Neural Network Based Energy-Efficient Multi-hop Hierarchical Routing Protocol for Wireless Sensor Networks

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Abstract-This paper presents a new neural network based routing protocol for Wireless sensor networks called Energy efficient Multi-hop Hierarchical Routing Protocol using Self organizing map (EMHRS). This new protocol has an innovative quality of service (QoS)-driven routing algorithm based on artificial intelligence that can select next hop cluster head using Self Organizing Map neural network capability in multi dimensional data routing. This intelligent method optimizes the routing according to the amount of energy of each CH node in the network and its computation power while insuring more network coverage. Simulation results approve the advantages of EMHRS over two similar protocols, EMHR and EMHR-FL in terms of postponement of first node death and preserving more network coverage. As results, our method makes a better decision of next hop CH selection than classical EMHR and EMHR based fuzzy logic.

Keywords: Wireless sensor networks (WSNs); Artificial neural networks (ANNs); Energy Efficient; Self-Organizing Map (SOM); Quality of Service (QoS).

I. INTRODUCTION

Radio communications are the most energy-consuming task of WSNs [5]. In order to extend this type of network, many research studies focused on energy-efficient routing protocols [6]. Routing protocols commonly are divided into three categories, flat based routing, hierarchical based routing, and location based routing [4]. Hierarchical (cluster based) routing protocols are potentially the most energy efficient organizations which have shown wide application in the past few years [7]. Numerous clustering algorithms, have been proposed in the literature such as LEACH [20], EMHR [6] and EMHR-FL [2]. In clustering protocols, geographically close nodes are organized into groups and each group is referred to as a cluster. In each cluster, a Cluster Head node acts as a local base station.

Energy-Efficient Multi-Hop Protocol (EMHR) [6] is an hierarchical routing protocol with multi-hop communication. Based on energy efficiency, this algorithm optimizes the clustering process using an energy strategy that effectively avoids nodes with low energy to be CHs.

EMHR-FL [2] is an extension of EMHR that uses Fuzzy Logic Inference System (FIS) to select next hop CH by taking in to consideration some related metrics (battery level of CHs, distance between CHs and node density of CHs) in order to maximize the total number of packets transmitted to BS (Base Station).

In a WSN platform which has a fuzzy nature and different parameters are involved in its behavior, neural networks can help through dimensionality reduction, obtained simply from the outputs of the neural-networks routing algorithms, leads to lower communication costs and energy savings [8]. Moreover due to centralized nature of WSNs in which all data from the sensor nodes often have to be sent to a BS, neural networks capability in prediction of sensor readings at Base Station, can highly decrease unneeded communications and save considerable energy [14].

The other important motivation to use neural network based methods in WSNs is the analogy between WSNs and ANNs [9]. ANNs exhibit exactly the same architecture as WSNs since neurons correspond to sensor nodes and connections correspond to radio links. They also conclude that applying of the neural network paradigm in the context of sensor networks can lead to gain deeper understanding and more perceptions. With this view point, we can see the whole sensor network as a neural network and within each sensor node inside the WSN there could run also a neural network to decide on the output action [1].

Therefore, efficient neural network implementations using simple computations can replace traditional signal processing algorithms to
enable sensor nodes to process data by using fewer resources [3].

In this paper, a novel centralizes Energy efficient Multi-hop Hierarchical routing through using Self organizing map neural networks called (EMHRS) is presented which can provide a uniform distribution of energy in all clusters. The difference of our proposed protocol with previous routing protocols is that it is able to adaptively select next hop CH not only based on their topological closeness (distances) but also based on their energy levels and their density in each set-up phase by using SOM neural network. We tried to develop the classic idea for topological routing and incorporate a topology-energy based routing method by using SOM neural networks in order to apply three unrelated variables (energy and distance and density) in selecting next optimal hop.

II. PROPOSED PROTOCOL (EMHRS)

The operation of the algorithm is divided into rounds. Each round begins with a cluster setup phase, in which cluster organization takes place, followed by a data transmission phase, throughout which data from the simple nodes are transferred to the CHs. Each CH aggregates the data received from other nodes within its cluster and relays the packet to the base station.

