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Development of Energy Efficient Routing Protocol in Wireless Sensor Networks using Probabilistic Neural Network (ERPPNN)

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ABSTRACT

Background: A wireless sensor network consists of a number of sensors spreading across a geographical area. The performance of the network suffers as the number of nodes grows in network becomes difficult to manage. It is essential that the network be able to self-organize. Clustering is an efficient technique to address the network scalability problem. **Objective**: We proposed a Probabilistic Neural Network (PNN) model to classify the sensor nodes in networks into minimum Weighted Connected Dominated Sets (WCDS) which consists of nodes having more connectivity and higher energy. The PNN consists of shrinking the hidden layers which is accomplished by performing K-means clustering on the training data of each WCDS separately. The means of the resultant clusters are presented in each class or cluster, instead of presenting energy parameter of all the sensor nodes in networks in the hidden layer nodes. Load balancing is achieved by selecting WCDS as random basis. The training parameter and WCDS are derived based on nodes having more connectivity and higher energy. **Results** :This technique achieved better results when the transmission range is short and equal performance when the transmission range becomes larger. The results show that it is important to select a suitable transmission range to make the network stable and to extend the lifespan of the network.. **Conclusion:** ERPPNN enhances the energy efficiency of the sensor nodes by selecting optimal WCDS consists minimum hops and higher energy sensor node and also provides effective routing that increase network lifetime.

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INTRODUCTION

Wireless Sensor Networks (WSNs) is a category of wireless ad hoc networks in which sensor nodes collect, process, and communicate data acquired from the physical environment and send it to an Base Station (BS). WSNs have several challenges such as sensor nodes are normally battery-powered, and hence energy efficient routing (N. Al-Karaki, A.E. Kamal, 2004) is very much essential in order to prolong the sensors' lifetimes. There are many challenges when designing energy efficient routing in WSNs. One of the key challenges is how to make full use of the limited energy to prolong the lifetime of the network because energy is a valuable resource in WSNs. The status of energy consumption should be continuously monitored after network deployment. Many research works have been pursued to WSNs, including power management in (F. Salvadori *et al*,2009), routing in (H. Karkvandi, E. Pecht, and O. Yadid-Pecht,2011), data gathering in(C.-T. Cheng, C. K. Tse, and F. C. M. Lau 2011) sensor deployment and coverage issues (A. Chen, T. H. Lai, and D. Xuan,2008), and localization (H.-S. Ahn and K. H. Ko,2009). Neural networks have solved a wide range of problems and have good learning capabilities including classification, adaptation, implementation, parallelization, speed, and flexibility. Neural Networks (NN) are used to model a sensor node, the node's dynamics, and interconnections with other sensor network nodes. The input to the NN is chosen to include previous output samples of the modeling sensor node and the current and previous output samples of neighboring sensors. The model is based on structure of a PNN type. The input to the NN and the topology of the network are based on a general nonlinear sensor model. Many research works done for Wireless Sensor Network Modeling Using Neural Networks in (Azzam I *et al*,2008) (Hongmei He *et al*,2009). In this paper, PNN is used to classify the networks into WCDS through which routing is involved that maximize the network life time.

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Related works:

Soft computing techniques (Hevin and Paramasivan,2013) are intelligent tools compatibility with WSNs characteristics and can be applied in different energy conservation schemes. Several supervised neural networks with incremental learning ability have been developed in the past years. PNN is a classification method based on Parzen's theorem (E. Parzen,1962) for estimating the probability density function, as well as Bayesian decision theory (A. M. Mood and F. A. Graybill,1962) for decision making that provides high computational efficiency and flexible structure of a PNN. The architecture of PNN is briefly described in (D. F. Specht,1990).

(Neeraj Kumar, Manoj Kumar and R.B. Patel,2010) proposed coverage and connectivity aware neural network based energy efficient routing in WSN. They used linear programming with coverage and connectivity aware constraints for maximizing the network lifetime. Cluster head selection is proposed using adaptive learning in neural networks followed by coverage and connectivity aware routing with data transmission.

