Neural Network Based Energy Efficient Clustering and Routing in Wireless Sensor Networks	Phân Cụm và Định Tuyến Có Hiệu Quả Về Mặt Năng Lượng Dựa Trên Mạng Nơron Trong Các Mạng Cảm Biến Không Dây
Abstract Energy is a valuable resource in Wireless Sensor Networks (WSNs). The status of energy consumption should be continuously monitored after network deployment. The information about energy status can be used to early notify	Tóm tắt Năng lượng là nguồn tài nguyên có giá trị trong các mạng cảm biến không dây (các WSN). Tình trạng tiêu thụ năng lượng cần được giám sát liên tục sau khi mạng đi vào hoạt động. Thông tin về trạng thái năng

both sensor nodes and Network Deployers about resource depletion in some parts of the network. It can also be used to perform energy-efficient routing in WSNs. In this paper, we propose a neural network based clustering and energy efficient routing in WSN with the objective of maximizing the network lifetime. In the proposed scheme, the problem is formulated as linear programming (LP) with specified constraints. Cluster head selection is done using adaptive learning in neural networks followed by routing and data transmission. The simulation results show that the proposed scheme can be used in wide area of applications in WSNs.

1. Introduction

Wireless Sensor Networks (WSNs) is a class of wireless ad hoc networks in which sensor nodes collect, process, and communicate data acquired from the physical environment to an external Base-Station (BS). But these networks have several challenges such as sensor nodes in WSNs are normally battery-powered, and hence energy has to be carefully used in order to avoid early termination of sensors' lifetimes [1]. As such, the concept of continuous monitoring of network resources becomes a very important topic in WSNs. This same concept has been already investigated in many other environments, e.g., power plants [2], and in many distributed systems [3].

Many recent experimental studies have

lượng có thể được dùng để thông báo sớm cho cả nút cảm biến và nhân viên triển khai mạng về sự cạn kiệt tài nguyên trong một số phần của mạng. Nó cũng có thể được dùng để định tuyến có hiệu quả về năng lượng trong các WSN. Trong bài báo này, chúng tôi đề xuất phương pháp phân cụm và định tuyến mạng có hiệu quả về mặt năng lượng dựa trên mạng nơron trong WSN nhằm mục đích tối đa hóa tuổi thọ mạng. Trong phương pháp đề xuất, bài toán được phát biểu dưới dạng một chương trình tuyến tính (LP) với các ràng buộc nhất định. Việc chọn nút chủ cụm được thực hiện bằng phương pháp học thích nghi trong các mạng nơ ron rồi sau đó là định tuyến và truyền tải dữ liệu. Các kết quả mô phỏng chứng tỏ rằng phương pháp đề xuất có thể áp dụng được trong nhiều ứng dụng của WSN.

1.Giới thiệu

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shown that, especially in the field of sensor networks where low power radio transmission is employed, wireless communication is far from being perfect [4,5,6].

In this paper, we address the issue of energy-efficient clustering and routing in WSNs using neural networks with the objective of maximizing the network lifetime. First, we propose an efficient neural network based clustering algorithm for WSNs. Secondly, we propose routing and data transmission algorithm for WSNs. We define an efficient metric to be used in taking the selection of next hop in routing. The problem is formulated as LP with specified constraints and routing metric

Rest of the paper is organized as follows: Section 2 discusses related work, section 3 defines the energy model used along with the defined routing metric and problem formulation, Section 4 describe the proposed solution, Section 5 provides the simulation and results obtained, and finally Section 6 concludes the article.

2. Related Work

There are number of clustering protocols have been proposed in literature e.g. LEACH [7], PEGASIS [8], HEED [9], EEUC [10], and FLOC [11]. The cluster formation overhead of the clustering protocols includes packet transmission cost of the advertisement, node joining and leaving, and scheduling messages from sensor nodes. All these protocols do not support adaptive multi-level clustering, in which

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the clustering level cannot be changed until the new configuration is not made. Therefore, the existing protocols are not adaptable to the various node distributions or the various sensing area. If the sensing area is changed by dynamic circumstances of the networks, the fixed-level clustering protocols may operate inefficiently in terms of energy consumption.

