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Energy aware cluster and neuro-fuzzy based routing algorithm for wireless sensor networks in IoT

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ABSTRACT

Wireless Sensor Networks (WSNs) are used in the design of Internet of Things (IoT) for sensing the environment, collecting the data and to send them to the base station and the locations used for analysis. In WSNs for IoT, intelligent routing is an important phenomena that is necessary to enhance the Quality of Service (QoS) in the network. Moreover, the energy required for communication in the IoT based sensor networks is an important challenge to avoid immense packet loss or packet drop, fast energy depletion and unfairness across the network leading to reduction in node performance and increase in delay with respect to packet delivery. Hence, there is an extreme need to check energy usage by the nodes in order to enhance the overall network performance through the application of intelligent machine learning techniques for making effective routing decisions. Many approaches are already available in the literature on energy efficient routing for WSNs. However, they must be enhanced to suite the WSN in IoT environment. Therefore, a new Neuro-Fuzzy Rule Based Cluster Formation and Routing Protocol for performing efficient routing in IoT based WSNs. From the experiments conducted in this research work using the proposed model, it is proved that the proposed routing algorithm provided better network performance in terms of the metrics namely energy utilization, packet delivery ratio, delay and network lifetime.

1. Introduction

Internet of Things (IoT) [35] is a new computing facility which consists of the features from networks, devices and software and it helps to connect many devices for co-ordinated working. The design of IoT must take care of challenging issues with respect to interconnection and communication. The existing protocols designed for wired, wireless and sensor networks cannot be used directly for enhancing the performance of IoT based networks due to the presence of heterogeneous devices including tiny devices and larger house hold devices. There are many applications in day to day life in which we use mobile phones, laptops, sensors and house hold devices such as air conditioner, fridge, coffee maker, microwave oven and washing machines that are collected with IoT for performing many of our activities. Moreover, IoT can be used along with our vehicles using vehicular adhoc networks and they can be used for data collection routing and an amount of intelligence can be introduced in IoT for effective co-ordination and communication.

The intelligence can be introduced in IoT devices through the application of machine learning techniques and soft computing approaches. In such a scenario, the sensors present in the IoT can use the rules formed by deep learning algorithms for making effective decisions on actions to be performed. Moreover, mobility of devices is also allowed in IoT devices and hence the formation of rules for mobility management, energy optimization and intelligent routing are the important challenges into be addressed in the design of IoT based networks. In an IoT system, the human-usable objects namely air fresheners and smart vehicles can be made intelligent by writing rule based programming techniques so that such devices can respond flexibly based on the decision made by the decision manager. An inference engine can also be designed for effective decision making with respect to improvement in quality of service in IoT environment. However, it is different from Ubiquitous Computing environment [34]. Internet Protocol Version 6 (IPV6) provides some support for routing of data in the IoT environment. However, the data collection, data representation, data storage and communication must all together cooperate for effective working

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of the IoT application. This can be achieved by developing machine learning and rule based approach for making data collection and communication intelligently.

An intelligent device can be designed by making a sensor for efficiently sensing the environment, an actuator which can take actions based on deductive inference by firing rules and a decision making module which can provide intelligent decisions by the skilful applications of rules. Such a design can be made effective through the mathematical modelling of the behaviour and by developing an intelligent data communication mechanism. So, IoT can be given as an equation with the sum of three main components namely Physical object, Controller, Sensor and Actuator (CSA) and the Internet. The Internet Protocol version 6 (IPv6) is the lowest power network used to connect the sensors that are incorporated in the IoT. There are many factors that will affect the working of IoT such as design, configuration, language communication, data flow, setting up of a generalized framework, compatibility, energy consumption at data centres and user interface to interact with the objects [37]. In such a scenario, energy efficient intelligent routing is a major aspect to be considered during data transfer between sensors and sink node and then to the internet in the IoT environment. An eventual and drastic change in data communication is possible only via WSNs in IoT. So, IoT is considered null without the support of WSNs.

In IoT environment, Wireless Sensor Networks (WSNs) [36] is an important component that has attracted the overall networking and IoT communities, especially with the advancement of Micro Electro Mechanical Systems that supported the change of smart and intelligent sensors. These sensor nodes present in WSN is capable of sensing the environment and to measure the environmental conditions for accumulating the corresponding data to be sent to the user through base station. In such a scenario, battery life is the most important resource to be considered in the design of such nodes [1]. A sensor node carries limited and generally irreplaceable power sources. Therefore, it is necessary to design the nodes of the WSN with energy efficiency and to make the related protocols to focus on the improvement of overall quality of the network.

Clustering of nodes in the network is the successful topology design and control technique that can be adopted to diminish energy utilization in the nodes of the WSN. Clustering and performing the cluster based routing improves the network conditions namely energy efficiency, reduction in delay and increase in scalability [15]. The two imperative steps that are used in the cluster based routing include the selection of Cluster Head (CH) and routing through CHs [16,17]. The energy can be conserved more by the CH by collecting the data from the nodes and forwarding them through the CHs to the sink node [2]. So, selecting the CH appropriately among the nodes can diminish the energy utilization and prolong the lifespan of the WSN. Moreover, most of the researchers focused on CH selection in clustering and cluster based routing. However, [2,3] and [7–9] energy consumption is the most important factor on cluster formation and routing only a few researchers have concentrated on cluster arrangement for effective routing this past [10–12]. In Low Energy Adaptive Clustering Hierarchy (LEACH) [22,23], clusters are formed for each round based on the space between the node and the CH, the nodes disregard the alternate components that impact the energy utilization and the system life span. In this protocol, energy is modelled and the node having the highest energy and the lowest distance from the member nodes are considered for the selection of CHs. Whenever the energy available in the CH becomes less than any of the available cluster members in the network then, a new CH is elected using the same criteria. In [10], cluster is formed using fuzzy logic by considering 3 factors. One limitation of this work is that it does not consider the cluster size in the network, which is an important component for the uniform energy utilization by the nodes in the network. In [9], a new member joining method is proposed where upon receiving the willing to join message, the CH allows the sensor node to join the CH. But they did not clearly mention on what factor the member can join with the CH. Other related works in this area include [18–21]. All these works attempted to reduce the energy consumption and provided techniques for optimal energy consumption. However, due to the uncertainty happening due to the movement of nodes, most of this works had the limitation in terms of energy optimization.

There are many works that are discussing about cluster based intelligent routing in WSN. Among them, the Fuzzy Logic based Cluster Formation Protocol (FLCFP) is considered in this work with extensions for performance improvement through the use of deep learning techniques by applying convolutional neural network (CNN) for predicting the energy requirements so that it is possible to make effective routing decisions. Comparing with FLCFP, the proposed model discussed in this paper enhances the network life time and reduces the energy consumption by the skilful application of fuzzy rules and the modification of knowledge base consisting of rules dynamically through the effective training of the neural network. In another work by Younis and Fahmy [3] called Hybrid Energy Efficient and Distributed (HEED) model for energy efficient cluster based routing, a probabilistic model is used to measure the network traffic and the probability values are used in the clustering and cluster based routing process. However, the probabilistic approach used in this work must be enhanced in order to improve the accuracy of decision making.