(Neda Enami1 *et al* ,2010) briefed about survey on Neural Network Based Energy Efficiency in Wireless Sensor Networks. They presented a classification for the most important applications of neural networks in energy efficiency of WSNs depend on different research studies have been done so far. The important application of neural networks in WSNs can be summarized to sensor data prediction, sensor fusion, path discovery, sensor data classification and nodes clustering which all lead to less communication cost and energy conservation in WSNs. Another classification for neural network based methods can be according to neural network topologies that applied such as Self Organising Maps, Back propagation neural networks, recurrent neural networks, and Radial Basis Functions.

(Chia-Hung Tsai and Yu-Chee Tseng, 2012) proposed a Path Connected-Cluster Wireless Sensor Network(PCC-WSN) and Its Formation, Addressing, and Routing Protocols. They contributed for defining the PCC-WSN topology and also formation scheme used to divide nodes into several paths and clusters. A two-level ZigBee hierarchical address assignment and routing schemes for PCC-WSN are conducted for making routing easily.

(Sang H. Kang and Thinh Nguyen ,2012) proposed Distance Based Thresholds for Cluster Head Selection in Wireless Sensor Networks for Investigating energy depletion of a node as a Cluster Head(CH) node and a non-CH node. They proposed a distributed CH selection algorithm for sensor networks based on the node distance to the BS to balance the energy consumption. This approach takes into account the distances from sensors to a base station that optimally balances the energy consumption among the sensors.

(Sheng-Shih Wang and Ze-Ping Chen, 2013) proposed a link-aware clustering mechanism (LCM) to determine an energy efficient and reliable routing path. The LCM considered node status, link condition and uses a clustering metric called the predicted transmission count (PTX) to evaluate the qualification of nodes for CHs and gateways to construct clusters. Each CH and gateway candidate depends on the PTX to derive its priority and the candidate with the highest priority becomes the CH or gateway. LCM can select the best nodes to become CH or gateways to efficiently construct a persistent and reliable routing path to guarantee the report quality.

(Jin Shyan Lee, and Wei Liang Cheng, 2012) discussed a fuzzy-logic-based clustering approach with an extension to the energy predication to prolong the lifetime of WSNs by evenly distributing the workload. This approach focused on selecting optimal CHs from existent sensor nodes which considering expected residual energy of the sensor nodes.

Generally, fuzzy clustering algorithms use fuzzy logic for blending different clustering parameters to select cluster heads. To overcome the defects of LEACH, (Gupta *et al, 2005*) proposed to use three fuzzy descriptors including residual energy, concentration, and centrality during the CH selection. The concentration means the number of nodes present in the vicinity, while the centrality indicates a value which classifies the nodes based on how central the node is to the cluster. In every round, each sensor node forwards its clustering information to the base station at which the CHs are centrally selected. However, this mechanism is a centralized approach. (Anno *et al,2008*) employed different fuzzy descriptors, including the remaining battery power, number of neighbor nodes, distance from cluster centroid, and network traffics, and evaluated their performance. The sensor nodes closer to the base station consume much more energy due to the increased network traffic near the base station. Hence, the sensor nodes closer to the base station quickly run out of battery. Besides the residual energy, (Bagci *et al,2010*) further considered a fuzzy descriptor, distance to the base station, during the cluster head selection. This unequal clustering approach is based on the idea of decreasing the cluster sizes when getting close to the base station.

(Nitin Mittal *et al*, 2010) have proposed the Improved LEACH (Low – Energy Adaptive Clustering Hierarchy) communication protocol which is an extension of the classic LEACH because classical LEACH do not dissipation of energy evenly throughout a network. In this, Cluster based mechanism is used for minimizing energy dissipation in sensor networks. Improved LEACH is performed well than classical clustering algorithms by using adaptive clustering mechanism and rotating cluster heads for load balancing.

