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Shortest Path Routing in Solar Powered WSNs Using Soft Computing Techniques

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The main objective of this paper is to develop a three phase genetic algorithm to find the shortest path routing in solar powered Wireless Sensor Networks (WSNs), and thereby reducing the energy loss and the time consumed in the communication between various nodes (sensors) of the same. A three phase hybrid genetic algorithm is proposed for solving the shortest Path (SP) routing problem. The performance of the proposed algorithm is compared with Dijkstra, Munemoto, and Ahn algorithms. Here we have classified the wireless sensors as clusters which uses k-means clustering algorithm and within each cluster the shortest path routing for communication is found out using proposed three phase genetic algorithms.

Keywords: Wireless Sensor Networks, *k*-means Clustering Algorithm, Three Phase Genetic Algorithms.

Introduction

A Wireless sensor networks (WSNs) is a wireless computing devices network comprising of spatially distributed autonomous devices using sensor to monitor physical and environmental conditions such as temperature, sound, vibration, motion, intrusion or pollutants at various locations. They play an important role in monitoring and collecting data from difficult geographical terrains. The inherent constraints such as limited battery life, memory and less processing capability of the sensors make the processing and routing of WSNs a tedious and challenging task. 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 WSN is a network of spatially distributed autonomous wireless computing devices to cooperatively monitor physical or environmental conditions using sensors. WSNs are used to collect data from physically challenging environments. The information about events can be detected, collected, processed and sent to the 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. The primary function of WSNs is to sense electronically measured ambient conditions of the environment around the sensors and transform them into electrical signals. Finally, the processed signal reveals some properties about objects located and/or events happening in the vicinity of the sensors. WSNs are typically battery powered and perform wireless communication to relay data to the base station. Though the processing capability of individual node is low, they can collectively and collaboratively perform the required task effectively. With recent advancements in Application Specific Integrated Circuits (ASIC) design, it is possible to create more compact and efficient electronic circuits suitable for various specific real time applications Akyildiz *et al*[2]. It is now possible to develop a small sized embedded system of good computing capability with cheaper commercial components that are readily available in the market. Figure 1 describes the basic operational phases of a sensor node. After the initial deployment, sensors become responsible for self-organizing an appropriate network infrastructure with multi-hop connections among them and tend to communicate with their neighbors by finding their locations and forming the topology of the network. Basically, each sensor node comprises sensing, processing, transmission, mobilize, position finding system, and power units. Sengupta *et al*[12] have proposed an evolutionary multi objective sleep scheduling scheme for differentiated coverage in

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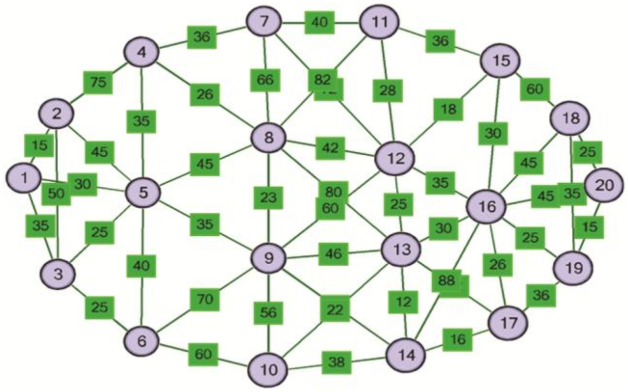

Fig.1—Example 20 Nodes Weighted Wireless Sensor Network

WSNs. Apetroaei *et al*[11] proposed a GA inspired spanning tree topology for WSNs that adapts (according to the nodes, residual energy) to maximize the usage of the network. A sequential GA solves the NP-hard problem by optimizing relay topology while eschewing the inter-cell interference[13]. A great emphasis is laid down on the development of alternate sources of power and energy efficient routing protocols to maximize the life of the network. This paper proposes the utilization of solar energy in the view of extending the life of the networks in WSNs perspective.

Routing in solar powered WSNs

Almost all the current multi-hop packet switching networks use SP routing computation based on routing algorithms in the network layer. Routing is one of the primary functions. Each node has to perform in order to enable connections between nodes that are not directly within each other's send range. The development of efficient routing protocols is a non trivial and challenging task because of the specific characteristics of a WSN: Due to node failures, the network topology may change randomly at unpredicted times. The available bandwidth is limited and can vary due to fading, noise, interference. Most sensor devices are battery powered; therefore energy consumption plays an important role. As per literature, so far the GA and other nature inspired algorithms based shortest path routing for WSNs were studied only by a few researchers. The algorithm proposed by Al-Karaki *et al*[3] is the only GA based routing algorithm in WSNs. They applied GA based aggregation and routing algorithm for WSN. The GA was used with in combination with other algorithms, therefore computation complexity is more.

