

[12] Devasena and Sowmya, Cluster Head Selection Methods in Wireless Sensor Network, International Journal of Advance Research in Computer Science and Management Studies, Volume 3, Issue 7, July 2015

[13] Chongdeuk Lee and Taegwon Jeong, FRCA: A Fuzzy Relevance-Based Cluster Head Selection Algorithm for Wireless Mobile *Ad-Hoc* Sensor Networks, Sensors (Basel). 2011; 11(5): 5383–5401.

[14] Taleb Tariq and Mejdi Kaddour, A Novel Cluster Head Selection Method based on HAC Algorithm for Energy Efficient Wireless Sensor Network, Proceeding IPAC'15 Proceedings of the International Conference on Intelligent Information Processing, Security and Advanced Communication, Batna, Algeria – November 23 – 25, 2015.

[15] Hongwei Chen, Chunhua Zhang, XinluZong, Chunzhi Wang, LEACH-G: an Optimal Cluster-heads Selection Algorithm based on LEACH, Journal of Software, vol. 8, no. 10, October 2013.

[16] K.Srikar ,M.Akhil ,V.Krishna reddy, "Execution of Cloud Scheduling Algorithms", International Innovative Research Journal of Engineering and Technology, vol 02,no 04,pp.108-111,2017.

[17] T.Padmapriya and V.Saminadan, "Utility based Vertical Handoff Decision Model for LTE-A networks", International Journal of Computer Science and Information Security, ISSN 1947-5500, vol.14, no.11, November 2016.

[18] S.V.Manikanthan and V.Rama"Optimal Performance Of Key Predistribution Protocol In Wireless Sensor Networks" International Innovative Research Journal of Engineering and Technology ,ISSN NO: 2456-1983,Vol-2,Issue –Special –March 2017.

[19] Rajesh, M., and J. M. Gnanasekar. "An optimized congestion control and error management system for OCCEM." International Journal of Advanced Research in IT and Engineering 4.4 (2015): 1-10.

[20] S.V.Manikanthan and K.Baskaran "Low Cost VLSI Design Implementation of Sorting Network for ACSFD in Wireless Sensor Network", CiiT International Journal of Programmable Device Circuits and Systems,Print: ISSN 0974 – 973X & Online: ISSN 0974 – 9624, Issue : November 2011, PDCS112011008.