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Reliable Routing using MNN

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***Abstract*— 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. Wireless Sensor Networks deployment process requires a continuous resource of energy. 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. 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 layer 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.**

Index Terms—WSN, adhoc network, Multilayer neural network

I. INTRODUCTION

The ideal wireless sensor is networked and scalable, consumes very little power, is smart and software programmable, capable of fast data acquisition, reliable and accurate over the long term, costs little to purchase and install, and requires no real maintenance.

Selecting the optimum sensors and wireless communications link requires knowledge of the application and problem definition. Battery life, sensor update rates, and size are all major design considerations. Examples of low data rate sensors include temperature, humidity, and peak strain captured passively. Examples of high data rate sensors include strain, acceleration, and vibration.

Recent advances have resulted in the ability to integrate sensors, radio communications, and digital electronics into a single integrated circuit (IC) package. This capability is enabling networks of very low cost sensors that are able to communicate with each other using low power wireless data routing protocols. A wireless sensor network (WSN) generally consists of a base station (or “gateway”) that can communicate with a number of wireless sensors via a radio link. Data is collected at the wireless sensor node, compressed, and transmitted to the gateway directly or, if required, uses other wireless sensor nodes to forward data to the gateway. The transmitted data is then presented to the system by the gateway connection. The purpose of this chapter is to provide a brief technical introduction to wireless sensor networks and present a few applications in which wireless sensor networks are enabling.

Sensor networks offer economically viable solutions for a variety of applications. For example, current implementations monitor factory instrumentation, pollution levels, freeway traffic, and the structural integrity of buildings. Other applications include climate sensing and control in office buildings and home environmental sensing systems for temperature, light, moisture, and motion.

Sensors embedded into machines and structures enable condition-based maintenance of these assets [3]. Typically, structures or machines are inspected at regular time intervals, and components may be repaired or replaced based on their hours in service, rather than on their working conditions. This method is expensive if the components are in good working order, and in some cases, scheduled maintenance will not protect the asset if it was damaged in between the inspection intervals. Wireless sensing will allow assets to be inspected when the sensors indicate that there may be a problem, reducing the cost of maintenance and preventing catastrophic failure in the event that damage is detected. Additionally, the use of wireless reduces the initial deployment costs, as the cost of installing long cable runs is often prohibitive. In some cases, wireless sensing applications demand the elimination of not only lead wires, but the elimination of batteries as well, due to the inherent nature of the machine, structure, or materials under test. These applications include sensors mounted on continuously rotating parts, within concrete and composite materials, and within medical implants.

One of the most recent applications of today’s smarter, energy-aware sensor networks is structural health monitoring of large civil structures, such as the Ben Franklin Bridge , which spans the Delaware River, linking Philadelphia and Camden, N.J . The bridge carries automobile, train and pedestrian traffic. Bridge officials wanted to monitor the strains on the structure as high-speed commuter trains crossed over the bridge.

A star network of ten strain sensors were deployed on the tracks of the commuter rail train. The wireless sensing nodes were packaged in environmentally sealed NEMA rated

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enclosures. The strain gauges were also suitably sealed from the environment and were spot welded to the surface of the bridge steel support structure. Transmission range of the sensors on this star network was approximately 100 meters.

The sensors operate in a low-power sampling mode where they check for presence of a train by sampling the strain sensors at a low sampling rate of approximately 6 Hz. When a train is present the strain increases on the rail, which is detected by the sensors. Once detected, the system starts sampling at a much higher sample rate. The strain waveform is logged into local Flash memory on the wireless sensor nodes. Periodically, the waveforms are downloaded from the wireless sensors to the base station. The base station has a cell phone attached to it which allows for the collected data to be transferred via the cell network to the engineers' office for data analysis. This low-power event-driven data collection method reduces the power required for continuous operation from 30 mA if the sensors were on all the time to less than 1 mA continuous. This enables a lithium battery to provide more than a year of continuous operation.

There are several characteristics available in wireless sensor networks and they are summarized as follows, Unique characteristics of a WSN include:

- Limited power they can harvest or store
- Ability to withstand harsh environmental conditions
- Ability to cope with node failures
- Mobility of nodes
- Dynamic network topology
- Communication failures
- Heterogeneity of nodes
- Large scale of deployment
- Unattended operation

Many networks are used in the field, each defined at a different level of abstraction and trying to model different aspects of neural systems. They range from models of the short-term behaviour of individual neurons, through models of how the dynamics of neural circuitry arise from interactions between individual neurons, to models of how behaviour can arise from abstract neural modules that represent complete subsystems. These include models of the long-term and short-term plasticity of neural systems and its relation to learning and memory, from the individual neuron to the system level.

