# Energy optimization of wireless sensor network using neuro-fuzzy algorithms

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## ABSTRACT

Wireless sensor network (WSN) is one of the recent technologies in communication and engineering world to assist various civilian and military applications. It is deployed remotely in severe environment that doesn't have an infrastructure. Energy is a limited resource that needs efficient management to work without any failure. Energy efficient clustering of WSN is the ultimate mechanism to conserve energy for long time. The major objective of this research was to efficiently consume energy based on the Neuro-Fuzzy approach particularly adaptive Neuro fuzzy inference system (ANFIS). The significance of this study was to examine the challenges of energy efficient algorithms and the network lifetime on WSN so that it could assist several applications. Clustering is one of the hierarchical based routing protocols, which manage the communication between sensor nodes and sink via Cluster Head (CH); CH is responsible for sending and receiving information from multiple sensor nodes and multiple sink nodes. There are various algorithms that can efficiently select appropriate CH and localize the membership of cluster with fuzzy logic classification parameters to minimize periodic clustering which consumes more energy and we have applied neural network learning algorithm to learn various patterns based on the fuzzy rules and measured how much energy was saved from random clustering. Finally, we compared it to our Neuro-Fuzzy logic and consequently demonstrated that our Neuro-Fuzzy model outperformed by saving more than 32% of energy than the random model with 50 and 100-sensor node deployment. We confirmed that by increasing the number of sensor nodes, it was possible to increase the energy utilization but not the energy saved from the network.

**Keywords:** ANFIS, CH, Sink Node, WSN
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## INTRODUCTION

To date, technological advances are facilitating the production and utilization of large amounts of sensor nodes with cheap cost (Hussain and Islam, 2007). It has

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the ability to sense the environment, process the information and communicate to the nearest sink node. In Wireless Sensor Network (WSN), sensor node is a small tiny sensor device that has the ability to sense important information from the surroundings and use their communication component in order to transmit sensed data over a wireless channel to other nodes and to a designated sink node. Due to the collaborative use of sensors, multiple sensor nodes perform data processing in an interleaved fashion and communicate to the sink node to existing conditions. WSN has various benefits to control and support different applications such as agriculture, traffic monitoring, environment and habitat monitoring, object tracking, fire detection and surveillance and reconnaissance (Zahmatkesh and Yaghmaee, 2012; Sujithra and Venkatesan, 2016).

However, despite the advantages, WSN is severely limited by energy constraint posed by sensor nodes. Energy consumption on wireless sensor nodes depends on the application we use and the place where sensor nodes are located remotely. Energy is depleted while the sensor node gathers vital information from the environment, processes data and transfers information to the neighbor node or sink. Therefore, most of the WSN protocols should consider power consumption. Routing protocols for WSN has additional overhead that can drain energy particularly in multi-hop environments.

WSN does not have any fixed infrastructure unlike wireless communication networks such as Mobile Ad hoc Network (MANET) and cellular network, it is extremely challenging task to assign the global IP address for a large number of deployed sensor nodes and is highly dynamic. Therefore, it has essential characteristics that support powerful application with highly dynamic network and specific for applications. There are mainly two basic reasons that it has dynamic infrastructure. The first reason is the energy; the sensor nodes have limited energy in the form of battery power and they are not mostly rechargeable because the nature of the deployment is not as such comfortable to extend battery life. If the protocol is unable to balance the load among the nodes, then the sensor node couldn’t save energy. It leads energy to the dynamic network structure (Rault *et al*., 2014). The second reason is the mobility; whereby in many cases after the deployment of WSN, sensor nodes are static but sink can move within the network. It makes the network dynamic, and the protocol that works for static sink may not be applicable for mobile sink (Rault *et al*., 2014). Consequently, several applications need to have their own infrastructure, deployment mechanism, load balancing and manage their energy through energy efficient algorithms.

Energy management can be defined as a collection of rules to manage various supply mechanisms and then efficient consumption of provided energy in a sensor node. In WSN power consumption is a crucial issue that should be optimized and conserve the energy depletion during routing, processing and communication. Routing technique plays an important role in WSN and various energy efficient routing protocols and algorithms are suggested for saving energy consumption (Akkaya and Younis, 2003).

