Improved fuzzy c-means algorithm based on a novel mechanism for the formation of balanced clusters in WSNs

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ABSTRACT

The clustering approach is considered as a vital method for many fields such as machine learning, pattern recognition, image processing, information retrieval, data compression, computer graphics, and others. Similarly, it has great significance in wireless sensor networks (WSNs) by organizing the sensor nodes into specific clusters. Consequently, saving energy and prolonging network lifetime, which is totally dependent on the sensor's battery, that is considered as a major challenge in the WSNs. Fuzzy c-means (FCM) is one of classification algorithm, which is widely used in literature for this purpose in WSNs. However, according to the nature of random nodes deployment manner, on certain occasions, this situation forces this algorithm to produce unbalanced clusters, which adversely affects the lifetime of the network. To overcome this problem, a new clustering method called FCM-CM has been proposed by improving the FCM algorithm to form balanced clusters for random nodes deployment. The improvement is conducted by integrating the FCM with a centralized mechanism (CM). The proposed method will be evaluated based on four new parameters. Simulation result shows that our proposed algorithm is more superior to FCM by producing balanced clusters in addition to increasing the balancing of the intra-distances of the clusters, which leads to energy conservation and prolonging network lifespan.

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1. INTRODUCTION

Wireless sensor networks (WSNs) is utilized in numerous applications since they are suitable for various environments. It can function independently in conditions of harsh or hazardous places, where these places impose great risks to human beings, and is not advisable for them to be present there. Nevertheless, the sensor's lifetime is only related to their batteries, which are impossible to be replaced or recharged [1-4]. Consequently, with a view of prolonging the network lifetime, WSN used clustering approach for the clustering of the nodes, where the segregation of the sensor nodes into small clusters are executed based on their Euclidean distance. Each cluster employs one node to be the cluster head (CH). The CH possesses numerous functions in addition to sensing the environment such as; data gathering from all cluster members, and its conveyance to the main node termed as base station (BS), the conveyance of other CHs data to the next hop, and the fusion of the cluster data. Clustering approach is the most popular energy efficient technique which provides various advantages such as prolonging the network lifetime, scalability and enabling less delay, where it is considered as an advantage for both the lifespan and the scalability of a network [5].

In general, clustering algorithms are signified as the compilation of unsupervised classification methods that assigns objects into groups, or the partitioning of datasets into subsets known as clusters. Through the utilization of suitable clustering algorithm, the formation of clusters with objects that have the same features into the same cluster as opposed to objects in differing clusters is enabled. This means, clustering entails the allocation of objects possessing certain similarities into the same cluster according to their characteristics [6-8]. One of the most important challenges faced by the clustering approach in WSN is how to improve the cluster structure and construct a balanced size of clusters. Cluster size in our study refers to the quantity of member nodes in individual cluster.

For this objective, several approaches were used based on classification algorithms for better clusters formation [9]. Due to the nature of the random distribution of nodes in the monitoring area, at times these algorithms construct imbalanced clusters size [10, 11]. In this situation, large and small size of clusters are produced, as shown in Figure 1. Consequently, when the clusters sizes are not similar, the situation will lead to an imbalance in the energy consumption among the nodes, which will result in a reduction in the lifespan of the network [12]. Here, the CH for the large cluster is burdened by data more than the CHs in the other clusters, where it needs to consume more energy to send that data. As a result, some nodes are depleting their energy earlier than others which adversely affects the lifetime of the network [13-15]. To overcome this problem, we propose a new clustering method called fuzzy c-means centralized mechanism (FCM-CM) by improving the FCM algorithm to form balanced clusters for random nodes deployment. The improvement is done by modifying the output of FCM based on the integration with a new Centralized Mechanism CM. The centralized mechanism is relying on the centroids that produce from FCM to doing the re-clustering process for the nodes if the resulted clusters are not balanced, based on the cluster threshold. This new clustering method ensures the formation of balanced clusters, which will result in prolonging the network lifespan.