Bandyopadhyay and Coyle [12] proposed the randomized clustering algorithm to organize sensors into clusters in a wireless sensor network. Computation of the optimal probability of becoming a cluster head was presented. Moscibroda and Wattenhofer [13] defined the maximum cluster-lifetime problem, and they proposed distributed, randomized algorithms that approximate the optimal solution to maximize the lifetime of dominating sets on wireless sensor networks. Pemmaraju and Pirwani []14 considered the k-domatic partition problem, and they proposed three deterministic, distributed algorithms for finding large k-domatic partitions. Tan and Korpeoglu [15] proposed two new algorithms under the name PEDAP, which are near optimal minimum spanning tree based wireless routing scheme. The performance of the PEDAP was compared with LEACH and PEGASIS, and showed a slightly better network lifetime than PEGASIS. Yi et. al[16] presents a Power efficient and adaptive clustering protocol PEACH

3 Models, Routing Metric and Problem Formulation

3.1 Network Model

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We consider a network of homogeneous and energy- constrained sensor nodes that are randomly deployed in a sensor field. Sensor nodes are initially powered by batteries with full capacities. Each sensor collects data which are typically correlated with other sensors in its vicinity, and then the correlated data is sent to the BS via Cluster Head (CH) for evaluation or decision making purposes. We assume periodic sensing with the same period for all sensors. To facilitate the operation of the network, we apply a novel clustering scheme that results in selection of cluster. Inside each fixed cluster, a node is periodically elected to act as CH through which communication to/from cluster takes place.

BS

3.2 Energy Model

To ascertain the amount of energy consumed by a radio transceiver, we apply the following energy model. For each packet transmitted by a sending node to one or more receivers in its neighborhood, the energy is calculated as according to [7]:

$$e = et + ner + (N - n)ehr \quad (1)$$

Where et and er denote the amount of energy required to send and receive, n the number of nodes which should receive the packet, and N the total number of neighbors in the transmission range. ehr quantifies the amount of energy required to decode only the packet header According to model described in [7], et and er are defined as

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for a distance d and a k byte message.

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We have
……………………..
For a given header size n bytes, ehr would be accordingly calculated.

3.2 Routing Metric and Problem Formulation

A proper routing metric has to be chosen that can be used to decide the next hop for data transmission. This metric always ensure the best shortest route and incurs the least energy to transmit the packet from source to destination. The cost of a link between two nodes Si and Sj is equal to the energy spent by these nodes to transmit and to receive one data packet, successfully.
The metric chosen is Routing cost is calculated as follows:

Where Ei is energy associated with the delivery ratio of the packet originating from source node Si and correctly received at destination node, while Et (Si, Sj) .is the energy used in transmitting from Si to Sj and Er (Si, Sj) is the energy used in receiving the packet. Data routing from every cluster head to the sink is done over multi-hop paths, which is given by minimizing equation (3)

4 Proposed Solution

The solution for the energy aware routing problem is proposed using an LP formulation. The objective of the LP is to select a number of nodes with higher levels of residual energy to form an optimal route, while minimizing the total routing cost. Let us label the base-station as node 0 and label the CH nodes as nodes 1 to n, where n is the total number of CH sensor nodes. So the

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problem reduces to
Minimize Z R _ C
Subject to following constraints
Constraint (4) specifies the amount of data transmitted bi between two nodes Si and S}- , Constraint (5) specifies amount of data to be transmitted from two nodes Si and Sj, Constraints (6) guarantees a minimum node lifetime and limits the maximum power consumption of any node in the network.

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The proposed protocol is divided into two phases namely as: setting up phase and energy aware routing and data transmission phase.

4.1 Setup Phase

In this part, the initial cluster head selection and cluster formation algorithm are introduced , followed by the energy aware routing.

Cluster Head Election

To ensure balanced energy consumption among the cluster head nodes throughout the network lifetime, many clustering protocols favor uniformly distributed clusters with stable average cluster sizes [7-11]. But we propose a new neural network based coverage aware clustering algorithm. The set of cluster head nodes can be selected based on the cost metric defined in equation 3.The densely populated parts of the network will be overcrowded with cluster head nodes, while the scarcely covered areas will be left without any cluster head nodes. 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 cluster head nodes, further reducing their lifetime. There are three

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layers in the proposed neural network: Input layer, Competition layer and Output Layer.

Fig.2: Selection of CH

Neural networks have solved a wide range of problems and have good learning capabilities. Their strengths include adaptation, ease of implementation, parallelization, speed, and flexibility. A two - layer feed forward neural network that implements the idea of competitive learning is depicted in Figure 2 above. The nodes in the input layer admit input patterns of sensor nodes competing for CH and are fully connected to the output nodes in the competitive layer. Each output node corresponds to a cluster and is associated with weight Wj, j = 1,2,...., m , where m is the number of clusters.

The neurons in the competitive layer then compete with each other, and only the one with the smallest EiD value becomes activated or fired. Each neuron in the proposed algorithm for CH selection has an adaptive learning. The learning rate jd determines the adaptation of the vector towards the input pattern and is directly related to the convergence. If /n equals zero, there is no learning. If ji is set to one, it will result in fast learning, and the prototype vector is directly pointed to the input pattern. For the other choices ofi , the new position of the vector will be on the line between the old vector value and the input pattern. Generally, the learning rate could take a constant value or vary over time.