TEEN (Threshold Sensitive Energy Efficient Sensor Network protocol) (A. Manjeshwar and D. P. Agrawal,2001) utilized multi level clustering mechanism to save the more energy. Cluster head broadcast three parameters including attribute, HT and ST to its members when changing the cell. Nodes in the networks are sensed information continuous from environment. If the information value beyond HT or the varied range of characteristic value beyond ST, the node will send sensed information to cluster head that reduces network traffic and increase networks life time.

PEGASIS (Power-Efficient Gathering in Sensor Information Systems) (Lindsey *et al*,2002) used greedy algorithm to form data chain for gathering data. Each node aggregates the data from downstream node and sends it to upstream node along the chain. The distance between nodes on chain is shorter than from member nodes to cluster head. PEGASIS save much energy because it reduces the routing overhead for dynamic formation of cluster. Greedy algorithm construct the chain result in distance between a pair of sensors is too long. In this condition, this pair of sensors will consume much energy than other sensors in transmitting data phase.

3. Proposed work:

In this paper PNN is used to classify the sensor nodes in networks into minimum Weighted Connected Dominated Sets. Nodes having more connectivity and higher energy are presented in WCDS. The PNN consists of shrinking the hidden layers which is accomplished by performing K-means clustering on the training data of each WCDS separately.

3.1 Selection of Training Data:

K-mean clustering approach involves the selection of training data. Clusters formed by k-mean are used as training data which is then fed into PNN to form energy efficient clusters because PNN take the account of higher energy nodes to form the WCDS. The nodes in WCDS are allowed to participate routing phase.

3.2 K-mean algorithm:

Clustering is the process of partitioning a group of data points into a small number of clusters. *K-mean clustering algorithm* performed on training data which is measured based on the distance metric. In general, WSNs have n senor nodes $\mathbf{x}i, i=1...n$ that have to be partitioned in k clusters. The goal is to assign a cluster to each senor nodes having closest distance and also it decides the number of clusters k. Initially the threshold value is set based on the distance to form the clusters.

Steps:

1. Initialize the center of the clusters. μi= T ,i=1,...,k
2. node the closest cluster to each distance of neighboring nodes. $\mathbf{c}i=\{j:d(\mathbf{x}j,\mu i)\leq d(\mathbf{x}j,\mu l),l\neq i,j=1,...,n\}$
3. Set the position of each cluster to the mean of all distance of neighboring nodes belonging to that cluster. $\mu i=1|ci|\sum j\in ci\mathbf{x}j,\forall i$
4. Repeat steps 2-3 until form the required clusters

where

$|\mathbf{c}|$= number of sensor nodes in $\mathbf{c}$

where $\mathbf{c}i$ is the set of distance of neighboring nodes that belong to cluster i.

K-means clustering uses the square of the Euclidean distance $d(\mathbf{x},\mu i)$

$C_k=\{d(x_1,y_1),d(x_2,y_2)\ldots\ldots d(x_i,y_j)$, i=1…n, j=1…n

where k is the number of clusters

3.3 PNN:

The PNN consists of shrinking the hidden layers which is accomplished by performing K-means clustering on the training data of each WCDS separately. In PNN, the nodes of the hidden layer are represented by the cluster means derived from the K-means clustering instead of the whole nodes in the networks. The training and classification modes of PNN are described in the following sections.

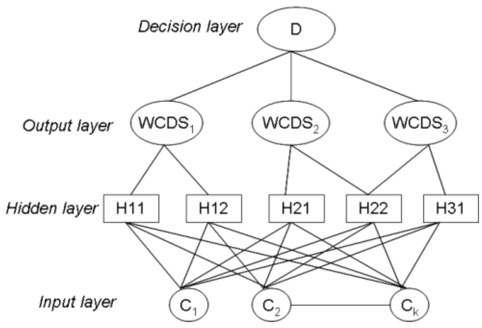

Fig. 1: PNN.

