

# NETWORK LIFE TIME OPTIMIZATION IN WIRELESS SENSOR NETWORKS THROUGH ROBUST ENERGY MANAGEMENT ROUTING WITH ARTIFICIAL NEURAL NETWORK

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**Abstract:** Energy efficiency is one of most important parameter to consider while designing the wireless sensor networks. In this paper, we proposed robust energy management routing scheme based on two methods using artificial neural network (ANN). First is Most Significant Sensor Node prediction and another is Group Head selection. We discuss both of these problems in any WSN and seek possible solutions using neural networks, which will actually use to determine the shortest routing path in any WSN for minimizing the energy consumption. Usually WSNs life-time ends by having a single sensor node which uses all its energy and the other sensors consuming the remaining energy. This sensor (which is the cause of the networks end of lifetime) is most likely located in a very significant sensor node which always is in the routing path of many nodes to the base station. By predicting these significant nodes, it is possible to allocate tasks to the nodes in a more efficient way and thus increase the lifetime of the network. Selecting Group Heads amongst all the nodes is also energy conserving scheme for a WSN is proposed herewith. Sensor nodes are initially powered by batteries with full capacities. Each sensor collects data which are typically associated with other sensors in its neighborhood, and then the associated data is sent to the Base Station through Group Head for evaluating the tasks more efficiently. The following sections describe briefly energy saving scheme for network life time optimization, the experiments performed and results achieved in this work, and the main conclusions drawn from our experimental results.

**Index Terms-** Wireless Sensor Network (WSN), Artificial Neural Network (ANN), Feed Forward Network (FFN), Base Station (BS)

## I. INTRODUCTION

A sensor network is a network of many smart devices, called sensor nodes, which are distributed in order to perform an application-oriented global task. The primary component of a sensor network is the sensor. Sensor nodes are used to monitor some real world physical phenomenon like pressure, temperature, humidity, presence/ absence of something, vibration, intensity, sound, pressure, motion and pollutant etc. Each of the sensor nodes is small and inexpensive but smart enough to perform several tasks. The smart tiny sensor nodes are equipped with microcontroller, a radio transmitter and an energy source. The most important design and implementation requirements of a typical sensor network are energy efficiency, routing decision type, memory capacity, computational speed and bandwidth. Sometimes a special central node is deployed to control all the operations of the network. Wireless sensor network, widely known as WSN, has become a wide area of research nowadays as the processing and storage technology became mature and feasible recently. We can now think of deploying hundreds of thousands of cheap sensor nodes to a target area to sense some special types of information. Sensor networks are used in a wide range of areas such as sensing ocean floor activities, volcanic activities, and phenomena in Mars etc. In most of the cases, sensor nodes are deployed in places where the physical condition is very adverse and human cannot go there. For this reason, there is no pre-existing network topology available in the target area. The major problem of the sensor network is the energy consumption. The battery technology is much lagging behind than the processing and storage technology. For this reason, the primary research on sensor network is how to efficiently use the power consumption of each of the sensor nodes to maximize the total lifetime of the network. In most of the cases, it is not feasible or even impossible to recharge the battery of the sensor nodes. The power consumption of the sensor nodes mostly depends on the routing of information in the network. Other means of power consumption include sensing and processing of the information. There is not much scope to reduce the power consumption related to sensing and processing. So, most of the research about sensor networks mainly concentrates on the power consumption due to the routing of information and there is still much scope to improve. Compression could reduce the amount of data transmitted in sensor network. However, data compression is out of the scope of this research and hence we will not discuss about data compression.