Energy efficient routing protocols are recommended and developed for several applications. In particular clustering technique is the dominant area to search and optimize energy of sensor node. Various researches have been done so far to optimize energy and most of the energy efficient protocol lies on clustering particularly Low Energy Adaptive Clustering Hierarchy (LEACH) and improve the energy consumption as well as the load balance distribution among the sensor nodes (Akkaya and Younis, 2003). One of the most popular solutions to minimize the long-distance communications is clustering. In Cluster formation, cluster head (CH) selection is the core function that most algorithms apply to save energy on sensor nodes as well as to improve the network lifetime and LEACH is the first cluster-based protocol in WSN (Heinzelman *et al.*, 2002).

LEACH is a major reference model for hierarchical clustering protocol that selects CH randomly and periodically. It saves energy and balances the load with the help of CH to aggregate and send individual sensor information to sink. However, LEACH introduces major problems that being addressed by many researchers and still it is a major issue. The first problem that arises on it is not applicable for multi hop communication (Akkaya and Younis, 2003; Al, 2016). The other problems with LEACH are it works on homogeneous sensor node and selects CH randomly (Selvara, 2017).

Global and Local sensors Clustering Protocol (GLCP) is introduced which enables sensors to optimize energy consumption based on fuzzy logic classification and Genetic Algorithm (GA) (Omari *et al.*, 2015). GLCP resemble LEACH-GA and improve the energy consumption with the help of local and global sensor clustering. The major parameter consideration of GCLP is residual energy life node per round.

Now days the adaptive Neuro fuzzy inference system (ANFIS) is improved to the neural network-based algorithm to enhance the capabilities of generating several types of patterns using neural network (Veena and Kumar, 2010; Nayak and Devulapalli, 2015; Singh *et al.*, 2016; Selvara, 2017). LEACH-ANFIS improves the performance of LEACH to save more energy. The authors assume that it selects 5% of CH of the total sensor node around the area and individual sensor nodes would be grouped into one or two CHs. Finally, cluster selection is similar to LEACH and the result has revealed that the proposed algorithm LEACH-ANFIS outperforms very well as compared with the other algorithms such as LEACH, LEACH-C and CHEF during the selection of appropriate CH.

However, those results are considered only static sensor nodes (Abhiruchi and Anurag, 2018).

Energy Aware Unequal Clustering Fuzzy (EAUCF) was proposed by Bagci and Yazici (2013) to utilize energy efficiently in consideration with distance to sink node and residual energy and the result has revealed that the proposed algorithm outperformed very well as compared with the former algorithms though it is also applicable for static sensor nodes.

The Neuro-fuzzy approach is supposed to optimize the energy utilization of mobile sensor nodes that are densely populated and deployed randomly. The performance of this approach has revealed with the metrics such as number of CH, network lifetime, end-to-end delay, packet drop rate, number of lively nodes and signal strength ratio. It is also compared with novel algorithms known as EAUCF and Energy efficient cluster formation (EECF). According to the experimental result, the EACNF approach has outperformed very well as compared with the above two approaches. As a future work they recommend increasing the energy optimization by adding more node density, signal strength and geographical positioning and train them with neural network training set (Arunraja *et al.,* 2015; Julie and Selvi, 2016; Robinson *et al.,* 2017).

Thus, the main target of this work focuses on optimization of energy consumption based on the hybrid of two algorithms neural network and Fuzzy logic and we call it Neuro-Fuzzy algorithm. Neuro-Fuzzy system is a type of soft computing methodologies and approaches to learn fuzzy systems from data by using learning algorithms derived from neural network theory. Neural network is good at recognizing patterns, though they are not good at explaining how they reach their decisions. Fuzzy logic is good at explaining decisions but cannot automatically acquire rules used for decision making.

## MATERIALS AND METHODS

In this research, we have used both qualitative and quantitative data; because routing information and related issues are not purely qualitative or quantitative, rather they are a combination of both approaches. Energy depletion among sensor nodes is a critical issue because sensor nodes are located in remote areas, and severe environments and the data may sense continuously or periodically. However, mostly continuous sensing on environment has many applications such as habitat monitoring, remote traffic monitoring and digital surveillance. Charging batteries periodically is not practical and therefore it requires some power saving mechanism in routing protocol while they communicate with each other or when they transfer data to the sink.