Our proposed methods will be evaluated based on four parameters, which are variation for clusters size, standard deviation for mean square error for intra-distances, clusters size range, and cost difference in the distance for the whole network. There are two differences between the proposed method and the existing methods, which will be considered as our contribution in this study, they are:

- The improvement will be executed through the modification of the output of the algorithm, where most of the existing studies focused on the modification of the initial selection for centroid to improve the algorithm [10, 11, 16]. These improvements do not guarantee the formation of balanced clusters.
- Most of the studies depended on the utilization of solely parameter only to evaluate the balanced size of clusters. This method is not accurate, where the clusters can become more balanced, but at the cost of other aspects. Consequently, our proposed algorithm conduct evaluation based on four new parameters.

The remainder of the current study will be ensued by the ensuing sections; section 2 entails the related works. Additionally, in section 3, we will explain the fuzzy c-means (FCM) algorithm. In section 4, the proposed algorithm will be explained, and in the simulation and performance evaluation will explain in section 5. Finally, section 6 consists of the discussion and conclusion.

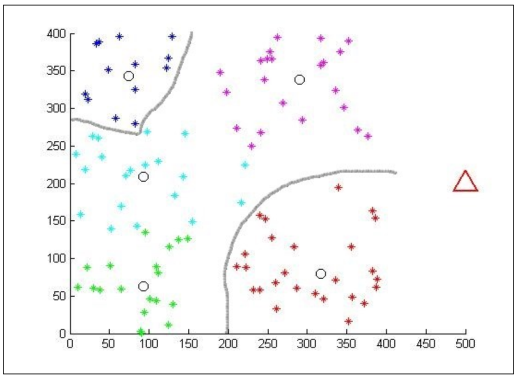


Figure 1. Formation an imbalanced clusters size by FCM

2. RELATED WORKS

Among the principle objectives in WSN is the effective clustering of the whole network, as it is able to decrease the energy being consumed [12], and also is able to offer balanced energy consumption. Hence, FCM is the most utilized algorithms to realize this purpose. FCM helps in the optimization of the clusters according to the minimization of the space between the sensor node and the cluster centroid. Consequently, in another work, Sua and Zhao [11] had recommended the energy efficient algorithm which was termed as optimal clustering mechanism fuzzy-c means (OCM-FCM). In that particular work, the fuzzy c-means clustering was utilized to form an optimal number of static clusters. The notion of coherence was utilized to remove surplus and unneeded data generation, and unnecessary transmission which averts unwarranted energy wastage. The utilization of the intra-cluster and inter-cluster gateways are to avert the nodes from transferring data over an extensive length. A new plan was recommended for choosing strong nodes proximate to the sink for straight data transmissions. Hadjila *et al.* [17] suggested a duo of algorithms utilizing a method which integrates the fuzzy c-means algorithm and the ant colony optimization in the construction of the clusters, and the management of the data transference within the network. Firstly, fuzzy c-means clustering algorithm is utilized in the formation of a predetermined number of clusters. Secondly, the ant colony optimization (ACO) algorithm was applied in the formation of a local minimal chain in individual clusters. Through Alia's work [18], a decentralized fuzzy clustering protocol (DCFP) was suggested.

The construction procedure of the framework for a particular WSNs is conducted one off at the starting of the protocol at a base station, that persists in its unaltered state transcending the entirety of the lifespan of the the network. At the beginning of the formation stage, an FCM algorithm is modified to assign the sensor nodes to their optimum suitable clusters. During the CH-election stage, the assignment of new CHs is executed locally within individual cluster, in which instance, a new multi-criteria objective function is recommended for the enhancement of the quality of assigned cluster heads. Furthermore, Bouyer *et al.* [19] suggested a new method for minimizing energy consumption within the wireless sensor networks with hybrid LEACH protocol and FCM algorithm. The FCM algorithm is utilized in the optimization of the number of the CHs and ascertaining their location and the allocation. The utilization of FCM in WSNs assists in changing the LEACH protocol parameters during the implementation. In another research done by Kaushik [20], a hybrid approach based on FCM clustering and neural network was suggested.