Wireless sensor networks are potentially one of the most important technologies of this century. Recent advancement in wireless communications and electronics has enabled the development of low-cost, low-power, multifunctional miniature devices for use in remote sensing applications. The combination of these factors has improved the viability of utilizing a sensor network consisting of a large number of intelligent sensors, enabling the collection, processing analysis and dissemination of valuable information gathered in a variety of environments. A sensor network is composed of a large number of sensor nodes which consist of sensing, data processing and communication capabilities. Sensor network protocols and algorithms must possess self-organizing capabilities. Another unique feature of sensor networks is the cooperative effort of sensor nodes. Sensor nodes are suitable with an onboard processor. Instead of sending the raw data to the nodes responsible for the fusion, they use their processing abilities to locally carry out simple computations and transmit only the required and partially processed data. Sensor networks are predominantly data-centric rather than address-centric. So sensed data are directed to an area containing a cluster of sensors rather than particular sensor addresses. Given the similarity in the data obtained by sensors in a dense cluster, aggregation of the data is performed locally. That is, a summary or analysis of the local data is prepared by an aggregator node within the cluster, thus reducing the communication bandwidth requirements. Aggregation of data increases the level of accuracy and reduces data redundancy. A network hierarchy and clustering of sensor nodes allows for network scalability, robustness, efficient resource utilization and lower power consumption. The fundamental objectives for sensor networks are reliability, accuracy, flexibility, cost effectiveness and ease of deployment.

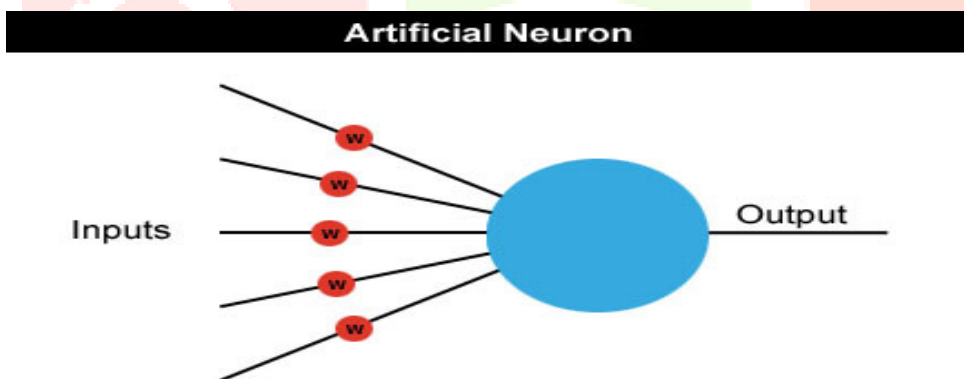
## II. ANN: ARTIFICIAL NEURAL NETWORKS

A neural network is mans crude way of trying to simulate the brain electronically. So to understand how a neural net works we first have a look at how the old grey matter does its business.

Our brains are made up of about 100 billion tiny units called *neurons*. Each neuron is connected to thousands of other neurons and communicates with them via electrochemical signals. Signals coming into the neuron are received via junctions called *synapses*, these in turn are located at the end of branches of the neuron cell called *dendrites*. The neuron continuously receives signals from these inputs and then performs a little bit of magic. What the neuron does (this is over simplified I might add) is sum up the inputs to itself in some way and then, if the end result is greater than some threshold value, the neuron fires. It generates a voltage and outputs a signal along something called an *axon*. Just have a good look at the illustration and try to picture what is happening within this simple little cell.

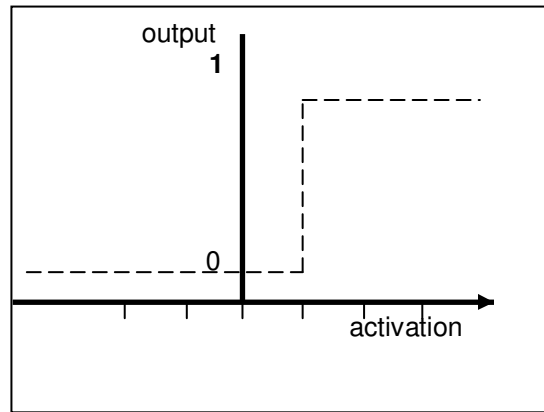
Neural networks are made up of many artificial neurons. An artificial neuron is simply an electronically modeled biological neuron. How many neurons are used depends on the task at hand. It could be as few as three or as many as several thousand.