1) Training Mode: The procedures of training the PNN include the following:

The K-means clustering algorithm is applied to the distance of all sensor nodes that are recorded as training data set of each cluster separately. Then, the weight vectors connected to the nodes of each class at the hidden layer are initialized to the normalized mean vectors of the class output clusters. The weight vector at any node can be represented as the normalized mean vector of the output clusters, μ_{ij}, where *i* and *j* are defined as follows.

a) $i = 1, \ldots, n$ is the cluster number, with *n* being the number of output cluster.

b) $j = 1, \ldots, k$ is the cluster number of *i*. Here, *k* is the number of clusters in *i*.

2) The weight vectors at the nodes of the output layer are all set to a value of one, as in the original PNN.

2) Classification Mode: In this mode. The energy of nodes in the clusters as used in the training mode that are entered to the PNN classifier. The main procedures of this mode are given as follows.

1) The pattern input clusters C = {C1, *C2,… Ck*) is presented to the input layer of the network.

2) The activation function at each node in the hidden layer is computed using the Gaussian model

$$H_{ij} = \exp[\sum(\mu_{ijE}.C_E - 1)/\sigma_{ij}] \tag{1}$$

where μ_{ijE} is the weight vector on cluster *j* of class WCDS *i*, σ_{ij} is the standard deviation of cluster *j* within class WCDS *i*, and C_E is the energy of the node in the clusters.

This paper, a radio hardware energy dissipation model was used where the transmitter dissipates energy to run the radio electronics and the power amplifier, and the receiver dissipates energy to run the radio electronics. Thus, to transmit a k-bit of message and distance *d*, the radio expends

$$E_{TX}(k,d) = E_{TX\_elec}(k) + E_{TX\_amp}(k,d) \tag{2}$$

To receive k-bit message, the radio expends

$$E_{RX}(k,d) = kE_{TX\_elec} \tag{3}$$

Where E_{TX_elec} - electronics energy for receiving k bit message, E_{TX_amp} - amplifier energy depends on the distance to the receiver

3) The activation function at each of the output nodes is computed by calculating the summation of output nodes that belong to that class WCDS

$$O_i = \frac{P_i}{N}\sum_{j=1}^{k} H_{ij} \tag{4}$$

where *Pi/N* is the prior probability of class WCDS *i*, *Pi* is the number of training patterns in class WCDS *i*, *N* is the total number of training pattern vectors, and *k* is the number of clusters within class WCDS *i*. Equation (2) is calculated for all class WCDS , $i = 1, \ldots, n$.

4) The decision as to which class the example is categorized is made by selecting the WCDS which consists nodes having higher energy for routing the data to destination.

RESULTS AND DISCUSSION

The proposed Energy Efficient Routing Protocol in Wireless Sensor Networks using Probabilistic Neural Network (ERPPNN) is evaluated and simulated in Network Simulator (NS2). In this evaluation, the ERPPNN has compared with two Cluster based routing protocols in sensor networks such as LEACH and PEGASIS. The Simulation parameters for WSNs are shown in table 1.

Table I: Simulation parameter.

Parameter	Value
number of nodes (N)	50,150,300
Area	200 m x 200 m
Source location	175 m, 175 m
Sink location	20 m, 20 m
Pause time	300ms
constant bit rate	1 packet/s
packet frame size	30 bytes
Initial Energy	2 joules

4.1 Average Energy Consumption:

Each node is initialized with initial energy source of 2J to evaluate the energy balancing performance. Fig. 2 shows that total amount of energy consumption in which ERPPNN consume less energy. Each node exchanges beacon signals with its neighbors every 50ms. A source node transmits data at 50ms. LEACH and PEGASIS shows higher energy consumption of the all nodes because maximum nodes are involved in routing. The ERPPNN has selected the optimal WCDS consists minimum hop and higher energy nodes for end to end data delivery than other two protocols. Because LEACH and PEGASIS has heavy control message exchange and high computational complexity. ERPPNN consumes lower energy compare to others.