- One layer Neural Network
- Single layer Neural Network
- Multilayer Neural Network
- Adaline

While initially research had been concerned mostly with the electrical characteristics of neurons, a particularly important part of the investigation in recent years has been the exploration of the role of neuro modulators such as dopamine, acetylcholine, and serotonin on behaviour and learning.

One layer neural networks that consists of solving a system of linear equations is presented, and formulas for the sensitivities of the sum of squared errors with respect to the input and output data are derived. Linear method to learn the parameters of two-layer neural networks and the sensitivities of the total sum of squared errors with respect to the intermediate output layer values, which are modified using a standard gradient formula until convergence, is presented. proposed method is compared with some other fast learning methods. The SBLLM method is presented as an initialization tool to be used with other learning methods.

The earliest kind of neural network is a single-layer perceptron network, which consists of a single layer of output nodes; the inputs are fed directly to the outputs via a series of weights. In this way it can be considered the simplest kind of feed-forward network. The sum of the products of the weights and the inputs is calculated in each node, and if the value is above some threshold the neuron fires and takes the activated value otherwise it takes the deactivated value. Neurons with this kind of activation function are also called Artificial neurons or linear threshold units. In the literature the term perceptron often refers to networks consisting of just one of these units

A perceptron can be created using any values for the activated and deactivated states as long as the threshold value lies between the two. Most perceptrons have outputs of 1 or -1 with a threshold of 0 and there is some evidence that such networks can be trained more quickly than networks created from nodes with different activation and deactivation values.

This class of networks consists of multiple layers of computational units, usually interconnected in a feed-forward way. Each neuron in one layer has directed connections to the neurons of the subsequent layer. In many applications the units of these networks apply a sigmoid function as an activation function.

The universal approximation theorem for neural networks states that every continuous function that maps intervals of real numbers to some output interval of real numbers can be approximated arbitrarily closely by a multi-layer perceptron with just one hidden layer. This result holds only for restricted classes of activation functions, e.g. for the sigmoidal functions.

Multi-layer networks use a variety of learning techniques, the most popular being back-propagation. The output values are compared with the correct answer to compute the value of some predefined error-function. By various techniques, the error is then feed back through the network. Using this information, the algorithm adjusts the weights of each connection in order to reduce the value of the error function by some small amount. After repeating this process for a sufficiently large number of training cycles, the network will usually converge to some state where the error of the calculations is small. To adjust weights properly, one applies a general method for non-linear optimization that is called gradient descent. For this, the derivative of the error function with respect to the network weights is calculated, and the weights are then changed such that the error decreases.

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The back-propagation can only be applied on networks with differentiable activation functions.

The problem of teaching a network to perform well, even on samples that were not used as training samples, is a quite subtle issue that requires additional techniques. This is especially important for cases where only very limited numbers of training samples are available. The danger is that the network over fits the training data and fails to capture the true statistical process generating the data. Computational learning theory is concerned with training classifiers on a limited amount of data. In the context of neural networks a simple heuristic, called early stopping, often ensures that the network will generalize well to examples not in the training set.

Other typical problems of the back-propagation algorithm are the speed of convergence and the possibility of ending up in a local minimum of the error function. Today there are practical solutions that make back-propagation in multi-layer perceptrons the solution of choice for many machine learning tasks.

Hop-by-hop data aggregation [1] is a very important technique for reducing the communication overhead and energy expenditure of sensor nodes during the process of data collection in a sensor network. However, because individual sensor readings are lost in the per hop aggregation process, compromised nodes in the network may forge false values as the aggregation results of other nodes, tricking the base station into accepting spurious aggregation results. A commitment-based hop-by-hop aggregation is performed in each group to generate a group aggregate. The base station then identifies the suspicious groups based on the set of group aggregates. Finally, each group under suspect participates in an attestation process to prove the correctness of its group aggregate

Wireless sensor networks are envisioned to be economic solutions to many important applications, such as real-time traffic monitoring, military surveillance, and homeland security A sensor network may consist of hundreds or thousands of low-cost sensors, each of which acts as an information source, sensing and collect- ing data from the environment for a given task. In addition, there may also exist one or more base stations which subscribe to specific data streams by distributing interests or queries

It is not really about data aggregation because it assumes the BS has already collected all the raw data. Also, abnormal data are discarded without further reasoning. By using divide-and- conquer, we partition the aggregation tree into groups to reduce the importance of high-level nodes in the aggregation tree; we use commit-and-attest so that the BS has a way to verify the aggregates. We may implement and show the benefits of Bloom Filter in our protocol.