Proposed routing algorithm for WSNs

The existing routing algorithms in WSNs are quite complex in nature and many of them use data-centric based concept. Almost all the algorithms consume considerable amount of time for data aggregation. Sometimes data loss may occur in the process of data aggregation. The route convergence time is also a critical factor in WSNs due to energy constraints existing in them. To avoid such types of drawbacks, this research proposes a simple location based hierarchical, straightforward point to point shortest path routing for solar powered wireless sensor networks. By using energy efficient clustering and routing concepts, the battery consumption and computational overhead will be considerably reduced. After deploying the sensors in the field, the nodes can be grouped into small sized clusters. The routing overhead will further be reduced with the grouping of sensors into small sized network topologies. One node will act as a cluster head for each cluster. The nodes can communicate through cluster heads, if any event occurs. A three phase genetic algorithm with k-means clustering is proposed for clustering and routing in WSNs. For clustering, the same k-means clustering algorithm is used. The nature inspired approximation algorithms such as genetic algorithm and neural networks have been seldom used so far for routing in WSNs. In this paper, the soft computing concepts like genetic algorithm are used for routing within the clusters. The shortest path route from source node to cluster head within the cluster is calculated using three-phase genetic algorithm. The three phase genetic algorithms provide efficient solutions for routing in WSNs with fast convergence rate. The results show that the three phase genetic algorithm is a suitable algorithm for providing routing solutions in WSNs perspective.

Procedure of the Proposed Algorithm

Step1:Initialize information of WSN nodes and their location.

Step2: Apply k-means clustering and create 'n' number of small sized clusters. For each cluster does the following.

Step 3: Initialize information table of network topology for each cluster.

Step 4: Do genetic encoding and generate the initial populations using basic solution algorithm according to the topology information table with the source and destination nodes.

Step 5: Calculate the fitness of the initial population
Step 6: Select individual chromosomes by using proposed fitness function.
Step 7: Perform crossover between chromosomes according to the proposed crossover method.
Step 8: Analyze the individual chromosome after crossover operation, remove infeasible chromosomes by using a repair function
Step 9: Perform mutation, according to the method.
Step 10: Generate new populations
Step 11: If stop criteria met, output result, and the algorithm would be finished, otherwise, go to step 5.

Problem formulation

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 an ordered set of m edges (arcs or links) 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 (Wang10). A cost C_{ij} is associated with the edge (i,j) in the graph G. In communication networks, the transmission time, distance between nodes, the energy need to travel from one node to another and the link capacity between nodes can be used to determine the cost of the edge. The costs Cij and Cji may not be the same, i.e. $C_{ij} \neq C_{ji}$. The costs for various links are specified by the cost coefficient matrix $C = [C_{ij}]$. In dynamic multi-hop networks for some nodes the links may not exist. The cost values for nonexistent links are taken as infinity. Highest cost values represent more loss and lowest values represent more gain. Source and destination nodes are named by'S' and'd' respectively. Each link is represented by L_{ij}. A link inclusion representation $(n \times n)$ binary matrix $L = [L_{ij}]$. represents the status of the link between any two nodes by using 1 or 0. Based on the link inclusion representation, the SP problem can be formulated as a linear integer programming optimization problem. The SP problem is considered as a minimization problem, to minimize the sum of the costs on the links in the shortest path. If each node is visited at most once, then each row and column in the link representation matrix can contain no more than one '1' element. The Cij of loops are assumed to be non –ve (i.e. $C_{ij} \geq 0 \; for \; i = 1,2,3, \ldots\ldots, n$, Therefore, all the diagonal elements of Lij are always zero. The link inclusion representation matrix can be simplified by excluding the diagonal elements Lii $(i = 1,2,3, \ldots.., n)$. The final simplified edge link inclusion representation matrix has only $n(n-1)$ binary elements. Based on the above assumptions, the SP problem can be formulated as a classical combinatorial optimization problem with constraints as follows:

Minimize

$$\sum_{i=s}^{d} \sum_{\substack{j=s \\ j \neq 1}}^{P} \mathbf{C_{ij}} . \mathbf{L_{ij}} \qquad \ldots (1)$$

