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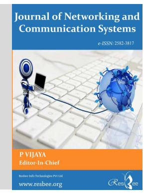

Hybrid FruitFly Optimization Algorithm and Wavelet Neural Network for Energy Efficiency in WSN

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Abstract: A WSN comprises more minimum-cost and minimum-power sensor nodes. In a particular area all the sensor nodes are located and form a WSN in terms of self-organizing. Usually they have the capability to employ at any of the particular or deprived environment that public cannot secure. Nevertheless, the broadcast of data between nodes in an effectual manner is approximately not probable because of the several intricate issues. The clustering is a famous method to create data transmission high effectual. Moreover, the clustering model partitions the SNs into several clusters. In network, each cluster has exclusive CHN that transmit the information to other SNs in cluster. In such cases, it is the important task of any clustering technique to select the optimal CH in several constraints like delay, less energy utilization, and hitherto. This article presents a new CHS model to increase the network lifetime and energy effectiveness. Furthermore, this article presents a novel Fruit Fly Optimization Method and WNN to select the optimal CH in WSN.

Keywords: WSN; cluster head selection; base station; energy; distance

Nomenclature

Abbreviations	Descriptions
WSN	Wireless Sensor Network
CH	Cluster Head
APTEEN	Adaptive Periodic TEEN
LEACH	"Low Energy Adaptive Clustering Hierarchy"
CMMA	Clustering Model For Medical Applications
IoMT	Internet of Medical Things
PSO	Particle Swarm Optimization
CHN	Cluster Head Node
PSNs	Public Safety Networks
CHESS-PC	Cluster-Head Selection Scheme with Power Control
FCM	Fuzzy C-Means
IoT	Internet of Things
LBCP	Load- Balanced Clustering Problem
FPT	Fixed-Parameter Tractable
BS	Base Station
NN	Neural Network
BP	Back Propagation
ABC	Artificial Bee Colony
TEEN	Threshold-Sensitive Energy Efficient Sensor Network
FF	Firefly
TDMA	Time Division Multiple Access
FOA	FruitFly Optimization Algorithm
TC	Topology control
SN	Sensor Nodes
WNN	Wavelet Neural Network
QoS	Qua;ity of Service

1. Introduction

A WSN is a gathering of several SN positioned in a precise region. The most important chore of a WSN is to examine few particular proceedings happening in the region or parameter measure like the pressure,

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temperature of the area. SN sense data from the region as well as transmit them to a BS, named sink. WSNs have been extensively exploited in a lot of areas like fire prevention, military, healthcare, disaster warning systems, surveillance systems, and defense reconnaissance. Each SN exploits a battery which provisions its requisite energy. This battery is not replaceable or rechargeable because of a few applications of these networks. Consequently, reducing energy utilization is considered as the major concerns in these networks.

In WSN, the network life cycle is a significant sign of the network topology quality that typically based on the instance while a definite numeral of nodes expire occurred by energy reduction [17]. TC is considered as the main problems in WSN that is significant for minimizing communication intervention and extended lifetime of the network. Generally, Hierarchical TC technique on the basis of the clustering method is generally exploited and significant topology control technique. The selection of CHN selection is a significant feature of hierarchical TC technique. Additionally, a variety of such techniques were presented in [1]. In [2], LEACH is considered a conventional technique in hierarchical topology control. The fundamental inspiration of LEACH is to arbitrarily choose the CHN by cyclic way, and the load energy of the complete network is consistently distributed to each SN. Subsequently the entire life span of the network is enhanced. On the other hand, there is huge randomness while LEACH choosing CHs.

In designing WSNs, minimization of power utilization has always been a root problem. The latest research result has arisen with different ideas to decrease energy as well as extend the life span of the network for appropriate usage of resources. So, routing method engages a vital role in the procedure. Clustering constructs a hierarchy of groups or clusters of SN that gathers and transports the data to its individual CH. Subsequently, the CH collects the data and transmits the merged to BS or sink node that performs as middleware among the network and the end-user. Amid the clustering technique, LEACH is a traditional protocol, which consists of hierarchical energy routing of data [8]. The network is collected into clusters, as well as the SN sends its data to the equivalent CH. The protocol arbitrarily chose CHs in a stochastic way for every round. The CH interfaces with every node of the cluster named member nodes to gather the sensed data. The CH allocates TDMA schedules to its equivalent cluster member [16]. The member node can put on the air data in the selected time slot. The data is subsequently analyzed for idleness as well as compressed prior to converse with the base station.