One optimistic researcher has even hard wired 2 million neurons together in the hope he can come up with something as intelligent as a cat although most people in the AI community doubt he will be successful. There are many different ways of connecting artificial neurons together to create a neural network but I shall be concentrating on the most common which is called a *feed forward* network.



Each input into the neuron has its own weight associated with it illustrated by the red circle.

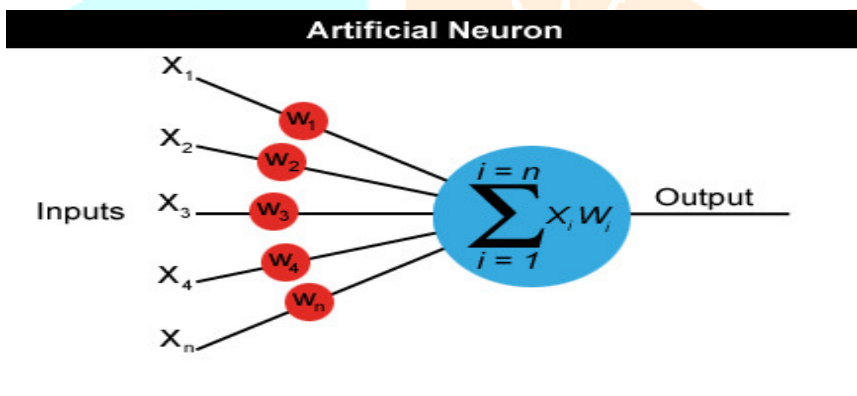
A weight is simply a floating point number and it's these we adjust when we eventually come to train the network. The weights in most neural nets can be both negative and positive, therefore providing excitory or inhibitory influences to each input. As each input enters the nucleus (blue circle) it's multiplied by its weight. The nucleus then sums all these new input values which gives us the *activation* (again a floating point number which can be negative or positive). If the activation is greater than a threshold value - lets use the number 1 as an example - the neuron outputs a signal. If the activation is less than 1 the neuron outputs zero. This is typically called a *step* function as shown in figure below:



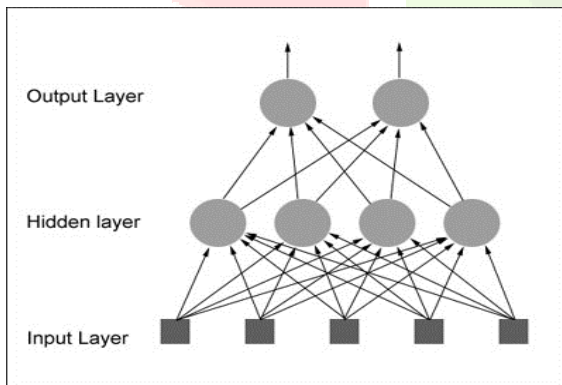
A neuron can have any number of inputs from one to  $n$ , where  $n$  is the total number of inputs. The inputs may be represented therefore as  $x_1, x_2, x_3 \dots x_n$ . And the corresponding weights for the inputs as  $w_1, w_2, w_3 \dots w_n$ . Now, the summation of the weights multiplied by the inputs we talked about above can be written as  $x_1w_1 + x_2w_2 + x_3w_3 \dots + x_nw_n$ . So, the activation value is

$$a = x_1w_1 + x_2w_2 + x_3w_3 \dots + x_nw_n$$

Fortunately there is a quick way of writing this down which uses the Greek capital letter sigma  $\Sigma$ , which is the symbol used by mathematicians to represent summation.



Well, we have to link several of these neurons up in some way. One way of doing this is by organizing the neurons into a design called a *feed forward network*. It gets its name from the way the neurons in each layer feed their output forward to the next layer until we get the final output from the neural network. This is what a very simple feed forward network looks like:



Each input is sent to every neuron in the hidden layer and then each hidden layer's neuron's output is connected to every neuron in the next layer. There can be any number of hidden layers within a feed forward network but one is usually enough to suffice for most problems you will tackle. Also the number of neurons I've chosen for the above diagram was completely arbitrary. There can be any number of neurons in each layer, it all depends on the problem.

