Robust Energy Management Routing in WSN using Neural Networks

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ABSTRACT

Abstract: Wireless Sensor Networks (WSNs) deployment process requires a continuous resource of energy. In this way, it become more important to monitor continuously the consumption of energy, trace where it is most required and utilized, and make a policy for uniform energy distribution at each node and energy efficient routing in WSNs. In this paper, we propose neural network based energy efficient routing path discovery and sensor energy management in WSNs with the objective of maximizing the network lifetime. Two experiments have been conducted with multi layered feed forward neural networks. One is used to predict the Most Significant Node in the network and another is used to determine the Group Head amongst the competitive sensor nodes.

Keywords- **Wireles Senor Networks, Energy Efficient Routing, Neural Networks.**

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I. INTRODUCTION

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].

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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 paper 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.

II. Neural Networks For Energy Efficient Routing

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.

III. Most Significant Node Prediction Using Neural Networks

In order to predict Most Significant Node (MSN) in a WSN we are depicting a set of input patterns for a five layered feed forward neural network. These input patterns belong to one wireless sensor node and by using them as the inputs of the neural network we can predict the energy level of the sensor at the last of WSN's lifetime. These patterns may be in the form of features coded from Sensor node's distance from sink,. Sensor node's distance from the neighboring border,. Sensor's number of neighbors, the number of neighbors which initially route their data through this sensor. After deploying sensor nodes, base-station receives sensor nodes positions and neighbors' information, thus it can easily calculate these patterns for each sensor and the neural network can be able to predict their final energy level. The neural network can be trained with different network parameters. A well-trained neural network would be able to receive each sensor's features as the inputs and predict its final energy level. Thus, if the neural network be executed for each one of WSN at the start of the WSN's lifetime it would be possible to predict the Most Significant Sensor nodes of the WSN. The result of this prediction is dependent of initial energy management scheme followed by the WSN. For example if in a WSN management algorithm the energy of those nodes which are located at the corners of the sensing field is mostly used, after successful training, the network would be able to understand this behavior of the algorithm and then it can predict that the final energy level of the nodes at the corner of the sensing environment must be the lowest to conserve the overall energy of the system.

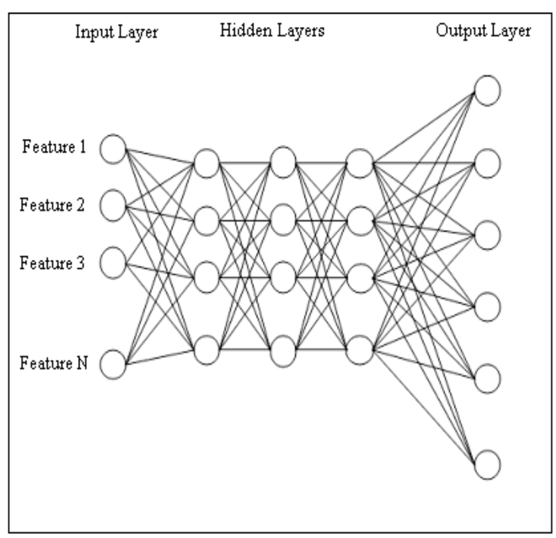

Figure 1 Architecture of Neural network

IV. EXPERIMENT-1

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.

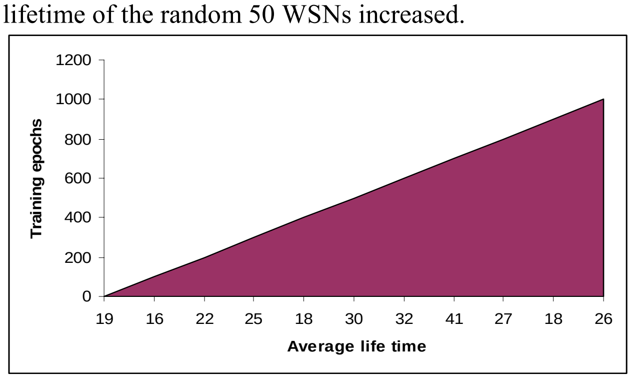

Figure 2 Average life time of WSN vs Training epochs of NN

V. GROUP HEAD SELECTION USING NEURAL NETWORKS

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

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

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.

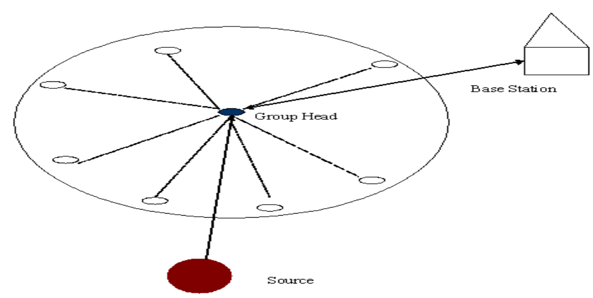

Figure 3 Layout of a simple WSN

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.

VI. EXPERIMENT-2

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.

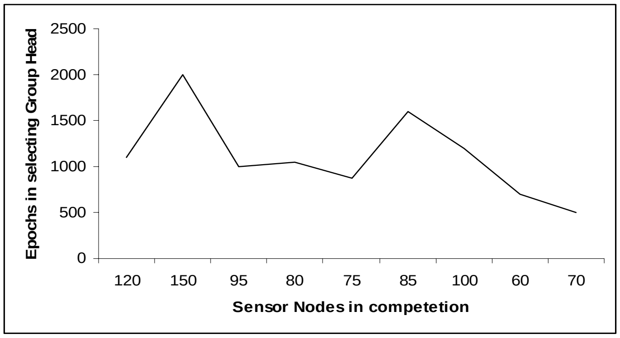

Figure 4 Selecting Group Head

VII. CONCLUSION

In this paper 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 paper, 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.

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