Numerous clustering methods have been exploited in WSN and been capable to create the network power-effectual. LEACH [6] is a decentralized clustering technique with two-hop topology. A node is arbitrarily chosen as CH in LEACH, for a cluster. In the network, it does not assurance the uniform distribution of CHs. On the other hand, it enhances life span of the network when comparing with the direct communication approach or low-transmission-energy [7]; also named non-clustering based approach [8] [9]. It works as same as the LEACH although in a centralized way. Other clustering techniques on the basis of the LEACH are “Power- Effectual Gathering in Sensor Information Scheme” [10], the TEEN [11], APTEEN [12], and Hybrid Energy-Effectual Distributed [13] protocols. These techniques do improvement in the life span of the network by enhancing the effectiveness of the network, other than they do not optimize the formation of the cluster. Therefore, to aforesaid concerns, this article presents a novel CHS model, to choose a best CH in WSN. In this article a novel fruit fly optimization technique with WNN to choose a best CH.

2. Literature Review

In 2019, Tao Han et al [1], developed a CMMA for CHS to present an effectual communication for IoMT on the basis of the applications. From the simulation analysis, it was exhibited that the presented performance of the CMMA. It was compared with conventional techniques with respect to energy consumption and sustainability. Consequently, it can be accomplished that the presented CMMA not merely lessen the energy consumption for edge-computing on the basis of the IoMT systems however it also uniformly distribute CHS in the network as a result to extend its life span of the network.

In 2016, Qingjian Ni et al [2] presented a solution on the basis of the fuzzy clustering preprocessing and PSO. Moreover, at first, fuzzy clustering technique was exploited to preliminary clustering for SN based on the geographical positions, whereas an SN goes to a cluster with a resolute probability, as well as the numeral of first clusters was evaluated. In addition, the fitness function was modeled taking into consideration both the distance factors and energy utilization of WSN. At last, the CHN in hierarchical topology were exploited on the basis of enhanced PSO.

In 2018, Abdul Rahim Ansari and Sunghyun Cho [3], have addressed the issue the power utilization and they have exhibited electrifying outcomes. Beside various clustering techniques, suitable CHS plays a vital job in creating WSN more power-effectual. Nevertheless, in conventional research, clustering was not utilized in PSNs. Therefore, this article presents a clustering-on the basis of CHESS-PC for PSNs, which utilizes FCM as a clustering tool. Finally, the outcomes exhibit that the developed system considerably minimizes the power utilization of the network.

In 2019, Trupti Mayee Behera et al [4] worked on a clustering technique, which plays a significant role in power preservation for the energy constraint network. CHS can suitably equilibrium the load in the network thus minimizing energy utilization as well as the life span of the network was enhanced. Moreover, this article concentrates on an effectual CHS method which turns the CH location between the nodes with maximum energy level while comparing with the conventional algorithms. The technique contemplates early energy, remaining energy and the best value of CH to select the subsequent collection of CHs for the network which ensembles for IoT technologies like smart cities, environmental monitoring, as well as systems.

In 2019, Ramin Yarinezhad and Seyed Naser Hashemi[5] worked on clustering sensor nodes, which was an effectual technique for routing in WSNs that enhances the lifetime of the network and minimizes the energy utilization. Nevertheless, in a WSN-clustered, the CHs stand a maximum load while comparing with the additional nodes that tend to their past decease. Hence, reducing the high load of the CHs was a significant issue that was termed as the LBCP. Hence, an FPT approximation technique was presented for LBCP with an approximation factor of 1.2. Additionally, an energy-balanced and energy-effectual routing technique was presented for routing among the sink as well as the CHS.

3. Problem Formulation for CHS in WSN

3.1WSN Model

Let us consider a WSN with Nc clusters, whereas the cluster is referred to as CL_i, whereas $i = 1,.......Nc$. Here, E_{ij} refers the conventional nodes in the cluster, in that $i = 1,2,.......P$ and $j = 1,2,........Q$. Amid the cluster nodes, the CH (ch_i) is selected, and so as to act as the head of residual nodes which subsist in cluster. When choosing the ch, the parameters such as distance between nodes, energy, delay of the packet is also presented. Only the CH does direct communication with the BS (bs). Moreover, this article develops a novel hybrid optimization technique for choosing the best ch by representing all the parameters such as distance, energy, and delay, to maximize the network life span. Fig 1illustrates the WSN model.