### III. ROBUST ENERGY MANAGEMENT ROUTING

#### a. INTRODUCTION TO SCENARIO

Wireless Sensor Networks (WSNs) comes under wireless ad hoc networks in which sensor nodes collect, process, and communicate data acquired from the physical environment to an external Base-Station (BS). Some of them are capable of sensing a special phenomenon in the environment and send the data back to one or several base stations. A quality of WSN that makes it unique is its flexibility in terms of the shape of the network and mobility of the sensor nodes. WSN can be deployed in areas where regular sensor networks (even wired networks) cannot operate. Also the self-shaping feature of WSN, along with the freedom of the wireless sensors movement makes it an ideal tool for the situations where the sensors are mobile. Today the application of Sensor Networks can be seen in different aspects of our lives; it is successfully applied in medical applications, military purposes, disaster area monitoring, etc [1, 2].

But these networks are facing various challenges such as, sensor nodes in WSNs are normally battery-powered, and hence energy has to be carefully utilized in order to avoid early termination of sensors' lifetimes [3]. Since wireless sensors are not physically connected to any central resource of energy, they are completely dependent on their battery source to operate; also wireless sensors positions are not determined prior to the network deployment, thus sensors should be able to operate in a way that can automatically generate an optimal routing path and deliver the sensed information back to the base-station. Base-station integrates the received data and applies a process over it and sends the results to the user or for further processing.

Each wireless sensor node is physically not connected to any source of energy, and thus its own battery is the only dependable power supply for it. Sensor nodes are also constrained on bandwidth. Considering these two limitations, it is necessary to design routing and sensing algorithms that use innovative methods to preserve the energy of the sensors [4]. Since the lifetime of the network is highly dependent on the lifetime of the sensor's batteries [5]. The lifetime of the network can only increase by preserving the energy in the sensor nodes. Number of techniques has been evolved to increase the lifetime of the wireless sensor network. Since most of the energy consumption of each node is due to sensing and routing operations, many of the proposed techniques try to optimize these two tasks. Some approaches update the routing path when a sensor node in a path is low in energy [6] thus that they would exclude the node from the routing path and preserve its energy. Many techniques such as MCFA, GBR and Rumor routing use the shortest path method to reduce the communication and energy consumption. Many of WSN management techniques use an agent-based method to manage the wireless sensor network and its energy consumption [7- 11].

For efficient energy management it is also important monitor a network resources continuously. This same concept has been already investigated in many other environments, e.g., power plants [12], and in many distributed systems [13]. Many recent experimental studies have shown that, especially in the field of sensor networks where low power radio transmission is employed, wireless communication is far from being perfect [14- 16].

In this chapter we are using neural networks to conserve the energy of WSNs and increase the lifetime of the network. Next sections describe how neural network can be used for efficient distribution of energy in WSNs.

#### b. FEED FORWARD NEURAL NETWORKS

The feed forward neural network can learn the input-output pattern pairs by defining the error between desired output and actual output

$$E_x = \frac{1}{2} \sum [T_j - A_j]^2 \quad (3.1)$$

This represents the total error performance of the network during the training. Here,  $T_j$  be the target output and  $A_j$  be the actual output. To minimize the error signal, each coupling-strength is to be updated by an amount proportional to the partial derivative of  $E_x$  with respect to  $w_{jh}$  (weights between hidden and output layer units)

$$\frac{\partial E_x}{\partial w_{hj}} = \frac{1}{2} \frac{\partial}{\partial w_{hj}} \left[ T_j - f \left( \sum_j w_{hj} S_j^h \right) \right]^2$$

$$\begin{aligned}
&= \{A_j - T_j\} \cdot f' \left( \sum_j w_{hj} S_j^h \right) \cdot S_j^h \\
&= [\{A_j - T_j\} A_j (1 - A_j)] \cdot S_j^h \\
\frac{\partial E_x}{\partial w_{hj}} &= \delta_j^o \cdot S_j^h
\end{aligned} \tag{3.2}$$

where  $S_j^h$  is the output from hidden layer.