Quantum neural networks (QNN's) [2] , a class of feedforward neural networks (FFNN's) inherently capable of estimating the structure of a feature space in the form of fuzzy sets. The hidden units of these networks develop quantized representations of the sample information provided by the training data set in various graded levels of certainty. Unlike other approaches attempting to merge fuzzy logic and neural networks, QNN's can be used in pattern classification problems without any restricting assumptions such as the availability of *a priori* knowledge or desired membership profile, convexity of classes, a limited number of classes, etc. Experimental results presented here show that QNN's are capable of recognizing structures in data, a property that conventional FFNN's with sigmoidal hidden units back.

FEED FORWARD neural networks (FFNN's) have been a natural choice as trainable pattern classifiers and adaptive controllers because of their function approximation capability and generalization ability. In QNN the FFNN creates its internal representations from the sample information provided by the training data. In order to function as fuzzy classifier, the FFNN must use the sample information as a mere reference for creating the internal representations.It should not encode the sample information accurately into the internal representations. Such an exact or faithful encoding of the sample information results in the FFNN memorizing the crispness" in the training data set. But an inherently fuzzy architecture should be capable of generalizing the sample information into various graded levels of certainty over the entire feature space.

Fuzzy logic systems and feed forward neural networks [3] are equivalent in essence. First, we introduce the concept of interpolation representations of fuzzy logic systems and several important conclusions. The nonlinear neural networks can be represented by rectangular wave neural networks.

Many researches focused on combining neural networks and fuzzy logic systems, such as neuro-fuzzy systems,or fuzzy neural networks . This paper takes a different approach to demonstrate the equivalent relationship between fuzzy logic systems and neural networks.To provide more significant theoretical result on combining both systems. Representations of fuzzy logic systems and the idea of interpolation representation of fuzzy logic systems and provide new results under some weaker conditions. That fuzzy logic systems and neural networks are equivalent essentially under some restriction. The antecedents of inference of a fuzzy logic system are the base functions of interpolation and the consequents of inference only relate to their peak values but not to the shape of the membership functions. where their activation functions are "rectan- gular waveforms." Then we prove that a nonlinear neural network can be represented by a rectangular wave neural network. By means of this result, the equivalence between fuzzy logic systems and feedforward neural networks. This conclusion provides an important theoretical tool or basis for fuzzy logic systems or neural networks.

Sensing coverage [4] is an important factor for a WSN, as it is one of the critical measures of performance or service quality offered by a sensor network . The achievable sensing coverage is strongly related to the deployment of nodes, . the network topology. some nodes may become invalid after they have used up their own energy resource, the achievable sensing coverage will gradually degrade as time passes. Various types of routing protocols have been proposed for WSNs which focus on the issues of reliability,

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efficiency and power saving. The design of a routing protocol is generally independent of the sensing coverage issue.

Some nodes may become invalid after they have used up their own energy resource, the achievable sensing coverage will gradually degrade as time passes. Different routing protocols may motivate different distributions of energy dissipation among nodes, and thus induce different changes in the network topology after some nodes have died out. This implies that different routing protocols will lead to different sensing coverage when some nodes are no longer available. Considering the impact on the sensing coverage of a network, we have proposed coverage-preserving routing protocols which are modified from the LEACH and virtual grid routing protocols. These proposed protocols can substantially improve the performance of sensing coverage. According to the simulation results, the sensing coverage degradation of the coverage-preserving protocols is slower than that of the other baseline protocols. For the time duration maintaining the network coverage over 50%, a gain of 20% in overall sensing coverage can be obtained by using the coverage preserving protocols.

Automation processes [5] are usually associated with instrumentation and control. Data acquisition in process control is usually accomplished by placing sensors close to the actual phenomenon and then transmitting the data via a wired communication infrastructure to the processing place. The evolution of sensor technology and communication networks has allowed employing intelligent sensors for improving the processing control. We present a monitoring system based on the intelligent wireless sensor concept. The system provides means for both wired and wireless communication to a supervisory system called Supervisory Control and Data Acquisition .The result is a single supervision system that provides flexibility, fault tolerance, high sensing fidelity, low cost, and rapid deployment. The intrinsic characteristics of wireless sensor networks (WSNs) make them an ideal platform for incorporating energy usage evaluation and condition monitoring functions and building a high-level intelligent power management system in industrial plants.