The benefits of both methods, which are the FCM clustering and neural network used to enable an energy effective network that prolonged the network lifespan had been utilized by the researcher. The formation of the cluster is conducted through the utilization of FCM to construct evenly sized clusters within the network. Furthermore, the determination of CH selection is executed through the neural network, by taking into consideration the factors such as the proximity from the base station and the node energy. In their work, Shokrollahi *et al.* [21] introduced an energy-efficient clustering algorithm founded on the fuzzy c-means algorithm and genetic fuzzy system (ECAFG). Through the utilization of the FCM algorithm, the formation of clusters is conducted, followed by the selection of the CHs through utilization of a genetic fuzzy system (GFS). The formed clusters will continue to be unchanged, however the cluster heads are chosen at the starting of every turn. The FCM algorithm constructs balanced static clusters to decrease the data expenses, and disseminate the used energy amongst the clusters. A majority of the current researches either only implement clustering algorithm or improved the algorithm by modifying the initial selection of algorithm. These improvements did not guarantee the formation of balanced clusters. Consequently, in our proposed algorithm the improvement is done by modifying the output to ensure the production of balanced clusters that maintained or enhanced other aspects of cost.

3. FUZZY C-MEANS

FCM is considered as one of the most efficient protocols [22], in actual life situations, where the fuzzy clustering techniques handle the indefiniteness, fuzziness, and ambiguity. Fuzzy clustering is perceived to be an efficient clustering technique. Amongst the fuzzy clustering techniques, the FCMs algorithm was the prevalent and extensively utilized clustering technique [23, 24]. The aim of FCM is in the minimization of the sum of distances between the points and the cluster centroids. In WSNs, the objective is to cluster the N sensor nodes into k distinguished clusters. The objective function of FCM for clustering in WSNs can be formulated as follows:

$$J = \sum_{i=1}^{n}\sum_{j=1}^{k}\mu^{m}\ \ d(x_i\,, x_c)^2\,,\quad i= 1, 2, ..., n \qquad j=1, 2, ..., k \tag{1}$$

$$\mu_{ij} = \frac{1}{\sum_{j=1}^{k}\left(\frac{d(x_i,c_j)}{d(x_i,c_k)}\right)^{\frac{2}{m-1}}}\quad , \mu_{ij}\in [0, 1] \tag{2}$$

$$C_j \ = \frac{\sum_{i=1}^{n}(\mu_{ij})^{m} * d(x_i,c)}{\sum_{i=1}^{n}(\mu_{ij})^{m}} \tag{3}$$

where μ is the membership of node i to cluster j, and m is the value of fuzzifier which is typically selected as 2 in the majority of applications [25]. Furthermore, Cj refers to cluster centroid. This function is different from K-Meas algorithm as it utilizes weighted squared errors instead of utilizing solely squared errors.

This clustering algorithm persist in having a few drawbacks which hinder its function, they are:

- The initial centroids are selected by the random way for the input data set.
- Sensitivity to outlier's points.
- The number of clusters K and the fuzzy weighted index (m) are determined manually.
- It relapses into the local extreme point or saddle point with ease; however, the optimal resolution is unattainable.
- In clusters formation, size of clusters is not considering.

4. PROPOSED CLUSTERING ALGORITHM

This section gives a brief overview of the proposed clustering method and the detail of its components. Based on the simulation results in the previous section, the proposed method is depended upon in FCM algorithm. In general, our proposed method is based on integrated FCM with a new clustering mechanism (CM), where CM receives benefit from the overlapping nodes among the clusters, to improve FCM and the formation of balanced clusters. Our proposed method will be applied by the Base Station, so it centralized the algorithm. The proposed algorithm consists of two phases: 1) initial cluster formation, which is based on FCM and 2) balanced clusters formation, which is based on CM. In the initial cluster formation, the FCM is applied to form the clusters as shown in Table 1, where threshold cluster ($Th_{cluster}$) is then determined. The FCM created balanced clusters, provided that, the minimum size of clusters is more than the $Th_{cluster}$ value, otherwise the clusters are not balanced, and the progression moves to the next phase.

$$Th_{cluster} = \frac{N*PA}{K} \tag{4}$$

Where N means the number of nodes, PA is the permittivity amount, which is equal to 0.85, and K signifies the number of clusters. In the balanced clusters formation phase, CM will be applied as shown in Table 2, CM considers the clusters centroids that were produced from the last phase as beacon points to form balanced clusters.

Table 1. Algorithm 1: fuzzy c-means (FCM)

Algorithm 1: Fuzzy c-means (FCM)
Input: N= the number of sensor nodes. K= the number of clusters. **Output:** A set of K clusters of nodes **Process:** 1- select the random K point as an initial centroid. 2- determine the memberships for each node to K centroids. 3- Allot each node to its closest centroid based on max. membership; 4- determine the new K centroids 5- repeat, until no change in the centroids of clusters or convergence criteria is met.