To overcome the issues in the previous cluster formation techniques, we propose a new protocol called neuro-fuzzy based cluster formation protocol (FBCFP), which performs learning of the network by considering four important components namely current energy level of the CH, distance of the CH from the sink node, change in area between the nodes present in the cluster and the CH due to mobility and the degree of the CH. For this purpose, the network is trained with convolutional neural network with fuzzy rules for weight adjustment. Moreover, we used fuzzy reasoning approach for powerful cluster formation and to perform cluster based routing. Once the CH has been selected, each of the non-CH nodes in the system apply these four factors for all CH in the proposed network using Mamdani Inference System and it uses the member join principle by considering the maximum value of energy for becoming the CH. In order to evaluate the proposed routing algorithm, its performance is contrasted with LEACH, FLCFP and HEED. The experimental results pertaining to this work has shown that the proposed technique namely FBCFP expands the system lifetime extensively than LEACH, FLCFP and HEED. In addition, it is shown that the proposed FLCFP reduces the energy utilization and enhances the QoS in IoT based sensor networks by keeping the cluster size uniform and the power utilization to become optimal by applying rules learnt from training of the system using machine learning algorithm and by applying the rules for making effective routing decisions. Through the simulations conducted in this research work, it has been proved that the packet delivery ratio is enhanced and the other QoS parameters namely delay and energy consumption are reduced due to the use of convolutional neural networks for learning in the proposed work.

The rest of the paper has been organized as follows: in Section 2, the related work in the areas of cluster based routing has been explored. In Section 3, the proposed work along with the fuzzy based routing protocol developed in this work has been detailed. In Section 4, assessment of the proposed work is performed and the results are depicted with suitable comparative analysis. Finally, we concluded this paper in Section 5.

2. Literature survey

Energy efficient design of sensor networks based IoT system is complex due to the energy constraints present in the sensor nodes. In such a scenario, energy conservation during the data collection and routing process is an important design issue that is also used for evaluating the performance of IoTs using WSN. To accomplish the energy efficiency, numerous routing algorithms based on clustering have been proposed in the literature [2–6,33]. LEACH [13] is an important routing protocol among the cluster based routing techniques developed for effective routing in WSN due to its energy efficiency through clustering. It performs routing through the cluster heads which are elected periodically based on the network conditions. In [14], apart from using residual energy, it provides facility for efficient rotation of cluster heads in order to enhance the network lifetime. In clustering, the CH bears some additional load for information gathering, aggregation and communication with the base station. Hence, it is necessary to balance the load of the Cluster Head nodes conditions including congestion must be modelled with the available information. This uncertainty can be handled by applying fuzzy rules since fuzzy logic provides features for gradation of truth values and making decision with partial information. In the past many researchers used fuzzy logic for handling the uncertainty issue in many applications. In [15], a new relay selection algorithm was proposed by applying fuzzy logic based decision making model. In [2], the authors used fuzzy rules for electing suitable cluster heads and to carry out the routing process through the cluster heads. Such models provided improvement in performance upto a certain extent. However, the accuracy is to be enhanced further for making more accurate decisions. The fuzzy rules can be expanded by considering additional number of attributes. Therefore in [8], the authors developed a fuzzy based routing model by considering the variables namely distance and energy. However, the energy efficiency problem could not be solved fully due to the nature of the sensor nodes. Hence, it is necessary to consider a better learning technique that can be integrated with fuzzy logic inorder to handle the uncertainty problem and to perform effective prediction

Wang et al. [30] briefed the usage of transport protocols for WSNs. Several design guidelines to maintain QoS fairness is also mentioned. Congestion Control algorithms are classified depending on three criteria namely the detection of congestion, providing notification on congestion to the sink node as well as the neighbour nodes and the adjustment of data flow rate. In this paper, the transport protocols are split into congestion control and reliability guarantee protocols in a simpler and consolidated grouping of existing protocols. The highlight of this paper is that it covers the basic design principles of WSNs for IoT from scratch till congestion control, QoS mechanisms and future research aspects.

Palattella et al. [31] presented a clear and a detailed study on how IoT is used today nearing towards the 5G era. The importance of connectivity factor to be ubiquitous, reliable, scalable, and cost-efficient is potential challenge to enable IoT becoming universal. The author has brought into limelight the distinction of how these technologies function for different application domains namely consumer IoT (cIoT) and industrial IoT (iIoT). The paper is written in such a way that it is focussing on the key development of 5G technology in IoT and its business inferences.

Betzler et al. [32] gave an IoT approach that is used for time estimation in a round-trip, done with a backoff factor considering age factor for retransmission timeouts. This dynamic nature is suitable for almost all IoT communications. Apart from these works, many researchers gave the importance to another step namely cluster formation in the clustering process for performing energy efficient routing [24–27]. Mhemed et al. [10] proposed a new approach on cluster formation. In their work, fuzzy logic was used to form the clusters in network based on three parameters namely energy, distance of nodes from cluster head and the distance of the sink node. They have shown the enhancement in the network life span of WSN. In [6], authors proposed fuzzy logic approach for unequal clustering. The authors used CH degree and the distance to the sink for the choice of CH. Taheri et al. [12] proposed a new and energy-aware routing protocol which is also a distributed and dynamic clustering based protocol that uses three steps namely probabilistic CH election process, application of fuzzy logic for decision making and the provision of on demand clustering. Their model focuses on all rounds and hence it performs clustering continuously like the LEACH protocol. The HEED algorithm which was proposed by Younis and Fahmy [3] is an energy efficient cluster based routing algorithm that selects the cluster heads randomly by using the probability values in order to perform cluster based routing effectively. However, HEED changes the CHs more uniformly across the sensor network in multiple iterations among smaller cluster ranges. Moreover, each node in HEED algorithm can become a CH through rotation policy using its own probability values when the algorithm is hearing no cluster head-declaration from the neighbour nodes. The main advantage of HEED is that the CHs are selected based on the rotation policy. Moreover, the decision process has been improved by applying rules more effectively. However, most of the above discussed algorithms worked on CH selection using fuzzy logic and only a few worked on cluster formation. In addition, the existing works focused on decision making using fuzzy logic and considered routing without deep learning of the network [6] and [10].

The proposed FBCFP algorithm also uses a fuzzy logic for cluster development. It is different from the above work in improving the performance of the WSN. The improper cluster formation may cause the CH over-burden, which brings about expansion the latency in communication, expends high energy of the CH and degrades the overall performance of the sensor networks. Subsequently, load balancing and routing using the CHs and nodes is one of the crucial problems for clustering sensor nodes. In [9], if the more number of members join the CH, then the CH gets overburden and it loses its energy very quickly. To address the problems in cluster formation, in this work, the cluster is formed based on four parameters, namely current energy of CH, space between CH and node, distance of CH from sink and the node degree. Grid based routing protocols also proposed in the past for enhancing the routing performance [28,29]. Among them, Logambigai et al. [28] proposed an intelligent fuzzy rule and grid and energy based intelligent routing algorithm for WSN by applying unequal clustering of nodes and proved that their work enhanced the network lifetime considerably. Lin et al. [29] developed a grid position based shortest path routing algorithm for the unnamed aerial systems. The authors could achieve improved network performance based on the quality of service metrics.