The advances in wireless communication, microelectronics, digital electronics, and highly integrated electronics and the increasing need for more efficient controlled electric systems make the development of monitoring and supervisory control tools the object of study of many researchers. This paper proposes a digital system for energy usage evaluation, condition monitoring, diagnosis, and supervisory control for electric systems applying wireless sensor networks (WSNs) with dynamic power management (DPM). To extend the SN lifetime, sensor nodes implement a DPM protocol.

II. PROPOSED SYSTEM

In this section, modules are presented from four aspects, data sensing, processing, transmission and duty cycle operation. From the user prospective, the controllable parameters of mote are important to optimize the system operative power consumption. Many other parameters are determined by components inherent characteristics. Although they can be modified from theoretical prospective, it is unrealistic to change once the device is finalized. Thus, the analysis of power consumption is focused on the parameters that can be modified by the users. The analysis is based on point to point data transmission to understand the hardware performance.

A. DATA SENSING

The power consumption of sensors is an area less addressed in previous literatures. Due to the fact that the power consumption highly relies on the type and specifications of the devices selected during design. Although data rate, sensing resolution and measurement range are critical for the sensor design, from the power consumption point of view, the most important parameters are different. The active mode power consumption, warm up time and active mode time are of particular importance. The settle time of microcontroller integrated ADC for analogue sensor will also impact the power consumption of sensor module. In the practical sensor layer design, a universal power MOSFET is often implemented to switch off the sensors when sensing is not required. This feature generally eliminates the power consumption of sensor module in sleep mode. However, switching the power mode from sleep to active requires an initialization phase. For analogue sensors, the initialization time is the settling time of microcontroller analog to digital converter (ADC). For digital sensors, the connection to the microcontroller is made either through an I2C interface or GPIO signal pins. Some of the digital sensors require initialization time TSI significantly longer than the actual sensing time TDP.

Although the initialization phase consumes less power than the active mode, the extended warm up time may lead to high energy consumption if not controlled properly. In addition, due to the fact sensors need to be activated by microcontroller, the extended initialization time also significantly increases the active time of microcontroller.

B. DATA PROCESSING

The power consumption of actual data process only represents a friction of the total power cost. In the case of BEM application, the volume of data generated from the sensor is limited. Most of the latest microcontrollers obtain a clock speed of 8MHz. The high computation capability is only partially utilized in BEM applications. For a significant percentage of the microcontroller operative time, the MCU device is set into idle mode in order to maintain the active mode and the capability to response to the forthcoming tasks without initialization. Although the power consumption of idle mode of MCU is lower than the data processing mode power consumption. It is still two orders of magnitude higher than the sleep mode power. In order to minimize the energy consumption, it is necessary to minimize the idle mode time in the programming and reduce the redundancy.

Two parameters can be modified to adjust the power consumption of microcontroller. The power supply voltage of micro controller is one parameter that has direct impact on the

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power. The minimum supply voltage of microcontroller is as low as 1.5V, however, other components e.g. sensors and RF module require higher voltage. In order to simplify the power supply design, the microcontroller is often directly connected to a 3V or 3.3V battery through a LDO type voltage regulator. The simple method doubles the power consumption in micro controller. An alternative method is to include a secondary voltage regulator to minimize the extra power consumption due to the relative high voltage from the universal LDO voltage regulator. A tradeoff between LDO efficiency loss and power saving from lower operative voltage is required to optimize the supply voltage.

Another parameter that poses a substantial impact on the data processing power consumption is the MCU clock frequency. Most micro controller used in WSN applications can obtain multiple operative clock frequencies. Between different frequencies, the power consumption variation is also significant. Some MCU devices show obvious correlation between the power supply voltage, while in other devices the correlation is less significant. In this work, a former type of MCU is considered and the correlation between the operative frequency and supply voltage is investigated and presented. The data sensing and data processing power consumption of a node is presented where the variations are the energy consumptions in data processing and sensing, respectively. Constants are the power consumption and time of sensing initialization.

