Feedforward Networks Based Straightforward Hierarchical Routing in Solar Powered Wireless Sensor Networks

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Abstract: - Wireless sensor networks play an important role in monitoring and collecting data from difficult geographical terrains. They find useful applications in various fields ranging from environmental monitoring to monitoring parameters within patients in hospitals. Constraints such as limited battery life and less processing capability of the sensors make the routing of WSNs a tedious and challenging task. A great emphasis is laid on the development of alternate sources of power and energy efficient routing protocol to maximize network life. This paper proposes clustering and shortest path based straight forward routing for solar powered wireless sensor networks. For clustering k-means clustering algorithm is proposed. A feedforward neural network based shortest path routing is proposed for routing within clusters. The simulation results show that the proposed neural networks provide quick solutions for route calculation comparing to other existing neural networks.

Key-words: - Solar powered wireless sensor networks, Feedforward neural networks, Shortest path routing, and k-means clustering.

1 Introduction

A sensor network is a network of a large number of sensor nodes which are densely deployed either inside the field or very close to it. A Wireless Sensor Network (WSN) is a network of spatially distributed autonomous wireless computing devices to cooperatively monitor physical or environmental conditions using sensors.

Wireless Sensor Networks (WSNs) are used to collect data from physically challenging environments. The information of events can be detected, collected, processed and sent to control room or sink by the sensors deployed in WSNs. The tiny nodes in WSNs are equipped with substantial processing capabilities of combining the data with adjacent nodes, compressing the data, intelligent gathering and processing of sensed data, understanding and controlling the processes inherent to the system [27].

WSNs can be deployed on a global scale for the applications of military surveillance and reconnaissance in battle field, search and rescue operations in case of emergency, infrastructure health monitoring in buildings, environmental applications in the forests and fields, or even within human bodies for monitoring the conditions of patients [4].

After the initial deployment, sensors become responsible for self-organizing an appropriate network infrastructure with multi-hop connections among them and tend to communicate to their neighbours by finding their locations and forming the topology of the network.

A major technical challenge for WSNs, lies in the node energy constraint and its limited computing resources [13]. Energy consumption is a dominant factor in the design of large-scale sensor networks. Since these constraints are highly specific for sensor networks, new improved power sources, wireless ad-hoc networking and efficient routing techniques are required. By providing improved power sources such as solar energy, it would solve the afore-mentioned constraints [14][16].

Voigt et al proposed to utilize solar power in wireless sensor networks establishing a topology where some nodes can receive and transmit packets without consuming the limited battery resources dynamically [24]. The solar cells can be utilized to power the sensors as well as to charge the batteries during node idle periods. The stored battery energy can be used to power the nodes during the time periods when sunlight is unavailable. The solar-rich nodes can take over the responsibility of relaying data to the Base Station (BS).

Polastre et al presented an extremely long duration solar power subsystem for the most recent wireless sensor network mote–Telos [21]. At the network layer, it is highly desirable to find methods for Energy-efficient route discovery and relaying of data from the sensor nodes to the BS so that the lifetime of the network is maximized. Recent advancements in WSN have led to many new routing protocols specifically designed for sensor networks where efficient energy utilization is an essential consideration [2][3]. The various routing algorithms are broadly classified and explained by Al-Karaki and Kamal [6].

1.1 Clustering and Routing in Solar Powered Wireless Sensor Networks

Clustering is required to reduce the routing complexity and overhead and for effective energy efficient communication between sensors [1]. Voigt et al proposed to extend LEACH, a well-known cluster-based protocol for sensor networks to become solar-aware [22]. The simulation results show that making LEACH solar-aware significantly extends the lifetime of sensor networks.

Ye et al proposed an energy conserving protocol called Probing Environment and Adaptive Sleeping (PEAS). PEAS keeps only necessary nodes active and puts the rest into sleepy mode to conserve energy [26].

The solar aware routing allows the routing only through solar powered nodes [23]. This will save the energy of the battery powered nodes. Among the nodes, some of them are solar powered and the rest of them are battery powered. They proposed two protocols to perform solar aware routing. One protocol is a simplified version of directed diffusion based mainly on local interactions between adjacent nodes, the other one is an extension of directed diffusion. The results show that the first protocol is more suitable for small sensor networks while the second protocol performs better on larger networks.

Corke et al discussed hardware design principles for long term solar-powered wireless sensor networks and straightforward non-energy aware protocols [9]. They presented data from a long-term deployment that illustrated the use of solar energy and rechargeable batteries to achieve 24x7 operations for over two years.

Lattanzi et al. discussed the problem of optimal routing for energy harvesting wireless sensor networks [17]. They presented a methodology for assessing the energy efficiency of routing algorithms of networks whose nodes drain power from the environment.