In spite of the availability of all these works in the literature on intelligent cluster based routing for WSN, most of the existing systems used only the clustering techniques based on distance. However in a sensor network, energy efficiency is an important parameter that must be considered for enhancing the network life time. Therefore, a deep learning based method has been proposed in this paper for effectively classifying the nodes which helps in forming effective clusters. Another challenge in the design of routing algorithms for sensor networks is the decision making process in the routing algorithms. In this work, fuzzy rules are used for making more efficient decisions to provide an optimal value in the route discovery process. The proposed model considered the sensors present in the IOT scenario and hence the existing routing protocols which were proposed for routing in wireless sensor networks are not able to provide optimal energy consumption solution. However, the proposed energy efficient approach for cluster formation and cluster based routing provides optimal results by reducing the energy consumption and delay. Moreover, the routing algorithm developed in this research work is increasing the packet delivery ratio by avoiding node failures. This is achieved by the effective monitoring of energy levels and thereby avoiding the packet drops occurring due to node failures by energy. Finally, it is observed that the proposed work provides optimal results with respect to the improvement with respect to QoS in IoT based WSNs.

3. Cluster formation protocol using neuro fuzzy rules

The most important goal of the proposed research work is to enhance the lifetime of the IoT based WSN. So, this work proposes a deep learning based approach integrated with Neuro-Fuzzy Inference System (NFIS) for the extension of network lifetime. NFIS is the method which is useful for decision making by taking multiple inputs to provide a single qualitative output. The proposed model works in many rounds starting with initial round, continuing with intermediate rounds and ending with the final round as it is done in cluster based routing protocols including LEACH. This proposed work differs from the existing works from cluster formation stage onwards when it is compared with the other related protocols namely LEACH, FLCFP and HEED. The main difference is the number of parameters considered to form the cluster. In LEACH, only one parameter is used, in FLCFP three parameters are used and in HEED also only two parameters are considered. In HEED, the nodes within the transmission range join the CH in a distributed way. The main problem in this if a node is within the transmission range of two or more CHs, it transmits the data to all the CHs which results in redundancy of communication. So, in our work, we used four factors for the cluster formation. Moreover, this work uses the deep learning approach by employing Convolution Neural Network (CNN) for forming rules on discovering energy efficient routing.

In this work, the CNN uses one input layer for providing the inputs, two hidden layers for processing and one output layer for providing the results. One of the hidden layers is used as the convolution layer. The neural network is trained with network trace data obtained from the past and present communications. The past data are used for the initial training. Weights are adjusted by using the current data and by applying fuzzy rules that are fired by the fuzzy inference system. The cluster members are dynamically updated based on the distance from the cluster heads and the energy availability. For this purpose the energy consumed in different nodes and the routing patterns are analysed using the convolution neural network. To find the most optimal route requiring minimum energy consumption, rules are formed through the training of convolution neural networks. Such networks are fully connected in nature and hence the training is carried out at the base station and the rules are only propagated to the sensor nodes. Testing is carried out at the sensor nodes by communicating a set of data collected by the sensor nodes. Using this testing, the route discovered by the proposed routing algorithm is validated with respect to energy efficiency. In this way, the proposed routing algorithm uses the convolution neural network for performing deep learning of the node behaviours with respect to communication so that it is possible to provide an energy efficient routing process.

3.1. Cluster formation

In this section we provide the details about the four parameters namely current energy level of the CH, space between Cluster Head and Sink, space between node and CH [10] and CH degree for effective cluster formation. After electing the CH, the other nodes are allowed to join the network by affiliating with a suitable CH in order to become a member of anyone of the clusters and they are approved by the CH based on the application of fuzzy rules. The architecture of the Fuzzy rule based routing system for the proposed protocol called FBCFP is shown in Fig. 1. The system has 4 inputs

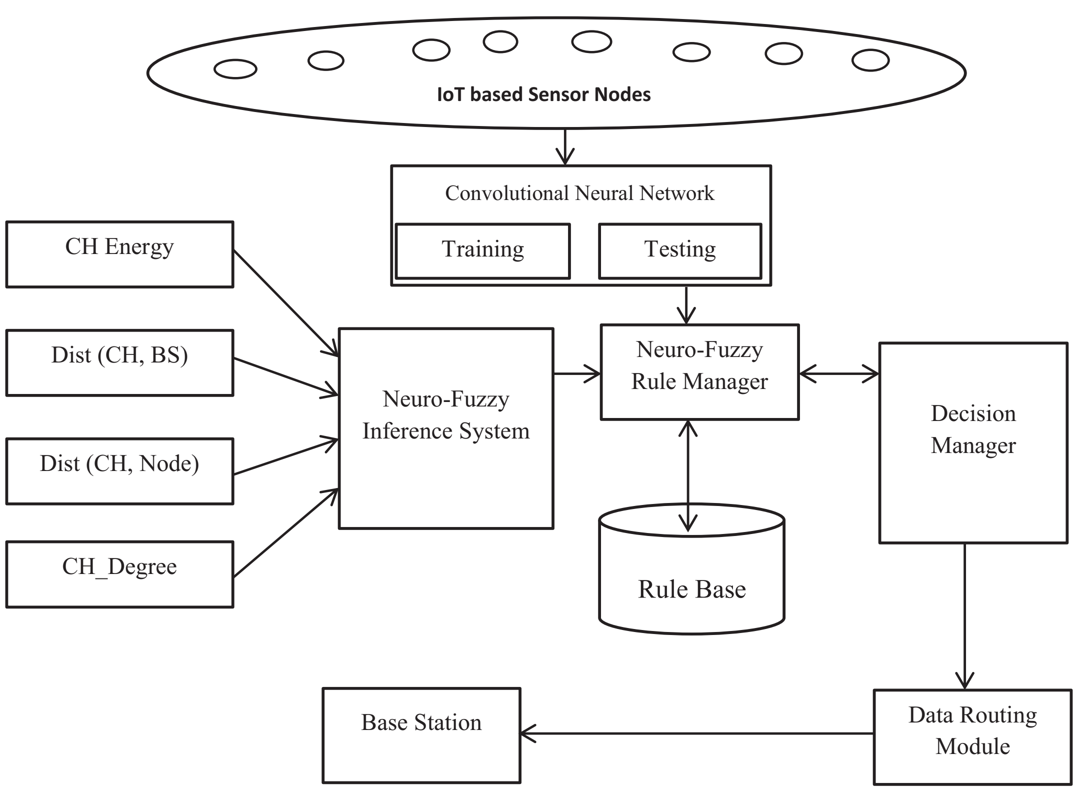


Fig. 1. Fuzzy rule based routing system architecture.

Table 1
Fuzzy rules.

CH Current Energy	Dist. Between CH and Sink	Dist. Between Node and CH	CH Degree	Member choice
Less	Distant	Distant	More	Very much weak
Less	Distant	Distant	More average	Weak
Less	Distant	Distant	Average	Less weak
Less	Distant	Distant	Low average	Less medium
Less	Distant	Distant	Low	Medium
Medium less	Medium distant	Medium distant	More	Weak
Medium less	Medium distant	Medium distant	More average	Less weak
Medium less	Medium distant	Medium distant	Average	less medium
Medium less	Medium distant	Medium distant	Low average	Medium
Highly medium	Medium closer	Medium	More	Less medium
Highly medium	Medium closer	Medium	More average	Medium
Highly Medium	Medium closer	Medium	Average	Less medium
Highly medium	Medium closer	Medium	Low average	Medium
Highly medium	Medium closer	Medium	Low	Highly medium
Highly	Closer	Closer	More	Medium
Highly	Closer	Closer	More average	Highly medium
Highly	Closer	Closer	Average	Less strong
Highly	Closer	Closer	Low average	Strong
Highly	Closer	Closer	Low	Very much strong

Table 2
Network simulation parameters.