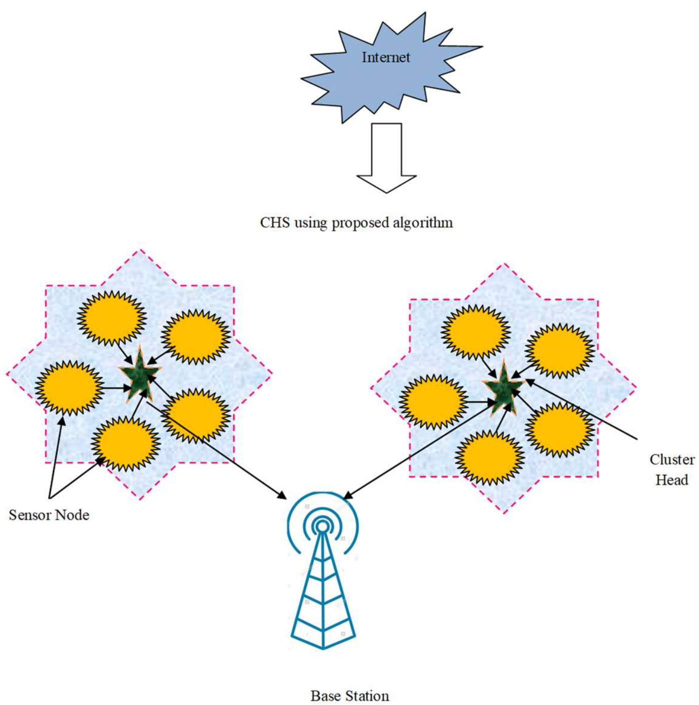

Fig. 1. *System model of WSN for CHS*

3.2 Objective Model

To select the optimal ch, the most important parameters of WSN like delay, energy and distance, are exploited to carry out the effectual CHS. Moreover, this presented method also contemplates the parameter of QoS is a significant parameter for the well-organized performance of the network. In reality, the performance of the network improves if it has maximum energy and QoS, as well as minimum delay. The objective model for the presented method shown in eq. (1), whereas α represents the constant which set the value to 0.3. In Eq. (2), δ^1, δ^2 and δ^3 represents the parameters of energy, distance, as well as delay, correspondingly and $||E_r - bs||$ in eq. (3) represents the distance among general node as well as BS.

$$CN = \alpha \times ff^2 + (1-\alpha) ff^1 \ ; \ 0 < \alpha < 1 \tag{1}$$

$$ff^1 = \delta^1 * ff_i^{dist} + \delta^2 * ff_i^{energy} + \delta^3 * ff_i^{delay} \tag{2}$$

$$ff^2 = \frac{1}{NC} \sum_{r=1}^{n^C} ||E_r - bs|| \tag{3}$$

The parameters that are defined in this work is mathematically modeled as follows:

Energy: In WSN it is determined in Eq. (4), whereas $ER(E_i)$ and $ER(ch_j)$ refers to the energy of i^{th} normal node and energy of j^{th} CH, correspondingly.

$$ff^{energy} = \frac{ff^{energy}(m)}{ff^{energy}(1)} \tag{4}$$

$$f^{energy}(m) = \sum_{j=1}^{Q} vER(j) \tag{5}$$

$$vER(j) = \sum_{\substack{i=1 \\ i \in j}}^{P} \left(1 - ER(E_i) * ER(ch_j)\right); \ 1 \le j < A \tag{6}$$

$$ff^{energy}(v) = A * \underset{i=1}{\overset{P}{Max}}\left(ER(E_i)\right) * \underset{j=1}{\overset{Q}{Max}}\left(ER(ch_j)\right) \tag{7}$$

Distance: Eq. (8) indicates the mathematical representation of parameter of the distance, whereas $ff^{dist}(q)$ refers to the distance among the CH and normal node between the network BSs and CH, that is stated in eq. (9) as well as $ff^{dist}(p)$ indicates the distance between two normal nodes, that is stated in eq. (10). The value of $ff^{distance}(q)$ must be between the range of [0, 1].

$$ff^{dist} = \frac{ff^{dist}(m)}{ff^{dist}(1)} \tag{8}$$

$$ff^{dist}(m) = \sum_{i=1}^{P} \sum_{j=1}^{Q} \left\| E_i - ch_j \right\| + \left\| ch_j - bs \right\| \tag{9}$$

$$ff^{dist}(1) = \sum_{i=1}^{P} \sum_{j=1}^{Q} \left\| E_i - E_j \right\| \tag{10}$$

Delay: By nodes the delay of the data transmission is stated in eq. (11), in that; the value of the delay must be between in the range [0, 1]. If the count of nodes in a cluster minimizes, then the delay as well acquires reduced considerably. In WSN, the eq. (11), in the numerator value the CH is represented, and in the denominator value the total node count is represented.

$$ff^{delay} = \frac{\underset{j=1}{\overset{Q}{Max}}\left(ch_j\right)}{P} \tag{11}$$

QoS: It comprises all the constraints or parameters aforesaid. All the constraints must be fulfilled to describe maximum QoS.