GRASS uses exact as well as heuristic approaches to find the minimum number of aggregation points while routing data to the BS. When compared to other schemes, GRASS improves network lifetime significantly [7].

2 Research Gap Analysis and the Literature Review

Routing is one of the major issues in the wireless sensor networks. The existing algorithms display different advanced characteristics on various areas but they still suffer from lot of drawbacks. Some early routing protocols in WSNs are actually existing routing protocols for mobile ad-hoc networks. These protocols are hardly applicable to WSNs due to their high power consumption. From the literature, almost all the existing routing algorithms in WSNs use complicated procedure for the routing such as data aggregation, flooding and advertising. These complicated procedures consume more time in computing and drain the node energy. So, a simple straightforward routing is required.

The battery life of sensors is directly linked with their computation time. The majority of the algorithms are not concentrated on the convergence time for the optimized route calculation. The softcomputing based routing concepts are rarely used in WSNs. From the literature, most of the researchers concentrated only on recurrent type Hopfield Neural Networks for Shortest Path (SP) routing in multi-hop networks. Finding a feed-forward neural network algorithm for SP routing in WSNs with fast convergence nature is focused on.

In general, routing in WSNs can be divided into the following categories depending on the network structure.

- Flat-based routing
- Hierarchical-based routing, and
- Location-based routing.

In flat-based routing, all nodes are typically assigned equal roles or functionality. In hierarchical-based routing, however, nodes will play different roles in the network. In location-based routing, sensor nodes' positions are exploited to route data in the network.

2.1 Review of Shortest Path Routing using Neural Networks

Almost all the current multi-hop packet switching networks use SP routing computation based on routing algorithms in the network layer. Normally, the weighted links concepts are used here. The weights of the links based on various factors related to routing like link transmission capacity, the signal strength of the link and the congestion of networks.

Literature shows that various Neural Networks (NN) concepts have been used to solve the SP problems. A neural network is a massive system of parallel distributed processing elements connected in a graph topology. By defining proper processing functions for each node and defining associated weights for each interconnection, it is possible to solve an optimization problem relatively rapidly.

Hopfield and Tank proposed a neural network of the recurrent type for solving different optimization problems [10]. The electronic hardware device implementation provides very high speed solution due to inherent parallel processing. Hopfield Neural Network (HNN) gives better optimality compared to other existing algorithms. All the results are relatively independent from network topology for almost all source destination pairs. The advantage of the HNN is the hardware based rapid computational capability of solving the CO problem. Subsequently, the shortest path routing problem was addressed using the HNN under various constraints. For some classes of neural networks such as the HNN, it has been found that while the size of the NN increases with the size of the application, the time required to obtain a solution remains almost constant.

Ali and Kamoun proposed a NN for solving SP problems [5]. They introduced a method that aimed at NN adaptability to external varying conditions as in a computer network where links or nodes may go up and down easily. But this method fails to converge towards an optimal solution for a considerable number of times and the performance of this algorithm decreases with an increasing number of nodes in the graph.

An algorithm for multi destination routing problem was introduced by Park and Choi [20]. This algorithm provided improved solutions with a higher number of nodes. This enhanced the convergence performance, which, however, was heavily dependent on the network topologies.

A modified two layer Hopfield neural network was presented by Araujo et al [8]. This algorithm increased the number of succeeded and valid convergences. The limitation of this algorithm was that it was not tested with different graph topologies. The size of the Hopfield network grows linearly with the number of links in the graph for the modified representation instead of growing in terms of the square of the number of nodes in the graph. Thus, the size of the Hopfield network is reduced substantially with this modified representation, especially for graphs which are sparsely connected and, therefore, it has a relatively small number of links.

A modified pulse coupled NN model based approach used the parallel pulse transmission characteristic of pulse coupled neural networks to find the shortest path quickly. The computational complexity is only related to the length of the shortest path, and is independent of the number of existing paths in the map [25].

Huang et al proposed a new tuning free Single Layer Feedforward Neural Network (SLFN) [11][12]. The speed of the algorithm is extremely fast and it is capable of solving complicated optimization and classification problems.

3 Methodology-Single Hidden Layer Feedforward NN for routing in WSNs

The time taken by a typical packet to travel from the source node to the linking node of the destination host is called the end-to-end delay of the network. The objective of a routing strategy is essentially to minimize the mean delay of the packets in a network subject to some reliability or capacity constraints.

In solar powered WSNs, a straight forward SP between source and Cluster Head (CH) could be used. This plays an important role in recent WSN applications that require a streaming service to deliver large amount of data [15].