Despite the advantages of clustering, selection of CH has introduced a problem of periodic clustering because the CH selection is based on linguistic variables such as distance to sink, energy level and mobility factor. Therefore, we have prepared rules that encompass above Fuzzy logic-based CH selection algorithm and Fuzzy logic membership optimization could help improve location-based management.

Adaptive Neuro-fuzzy is the hybrid system, which has the characteristics of neural network and fuzzy logic. Neural network can have a capacity to learn from the data easily. However, it has low interpretation of the knowledge gained and in contrast fuzzy logic cannot learn from data but fuzzy logic model utilizes linguistics variables to interpret the knowledge easily.

## Simulation Tools

Based on experimental results, Network simulator (NS-3) has revealed a good performance as compared with others (Helkey *et al.,* 2016). However, energy model is not implemented yet for NS-3. Therefore, NS-2 is selected as our experimental simulation tool to model energy and clearly demonstrates the real sensor environment while allowing dynamic reconfiguration of network parameters based on feedback from an end application. It has a large number of actively maintained models with which to work and is relatively easy to use. In addition to NS-2, matlab software encompasses several features for visualization tool, Neuro- fuzzy tool and other complex computation and functions (Nayyar and Singh, 2015). Our experiment needs to have a Fuzzy based clustering rule that has been designed with the support of fuzzy toolbox in matlab. The fuzzy toolbox is the easiest way of changing our fuzzy dataset to crisp dataset, which we have taken that fuzzy inference system file for further processing.

We have reviewed literature, which compares SAS, python and both have their own performance on different situations. This time R has also better acceptance on the scientific and academic community who move their dataset to R so that we implemented R too (Brittain *et al*., 2018).

## Neuro- Fuzzy Design

The experiment of our research needs to have a dataset for optimization of WSN. There are several data, which can be collected from the wireless sensor network environment such as residual energy, speed and location of individual sensor nodes. We have deployed 50 and 100 wireless mobile nodes randomly on 1000

× 1000 m geographical locations. Those mobile nodes are grouped together in a cluster and the size of each cluster is 10 mobile sensor nodes and then we have 5 and 10 clusters in WSN which are deployed randomly with 50 and 100-sensor node deployment, respectively. Several researches have demonstrated that the number of CH on WSN should be between 5-10 % of the total number of sensor nodes. Therefore, we have used 10 CH and the sink is responsible to selects CH randomly from each group for the first time and then selection of CH proceeds based on the remaining energy, proximity to sink and speed of mobility. Every mobile node would send the default size of packet through 1000 bytes to the CH and those packets will be sent to the sink node. Moreover, the three parameters are supposed to select CH with respect to sink node because the sink node is static and any measurement has to be taken from sink node. The clustering is based on fuzzy logic and the main goal of clustering of WSN is to provide mapping between input and output with the help of fuzzy inference system (FIS). It is a known approach to group sensor nodes to keep track of individual sensor node information with the help of CH. We proposed the clustering technique which group sensor nodes and selects CH on each group using fuzzy logic algorithm. In our experiment we have considered each of the wireless sensor nodes as mobile except sink node. The fuzzy logic controller had three inputs such as proximity to sink node, speed of mobile nodes and residual energy. These three inputs are very crucial to create membership function and to generate several rules to examine CH chance. The Process followed several steps as described below. The first process is fuzzification, which is the process to convert the given crisp input variables into output through membership function. Each crisp value would be affiliated into their corresponding linguistic values and variables that belong to some degree of similarity. We had three linguistic variables and their corresponding linguistic values such as proximity to sink, residual energy and node speed as shown in Table 1. During sensing vital information from the environment, because of random mobility pattern of every sensor node it would report its information to the nearest CH. The CH is also mobile and was selected from the group based on the vicinity to the sink node. The fuzzy approach needs to have calculated distance with a known mathematical formula called Euclidean distance shown in Equation 1 below.

$$d = \sqrt{(x-a)^2 + (y-b)^2} \tag{1}$$

Where, the Euclidean distance formula is used to measure how much each sensor nodes is close to the sink. Sink is always static and located at point (a, b) in the x-y coordinate and the coordinate point for sensor node is (x, y).