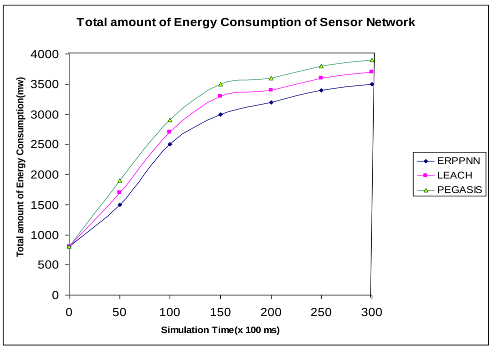

Fig. 2: Total amount of Energy Consumption of sensor networks.

4.2 Packet delivery Ratio:

Packet delivery ration (PDR) is the ratio of successful received packets from source to sink. PDR is evaluated for three routing algorithms with varied pause time. When the pause time increases, more packets are received prior to the pause time. Optimizes the number of relaying hops in routing phase. Figure 3 shows that dead line Delivery Ratio in case of one source. ERPPNN has the highest PDR and provides better performance as compared to other two protocols. ERPPNN is also used the WCDS for forwarding data to sink. Fig.5 noticed that ERPPNN achieved more than 89% of PDR because it has forwarded the packets to destination using WCDS consists of minimum hops and higher energy nodes with less message exchange overhead.

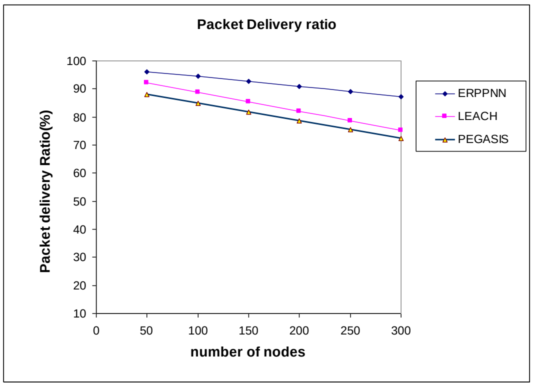

Fig. 3: Packet Delivery Ratio.

4.3 Routing Overhead:

In this simulation, the routing overhead is evaluated for ERPPNN, LEACH and PEGASIS while varying nodes in data forwarding. Figure 4 shows that the minimal routing overhead caused by ERPPNN than other two protocols. ERPPNN is taken optimal WCDS for routing and also it is exchanged minimum of routing control message. It is forwarded the packets using minimum number of hops with higher energy nodes in WCDS that reduces routing overhead.

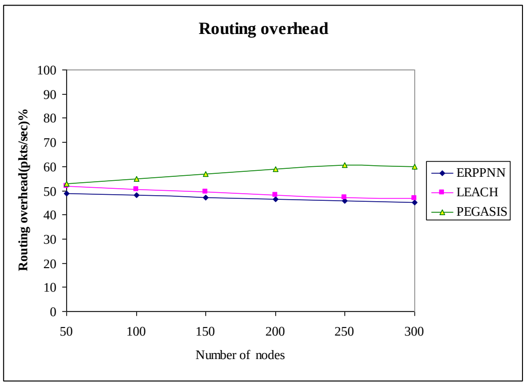

Fig. 4: Routing overhead.

Australian Journal of Basic and Applied Sciences, 8(10) July 2014, Pages: 302-308

Conclusion:

In this paper, an Energy Efficient Routing Protocol in Wireless Sensor Networks using Probabilistic Neural Network is proposed for optimal routing and reduces energy consumption of senor nodes. Simulation results have shown that the ERPPNN used PNN for achieving better performance with respect to energy efficiency and PDR compare to other two protocols like LEACH and PEGASIS. PNN model to classify the sensor nodes in networks into minimum Weighted Connected Dominated Sets which consists of nodes having more connectivity and higher energy. Load balancing is also achieved by selecting WCDS which is suitable for routing. The PNN consists of shrinking the hidden layers which is accomplished by performing K-means clustering on the training data of each WCDS separately. In addition, the ERPPNN enhances the energy efficiency of the sensor nodes by selecting optimal WCDS consists minimum hops and higher energy sensor node and also provides effective routing that increase network lifetime.

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