Similarly the partial derivative of  $E_x$  with respect to  $w_{ih}$  (weights between input and hidden layer units)

$$\begin{aligned}
\frac{\partial E_x}{\partial w_{ih}} &= \frac{1}{2} \frac{\partial}{\partial w_{ih}} [T_j - f(\sum w_{hj} S_j^h)]^2 \\
&= \sum_j \{A_j - T_j\} \frac{\partial}{\partial w_{ih}} f(w_{hj} S_j^h) \\
&= \sum_j \{T_j - A_j\} f'(\sum w_{hj} S_j^h) \left( w_{hj} \frac{\partial S_j^h}{\partial w_{ih}} \right) \\
&= \sum_j \{A_j - T_j\} [A_j (1 - A_j)] \left[ w_{hj} \left\{ \frac{\partial f(\sum w_{hj} S_j^h)}{\partial w_{ih}} \right\} \right] \\
&= \left[ \sum_j \{A_j - T_j\} [A_j (1 - A_j)] [w_{hj} S_j^h (1 - S_j^h)] \right] S_j^i \\
\frac{\partial E_x}{\partial w_{ih}} &= \delta_j^h \cdot S_j^i
\end{aligned} \tag{3.3}$$

Here  $S_j^i$  is the input, which are critical temperatures

$$\begin{aligned}
\delta_j^h &= \sum_j \{A_j - T_j\} A_j (1 - A_j) S_j^h (1 - S_j^h) w_{hj} \\
\delta_j^h &= \delta_j^o S_j^h (1 - S_j^h) w_{hj}
\end{aligned}$$

So that we can write equation (2.3) as

$$\frac{\partial E_x}{\partial w_{ih}} = \delta_j^o S_j^h (1 - S_j^h) w_{hj} S_j^i \tag{3.4}$$

In both equation (3.2) and (3.4),  $\delta_j^o$  is common, which is back-propagated from the units of output layer to the units of hidden layer and coupling strengths will be changed in order to reduce the error signal of the network.

The coupling strengths of output and hidden layers can be updated by following equations.

$$\Delta w_{jh} (s + 1) = -\eta \sum_{n=1}^{N_n} \frac{\partial E_x}{\partial w_{hj}} + \alpha [\Delta w_{jh} (s)] \quad (3.5)$$

and

$$\Delta w_{ih} (s + 1) = -\eta \sum_{n=1}^{N_n} \frac{\partial E_x}{\partial w_{ih}} + \alpha [\Delta w_{ih} (s)] \quad (3.6)$$

where,  $s$  represents the sweep number (i.e. the number of times the network has been through the whole set of cases at which time the coupling strengths are updated),  $n$  runs over all cases,  $N_n$  is the total number of cases,  $\eta$  represents the learning rate parameter and  $\alpha$  represents the momentum term which is the relative contribution of previous change in coupling strengths.

### c. EXPERIMENTAL RESULTS

There are two methods suggested here for energy efficient routing in WSNs. First is Most Significant Sensor Node prediction and another is Group Head selection. Now, we discuss both of these problems in any WSN and seek possible solutions using neural networks, which will actually use to determine the shortest routing path in any WSN for minimizing the energy consumption.