A. Cluster Setup and Cluster Head selection phases

In the first round of networks, the process of clustering is the same as the LEACH [19][20], if the value specified by node i > T (n), the node i has become the CH. In the next round, based on the energy strategy of electing CHs, states of cluster member energy are compared to find the largest energy node that becomes the CH.

B. Transmission phase

In classic EMHR protocol [6], the information in CHs can be transmitted by multi hop, after computing a weighting function, to next hop CHs selected by finding the optimization next-hop to ensure the minimize energy dissipation of data transmission to BS. By this way of continuous selection of next hop CHs based on weight function. Each time, the one with the minimum value of this function is selected for the next hop, and then the last CH sends all data to BS. The weighting function is constructed as described in following equation.

\[ F(i,j) = \frac{E_i}{E_{max}} + \left[ \left| d(i,j) \right|^2 + d(j,S) \right]^2 \]

\[ / d(i,S)^2 \]

Where: \( E_i \) is the remaining energy of the cluster head emitter CH\(_i\), \( E_{max} \) is the initial energy of the cluster head emitter CH\(_i\), \( d(j,S) \) and \( d(i,S) \) are respectively the distances between the cluster heads emitter and receiver in one hone and the sink \( S \) in other hand.

By considering only the distance between the CH emitter \( (CH_i) \) and the CH receiver \( (CH_j) \) and taking into account only the residual energy of the \( CH_s \), this weighting function do not discuss other factors that affect the energy consumption and the network lifetime. In fact, in cases where the CH receiver is depleted of energy, or when it is overloaded, the data sent will be certainly lost.

To solve this problem, a EMHR-FL protocol is proposed in [2] where fuzzy logic is used in the next hop CH selection phase. But the rate of energy consumption of the proposed system is always more than EMHR protocol. However, EMHR-FL is more efficient in terms of total data received by the BS. For this, our work has as objective the use of neural network for helping energy conservation methods as intelligent tools to work in more efficient, desirable and easier way.

Due to the sensor constraints, the design of the routing algorithm has to consider the Quality of Service (QoS) provided to the applications, in order to improve the related goals [15] [16]. In this sense, the use of distributed artificial intelligence (AI) techniques in WSNs offers an alternative way to route data through the network [10]. We present in this paper a new routing algorithm which introduces Self-organizing map neural network (SOM) technique to measure the QoS supported by the network, then select the next optimal hop according to value of QoS.

We use a definition based on three types of QoS parameters: Residual energy (Remaining battery energy) of CHs emitters, distance between CHs emitters and its adjacent next-hop CHs receivers, distance between CHs receivers and the sink, density of CHs receivers. Each CH emitter tests every neighbor link quality using SOM algorithm and obtains mean values of four metrics previously described.

Possibility of using artificial intelligence for efficient consumption in both processing and in transmission provides a chance of using Self Organizing Map or Kohonen self-organizing Networks concept [8]. It is one of the most powerful mechanism developed in AI [11], created by Teuvo Kohonen in 1982, at the University of Helsinki, Finland.

Once a CH has tested a neighbor link QoS using SOM, it select the next hop with the best quality of service and transmit data to the next receiver CH. According to this strategy, data from CHs travel through dynamic paths, avoiding the region with the worst quality of service levels.

SOM gives an output denoted by QoS. This value is returned by a function defined by the SOM.
user, according to its aims. This function depends on the winning neuron and return the CH node’s final power level.

After a CH has collected a set of input samples from member nodes, it runs the winning neuron election algorithm. After the winning neuron is elected, the CH emitter (CH_E) uses the value returned by the output layer to assign a QoS estimation. Finally, this value is employed to select the next hop and the CH receiver (CH_R).

![Diagram of Back Propagation neural network to predict the final power level of the node](image)

**Figure 1.** Back Propagation neural network to predict the final power level of the node

C. **SOM creation**

SOM is an unsupervised neural network. The neurons are organized in an unidirectional two layers architecture and we can distinguish two phases, the learning phase (also called training process) and the execution phase (also called mapping process) [18].