4. Optimized Cluster Head Selection using FOA and WNN

4.1 Conventional Fruitfly algorithm

The conventional FOA [18] is a technique to derive the global optimum on account of the foraging fruit flies behavior [19]. Since the FF has understandable dominance against other species in vision and olfactory system, the group of fly can discover food rapidly, subsequently decide the location, and fly to the goal. Subsequently the position of the food is decided, fruit flies collect with their mates. The description for the iterative procedure for conventional FOA can be stated as below [19]:

a) Generate the population location. Set the first position of the flies group to (y_0, z_0); then decide the count of fruit flies as well as the utmost number of iterations.

b) Set the arbitrary distance and direction of the individual.

$$\begin{cases} Y_i = y_0 + Rn \\ Z_i = z_0 + Rn \end{cases} \tag{12}$$

c) Due to the group, it does not identify the position of the best solution, the distance among the origin and the group distance D is computed initially, as well as subsequently the smell attention value of the judgment J can be computed as below, that is the reciprocal of the distance.

$$D_i = \sqrt{Y_i^2 + Z_i^2}$$

$$J_i = \frac{1}{D_i} \tag{13}$$

d) By replacing J into the smell concentration S judgment model, which is referred to as a fitness model, the position of the fruit fly can be attained by its smell concentration.

$$S_i = fun(J_i) \tag{14}$$

e) Locate the individual with the uppermost smell between all fly groups.

$$[\text{optimal } S_i \text{ optimal index}] = \max(S) \tag{15}$$

f) Maintain the best concentration value and location coordinate (y_i, z_i), for all fruit flies, will fly toward it.

g) To reach iterative optimization, repeat the steps (b)–(f), and decide whether the value of the taste concentration at the present instant is superior to the iterative flavor concentration value at the preceding moment.

$$S \text{ optimal} = \text{optimal } S$$
$$y_i = Y(\text{optimal Index})$$
$$z_i = Z(\text{optimal Index}) \tag{16}$$

4.2 WNN

WNN [20] is a type of feed-forward NN that comprise wavelet transform and BP NN. It is a network model, which is the topological model of BP-NN, and it obtains the wavelet foundation model as the hidden layer excitation model [21].WNN is integrated with the time-frequency domain local properties of wavelet evaluation as well as the self-adaptive ability, self-learning of NN, hence WNN posses' superior simplification capability than NN. Generally, the WNN can be classified into two kinds such as tight WNN and lose WNN [22]. The Loose WNN refers before the NN is trained, by wavelet analysis the data is processed and subsequently trained by BP NN. By exploiting wavelet basis function tight WNN is the training of NN in wavelet analysis rather than excitation model in NN.

In this paper, Tight WNN is exploited to set up the prediction model. In this model, the p signifies the number of input layer nodes, n signifies the number of hidden layer nodes, y_i signifies the input signal, q signifies the number of output layer nodes, z_k signifies the output signal, ϖ_{ij} refers the relation weight among hidden and input layer, $\theta(y)$ indicates wavelet basis model, ϖ_{jk} indicates the linked weight among output and hidden layer , g_j indicates the hidden layer output. The training method flow of WNN is similar as that of BP NN. Its training is partitioned into two kinds such as reverse error correction and forward propagation. The computation steps are stated as below [26]:

Compute the hidden layer output g_j using eq. (17) whereas c_j represents the scaling factor of the wavelet cornerstone, d_j represents the translation factor of the wavelet cornerstone model, and g indicates the wavelet cornerstone function. The wavelet cornerstone model is the important model of the wavelet transform.

$$g_j = g\left(\frac{\sum_{i=1}^{i=p} \varpi_{ij} y_i - d_j}{c_j}\right); j = 1,2,\ldots,p \tag{17}$$

Eq. (18) is used for the Morletmother wavelet model, and the eq. (19) is used to compute the NN z_k .