Parameters	Values
Simulation area	100×100 m^2
No. of sensor nodes	100
Initial energy of nodes	0.5 J
E_{elec}	50 nJ/bit
ε_{fs}	10 pJ/bit/m^2
ε_{mp}	0.0013 pJ/bit/m^4
Packet size	4096 bits

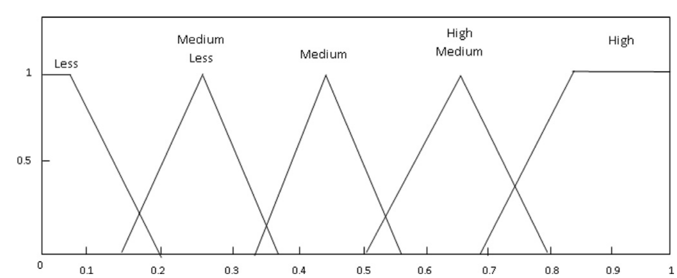


Fig. 2. Linguistic values for energy level of CH.

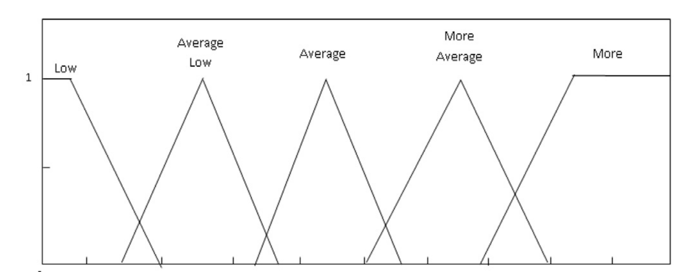


Fig. 3. Linguistic values for distance between CH and Sink.

from the input layer, 256 rules from the hidden layers and 1 output from the output layer. In this system, we used four linguistic variables each with three levels including the proposed parameter CH degree.

The architecture of the proposed routing system is shown in Fig. 1 consists of major modules namely IoT based Sensor Nodes, Neural Network module for training and testing, Neuro-Fuzzy inference system, Neuro Fuzzy rule manager, Rule base, Base station, Data Routing Module, Decision Manager and Cluster Distance Management modules. All these modules cooperate to perform the data collection, routing and decision making more efficiently to achieve energy efficiency.

3.1.1. Cluster head degree

Cluster members are very important for balancing the load in a cluster. For that purpose, we introduced a new computation technique for selecting the CH. Here, the members before join with the CH, it considers the count of the members which are already present in the respective cluster. Moreover, this work calculates the Cluster Head degree using Eq. (1). If the CH_{degree} is high then there is very less chance for a node to join as a cluster member with that CH.

$$CH_{degree} = \frac{\text{Number of nodes in the cluster}}{\text{Total number of nodes}} \tag{1}$$

For example, if the number of nodes in the network is 100 and the number of nodes in cluster 1 is 10 then the cluster head degree of node 1 is 0.1.

3.1.2. Neuro-fuzzy membership functions

In this work, convolutional neural networks are used for performing training of the sensor nodes and the structure of the communication links present in the IoT based WSN. This technique enables the network for finding the shortest path of the nodes to the cluster heads and then to the sink node by applying neuro-fuzzy rules. For this purpose, the NFIS uses the triangular and trapezoidal membership functions as in [10] along with convolutional neural network in order to form decision rules. Moreover, the neuro-fuzzy rule system uses the fuzzy membership functions which are given in the below equations.

$$\mu_{A1}\ (z) = \begin{cases} 0 & z \le a1 \\ \frac{z-p1}{q1-p1} & p1 \le z \le q1 \\ \frac{r1-z}{r1-q1} & q1 \le z \le r1 \\ 0 & r1 \le z \end{cases} \tag{2}$$

$$\mu_{A1}\ (z) = \begin{cases} 0, & z \le a2 \\ \frac{d2-x}{d2-r2}, & r2 \le z \le d2 \\ 1, & q2 \le z \le r2 \\ \frac{d2-x}{d2-r2}, & r2 \le z \le d2 \\ 0, & d2 \le z \end{cases} \tag{3}$$

Here, the variables z and x represent the fuzzy and actual distances in which the fuzzy distance value is measured using the

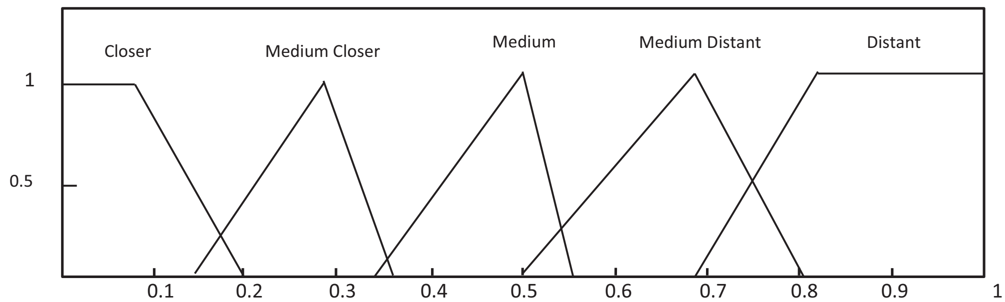


Fig. 4. Linguistic values for distance between CH and Node.

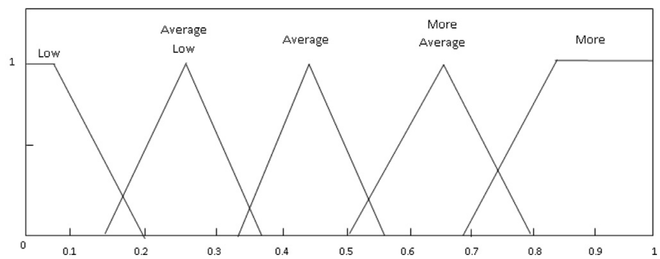


Fig. 5. Linguistic values for CH Degree.

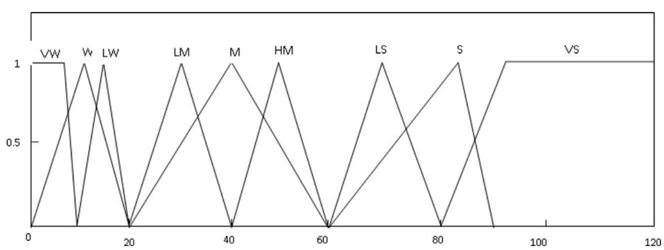


Fig. 6. Linguistic values for member choice.

membership functions. In this work, the energy model used is similar to [10] is given in (4) and (5). The E_{elec} represents the electronics energy and ε_{fs} and ε_{mp} are representing the amplifier energy present in the free space and also the multipath respectively. In this model, the energy which is required for transmission of an l-bit message through the WSN for a distance called *dist* is computed as follows:

$$E_T(l, dist) = \begin{cases} l\ E_{elec} + l\ \varepsilon_{fs} dist^2\ \ for\ dist < d_0 \\ l\ E_{elec} + l\ \varepsilon_{mp} dist^4\ \ for\ dist \geq d_0 \end{cases} \quad (4)$$

Here, d_0 is the threshold distance for defining the energy levels.