Table 2. Algorithm 2: novel balanced clustering mechanism (NBCM)

Algorithm 2: Novel balanced clustering mechanism (NBCM)
Input: C_{FCM} = The final set of centroids (beacon points) are determined by FCM. N= the number of sensor nodes. K= the number of clusters. **Output:** A set of K Balanced clusters **Process:** 1- find the minimum cluster size. 2- determine the cluster threshold ($Th_{cluster}$). 3- **if** minimum cluster size < $Th_{cluster}$, **then** 4- Compute the distance from beacon points to each node. 5- Each beacon point sorts the nodes based on the distance from it. 6- Each beacon point selects the nearest nodes that equal to $Th_{cluster}$ value to joint it. 7- The rest nodes joint to nearest beacon point. 8- Re-determine a new centroid for each cluster based on: Centroid (x, y) = $\left((\frac{1}{n} \sum_{i=1}^{n} x_i), (\frac{1}{n} \sum_{i=1}^{n} y_i) \right)$

Each beacon point determines the Euclidean distance from all nodes in a network, where each beacon point then joins the number of nearest nodes equal to $Th_{cluster}$ value. The remaining nodes that are still non-jointed will join the nearest beacon point to construct the final clusters, this procedure ensures that the minimum cluster size is equal to or greater than the threshold limit. After this step, each cluster will determine the new centroid. Figure 2 illustrates our proposed method, and Figure 3 shows the clusters formation by FCM and our proposed algorithm.

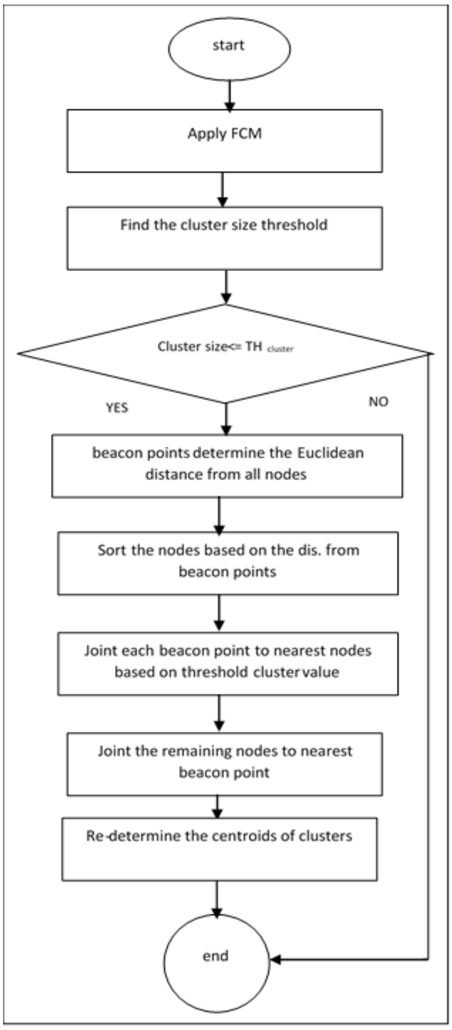
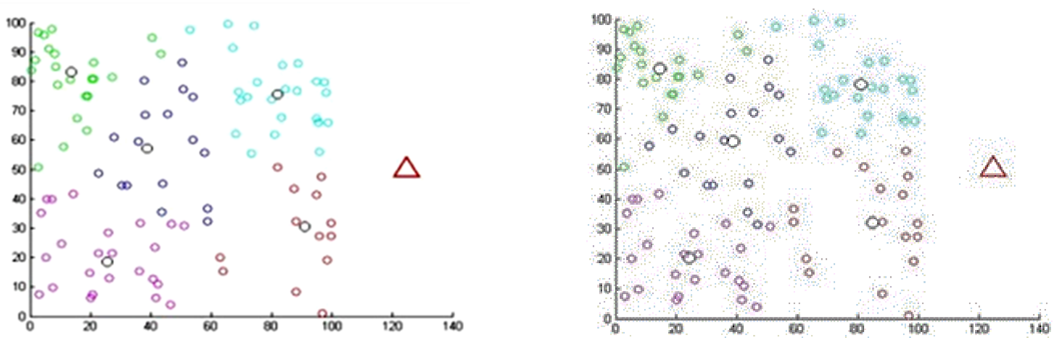