Table 1. Linguistic Variables and values.

| | Linguistic variables | Linguistic values | Type of MF |
|---|---|---|---|
| | Near | 12.5, 113, 138, 249 | Trapezoidal |
| Proximity to | Medium | 250, 375, 500 | Triangular |
| Sink | Far | 515, 615, 640, 750 | Trapezoidal |
| | Very far | 750.5, 850.5, 887.5, 1000 | Trapezoidal |
| | Low | 1.65, 14.85, 18.15, 32.35 | Trapezoidal |
| Residual | Medium | 33, 50, 66 | Triangular |
| Energy | High | 66.7, 82.3, 85.7, 100 | Trapezoidal |
| | Low | 2.5, 22.5, 27.5, 49.5 | Trapezoidal |
| Node Speed | Medium | 50, 75, 100 | Triangular |
| | High | 100.5, 123.5, 130.5, 150 | Trapezoidal |

The second major parameter to select CH is remaining energy of the node at specific time. The node should fulfill the requirement of threshold value of the residual energy of the fuzzy logic control values. In comparison with other parameters for clustering of node; the residual energy has higher priority and influences other parameters to select CH.

We have considered the available energy at hand and their distance to the sink would be as nearby as possible to have enough communication to all sensor nodes. In our experiment we have used the energy model of NS2 in order to design their communication architecture, what it looks like and how they communicate with each other and how much energy is provided to send and receive a packet. Similarly, the speed of sensor nodes has a great impact on clustering and directly related to the mobility factor of sensor nodes. Energy preservation could be maintained through mobile nodes, which has a chance to move easily and provide the available information with a specified time. It is demonstrated that mobile sink nodes can preserve energy 5-10 times of the static nodes in a predicted and unpredictable mobility factor. The faster the speed of the node, the faster available information moves while consuming more energy. Next, we have generated the rules based on the linguistic variables and values as shown in Table 2 where the membership function has taken three parameters and the combination of them to create several rules which decide the cluster head chance of every mobile node that are found on a specific location and time. The rules have been generated from the fuzzy membership type Sugeno. The fuzzy sugeno membership function is actually designed and applicable with neural network. The hybrid of the two known algorithms has been modeled on matlab toolbox known as ANFIS. ANFIS is a part of adaptive neural network, which has the same functionality of FIS. It encompasses the framework of adaptive neural network to work on ANFIS. The fuzzy rules and membership functions were done based on the type of fuzzy sugeno inference system. The generated rules have to fall on two extreme cases, where for the first case if energy is low and proximity to sink is very far and speed of node is slow then the chance is very weak, and for the second case if energy is high and proximity to sink is near and speed of node is fast then the chance is very strong. The detail of if-then rule is shown in Table 2.

Table 2. If-then rules.

| Proximity to sink (m) | Residual energy (J) | Mobility factor (speed/sec) | CH chance |
|---|---|---|---|
| Very far | Low | Slow | Low |
| Medium | Medium | Medium | Medium |
| Near | High | Fast | High |
| Medium | High | Medium | High |
| Very far | Low | Fast | Low |
| Far | Medium | Slow | Medium |
| Medium | Medium | Fast | Medium |
| Very far | Low | Medium | Low |
| Near | Low | Fast | Medium |
| Near | Low | Slow | Low |
| Far | High | Fast | High |
| Near | Medium | Fast | High |
| Far | Medium | Fast | Medium |
| Medium | Medium | Slow | Medium |
| Very far | High | Fast | Medium |
| Near | High | Slow | Medium |
| Very far | High | Slow | Low |
| Medium | Low | Fast | Low |
| Far | Low | Fast | Low |
| Far | Low | Slow | Low |

Defuzzification step is a process of generating the crisp set result and mapping with how much it is near to a specific fuzzy set. It is performed according to membership function for output variable. The fuzzy inference system has been designed with fuzzy sugeno membership function and its dataset analysis would be handled through ANFIS. In order to develop ANFIS, we have collected vital information for our experimental analysis such as location information while sensor nodes are moving on the topography of x, y and z position. The remaining energy of a node has been collected while they are moving, transmitting and receiving packets to and from ordinary sensor nodes and sink node. Finally, the movement of the nodes with varies speed has been also considered as important factor for our experiment. The ANFIS system has training and testing steps where training is the first and the major step to analyze our dataset. The collected data from the simulation was not clean data. Therefore, we had cleaned the noise and erroneous datasets as well as computed the Euclidean distance from the dataset that was directly found from x and y positions of the node on the Adhoc on Demand Routing Protocol (AODV) routing protocol. The dataset that we have provided to the ANFIS has four variables, three of which were inputs and one was output.