The energy $E_R(l)$ that is required for receiving a message of size l-bit is as follows:

$$E_R(l) = \ l\ E_{elec} \quad (5)$$

3.2. Neuro fuzzy rules

In this work, first we performed training of the convolutional neural network with fuzzy approach for weight adjustment and hence Mamdani Fuzzy inference model has been used in this work due to the nature of the convolutional neural network [2,8] and [10]. The proposed NFIS has 4 input variables and each input has 3 levels. The levels used for each of the fuzzy variables are as follows:

CH Current Energy – Less, medium less, medium, highly medium and highly,

Dist. between CH and Sink – Closer, medium closer, medium, medium distant and distant

Dist. between CH and Node – Closer, medium closer, medium, medium distant and distant

CH Degree – Low, low average, average, more average and more

So, 4^4=256 possible member choice values are worked out using fuzzy IF-THEN rules. For implementing the member choice output variable in this work, 9 levels have been used namely Very much weak, weak, less weak, less medium, medium, highly medium, less strong, strong and Very much strong. The triangular and trapezoidal functions are used to represent member choice levels. The fuzzy logic based IF-THEN rules used in the proposed system are shown in Table 1.

The last step in the fuzzy rule based inference process is the de-fuzzification step. To obtain the crisp output value corresponding to the fuzzy values, the de-fuzzification step has been applied in this work. Among the de-fuzzification methods which are available in the literature, the Centre of Area method is the most widely used method and hence this work adopted the COA method shown in (6).

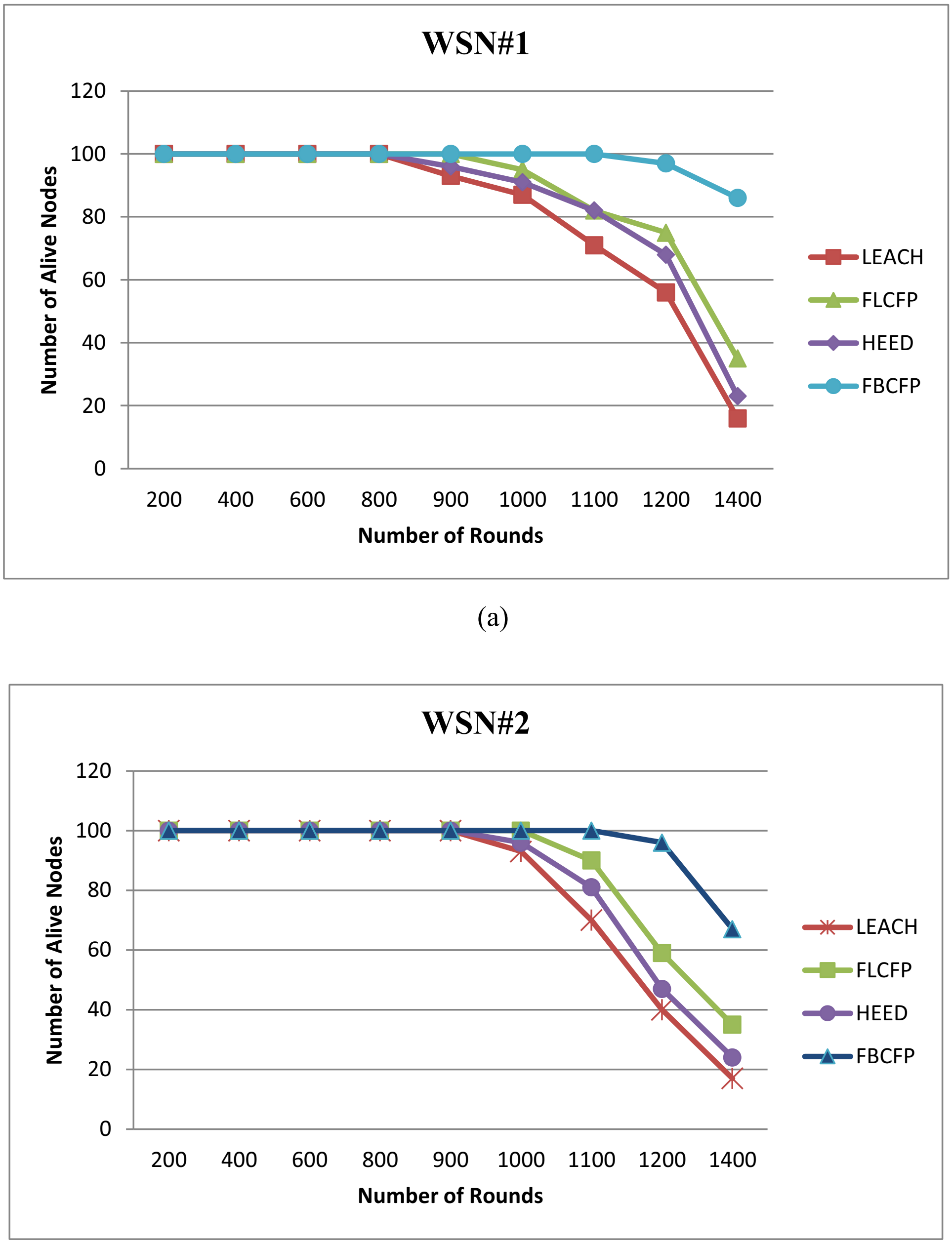
$$\mathrm{COA} = \frac{\int \mu_A\ (z).z\ dz}{\int \mu_A\ (z) dz} \quad (6)$$

3.3. The cluster based routing process

The cluster based routing protocol proposed in this research work for effective routing in WSN performs routing of the packets that are collected by the sensor nodes to the cluster heads through the cluster member nodes or directly. The cluster head nodes find the shortest path by applying a route discovery process and maintain the route for performing effective routing of the data packets. The network is trained for conditions such as traffic level, bandwidth availability and congestion status using convolutional neural networks. Moreover, a fuzzy rule based approach is used in this work to perform the clustering process and also the route discovery process. In the cluster based routing protocol proposed in this work if a source node wants to find the shortest path for sending the packets to the sink node, they send the packets first to their respective cluster heads and then the packets are routed to the sink node by the cluster head nodes. In this way, the network is trained periodically and the route discovery process uses the rules obtained from training for performing effective routing. Moreover, uncertainty is handled in this work by the effective application of fuzzy rules for optimal cluster formation and also to perform cluster based routing.

3.4. Proposed algorithm

In this work, a cluster based routing algorithm that uses fuzzy rules and convolutional neural network has been proposed for performing energy efficient routing.



(b)

Fig. 7. Comparison on number of active nodes in (a) SCENARIO #1 (b) SCENARIO #2.

Table 3
Average network lifetime and SDs in SCENARIO #1.