Figure 2. Proposed algorithm



(a) (b)

Figure 3. Clusters formation by FCM and our proposed algorithm; (a) FCM, (b) Proposed algorithm

5. SIMULATION AND PERFORMANCE EVALUATION

In this study, we used Matlab simulation and depended on the most frequent scenarios in the literature, where the number of nodes is 100, monitoring area is 100*100, the number of clusters is 5, and the Base Station is located outside the network at position (50, 125). We applied FCM and FCM-CM for several observations as shown in Table 3. Moreover, based on literature, the squared euclidean distance norm was utilized as the distance measure in both FCM and FCM-CM algorithms.

In this study, we utilize four parameters together, which had used in our previous work [26], where the dependency on measuring the size among the clusters alone is insufficient as a unique evaluation parameter for the consideration of this network to have balanced clusters. For that reason, this study relies on a set of parameters to evaluate the proposed algorithm.

Table 3. Size of clusters using FCM and the proposed algorithmmm

Observations	FCM					Proposed algorithm				
	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
1	15	18	21	22	24	18	18	20	20	24
2	24	17	20	19	20	24	18	19	18	21
3	16	27	16	18	23	18	23	18	19	22
4	25	23	14	21	17	23	21	17	21	18
5	19	25	21	15	20	18	24	21	18	19
6	23	23	17	15	22	22	22	18	17	21
7	20	15	20	22	23	20	17	19	22	22
8	15	23	21	25	16	18	23	21	21	17
9	25	17	16	24	18	23	18	18	23	18
10	22	13	24	24	17	20	17	23	22	18

5.1. Variation for clusters size (V)

Which measures the dissimilarity of the size among the clusters (number of member nodes in each cluster). Where the smaller the factor, the better. This signifies that, there is initially balance in clusters size.

$$V = \frac{\Sigma|S_j - \mu|^2}{k} \tag{5}$$

$$\mu = \frac{\sum_{j=1}^{k} S_j}{k} \tag{6}$$

Where S_j refers to cluster size (j) and μ refer to the mean of clusters size. The evaluation of the variation in the formation of the cluster that utilized FCM algorithm and our recommended algorithm from an optimal one may be realized through the utilization of the parameter variation. Variation for clusters size as shown in Figure 4. The quantity of 5-clusters nodes using FCM and FCM-CM are summarized in Tables 3. Given the circumstances of the deployment of the total 100 sensor nodes, thus for 5-clusters, the value of μ = 20. From Table 4-observation 10 for example, Furthermore, it is obvious that the dissimilarity in FCM is much higher than our proposed FCM-CM algorithm, as shown in Figure 5, where the variation for FCM is 23.5 while the variation for FCM-CM is 6.5. Based on Table 2 our proposed approach produced more balanced clusters than FCM, eventually balancing the load of CHs and extending network lifespan.

5.2. Standard deviation (STD) of mean square error (MSE)

For intra-distances: it measures the difference in the homogeneity for the average of intra-distance for each cluster [27]. This norm shows how the average intra-distances of nodes to the cluster's centroid are different from one cluster to the others. Based on the fact that the energy expended is proportional to the square of the distance, the distances within the clusters should be as homogeneous as possible in order to obtain a balanced energy consumption among the clusters. Furthermore, the smaller the factor, the better it is, denoting that there is a uniformity of the intra-distances of clusters.

$$STD\ (MSE) = \sqrt[2]{\frac{\Sigma|MSE(j) - \mu|^2}{k}} \qquad J=1, 2, \ldots, k \tag{7}$$

where $STD\ (MSE)$ signifies the standard deviation of mean square error, k is the number of clusters, and μ is the average of MSE for distances. $MSE\ (j) = \left(\frac{1}{n}\right) * \sum_{i=1}^{n} D(x_i, x_c)^2$ $i=1, 2, \ldots, n$ $c=1, 2, \ldots, k$. The acronym

MSE refers to the average of square intra-distances of nodes to the cluster's centroid, n is the number of nodes in each cluster, and $D(x_i, x_c)^2$ square intra distances for node (x_i) to its cluster centroid (x_c) in the cluster (c).

$$\mu = \frac{\sum_{j=1}^{k} MSE}{k} \tag{8}$$

From Table 4 and Figure 5, the intra-distances of clusters are more balanced for our proposed algorithm as compared with FCM, where the $STD\ (MSE)$ for FCM is much higher than our proposed CSWM algorithm. As a result, the energy consumption in each cluster is almost the same, which leads to prolonged network lifetime.