$$g = \cos(1.75y)e^{-y^2/2} \tag{18}$$

$$z_k = \sum_{j=1}^{p} \varpi_{jk} g_j, \quad k = 1,2,\ldots,n \tag{19}$$

By adjusting the WNN parameters by error, the error among the WNN output and the perfect outcome is calculated as eq. (20).

$$e_k = z'_k - z_k \tag{20}$$

In eq. (20) z_k indicates the actual output of the WNN and z'_k indicates the ideal output of the WNN. The weights of the WNN and the coefficients of the wavelet cornerstone model are modified based on e_k, that are computed using eq. (21).

$$\begin{cases} \varpi_{ij}^{(n+1)} = \varpi_{ij}^{(n)} + \delta\varpi_{ij}^{(n+1)} \\ \varpi_{jk}^{(n+1)} = \varpi_{ijk}^{(n)} + \delta\varpi_{jk}^{(n+1)} \\ c_j^{(n+1)} = c_j^{(n)} + \delta c_j^{(n+1)} \\ d_j^{(n+1)} = d_j^{(n)} + \delta d_j^{(n+1)} \end{cases} \tag{21}$$

The improvement items of the weights of the NN like $\delta\varpi_{ij}^{(n+1)}$, $\delta\varpi_{jk}^{(n+1)}$, $\delta c_j^{(n+1)}$ and $\delta d_j^{(n+1)}$ can be computed as using the error of the network, whereas λ refers to the learning rate.

$$\begin{cases} \delta\varpi_{ij}^{(n+1)} = -\lambda \dfrac{\partial e}{\partial \varpi_{ij}^{(n)}} \\ \delta\varpi_{jk}^{(n+1)} = -\lambda \dfrac{\partial e}{\partial \varpi_{jk}^{(n)}} \\ \delta c_{ij}^{(n+1)} = -\lambda \dfrac{\partial e}{\partial e_j^{(n)}} \\ \delta\varpi_{ij}^{(n+1)} = -\lambda \dfrac{\partial e}{\partial b_j^{(n)}} \end{cases} \tag{22}$$

.

The training of WNN indicates to the achievement of one reverse error correction and one forward propagation. While the NN is incessantly trained as well as the output parameters convene the particular needs, the WNN will terminate training. The data is going into into trained WNN, and subsequently, the output signal will be obtained.

4.3 Proposed WNN-FOA Algorithm

The thresholds and weights of WNN are optimized using FOA, and at first nonlinear time series are normalized. The primary location of the FF $Y_i = (y_{i1}, y_{i2}, \ldots, y_{iN})^T$ is defined, $Z_i = (z_{i1}, z_{i2}, \ldots, z_{iN})^T$, whereas i indicates the count of FF population and N indicates the count of all thresholds and weights in the WNN. The distance and direction of the movement of FF are generated, subsequent the steps to iterate. Optimized thresholds and weights are exploited into WNN for prediction. The proposed WNN-FOA prediction approach procedure is described below:

a) Load the data that is partitioned into testing and training groups, and primary processing, correspondingly.

b) Generate the population and iteration number of the fly optimization approach, the distance of individual search, the position of FF, and the arbitrary direction.

c) Using the fruitfly optimization method, the best value is computed.

d) The optimized thresholds and weights are replaced into the created WNN for training.

5. Results and Discussions

5.1 Experimental Procedure

The experimenttion of propoed algorithm on the basis of the CHS in WSN model was performed in MATLAB 2017. Moreover, the nodes were dispersed within the network region $100\text{m} \times 100\text{m}$ with BS at center. The primary energy EN^{In} of the network has value 0.5, the free space model energy EN^{fr} has

$10 pJ/bit/m^2$. Moreover, the transmitter energy E^{tr} is set as $50 nJ/bit/m^2$, the energy of power amplifier E^{power} is set as $0.0013 pJ/bit/m^2$, and the data aggregation energy E^{Da} was set as $5 nJ/bit/signal$. The presented CHS was performed for 2000 rounds.

5.2 Performance Analysis

Fig. 2 illustrates the graphical demonstration of the proposed and conventional method with respect to the distance. Here, the overall analysis shown the proposed method performs better than the conventional algorithms. Fig 3 summarizes the statistical analysis of the proposed and traditional technique regarding the alive nodes. Here, the mean, median and standard deviation are considered to analyse the proposed method. Fig 4 demonstrates the performance analysis of the proposed and conventional methods regarding the normalized energy.