Algorithms	100 nodes		200 nodes		300 nodes	
	Mean values	Values of SDs	Mean values	Values of SDs	Mean values	Values of SDs
LEACH	1049.33	32.29	1004.60	11.59	962.20	17.79
FLCFP	1380.40	33.38	1236.73	57.05	1136.40	20.27
HEED	1398.35	28.67	1286.56	35.87	1168.29	22.69
FBCFP	1402.53	8.733	1292.73	14.88	1174.13	24.77

The steps of the proposed routing algorithm are as follows:

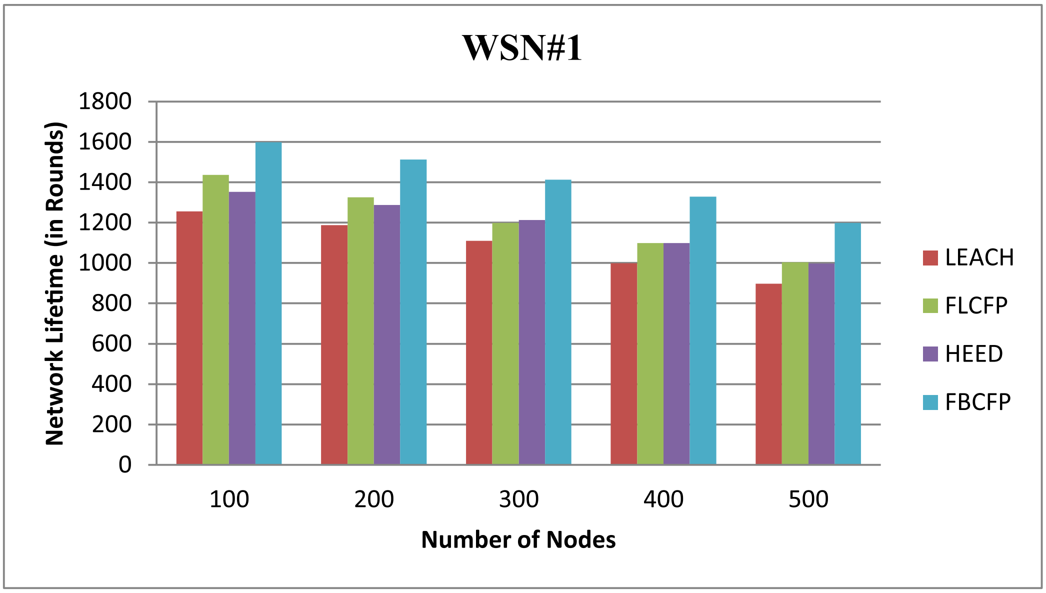
Step 1: Read the energy levels and location (x_i, y_i) of sensor nodes Si, i={1,2,…,n}

Step 2: Send “HELLO” packets to all the neighbour nodes from the base station and find the distances of nodes from the base station and between the nodes.

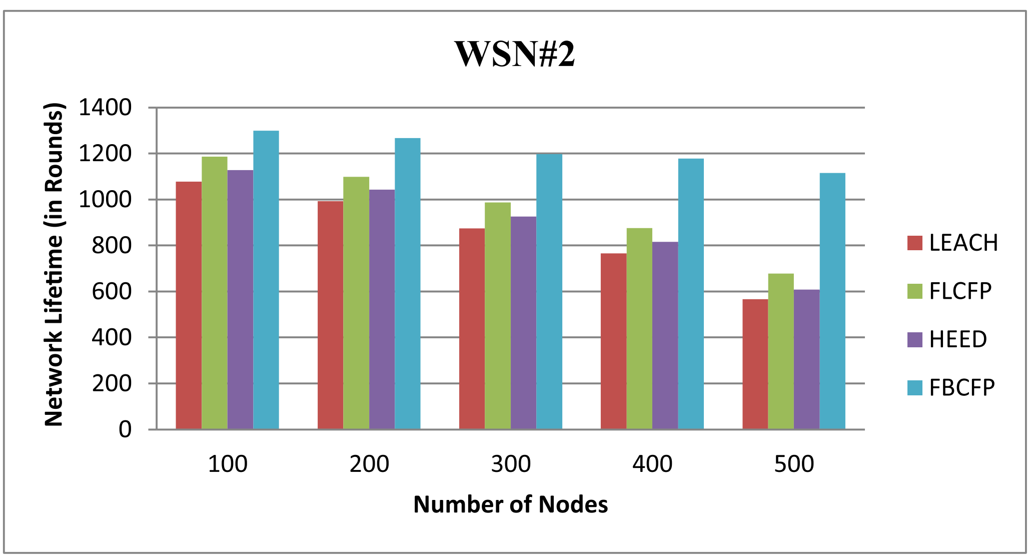
Step 3: Call the k-means clustering algorithm to form k clusters by grouping the nodes based on distance.

Step 4: Using base station as the co-ordinator, perform the cluster head selection for each cluster by considering the distances and energy levels of nodes.

Step 5: Perform route discovery by finding the shortest path from each node to the base station through the cluster head nodes.



(a)



(b)

Fig. 8. Analysis of network lifetime in (a) SCENARIO #1 and (b) SCENARIO #2.

Step 6: Send data collected by nodes through the cluster heads using the shortest path found in step 5: and also by applying fuzzy rules.
Step 7: Collect data at base station.
Step 8: If energy levels of atleast 50% nodes are drained then STOP.
Step 9: Check if cluster head rotation if necessary.
Step 10: If yes go to step 4. Else go to step 6.

Using this algorithm, the data collected by the sensor nodes are sent to the base station periodically. The algorithm is terminated whenever the energy level of 50% of the nodes are exhausted and has only less than 10% of the original energy level.

4. Results and discussions

The proposed cluster formation protocol was tested through simulations using the MATLAB software. Moreover, experiments have been conducted by varying the number of nodes starting from 100 nodes and tested upto 500 nodes. These nodes have been deployed over an area of (100×100) m^2. The parameters that have been used in this work for the simulation are presented in Table 2.

The proposed algorithm is tested broadly and the outcomes are presented. In our simulation, we conducted two set of experiments and they are named as SCENARIO #1 and SCENARIO #2. In SCENARIO #1, the sink was positioned at (50, 50) and in SCENARIO #2, the sink was positioned at (100, 50).We designed our inference system with 4 input variables namely CH Energy Level, Distance between CH & BS, Distance between CH and Node and also the