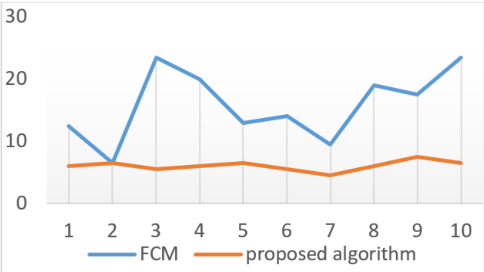


Figure 4. Variation for clusters size

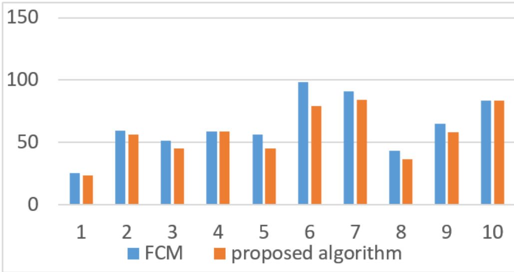


Figure 5. STD (MSE) for FCM and proposed algorithm

5.3. Clusters size range (CSR)

Which measures the ratio of minimum cluster size to the maximum cluster size. Thus, the range of clusters size are limited within this range (min($\frac{CS_j}{max.CS}$) to1), and the narrower the range will be much better (close to zero). That means there is no big difference in the size between the minimum cluster size to the maximum cluster size, which leads to a more balanced in energy consumption between the minimum and the maximum clusters.

$$\text{CSR} = 1 - \min\left(\frac{CS_j}{max.CS}\right) \tag{9}$$

Where CSj refers to the clusters sizes and max. CS refers to the maximum cluster size in the network. In certain instances, the clusters size possesses good homogeneity but with high difference value between the minimum cluster size to maximum cluster size. This signifies that the sizes of the clusters are homogeneous, but the difference between the largest sizes to the lowest size must be at an acceptable range, and is evaluated by CSR parameter. As shown in Table 2 and Figure 6, in the observation 2, FCM possesses good value of variation (low value) the same as the proposed algorithm, but the ratio between min cluster size to max cluster size is equal to 0.292, but in proposed algorithm is equal to 0.25. Figure 6 illustrated the clusters size range.

5.4. Cost difference in the distance

This evaluation parameter is considered as extremely important for the total energy consumption in the network. Moreover, the clusters can be changed to be more evenly balenced, however compromising certain factors such as the cost of increased total distance. Hence, any enhancement on the cluster's formation should take in the consideration the balancing between the improvement and the costof distance. This parameter showed the impact of the cluster's formation improvement on the total distance. The cost of distance is equal to the difference between the sum of intra-distance for clusters in the improved algorithm to the sum of intra-distance for clusters in the original algorithm. The cost of distance should be very small, for an efficient energy consumption. Based on Table 4, the maximum cost difference in the distance is 0.014 in the observation 8, which signifies that when the total distance in FCM is 1633 m, there is only 14 m as a difference in cost distance for the proposed algorithm, where the total distance in the proposed algorithm is 1647 m. Thus, there is no big difference in the cost of distance between the FCM and our proposed algorithm.