C. DATA TRANSMISSION

A Zigbee RF module provides a maximum data transmission rate at 250Kbit/sec. For BEM applications, the small packet size of sensing data allowed it to be transmitted in a short period of time. Based on a Texas Instruments CC2420 Zigbee module, the data transmission time of a 50 bytes packet is 16msec. Although power consumption of wireless communication module is considerable higher than microcontroller in active mode, the actual energy dissipated in data transmission is substantial lower. The power consumption of communication is mainly determined by the transmission power mode. However, the chip level drain efficiency (the ratio of output RF power to total input power supply DC power) is inherently low for 2.4GHz Zigbee RF modules. The ratio is between 1% and 2% when 0 dBm transmission power is selected, whilst it drops significantly when lower transmission power is used. The low and variable efficiencies lead to the fact that the measured power consumption difference between high transmission power mode (29.7mW for 0 dBm) and low power mode (52.2mW for -15 dBm) is substantially lower than the transmission power difference (0 dBm and -15dBm). The small data packet size and resultant short transmission time enable relative low energy consumption when transmitting with maximum power mode.

Due to the low energy consumption nature of the data transmission in BEM application, the acknowledgement (ACK) packet of network protocol is considered in the power consumption analysis. The acknowledgement packet transmission time is 12msec with one transceiving ACK and one receiving ACK. The transmission power is on maximum power transmission mode to extend the transmission range. Thus, the energy consumption of acknowledgement transmission is comparable to the energy dissipated in data transmission. To improve the data transmission reliability, when a transmission is failed or incomplete, the gateway node will send an ACK requiring a repeat transmission from the mote. Upon receiving the repeat ACK, the mote will transmit the previous data stored in flash memory. The energy consumption in ACK and data transmitting of a single input single output (SISO) wireless communication is summarized. The correlation between measured module power consumption and transmitting power is described by the coefficient and the variable is the power consumption in receiving mode. It is a constant value in most of current Zigbee modules and is 15-20% higher than the maximum transmitting power. x and y are the transmitting time and receiving mode time, respectively. The ACK packet has a single and preset data format, only the actual packet length and the repeat rate are relevant to the receiving mode time. In the case of transmission time, the number of data packet and length of data packet are main parameters.

D. DUTY CYCLE

To reduce the energy consumption during long term deployment, it is crucially important to operate the mote in a low power "sleep" mode when no data sensing and transmission is required. As shown, the sleep mode power consumption is measured at 42MW. When compared with the data transmitting power, the sleep mode power is 3 orders of magnitude lower. The requirements of BEM application allow relatively long time intervals between measurements, 5 to 15 minutes measurement intervals are often sufficient, while the total active mode time is shorter than 400msec, the mote is able to operate in ultra-low duty cycle. The total energy consumption including sleep mode power consumption is shown in the following Where is the period of one measurement including active mode and sleep mode time, is the duty cycle. is the sleep mode power consumption. In a case of 5 minutes per measurement and a 6% repeat rate, the total energy consumption is measured at 25.9 mJ. The energy consumption divided by each functions of the measurement is illustrated. The sleep mode energy contributes to a significant percentage of the total energy consumption of WSN in low duty cycle applications. By improving the power regulators, adjusting impedance between power supply and ground pin and effectively isolating the sensor layers from power supply in sleep mode, the energy consumption of this mode can be further minimized.

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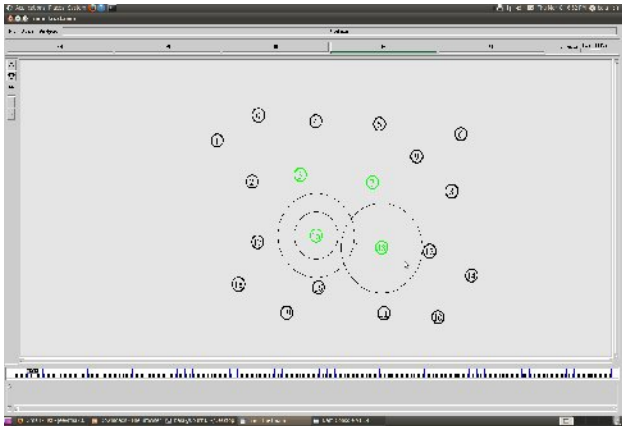

Fig.1. Processing of data to the nearer nodes and selecting the maximum energy level