In the testing phase, we have datasets that were found from the simulation after clustering nodes based on the sugeno fuzzy inference system. The energy data were collected from the trace file by writing AWK script; however, location information was computed from the TCL file while they communicate with each other. Then the data were aggregated into a file and tested.

Thus, the datasets were divided into training and testing data where 70% of the dataset was meant for training and 30% for testing. Therefore, we trained our model with 423 datasets, which was found from the simulation with several mobility factors and tested our Neuro-Fuzzy model with 181 datasets. The model evaluation results for both training and testing data are obtained based on the ANFIS' parameters of 98 numbers of nodes, 36 linear parameters, 30 non-linear parameters, 423 training data pairs and 36 fuzzy rules. By considering ANFIS' parameters listed above Figure 1 and 2 indicate the training and testing data respectively.

As it can be seen from Figures 1 and 2, the testing and training results resemble each other to the same level of decimal points. From the testing and training data we have recognized that Root Mean Square Error (RMSE) of the average testing error over training data is 0.25559 and the average testing error over testing data is 0.419. Thus, our model supports the experiment in precisely selecting CH for various mobility factors while we deploy large number of sensor nodes from time to time. Consequently, testing and training errors were closer to each other confirming the selected CH closely related to the actual scenario.

## RESULTS AND DISCUSSION

We have demonstrated our experiment with network simulator based on the parameters shown in Table 3. On separate simulation setups, 50 and 100 sensor nodes were deployed randomly in 1000 m by 1000 m topography, each of which had one sink. Five sensor nodes were deployed for 50 clusters and 10 for 100 clusters. Each cluster possessed a randomly selected CH and each sensor node transmitted sensed information to the sink through CH. The following conditions were considered in the experimental process: sink was a stationary at (x=560.16, y=522.225) and received packets from the CH, all sensor nodes were mobile and deployed randomly in the field and the nodes were considered to die only when their residual energy rose below the threshold level. The experiments were done on two separate major scenarios.

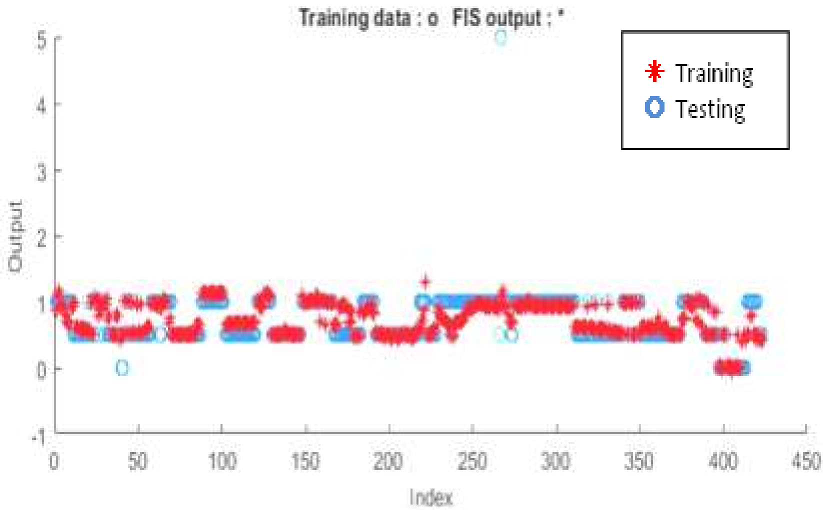


Figure 1. Training data

The first scenario considered that cluster selection has been done randomly without the concern of energy and proximity to the sink issues and the second scenario considered that cluster selection was done on the residual energy, proximity to the sink and speed of the node in which their values were determined with the FIS. The performance was measured based on overall residual energy, total energy consumption, average energy consumption and average residual energy metrics.