Figure 6. The clusters size range

Table 4. Comparison between FCM and Proposed algorithm according to evaluation parameters

Observations	FCM Variation	FCM STD of Mean Square Error	FCM Clusters Size Range	Proposed algorithm Variation	Proposed algorithm STD of Mean Square Error	Proposed algorithm Clusters Size Range	Cost difference CSWM/FCM
1	12.5	25.261	0.375	6	23.499829	0.25	< 0.001
2	6.5	59.647	0.292	6.5	56.439586	0.25	0.002
3	23.5	51.432	0.408	5.5	45.042217	0.218	0.006
4	20	58.856	0.44	6	58.832325	0.261	0.011
5	13	56.714	0.4	6.5	45.302111	0.25	0.010
6	14	98.335	0.375	5.5	79.362672	0.218	0.013
7	9.5	91.032	0.292	4.5	84.48205	0.261	0.003
8	19	43.606	0.408	6	36.624377	0.25	0.014
9	17.5	64.870	0.44	7.5	58.441036	0.218	0.010
10	23.5	83.521	0.4	6.5	83.342818	0.261	0.011

6. CONCLUSION

In this study, an improved fuzzy c-means algorithm (FCM) for the formation of clusters in WSNs has been proposed to overcome the imbalanced clusters formation problem, which has adversely impacted the network lifetime. This problem was the result of random nodes deployment, which forces FCM to produce unbalanced clusters, what detrimentally affected the lifetime of the network. The enhancement of FCM was conducted based on a cluster's mechanism, where this mechanism modifies the output of FCM through the reliance on the produced centroid from the FCM algorithm to re-form the clusters into balanced sizes. Our proposed algorithm is more superior to the conventional FCM in the construction of balanced clusters in three aspects, which are: the member nodes in each cluster, intra-distance for clusters, and the clusters size range, with trivial Cost of the total distance in the whole network. Limitation of this work that the initial centroids of the FCM are selected randomly and this may affect the final result, where this issue will address in the future work.

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REFERENCES

[1] E. C. I.F. Akyildiz, W. Su, Y. Sankarasubramaniam, "Wireless sensor networks: a survey," *Computer Networks*, vol. 38, no. 4, pp. 393-422, March 2002.
[2] A. A. Hassan, *et al.*, "Unequal clustering routing algorithms in wireless sensor networks : A comparative study," *Journal od Advanced Research in Dynamical and Control System,* vol. 10, no.02, pp. 2142-2156, September 2018.
[3] S. Al-Khammasi, D. Alhelal, and N. S. Ali, "Energy efficient cluster based routing protocol for dynamic and static nodes in wireless sensor network," *TELKOMNIKA (Telecommunication Comput. Electron. Control.*, vol. 16, no. 5, pp. 1974-1981, October 2018.