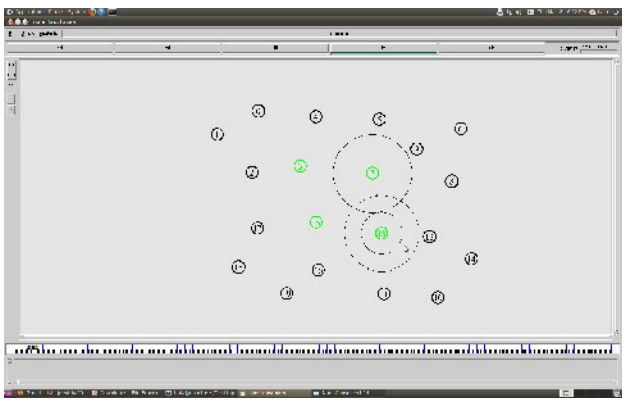

Fig.2. Data Processing to another node

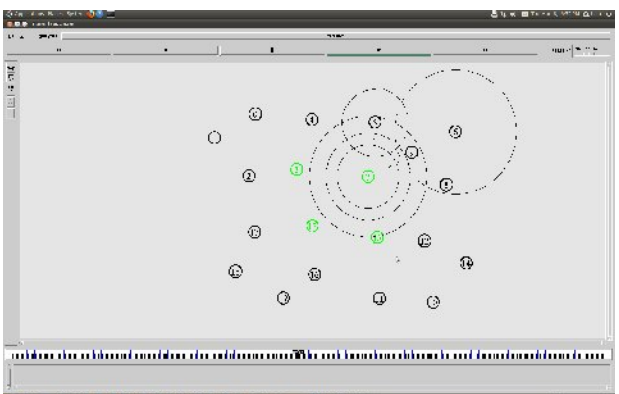

Fig.3. Packet transmission to nearer nodes and finding maximum energy level node

III. CONCLUSION

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. Wireless Sensor Networks deployment process requires a continuous resource of energy. 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. 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 layer 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.

REFERENCES

[1] Heinzelman W, Chandrakasan A, Balakrishnan H.Energy-Efficient Communication Protocol for Wireless Microsensor Networks. In: Proc. 33rd Hawaii Int'l. Conf.Sys. Sci, 2000.

[2] Intanagonwiwat C, Govindan R, Estrin D. Directed Diffusion: a Scalable and Robust Communication Paradigm for Sensor Networks. In: Proc. ACM Mobi-Com 2000, Boston, MA, 2000.

[3] Lindsey S, Raghavendra C. PEGASIS: Power-Efficient Gathering in Sensor Information Systems. In:IEEE Aerospace Conf. Proc., vol. 3, 9–16, 2002.

[4] Mario Cordina and Carl J. Debono, Increasing Wireless Sensor Network Lifetime Through The Application Of Som Neural Networks. ISCCSP 2008, Malta, 12-14 March 2008.

[5] Martin A. Kraaijveld, Jianchang Mao And Ani1 K. Jain, A Nonlinear Projection Method Based On Kohonen' S Topology Preserving Maps. IEEE Transactions On Neural Networks, Vol. 6, No. 3, May 1995.

[6] Moustafa A. Youssef, Adel Youssef, Mohamed F. Younis, Overlapping Multihop Clustering For Wireless Sensor Networks. IEEE Transactions On Parallel And Distributed Systems, Vol. 20, No. 12, December 2009.

[7] Murata T, Ishibuchi H.Dynamic clustering for wireless sensor networks IEEE 2010.

[8] Onaiza Maqbool And Haroon A. Babri, Hierarchical Clustering For Software Architecture Recovery. IEEE Transactions On Software Engineering, Vol 33, No. 11, November 2007.

[9] Raghunathan V, Schurghers C, Park S, Srivastava M.Energy-aware Wireless Microsensor Networks.In: IEEE Signal Processing Magazine, March 2002.

[10] Santosh Kumar, Ten H. Lai, Marc E. Posner, and Prasun Sinha, Maximizing The Lifetime Of A Barrier Of Wireless Sensors. IEEE Transactions On Mobile Computing, Vol. 9, No. 8, August 2010.

[11] Shahbazi H, Araghizadeh M.A, Dalvi M. Minimum Power Intelligent Routing In Wireless Sensors Networks Using Self Organizing Neural nNetworks. In: IEEE International Symposium on Telecommunications, 2008.

[12] Teuvo Kohonen, Fellow, Samuel Kaski, Krista Lagus, Jarkko Salojärvi, Jukka Honkela, Vesa Paatero, And Antti Saarela, Self Organization Of A Massive Document Collection. IEEE Transactions On Neural Networks, Vol. 11, No. 3, May 2000.