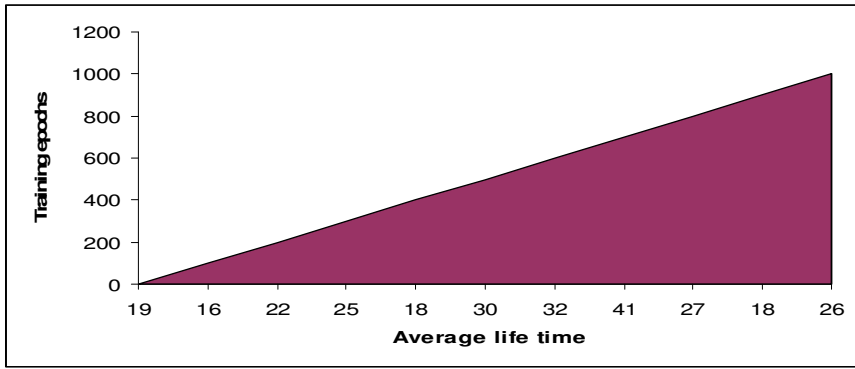
Usually WSNs life-time ends by having a single sensor node which uses all its energy and the other sensors consuming the remaining energy. This sensor (which is the cause of the networks end of lifetime) is most likely located in a very significant sensor node which always is in the routing path of many nodes to the base station. By predicting these significant nodes, it is possible to allocate tasks to the nodes in a more efficient way and thus increase the lifetime of the network. In order to predict WSN's most significant nodes, we propose a method based on Neural Networks. With it we would be able to know the energy level finally at the last of a WSN's life time also we can be able to conclude that which node is consuming more energy. Such nodes which are blocking most of the energy in the network are the most significant nodes of the network.

Selecting Group Heads amongst all the nodes is also energy conserving scheme for a WSN is proposed herewith. Sensor nodes are initially powered by batteries with full capacities. Each sensor collects data which are typically associated with other sensors in its neighborhood, and then the associated data is sent to the Base Station through Group Head for evaluating the tasks more efficiently. Assuming the periodic sensing of same period for all the sensors and Group Head is selected as in [17]. Inside each fixed group of nodes, a node is periodically elected to act as Group Head through which communication to/from Group nodes takes place. In next two sections we will discuss Most Significant Node prediction method using neural networks and Group Head selection using neural networks.

#### Experiment-I

To train our neural network architecture we did an experiment. Our experiment generates random WSNs and calculates all the mentioned characteristic features for each sensor, then it continues to operate until the lifetime of the network ends; at this point our experiment calculated all the sensor's final energy levels and thus it can use them as the training output of our neural network. Having all the characteristic features and final energy levels of each sensor, the experiment trains the neural network with these input-output feature patterns. Considering equal energy level for all the sensor nodes, the wireless sensor network starts to operate and use the battery of all the sensor nodes. We have also considered a working cycle for all the nodes, meaning that each node is equipped with an internal clock and operates at specific time periods which give the node enough time to route the gathered data. Thus the WSN works in discreet amount of time. The experiment implemented in Visual C++ and Matlab. In our experiment we used 150 randomly generated WSNs with 90 sensor nodes. At the end of each WSN's lifetime our experiment runs a training operation on the neural network and trains the neural network using the information from all 90 sensors. The experiment repeats this operation for each one of the 150 random WSNs. After training, we tested the neural network with some newly generated WSNs and the results thus obtained are according to our predictions.

Each WSN is simulated to have 50 randomly scattered sensor nodes. The simulation results showed that in average the lifetime of the network is 24.09. This value is very much dependent on the neural network precision in predicting the energy levels of the sensor nodes; thus it is possible to increase this average lifetime of the WSN by increasing the training iterations which results in creating a more precise neural network. We applied different iterations to our neural network and for each one of these iterations, we observed the average lifetime of 50 random networks. Figure 1 showing the result thus obtained. It can be seen that on increasing the number of iterations and having a more precise neural network, the average lifetime of the random 50 WSNs increased.