The proposed technique for CH selection was Neuro-Fuzzy algorithm which enhanced the performance of energy optimization. As shown in Figure 3, the random clustering and Fuzzy based clustering of 50 sensor nodes was demonstrated. It was demonstrated that the random clustering had higher values on average energy consumption and total energy consumption when we compared it with Fuzzy based clustering. On the other hand, its average residual energy and overall residual energy had lower values in comparison with the Fuzzy based clustering. Similarly, Figure 4 describes the comparison of random clustering and Fuzzy clustering of 100 sensor nodes. The Fuzzy based clustering of energy performance had higher value in average residual energy and total energy consumption as compared with the random clustering.

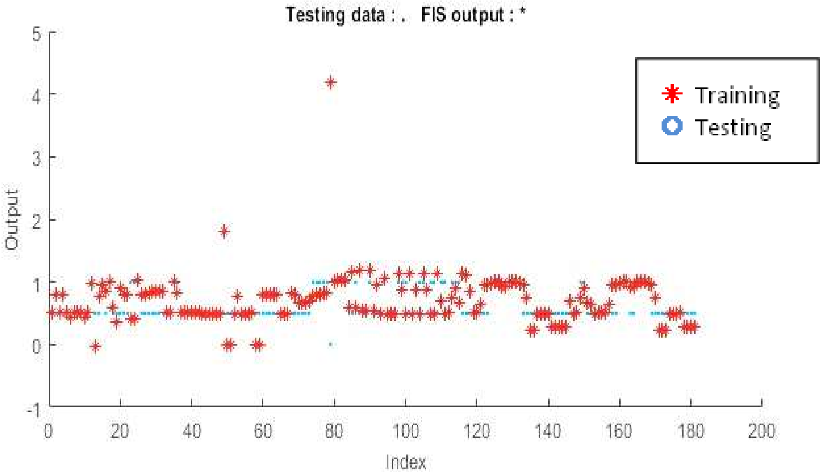


Figure 2. Testing data

On the other hand, the average energy consumption and overall energy consumption was lower compared with random clustering. The Fuzzy based clustering on 100 nodes deployment was lower when compared with Fuzzy clustering of 50 sensor nodes on different mobility factors. The performance of Fuzzy Clustering model improved the performance of the random clustering mechanism. Because fuzzy parameters namely proximity to sink, mobility factor with random motion and residual energy for CH selection were used with equal number of clusters considered for our experiments. Consequently, one can observe Figures 3 and 4 that the average residual energy of proposed Fuzzy clustering technique outperformed very well as compared with random model. The energy consumption of our model was also lower, by saving more energy in comparison with random clustering technique.

The randomly deployed over proposed Neuro-Fuzzy model was measured with 50 sensor nodes in average residual energy (Figure 3). The random model had lower residual energy as well as packet delivery ratio; number of packets sent and received was also smaller. Furthermore, packet dropping ratio and normalized routing overhead was very high. As a result, the proposed model had higher residual energy than the random model. The random and our Neuro-Fuzzy model were compared with respect to average and total energy consumptions (Figure 3). The random model consumed more energy with different mobility factor and the number of packets sent and received; packet delivery ratio was very small whereas its packet-dropping ratio was higher. However, the random model with 50-sensor node deployment has smaller energy consumption in comparison with 100-sensor node deployment on random model.

Table 3. Simulation Parameters.

| Number **of** Item description | Values |
|---|---|
| Simulation area | 1000×1000 |
| Number of nodes | 50 and 100 |
| Channel type | Channel\wireless |
| Radio propagation model | Two ray ground |
| Simulation time | 400 and 500 |
| Antenna setup | Antenna/Omni directional antenna |
| Energy model | Battery |
| Link layer type | LL |
| Routing protocol | AODV |
| Network interface type | Phy/WirelessPhy/802_15_4 |
| Sensing range | 500 meter |
| Communication range | 500 meter |
| Max packet in ifq | 50 |
| Power for receiving | 35.28 mW |
| Power for transmitting | 31.32 mW |
| Power consumed during idle state | 712 μW |
| Power consumption during sleep time | 144 nW |
| Power consumed during state transition from idle to sleep | 600μW |
| Energy of the node at the beginning (initial energy) | 100Joules |