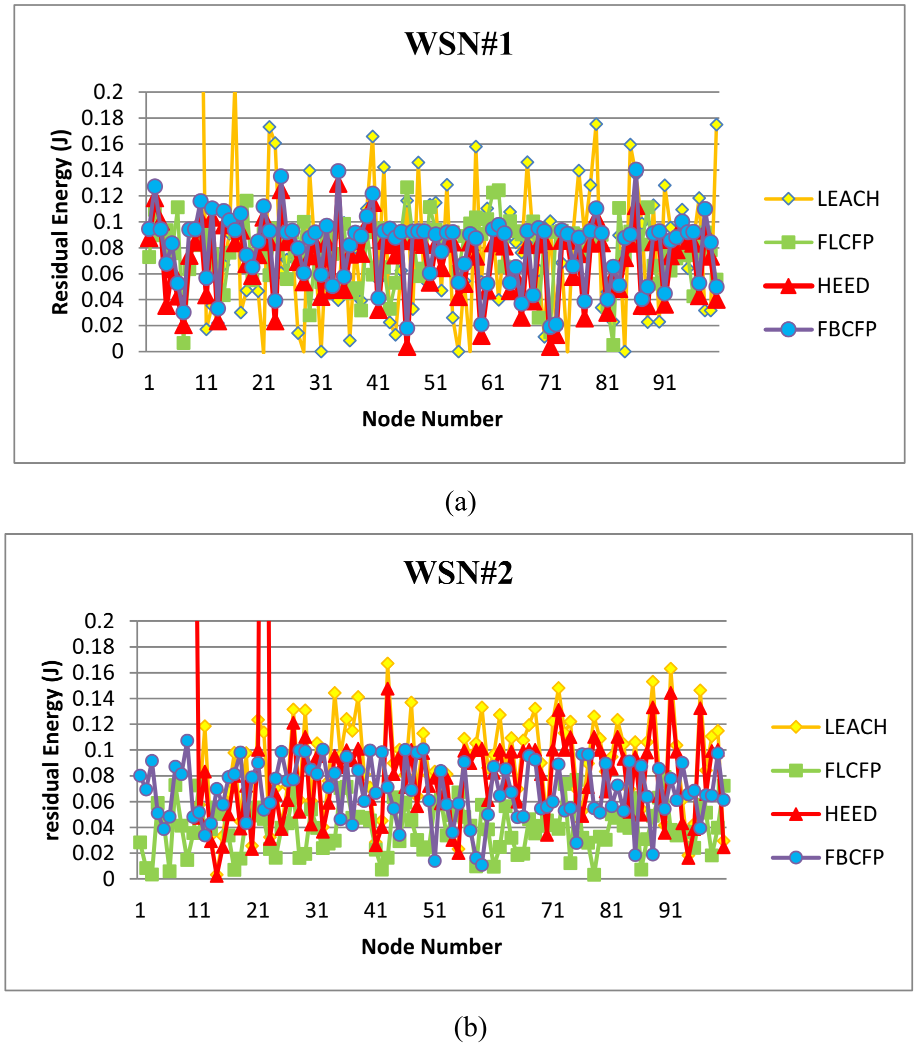


Fig. 9. Comparison of residual energy of Sensor Nodes just before FND in (a) SCENARIO #1 and (b) SCENARIO #2.

CH Degree. The linguistic variable, energy level of CH and its values used in the SCENARIO #1 is depicted in Fig. 2. The values used for this fuzzy set are less, medium less, medium, high medium and high. The less and high values are computed by applying the membership functions namely trapezoidal and the medium values are represented by applying the triangular membership function.

The second linguistic variable that represents space between the CH and the sink node is given in Fig. 3. Moreover, the values used for this simulation are namely close, medium close, medium, medium distance and distance. The less and high values are represented using trapezoidal function and medium is using triangular function.

The third linguistic variable represents the distance between Node and CH is given in Fig. 4. The linguistic values are Distant, medium distant, medium, medium closer and closer. Here also the boundary values are represented using trapezoidal function and the other value is represented using triangular function.

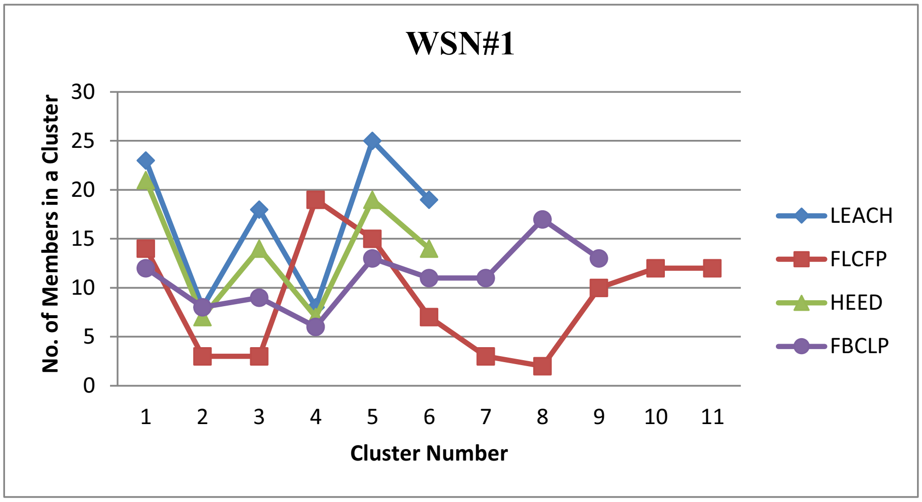
The fourth linguistic variable degree of the CH is shown in Fig. 5. The values used for this set are Low, Low average, average, more average and more. Once again, we have used trapezoidal function for the values low and more and triangular function for other values.

The fuzzy output variable member choice is presented in Fig. 6. There are 9 values which are Very much weak (VW), Weak (W), Less weak (LW), Medium (M), Low medium (LM), High medium (HM), Less strong (LS), Strong (S) and Very much strong (VS). For the boundary values of output linguistic variable the Trapezoidal function is used and triangular function is used for other values.

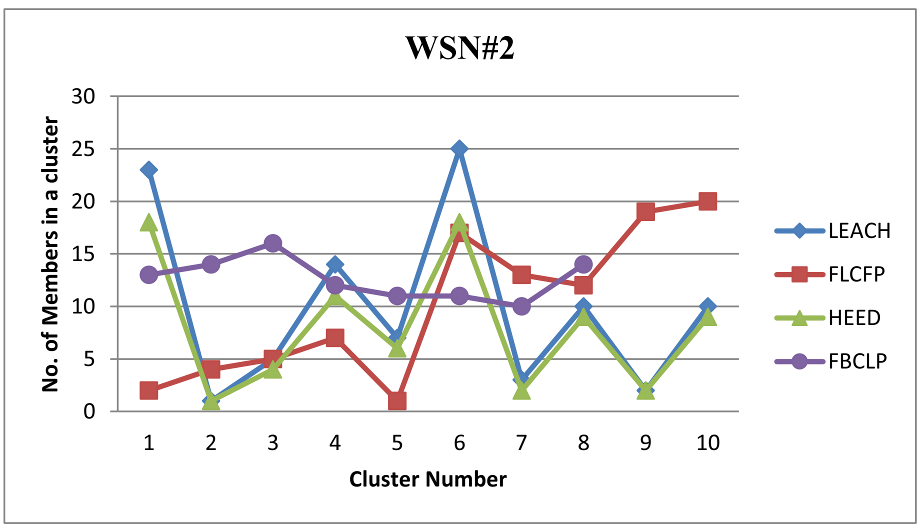
First, we run the three algorithms for comparing the number of active nodes on both SCENARIO #1 and SCENARIO #2. In this model, a sensor node is said to be an active node when its current energy is non-zero. The system was run for different number of rounds with 100 nodes to measure the system lifetime.

The outcomes are presented in Fig. 7(a) and (b). From both the figures, it is observed that the number of active nodes in the system using the proposed routing algorithm is more than the other existing algorithms. In our proposed work, the first node gets drain out of energy after a longer period than the other two algorithms. This is because, for longer network period the energy of the nodes are very important. So in our proposed work, the nodes conserve the energy by balancing the load of CH. In the cluster formation stage, each node joins the CH in such a way that it balances the energy and the energy gets drained after a long period of time. The analysis of network lifetime for varying number of nodes for both the scenarios is presented in Fig. 8.