[4] M. El Fissaoui, S. Benkirane, A. Beni-hssane, and M. Saadi, "Scalability Aware energy consumption and dissipation models for wireless sensor networks," *International. Journal of Electrical. Computer. Engineering.*, vol. 7, no. 1, pp. 424-431, February 2017.
[5] P. Maratha and P. Kapil, "A Comparative study on prominent strategies of cluster head selection in wireless sensor networks," *IIntegrated Intelligent Computing, Communication and Security. Springer*, pp. 373–384, September 2018.
[6] S. Al-Augby, S. Majewski, A. Majewska, and K. Nermend, "A comparison of K-means and fuzzy C-means clustering methods for a sample of gulf cooperation council stock markets," *Folia Oeconomica Stetin.*, vol. 14, no. 2, pp. 19-36, June 2015.
[7] Z. Cebeci and F. Yildiz, "Comparison of K-Means and Fuzzy C-Means algorithms on different cluster structures," *J. Agric. Informatics*, vol. 6, no. 3, pp. 13-23, October 2015.
[8] S. W. Guangul, "The effects of segmentation techniques in digital image based identification of ethiopian paper currency," *Indonesian Journal Electrical. Engineering. Computer Science*, vol. 12, no. 3, pp. 1106-1110, December 2018.
[9] A. A. Hassan, *et al.*, "Clustering approach in wireless sensor networks based on K-means : limitations and Recommendations," *International Journal of Recent Technology and Engineering (IJRTE)*, vol. 7, no. 6, pp. 119-126, April 2019.
[10] A. Ray and D. De, "Energy efficient clustering protocol based on K-means (EECPK-means)-midpoint algorithm for enhanced network lifetime in wireless sensor network," *IET Wireless Sensor System*, vol. 6, no. 6, pp. 181-191, December 2016.
[11] S. Su and S. Zhao, "An optimal clustering mechanism based on Fuzzy-C means for wireless sensor networks," *Sustainable Compuer. Informatics and System*, vol. 18, pp. 127-134, June 2018.
[12] S. Dehghani and B. Barekatain, "An enhanced energy-aware cluster-based routing algorithm in wireless sensor networks," *Wirel. Pers. Commun.*, vol. 98, no. 1, pp. 1605-1635, September 2018.
[13] K. Haseeb, K. A. Bakar, A. H. Abdullah, and T. Darwish, "Adaptive energy aware cluster-based routing protocol for wireless sensor networks," *Wireless Networks*, pp. 1-14, 2016.
[14] A. K. Kaushik and A. I. Khan, "An improved fuzzy-control based energy efficient heterogeneous wireless sensor network," in *2016 3rd International Conference on Signal Processing and Integrated Networks (SPIN)*, pp. 610-615, February 2016.
[15] K. Yang, Y. Wu, and H. Zhou, "Research of optimal energy consumption model in wireless sensor network," in *2010 2nd International Conference on Computer Engineering and Technology,* pp. 421-424, April 2010.
[16] E. Rezaei, A. A. Baradaran, and A. Heydariyan, "Multi-hop routing algorithm using steiner points for reducing energy consumption in wireless sensor networks," *Wirel. Pers. Commun.*, vol. 86, no. 3, pp. 1557-1570, 2016.
[17] M. Hadjila, *et al.*, "A Hybrid Cluster and Chain-based Routing Protocol for Lifetime Improvement in WSN," 2015.
[18] O. M. D. Alia, "A decentralized fuzzy c-means-based energy-efficient routing protocol for wireless sensor networks," The *Scientific World Journal*, August 2014.
[19] A. Bouyer, "A New Approach for Decreasing Energy in Wireless Sensor Networks with Hybrid LEACH Protocol and Fuzzy C-Means Algorithm," *International Journal of Communication. Networks and Distributed Systems*, vol. 14, no. 4, Oct 2014.
[20] A. K. Kaushik, "A Hybrid Approach of Fuzzy C-means Clustering and Neural network to make Energy-Efficient heterogeneous Wireless Sensor," *International Journal Electrical and Computer Engineering*, vol. 6, no. 2, pp. 674-681, April 2016.
[21] Ayub S. and Babak M., "An Energy-E ± cient Clustering Algorithm Using Fuzzy C-Means and Genetic Fuzzy System for Wireless," *Journal of Circuits, Systems and Computers,* vol. 26, no. 1, pp. 1-22, 2017.
[22] D. Thanh, L. Hoang, and V. Trong, "Novel fuzzy clustering scheme for 3D wireless sensor networks," *Applied Soft Computing Journal*, vol. 54, pp. 141-149, May 2017.
[23] E. G. Nihad, E. El Mokhtar, Z. Abdelhamid, and A. A. Mohammed, "Hybrid approach of the fuzzy C-means and the K-nearest neighbors methods during the retrieve phase of dynamic case based reasoning for personalized follow-up of learners in real time," *International Journal Electrical Computer Engineering*, vol. 9, no. 6, pp. 4939-4950, December 2019.
[24] R. Amin, *et al.*, "Design of an anonymity-preserving three-factor authenticated key exchange protocol for wireless sensor networks," *Comput. Networks*, vol. 101, pp. 42-62, June 2016.
[25] K. V. Rajkumar, A. Yesubabu, and K. Subrahmanyam, "Fuzzy clustering and Fuzzy C-Means partition cluster analysis and validation studies on a subset of CiteScore dataset," *International Journal Electrical Computer Engineering*, vol. 9, no. 4, pp. 2760-2770, August 2019.
[26] A. A. Hassan, W. Shah, M. Fairuz, and I. Othman, "Evaluate the performance of K-Means and the fuzzy C-Means algorithms to formation balanced clusters in wireless sensor networks," *International Journal Electrical Computer Engineering.*, vol. 10, no. 2, pp. 1515-1523, April 2020.
[27] H. Karim, S. R. Niakan, and R. Safdari, "Comparison of neural network training algorithms for classification of heart diseases," *IAES International Journal of Artificial Intelligence.*, vol. 7, no. 4, pp. 185-189, December 2018.
[28] V. Pal, G. Singh, and R. P. Yadav, "Balanced cluster size solution to extend lifetime of wireless sensor networks," *IEEE Internet of Things Journal*, vol. 2, no. 5, pp. 399-401, Oct 2015.