1) **Learning phase**

In order to organize the neurons in a two dimensional map, we need a set of input samples $x(t) = [\text{Residual-energy-CH}_1(t), \text{Distance-CH}_1-\text{CH}_1(t), \text{Distance-CH}_1-\text{BS}(t), \text{Density-CH}_1(t)]$.

These are the set of variables that we want to consider as SOM input dataset, this samples should consider all the QoS environments in which a communication link between a pair of cluster heads nodes can work.

So we will have a $D$ matrix with $n*4$ dimensions. Since we are applying two different type variables, first we have to normalize all values. We used a Min-Max normalization method [12] in which $min_a$ and $max_a$ are the minimum and maximum values for attribute $a$. Min-max normalization, maps a value $v$ in the range of $(0, 1)$ by simply computing:

$$V' = \frac{v - \min_a}{\max_a - \min_a}$$

By means of above equation, the dataset $D$ matrix will be:

$$D = \begin{bmatrix}
ECR_1 & DCC_1 & DCS_1 & DEC_1 \\
ECR_{max} & DCC_{max} & DCS_{max} & DEC_{max} \\
ECR_2 & DCC_2 & DCS_2 & DEC_2 \\
ECR_{max} & DCC_{max} & DCS_{max} & DEC_{max} \\
ECR_n & DCC_n & DCS_n & DEC_n \\
ECR_{max} & DCC_{max} & DCS_{max} & DEC_{max}
\end{bmatrix}$$

Where $D$ is the data sample matrix or input vectors of SOM, $ECR=(ECR_1,.,ECR_n)$ are energy levels (remained energy) of CHs receivers, $DCC=(DCC_1,.,DCC_n)$ are distances between CHs emitters and CHs receivers, $DCS=(DCS_1,.,DCS_n)$ are distances between CHs receivers and the Sink, $DEC=(DEC_1,.,DEC_n)$ are densities of CHs receivers. $ECR_{max}$ is the remain energy of maximum energy node of CHs receivers of network space, $DCC_{max}$ is the maximum value for distances between CHs emitters and CHs receivers of network space, $DCS_{max}$ is the maximum value for distances between CHs receivers and the Sink, and $DEC_{max}$ is the maximum value for CHs receivers densities of the network space.

In order to determine weight matrix, BS has to select $m$ cluster heads nodes corresponding to $m$ regions of the network space. We need four variables of these selected CHs to apply them as weight vectors of our SOM: remained energy of CHs receivers, distances between CHs emitters and CHs receivers, distances between CHs receivers and the Sink, densities of CHs receivers. Therefore our weight matrix would be:

$$W = \begin{bmatrix}
ECR_1 & \ldots & ECR_n \\
ECR_{max} & \ldots & ECR_{max} \\
DCC_1 & \ldots & DCC_n \\
DCC_{max} & \ldots & DCC_{max} \\
DCS_1 & \ldots & DCS_n \\
DCS_{max} & \ldots & DCS_{max} \\
DEC_1 & \ldots & DEC_n \\
DEC_{max} & \ldots & DEC_{max}
\end{bmatrix}$$

Where $W$ is the weight matrix of SOM, we have a $4*m$ weight matrix. The SOM topology structure would be as Fig.2.
In our application, learning is done by minimization of Euclidian distance between input samples and the map prototypes weighted by a neighborhood function \( h_{i,j}(t) \):

\[
E_{SOM} = \frac{1}{2} \sum_{k=1}^{N} \sum_{i=1}^{M} h_{i,j}(k) \| W_i - x(k) \|^2
\]

Where \( N \) is the number of data samples, \( M \) is the number of map units; \( N(x^k) \) is the neuron having the closest referent to data sample \( x^k \) and \( h \) is the Gaussian neighborhood function defined by:

\[
h_{i,j}(t) = \exp \left( -\frac{\| r_j - r_i \|^2}{2\sigma_i^2} \right)
\]