The random model and Neuro-Fuzzy model with respect to average residual energy on different mobility factors was compared (Figure 4). The random model has lowest residual energy on both scenarios. Furthermore, the number of packets sent and received, packet delivery ratio and throughput has the lowest value on the other hand delay, control overhead and packet dropping ratio has increased in all parameters. As a result, random model had also the lowest value in all deployments. We have measured the performance of the randomly deployed model with 100 sensor nodes and one sink and its energy consumption for different mobility factors (Figure 4).

As it can be seen from the figure packet delivery ratio, number of packets sent and received had inconsistently changed with different mobility factors and their packet-dropping rate and normalized routing overhead was high. Compared with the proposed Neuro-Fuzzy model with 100 sensor nodes, their average and total energy consumption is high.

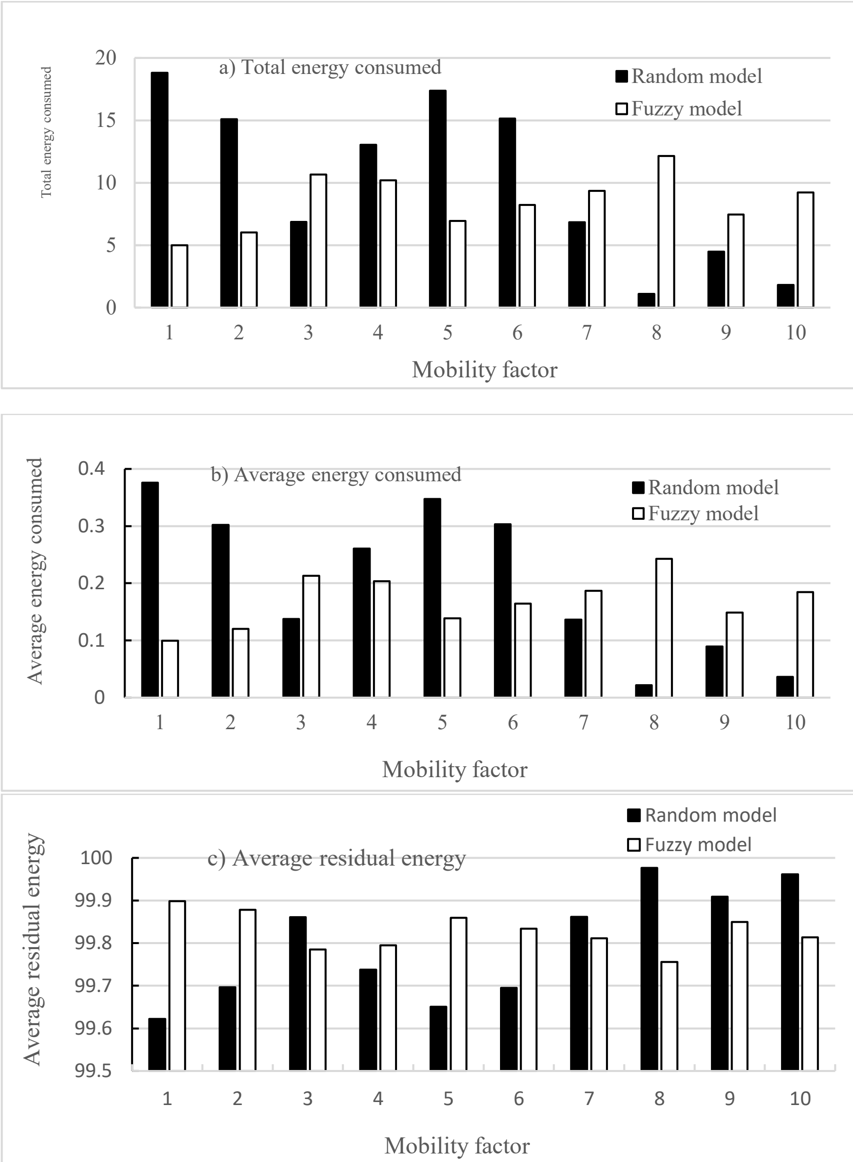


Figure 3. Average Residual Energy on 50 sensor nodes

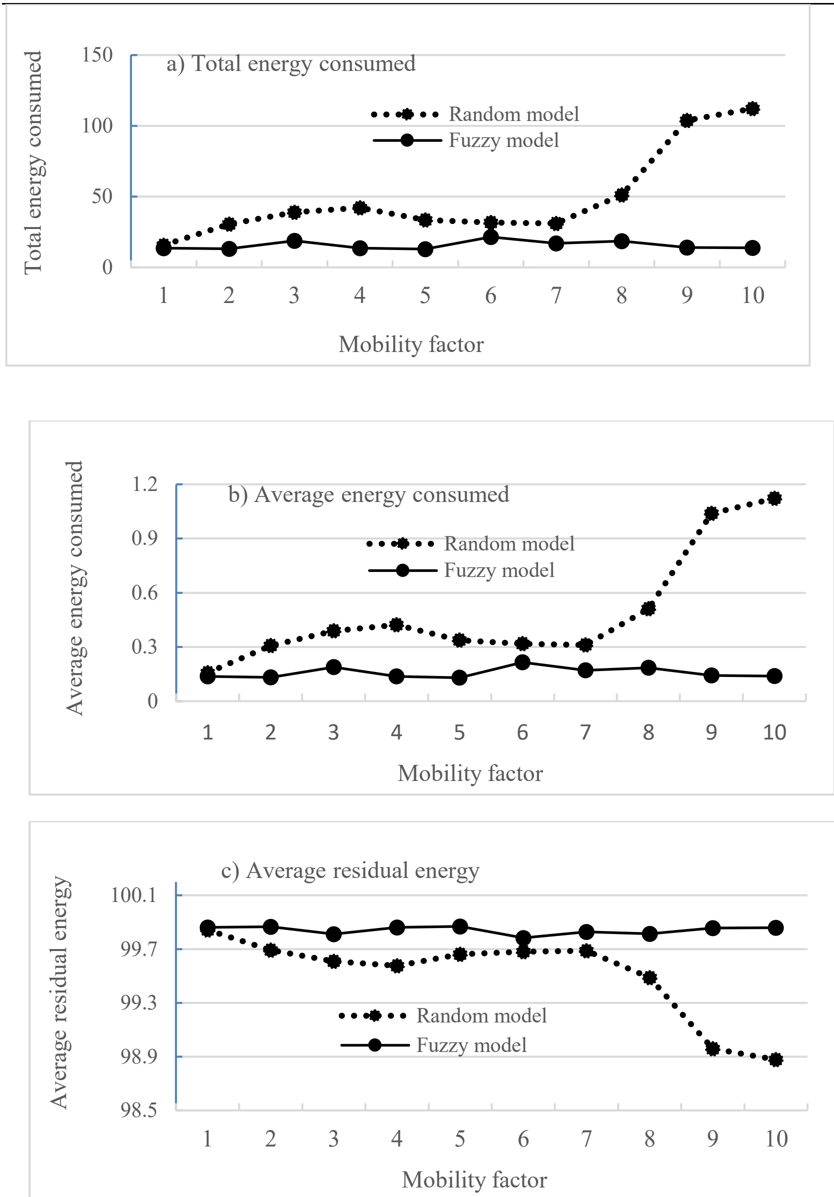


Figure 4. Average Residual Energy on 100 sensor nodes

## CONCLUSION

Energy efficient clustering algorithm has been developed to optimize energy utilization of WSN. We proposed energy efficient equal cluster of Neuro-Fuzzy to select CH based on available energy, proximity to sink and mobility factor with different node speeds to increase the network lifetime and decrease dying of the node. We have compared our Neuro-Fuzzy with others namely EACNF, EAUCF and EECF which were followed similar approaches. The results confirmed that our model performed very well. More features were added in related with mobility, communication range, sensing range, and node speed. Consequently, the performance of proposed Neuro-fuzzy model was increased significantly. Possible future directions would include adding more parameters to elect CH such as node density, geographical positioning and more member functions. Moreover, we highly recommend to include explicit inter cluster communication among CH and data aggregation to increase the optimization of energy.

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