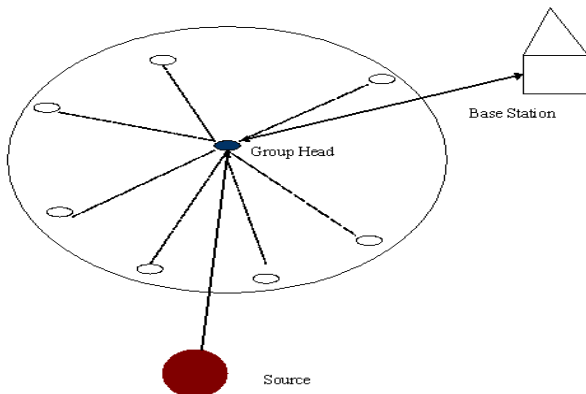
**Figure 3.1 Average life time of WSN vs Training epochs of NN**

The set of Group Head nodes can be selected on the basis of the routing cost metric explored by the equation

$$R_{CM} = \frac{E_k}{A_r \{E^T(N_k^S, N_m^D) + E^R(N_k^S, N_m^D)\}} \quad (3.7)$$

Where,  $E_k$  be the energy associated with the delivery ratio of the packet, delivered correctly from source node  $N^S$  to the destination node  $N^D$ ,  $E^T(N_k^S, N_m^D)$  is the energy transmitted from  $N^S$  and  $E^R(N_k^S, N_m^D)$  is the energy received at  $N^D$ ,  $A_r$  be the range area of the network.

The densely populated areas of the network will be overcrowded with Group Head nodes, while the barely populated areas will be left without any Group Head node. In such a situation, it is likely that the high cost sensors from poorly covered areas will have to perform expensive data transmissions to distant Group Head nodes which will further reduce their lifetime.



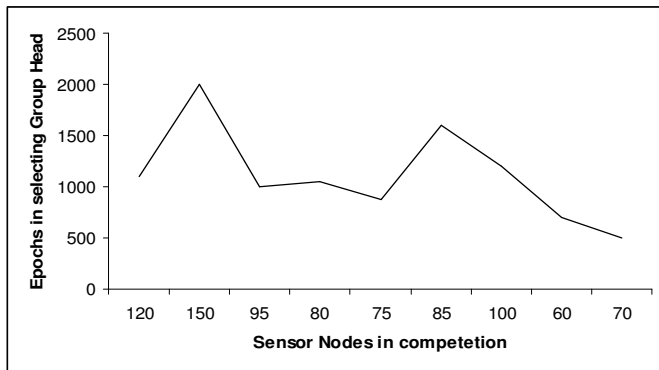
**Figure 3.2 Layout of a simple WSN**

We are using here, five layered feed forward neural network architecture system just like in figure 1. We have provided input patterns in form of the sensor nodes competing for Group Head. The node with smallest value of  $E_k$  is selected as Group Head.

### Experiment-II

Now, we have designed the similar experiment to Experiment 1 with a different task. In this experiment we used 600 randomly generated WSNs with 400 sensor nodes. The node's sensing range was considered 50 meters. We provide arbitrary number of

competing sensor to our neural network system and seek the convergence for selecting Group Head. The experiment convergence was found to be extremely slow for large data range but is quite good for low range data. Figure 4 reports the convergence of the network while successful selection of the Group Head.



**Figure 3.3 Selecting Group Head**

## CONCLUSION

We proposed a neural network approach for energy conservation routing in a wireless sensor network. Our designed neural network system has been successfully applied to our scheme of energy conservation. We have applied neural network to predict Most Significant Node and selecting the Group Head amongst the association of sensor nodes in the network. After having a precise prediction about Most Significant Node, we would like to expand our approach in future to different WSN power management techniques and observe the results. In this Chapter, we used arbitrary data for our experiment purpose; it is also expected to generate a real time data for the experiment in future. The selection of Group Head is proposed using neural network with feed forward learning method. And the neural network found able to select a node amongst competing nodes as Group Head.