Where \( \| r_j - r_i \|^2 \) the distance between map unit \( j \) and input sample \( i \) and \( \sigma_i \) is the neighborhood radius at time \( t \), which is defined by:

\[
\sigma(t) = \sigma_0 \exp(-\frac{t}{T})
\]

Where \( t \) is the number of iteration, \( T \) is the maximum number of iteration or the training length. The distance between \( X_i \) and weight vectors of all map neurons are computed. A neuron \( N(x_j) \) which has the minimum distance with input sample \( X_k \), would win the competition phase:

\[
N(X_k) = \arg_{1<j<m} \min \| W_j - X_k \|^2
\]

The neighborhood radius is a large value at the beginning and it will reduce with increasing of the time of the algorithm in every iteration. After competition phase, SOM should update the weight vector of the winner \( N(X_k) \) and all its neighbors which placed at the neighborhood radius of \( (R N(X_k)) \). If \( W_j = R_{N(X_k)} \) then:

\[
W_j(t + 1) = W_j(t) + \alpha(t) h_{j,N(X_k)}(t) x(t) - W_j(t)
\]

Else

\[
W_j(t + 1) = W_j(t)
\]

Where \( h_{j,N(X_k)}(t) \) is the neighborhood function at time \( t \) and \( \alpha(t) \) is the linear learning factor at time \( t \) define by:

\[
\alpha(t) = \alpha_0 (1 - \frac{t}{T})
\]

Where \( \alpha_0 \) the initial learning rate, \( t \) is the number of iteration and \( T \) is the maximum training length. The learning phase repeats until stabilization (no more change) of weight vectors.

With this information, we construct a self organizing map using a high performance neural network tool, such as MATLAB. This way, we obtain a map formed by cluster heads receivers, where every CH corresponds with a specific QoS and is assigned a neuron of the output layer. Furthermore, a synaptic weight matrix \( W'_{ij} = [W'_{i1}, W'_{i2}, ..., W'_{in}] \) is formed, where every synapsis identifies a connection between input and output layer.

In order to quantify the QoS level, we study the features of every CH receiver and, according to the QoS obtained in the samples allocated to the CH, we assign a value of cost between 0 and 10. The highest assignment (10) must correspond to that scenario in which the link measured has the highest cost and the worst QoS predicted. On the other hand, the lowest assignment (0) corresponds to that scenario in which the link measured has the lowest and the best QoS predicted.

2) Execution phase

In this phase the weights are declared fixed. First, every neuron \( i, j \) calculates the similarity between the input vector \( x(t) \), \( \{x_k|1<k<m\} \) and its own synaptic weight vector \( W_{ij} \). This function of similarity is based on a predefined similarity criterion. Next, it is declared a winning neuron, with a synaptic weight vector \( W_{ij} \) similar to the input \( x \). Every CH implements a SOM as a function. SOM gives an output denoted by QoS. This value is returned by a function defined by the SOM user, according to its aims.
In the execution phase, we create a WSN with 100 nodes. Every CH node measures the QoS periodically with every neighbor CH, which determines an input sample. After a CH node has collected a set of input samples from member nodes, it runs the winning neuron election algorithm. After the winning neuron is elected, the CH uses the output function to assign a QoS estimation. Finally, this value is employed to select the CH receiver for next hop.

The proposed algorithm is based on the radio model used by LEACH protocol, by the way there are two different radio models proposed in [17]:

\[ E_{Tx}(k, d) = E_{Rx}(l) + E_{Txamp}(k, d) \]

\[ E_{Rx}(k, d) = k.E_{elec}(k, d) + k.E_{elec}d^2 \text{ if } d \leq d_c \]

\[ E_{elec}(k) = E_{fs} + \frac{k.E_{elec}}{d^2} + \epsilon_{amp} \]

Where \( E_{elec} \) is the energy consumption of the transmitter who sends an \( k \)-bit message to the receiver up to a distance of \( d \); \( E_{elec}(k) \) is the energy consumption of the receiver who receives an \( k \)-bit message; \( E_{elec} \) is the energy consumption of the wireless send-receive circuit; \( E_{fs} \) and \( \epsilon_{amp} \) represent the energy consumption factor of amplification in the two radio models.