Unlike the popular thinking and most practical implementations that all the parameters of the feedforward networks need to be tuned, one may not necessarily adjust the input weights and first hidden layer biases in applications. The input weights and hidden layer biases of SLFNs can be randomly assigned if the activation functions in the hidden layer are infinitely differentiable. After the input weights and the hidden layer biases are chosen randomly, SLFNs can be simply considered as a linear system and the output weights (linking the hidden layer to the output layer) of SLFNs can be analytically determined through simple generalized inverse operation of the hidden layer output matrices [11].

Huang et al provided a mathematical model for SLFNs as follows [10]. For N arbitrary distinct samples $(x_i , t_i) \in R^n \times R^m$, standard SLFNs with L hidden nodes and activation function $g(x)$ are mathematically modeled as

$$\sum_{i=1}^{L} \beta_i G(a_i\ ,\ b_i\ ,\ x_j\ )\ =\ t_j\ ,\ j\ =\ 1,\ \cdots,\ N \quad (1)$$

where, a_i : the input weight vector connecting the ith hidden node and the input nodes or the center of the ith hidden node.

β_i : the weight vector connecting the ith hidden node and the output node.

b_i : the threshold or impact factor of the ith hidden node.

g_i or $G(a_i\ ,\ b_i\ ,\ x_j)$: the hidden node output function.

$\sum_{i=1}^{L} \beta_i G(a_i\ ,\ b_i\ ,\ x_j\ )\ =\ t_j\ ,\ j\ =\ 1,\ \cdots,\ N$ is equivalent to $H\beta = T$. H is called the hidden layer output matrix of the neural network.

The nodes placed inside the cluster of WSN can be assumed as a multi hop network. A multi-hop network topology can be described by the directed graph G= (N,E), where N is a set of n nodes (vertices) and E is a ordered set of m edges where $m \leq n^2$. Each edge *(i,j)* is associated with an integer representing the cost of sending data from node *i* to node *j* and vice versa. A cost C_{ij} is associated with the edge (i,j) in the graph G. Each link is represented by L_{ij}.

A link inclusion representation (n x n) binary matrix L= [L_{ij}], represents the status of the link between any two nodes by using 1 or 0. The SP problem is considered as a minimization problem, to minimize the sum of the costs on links in the shortest path [18][19]. The SP problem can be formulated as a classical combinatorial optimization problem with the objective function as follows:

Minimize

$$\sum_{i=s}^{d} \sum_{\substack{j=s \\ j \neq i}}^{d} C_{ij}\ .L_{ij} \quad (2)$$

4 Results and Discussion

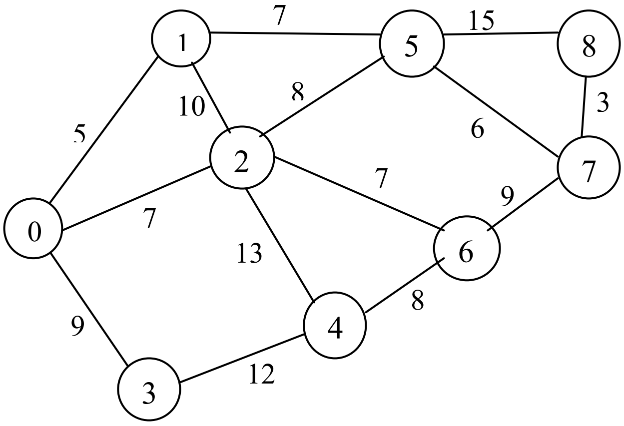
Clustering of the sensor nodes makes the calculations much simpler. The search space for the solution increases as the number of nodes (N) decreases and vice-versa. In order to reduce the burden of mathematical complexity N should be reduced and this is achieved by clustering.

For each cluster one node will act as a cluster head (CH). The nodes can communicate to the cluster head. CH can communicate to the BS as well as to other CHs. Here, the sensor nodes are clustered into small groups by using k-means clustering [18][19].

After the deployment of large number of sensors in the field, they will self-organize themselves and collect the location details of them. To group the sensors into small sized clusters the k-means clustering algorithm could be used. After clustering, the SP route has to be calculated using the proposed NN. The network topology will be formed based on the location details of the sensors within the clusters.

For simulation purpose the network size of clusters are assumed as 10,15,20,25,30,35, 40,45, and 50. All the simulations are made using MATLAB 7.0 on Pentium IV machine. The sensor network topologies are created randomly. The Cartesian distance between two nodes is assumed as the link weight or cost. A total of 100 random network topologies in each category with varying size (10 to 50 nodes) and randomly assigned link costs were investigated.

The network field size is assumed as 100 x 100 units. Maximum segmentation size is assumed as 40 units. Link cost matrix and link state matrix are used as inputs. The activation function used in the proposed algorithm is a simple sigmoidal function. Each line in the WSN defines a bi-directional link between two nodes and its respective cost.