## REFERENCES

- [1] Akyildiz, I.F.; Weilian Su; Sankarasubramaniam, Y.; Cayirci, E., "A survey on sensor networks", Communications Magazine, IEEE, vol.40, no.8, pp. 102-114, Aug 2002.
- [2] Chee-Yee Chong; Kumar, S.P., "Sensor networks: evolution, opportunities, and challenges", Proceedings of the IEEE, vol.91, no.8, pp. 1247-1256, Aug. 2003.
- [3] N. Al-Karaki, A.E. Kamal, "Routing techniques in wireless sensor networks: a survey", IEEE Wireless Communications, 11:6, 6-28, 2004.
- [4] Al-Karaki, J.N.; Kamal, A.E., "Routing techniques in wireless sensor networks: a survey", Wireless Communications, IEEE, vol.11, no.6, pp. 6-28, Dec. 2004.
- [5] Heinzelman, W.; Chandrakasan, A.; and Balakrishnan, H.; "Energy- Efficient Communication Protocol for Wireless Microsensor Networks", Proceedings of the 33rd Hawaii International Conference on System Sciences (HICSS '00), January 2000.
- [6] Li Hu; Yun Li; Qinbin Chen; Jia-yi Liu; Ke-ping Long, "A New Energy-Aware Routing Protocol for Wireless Sensor Networks", International Conference on Wireless Communications, Networking and Mobile Computing (WiCom 2007), pp.2444-2447, 21-25 Sept. 2007.
- [7] Hosseingholizadeh, A.; Abhari, A.; "A new Agent-Based Solution for Wireless Sensor networks Management", 12th Communications and Networking Simulation Symposium (CNS), San Diego, CA, USA, 22- 27 March 2009.
- [8] Tynan, R.; Marsh, D.; O'Kane, D.; O'Hare, G.M.P., "Agents for wireless sensor network power management", International Conference Workshops on Parallel Processing (ICPP 2005), vol., pp. 413-418, June 2005.
- [9] Fok, C.-L.; Roman, G.-C.; Lu, C., "Mobile agent middleware for sensor networks: an application case study", *Fourth International Symposium on Information Processing in Sensor Network. (IPSN 2005)*, pp. 382-387, April 2005.
- [10] Hussain, S.; Shakshuki, E.; Matin, A.W., "Agent-based system architecture for wireless sensor networks", 20th International Conference on Advanced Information Networking and Applications (AINA 2006), vol.2, April 2006.
- [11] Zhou Ying; Xiao Debao, "Mobile agent-based policy management for wireless sensor networks," Proceedings of 2005 International Conference on Wireless Communications, Networking and Mobile Computing, vol.2, pp. 1207-1210, 23-26 Sept. 2005.
- [12] P. Bates, "Debugging heterogeneous distributed systems using event based models of behavior", ACM Transactions on Computer Systems, 13: 1, 1995.



- [13] C. Frei, "Abstraction techniques for resource allocation in communication networks", Ph.D. dissertation, Swiss Federal Inst. Technology (EPFL), Lausanne, Switzerland, 2000.
- [14] Cerpa, N. Busek, D. Estrin, "Scale: A tool for simple connectivity assessment in lossy environments", Tech. Rep. 21, Center for Embedded Networked Sensing, University of California, Los Angeles, CA, USA, 2003.
- [15] M. Yarvis, W. Conner, L. Krishnamurthy, J. Chhabra, B. Elliott, "A. Mainwaring, Real-world experiences with an interactive ad hoc sensor network", in: Proceedings of the 31st IEEE International Conference on Parallel Processing Workshops, ICPPW, IEEE Computer Society, Vancouver, BC, Canada, 2002.
- [16] J. Zhao, R. Govindan,, "Understanding packet delivery performance in dense wireless sensor networks", in: Proceedings of the 1st ACM International Conference on Embedded Networked Sensor Systems, SENSYS, ACM Press, Los Angeles, CA, USA, 2003.
- [17] W.R. Heinzelman, A. Chandrakasan, H. Balakrishnan, "Energy efficient communication protocol for wireless micro sensor networks", in: Hawaii International Conference on System Sciences (HICSS), 2000.