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1. Initialize the Vector S = (S1, S 2,...., Sm }of sensor nodes competing for Cluster head. //Processing at Input Layer
2. Choose a winner k from sensor nodes as CH whose EiD is minimum as follows

k = arg min(EiD } // Competition Layer

3. Also EiD smallest Euclidean distance to BS i.e. e,d = k 2\S _BS\, where k is proponality constant

4. Update the value of weight vector as follows:
w j (new) = w j (old) + y,(Si _ w j (old)), where U is learning rate of the neurons. 0 < u < 1
5. Repeat Steps (2-4) iteratively.

6. Neuron with smallest value of Ei D is winner.// Output Layer
Fig.3: Algorithm for Cluster head selection
4.2 Routing and Data Transmission
An algorithm for routing and data transmission is proposed in Figure 5.

Let us denote by R the maximum number of routes that exist between each source-destination pair, and l indicate by a route in R. Also, denote by pow(Si, l) the power consumed by node S i in transmitting to the next node on route l . For the sake of simplicity, we assume that this parameter depends only on the distance between the transmitting and the receiving node. Then, we associate with each route l an energy cost routing metric defined in equation (3) above. The proposed algorithm scan all routes in R and determine the least expensive route to reach the BS. A

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source will select the route that has the least energy consumption or the one that maximizes the network lifetime. routes, the sink node first generates a Route Discovery message that is broadcasted throughout the network. Upon receiving the broadcast message, each sensor node introduces a delay proportional to its cost before it forwards the Route Discovery message to nodes in range R . In this way a message arrives at each node along the desired minimum cost path. The cumulative cost of the routing path from the sink to the node obtained in this phase is called the energy aware routing cost of the node described in (3). 1. Sort the paths p1, p 2, pm according to E,d as EiD1 < E,+1D+11 < EmDm 2. j = 1 // initialize the counter for available paths. 3. repeat and calculate E < Pmax imum (Constraint 6) 4. repeat 5. EC,m = 2 mEmax L // EC,m is use to i=1,2...m store the minimal energy consumption per bit with m paths and is assigned maximum value initially. 5. R _ C = 0 // initialize the value of routing cost 6. repeat 7. Solve equation (3) and get the corresponding optimal energy	[redacted] [redacted]

distribution with respect to constraints defined in equations (4),(5),(6).

8. Calculate ECm = 2 E,L
i=1,2...m
9. Calculate the value of R _ C from equation (3)
and R _ Cupdated = R _ C // Update value of routing cost
10. Until \ R_Cupdated - R_C \< S1 (predefined threshold)
11. Update the values of energy for each data
. • T-- Updated 7-.
transmission as Ec,m = EC,m
Until \EcmUpdated _Ecm \< ^2

12. j = j +1 // Update the counter of the paths
13. Until m > Destination _ node

14. Compare all paths using R _ C metric and select the smallest one.

15. Send the data across the multiple paths defined.
Fig. 5: Algorithm for Routing and Data Transmission
Given m available paths, the overall energy consumption per packet, E, can be written as
E = Z EiL , where Ei is the energy consumption for one bit along path i and L is the packet length in bits.
5. Simulation and Results
We have considered a stationary WSN of size 400*400 with a maximum transmission range of 50 m. The message length is assumed to be 48 bytes, including an 12 byte packet header. The energy used to receive and transmit data is modeled according to the energy model presented in Section 3. Other sources of energy consumption

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like sensing, processing, and idle listening are neglected. MAC-layer behaviors such as contention, duty cycles, or packet buffering are not addressed. We have simulated the proposed scheme on ns-2[17].

Figure 6 presents the energy consumption of the proposed scheme with well known PEACH clustering protocol [16] when the maximum transmission range is 60 m. The results demonstrate that the energy consumption of proposed neural network based clustering is smaller than PEACH.

Number of Rounds

Fig.6: Mean residual Energy in PEACH and Proposed Scheme

Figure 7 presents the number of nodes alive when using clustering in proposed scheme and PEACH. This result directly reflects the network lifetime of the wireless sensor networks. In the case of networks using PEACH with the maximum transmission range r = 60 m, where a node runs out of energy occurs nearly after 4000 rounds, while in propped scheme there is a slight improvement and node runs out of energy in nearly 4200 rounds.

The percentage of nodes alive and the mean of residual energy versus the number of nodes after 1500 rounds are presented in Figures 8 and 9. Proposed scheme has highest percentage of residual energy compared with PEACH protocol. Also, the variation in the mean of residual energy of proposed scheme is smaller than PEACH

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after 1500 rounds 6. Conclusions This paper has proposed a neural network based energy efficient routing and clustering protocol for WSNs. The selection of CH is done using adaptive learning mechanism. Simulations results show that it performs better than existing routing protocol PEACH in terms of residual energy and .number of alive nodes. So the proposed scheme can be used in wide areas of sensor networks where energy efficiency is a critical issue.	[redacted]