III. SIMULATION RESULTS

MATLAB and SOM toolbox [13] are used to simulate and compare the proposed algorithm (EMHR) with previous similar protocol EMHR and EMHR-FL. For this, we use 100 nodes positioned randomly between \((x=0, y=0)\) and \((x=100, y=100)\). The location of BS is \((50, 175)\). The simulation parameters are described in Table 1.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of nodes</td>
<td>100</td>
</tr>
<tr>
<td>Number of rounds</td>
<td>2300</td>
</tr>
<tr>
<td>Field size</td>
<td>100m x 100m</td>
</tr>
<tr>
<td>Data packet size</td>
<td>6400 bits</td>
</tr>
<tr>
<td>Control packet size</td>
<td>200 bits</td>
</tr>
<tr>
<td>Electronics energy</td>
<td>50 nJ / bit</td>
</tr>
<tr>
<td>Efs</td>
<td>10 pJ/bit/m2</td>
</tr>
<tr>
<td>Emp</td>
<td>0.0013 pJ / bit / m4</td>
</tr>
<tr>
<td>Initial energy of node</td>
<td>0.3 J</td>
</tr>
<tr>
<td>Energy of aggregation (EDA)</td>
<td>5 nJ / bit / signal</td>
</tr>
</tbody>
</table>

In the first round of network, the process of clustering (number of cluster and of CHs) is the same compared to the LEACH, if the specified value by node \( i \) > T (n), the node \( i \) has become the CH. In the next round and based on the energy strategy of electing CHs, states of cluster member energy are compared to find the largest energy node that becomes the CH. The model of energy dissipation adopted and wireless channel models are in the reference [6].

We choose two metrics to analyze the performance of EMHR and to compare it to others schemes. These metrics are: Residual energy and Number of sensor nodes alive.

In the computation of the energy consumption, the AI algorithm execution (Learning phase, execution phase, winning neuron election,...) is considered a special treatment that the processing unit of the sensor node treats. For this the energy consumption due to neural network algorithm is included in the total energy consumption.

Fig. 3 shows the rate of energy consumption by all the nodes and their residual energy depending on the lifetime of the network starting with an amount of energy equal to 50 J. A\n
![Figure 3. Residual energy VS Time in EMHR, EMHR-FL and EMHR](image-url)

All nodes are depleted of energy that after 2300 rounds using the proposed protocol, however, they are depleted of energy at the round 1800 using EMHR-FL and at the round 1600 using EMHR protocol. We can easily notice that the proposed protocol is more efficient in terms of energy consumption. In effect during the first 1000 rounds, nodes consume only 5 J using EMHR, but they consume 15 J using EMHR-FL and more than 20 J using EMHR for the same lifetime of the network.

Fig. 4 shows the number of sensor nodes alive using proposed protocol, EMHR-FL and EMHR protocols during the total lifetime of the network.
The results on “Fig.4” show that the proposed protocol can insure total survival (network coverage) during 83% of network lifetime (1000 rounds). Also it is shown that the new intelligent method can increase the lifetime of the network up to 80% over EMHR and EMHR-FL in the terms of first node death time (FND) and 41% over EMHR and 31% over EMHR in the terms of last nodes death time (LND).

VI. CONCLUSION AND FUTURE WORK

We have presented a new neural network based routing protocol for Wireless sensor networks called Energy efficient Multi-hop Hierarchical Routing protocol using Self organizing map (EMHRS). EMHRS elects the intermediate CHs nodes for next hop running an AI-algorithm. Thus, the path created by EMHRS avoids the election of intermediate CHs nodes that are prone to failure because of battery draining.

The inclusion of AI techniques (e.g. neural networks) in WSN has been proved to be an useful tool to improve network performances. According to this idea, we are working on the design of new protocols using these kinds of tools.

REFERENCES