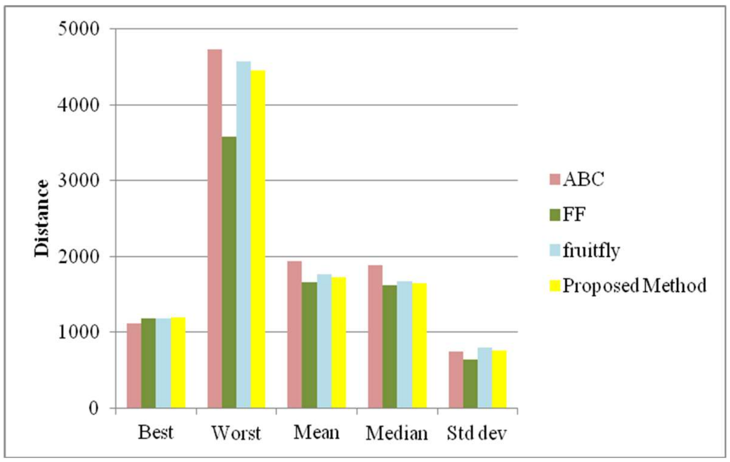

Fig. 2. *Graphical demonstration of the proposed and traditional techniques regarding distance*

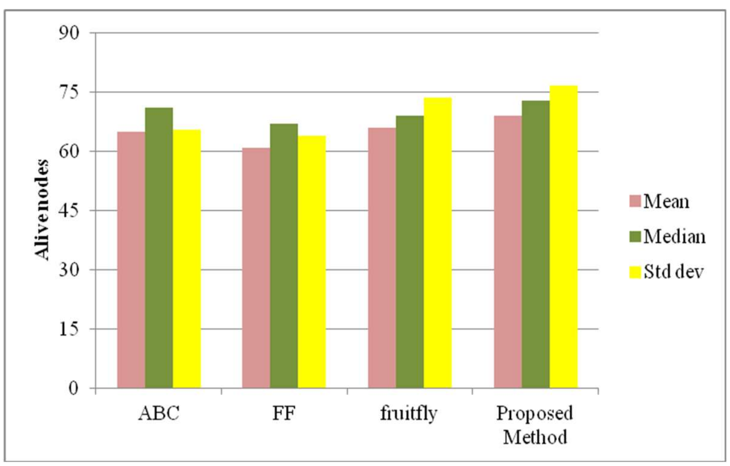

Fig. 3. *Graphical demonstration of the proposed and traditional techniques regarding alive nodes*

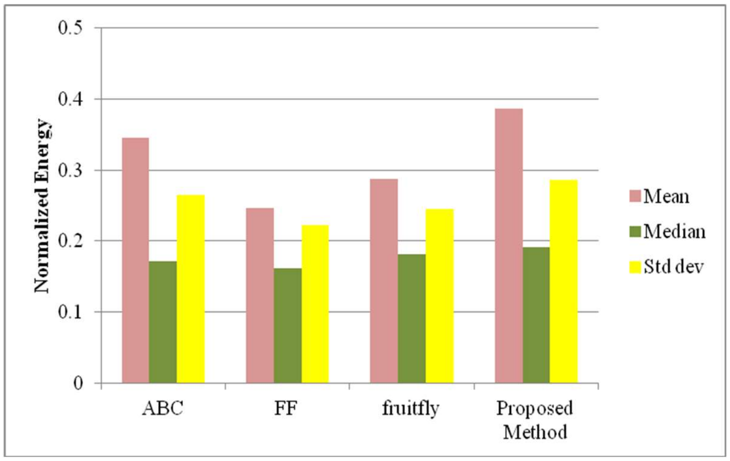

Fig. 4. *Graphical demonstration of the proposed and traditional techniques regarding normalized energy*

6. Conclusion

The WSN comprises of battery-operated nodes, the power utilization of the network is considered as important problems to cautiously deal with the efficiency of the network lifetime. Various clustering techniques were exploited in wireless networks to deal with the power utilization problem as well as they possess exhibits stimulating outcomes. Beside various clustering techniques, suitable CHS plays an important task in making WSN more power-competent. To obtain extend the lifetime of the network, less energy utilization, delay and hitherto. Moreover, this article has developed a novel CHS technique and presented a novel FruitFly Optimization Algorithm and Wavelet Neural Network for choosing the best CH in WSN. Finally, the performance analysis of the presented method was compared with conventional techniques like ABC, FF and fruitfly algorithms regarding the distance, normalized network energy, and alive nodes.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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