From the results obtained in this work, it is observed that the proposed routing algorithm provides better network lifetime than LEACH, FLCFP and HEED. This is due to the cluster formation phase. In our proposed work, each node joins with the CH by considering the residual energy, distance and more important factor the exist-



(a)



(b)

Fig. 10. Comparison of no. of member nodes in each cluster for (a) SCENARIO #1 and (b) SCENARIO #2.

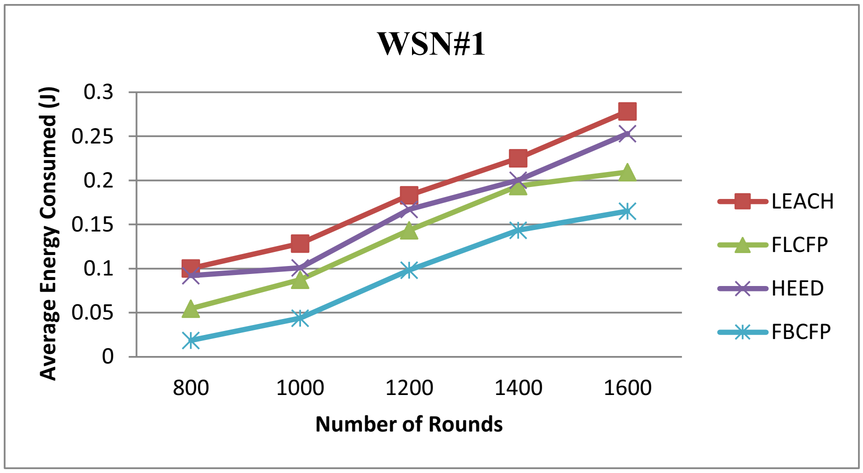
Table 4
Average network lifetime and SDs in SCENARIO #2.

Algorithms	100 nodes		200 nodes		300 nodes	
	Mean values	Values of SDs	Mean values	Values of SDs	Mean values	Values of SDs
LEACH	1051.67	14.56	979.27	9.79	953.87	21.43
FLCFP	1103.60	29.99	1066.73	13.34	1063.67	17.66
HEED	1121.56	24.74	1098.78	12.47	1087.32	15.34
FBCFP	1139.53	14.28	1105.07	11.53	1096.27	12.87

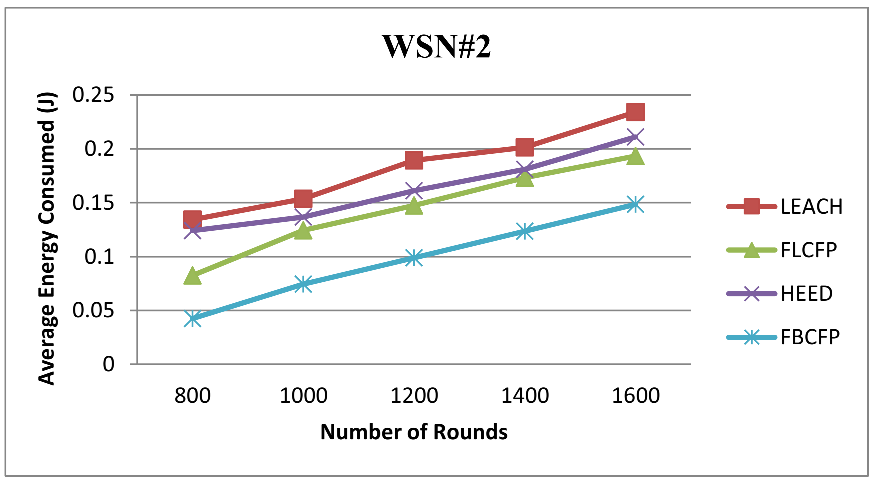
ing size of the cluster. This causes the balancing of load among the CH, which in turn helps to extend the network life span by delaying the death of first node in the network. The average network life-time for 15 different runs of the proposed and existing algorithms for both the SCENARIO #1 and SCENARIO #2 are shown in Table 3 and Table 4. From the results statistics, we observe that the average network lifetime is the highest when the proposed algorithm is used for routing. It also performs a comparison based on Standard Deviations (SDs).

The remaining energy present in the sensor nodes that are measured just before the First Node Dies (FND), the energy consumption in all rounds are taken as the metrics for comparison [3,10]. From the experiments conducted in this work, it is proved that the energy consumed by the network is less when the proposed routing technique is used for communication.

Fig. 9 shows the current energy levels of all the sensor nodes before the FND for SCENARIO #1 and SCENARIO #2. It is clear that the current energy level of sensor nodes in FLCFP, HEED and FBCFP are uniform than in LEACH. And in particular the remaining energy of the nodes in FBCFP is more than FLCFP and HEED. This shows that in our proposed work, the nodes not only consume energy uniformly but it also consumes less energy than FLCFP, HEED and LEACH. The reason is that, in our proposed work the cluster is formed by concentrating on all important factors to extend the



(a)



(b)

Fig. 11. Comparison of average energy consumed in (a) SCENARIO #1 and (b) SCENARIO #2.

lifetime. This results in cluster with uniform size which consumes energy uniformly among the nodes.

In Fig. 10, comparison of cluster sizes that are measured using the number of members joined in each cluster for LEACH, FLCFP, HEED and FBCFP for SCENARIO #1 and SCENARIO #2 are presented. It is clear from the figure that, the LEACH has high variation in the number of cluster members when compared to other algorithms. The variation in the number of cluster members in each cluster is less in our proposed work than FLCFP, HEED and LEACH. This is due to, in the clustering phase, each node is joined with the CH not only based on the remaining energy of the CH and the space between the CH and node but it also consider the number of nodes already joined with the CH, which results in cluster with uniform size.

The comparison of average energy utilization of the network for 100 nodes with variable number of rounds in SCENARIO #1 and SCENARIO #2 are shown in Fig. 11. Though the proposed work, FLCFP and HEED consume similar amount of energy for few clusters, the proposed model provides improved energy optimization in all type of clusters when it is compared with the existing works. This improvement in energy optimization has been achieved by providing effective training of the deep neural networks and by applying a combination of fuzzy rules and learned rules from the deep neural network

5. Conclusion and future enhancement

In this paper, a new routing algorithm for IoT based sensor networks that uses neuro-fuzzy rule based clustering approach for performing cluster based routing in order to enhance the network performance. In this approach, the cluster formation in WSNs utilized the energy modelling for efficiently routing the packets through the application of machine learning using convolutional neural network with fuzzy rules for weight adjustment and hence the network lifetime is prolonged. Moreover, we considered four components namely residual energy of the CH, space between the CH and the sink node, space between the sensor node and the CH and the degree of the CH which are important factors for the energy utilization and network life span. We have evaluated the proposed algorithm using simulations with MATLAB in which the above mentioned components were used as fuzzy variables in NFIS. The output value of NFIS was used to determine the CH for the node to join as a member. From the results obtained in this work, it has been observed that the proposed protocol performed better when this is compared with LEACH, FLCFP and HEED in terms of energy utilization and system life span due to the use of neuro-fuzzy rules obtained through learning and by applying cluster based routing. One limitation of this work is the assumption that all nodes are trustful nodes which is not always possible.

Therefore, future work in this work can be the use of new trust mechanism for enhancing the routing protocol to provide effective secure routing.

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