0 1 5
0 2 7
0 3 9
1 2 10
1 5 7
2 4 13
2 5 8
2 6 7
3 4 12
4 6 8
5 7 6
5 8 15
6 7 9
7 8 3

Fig. 1 Example Network with 9 Nodes

For example:

0 9 4

defines the bi-directional link between nodes 0 and 9 with cost 4. The output for neural networks contain number of neural network iterations and path cost. A simple example network with nine nodes is given in fig. 1 with their link and cost details. Fig. 2 shows the calculated shortest path between nodes 0 and 8 with a path cost of 21.

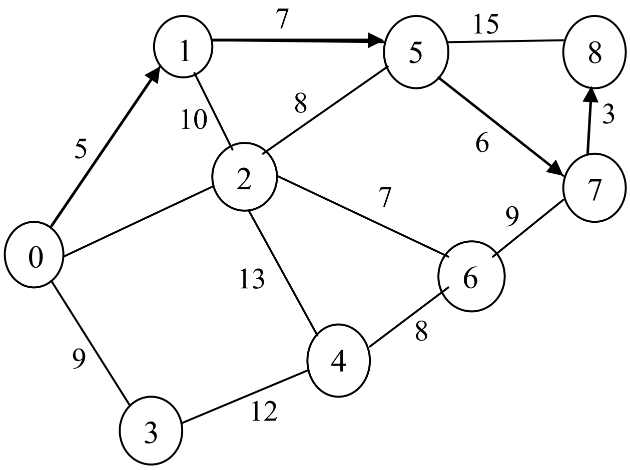


Fig. 2 Example Graph with Shortest Path

The performance of the proposed algorithm is compared with Hopfield, Ali & Kamoun and Park & Choi's algorithms through computer simulations. The results show that the proposed algorithm exhibits the fastest rate of convergence as well as the good quality of solution on par with other algorithms.

Table 1 compares the algorithms based on convergence time. The proposed algorithm converges to a stable state in 0.1240 seconds (for 20 nodes) and 0.1457 seconds (for 30 nodes). In addition, the proposed algorithm retains its robustness amidst changing network topologies. The results show that the proposed algorithm improves the converge time about 70% almost for all cases. From table 2, it shows that the proposed algorithm performs almost similar to other algorithms. The success rate of proposed NN is slightly lower than other algorithms for all cases. During non-success convergences also the algorithm produces valid sub optimal paths. It is an advantageous in WSNs for distributed energy consumption. The same nodes will not be used frequently.

Table 1 Performance Comparison of Algorithms- Convergence Time

Algorithm	Convergence time (sec.)								
	10 nodes	15 nodes	20 nodes	25 nodes	30 nodes	35 nodes	40 nodes	45 nodes	50 nodes
Proposed SLFN	0.0617	**0.0622**	**0.1240**	**0.1284**	**0.1457**	**0.1862**	**0.1937**	**0.2245**	**0.2637**
Hopfield	0.1029	0.228	0.4739	0.6012	0.7306	0.8226	0.885	0.9236	1.1231
Park & Choi	0.099	0.2824	0.4241	0.5347	0.6178	0.7431	0.8218	0.9012	1.0288
Ali & Kamoun	0.0604	0.1863	0.3954	0.4832	0.6172	0.6985	0.8122	0.8997	0.9876
Improvement of covergence time over Ali & Kamoun NN (%)	-	66.61	68.64	73.43	76.39	73.34	76.15	75.04	73.30

Table 2 Performance Comparison of Algorithms- Success Rate

Algorithms	Success rate (%)								
	10 nodes	15 nodes	20 nodes	25 nodes	30 nodes	35 nodes	40 nodes	45 nodes	50 nodes
Proposed SLFN	84.7	83.49	79.54	77.58	74.93	72.56	71.86	70.78	70.12
Hopfield	89.27	88.35	84.26	84.06	81.51	80.26	80.11	78.34	78.17
Park & Choi	92.32	91.87	88.47	85.26	83.19	82.87	81.33	80.16	80.01
Ali & Kamoun	98.54	92.39	89.43	89.28	85.71	84.29	83.98	82.53	81.37

4 Conclusion

A neural network based straightforward hierarchical routing algorithm employing a single hidden layer feedforward neural network that guarantees a highly efficient computation has been proposed in this paper. It is suitable for multi-hop wireless sensor networks due its fastness. The results show that the proposed NN needs much less computation time compared to other neural networks. The results of accuracy of the proposed algorithm are almost similar to Hopfield and other NN for shortest path problems. Simulation studies show that the proposed routing algorithm is insensitive to variations in network topologies. Due to its fastness, the algorithm is highly suitable for routing in WSNs.

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