Subject to

$$\sum_{i=s}^{d} \sum_{\substack{j=s \\ j \neq 1}}^{P} \boldsymbol{C_{ij}} . \boldsymbol{L_{ij}} = \begin{Bmatrix} 1, if \; i = s \\ -1, if \; i = d \\ 0, otherwise \end{Bmatrix} \quad \text{and} \quad \sum_{\substack{\mathbf{j=s} \\ \mathbf{j \neq i}}}^{\mathbf{d}} \mathbf{L_{ij}} \begin{Bmatrix} \leq 1, \text{if i} \neq \text{s} \\ = 0, \text{if i} = \text{d} \end{Bmatrix} \qquad \ldots (2)$$

$$\mathbf{L_{ij}} \in \{0,1\} \text{ , for i} \neq \text{j , i,j= 1,2,……,n …} \qquad (3)$$

Equation (1) represents the objective function. Equation (2) ensures that the calculated path is a continuous path between a source and a destination without cycles. Equation (3) represents the integrity constraint. They ensure that the computed result is indeed a path without loops between a source and a destination.

Routing using three phase GA with a case problem

Assumptions

We assume that after clustering the clusters contain a fixed number of nodes such as 20, 25, 30, 35, 40, 45, or 50. To demonstrate the algorithm only a single cluster is taken for the computation of SP route. The solar energy based sensors are assumed for WSNs.

Case study

Here a cluster with 20 nodes is assumed for routing. After clustering, the SP routing algorithm is applied for each cluster. In this section, the proposed GA is compared with Ahn's[1], Munemoto's[5] and Dijkstra's algorithms through computer simulations. All the simulations were performed with MATLAB 7.0 on a Pentium IV processor. Selection, crossover and mutation concepts are used. The pair-wise tournament selection with size 2 without replacement is used. In all the experiments, the mutation probability is set to 0.05, and each experiment is terminated when all the chromosomes have converged to the same solution. The simulation studies involve the weighted network topology with 20 nodes shown in Figure 1. With a view to focus exclusively on fair comparison of algorithms on the basis of performance, the population size is taken to be the same as the number of nodes in the network. A link state matrix and cost coefficient matrix are given below for the network shown in figure 1.

If the WSN contains ‘n’ nodes, then the link state matrix L contains $n \times n$ elements. ‘0’ in the matrix indicates that no link between the given nodes. ‘1’ indicates that there is a link between the nodes. For example the value at the position connecting row 5 and column 6 in L is 1. Therefore, there is a link between node 5 and 6. The link weight can be identified in the same manner by referring the cost coefficient matrix C. C contains the weights of the edges. The weight is 40 for the edge connecting node 5 and 6. Figure 2 shows the shortest path in bold line found by the proposed GA for the given source–destination pair.

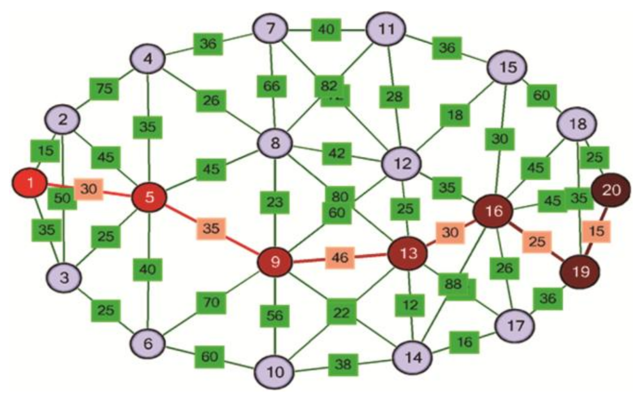

Fig. 2—Given Network with Shortest Path

Result and Discussion

The weight of the shortest path is 181. Figure 3 compares objective-function values returned by the algorithms. The results are also shown in table 1. The figure shows that the proposed GA converges to stable state faster than other algorithms. The results computed by the proposed algorithm coincide with that found by Dijkstra’s algorithm. The algorithm converging through smaller generations has better convergence performance because all the algorithms have the same population size in the simulation. To analyze the performance of the proposed and existing algorithms further with different network topologies, networks with 25–50 nodes, and randomly assigned link costs were investigated. The various applications of WSNs involve networks with sizes that range from small to large. Simulations reflect this practical reality. A possible implication is that the proposed algorithm scales well to larger networks. Next, the convergence time of the proposed GA is compared with that of Dijkstra’s algorithm. Convergence performance is investigated in terms of the average time required to reach the optimal solutions. The total execution time required to find a solution of the same average quality as a fair comparison criterion. The convergence performance of the proposed GA and the

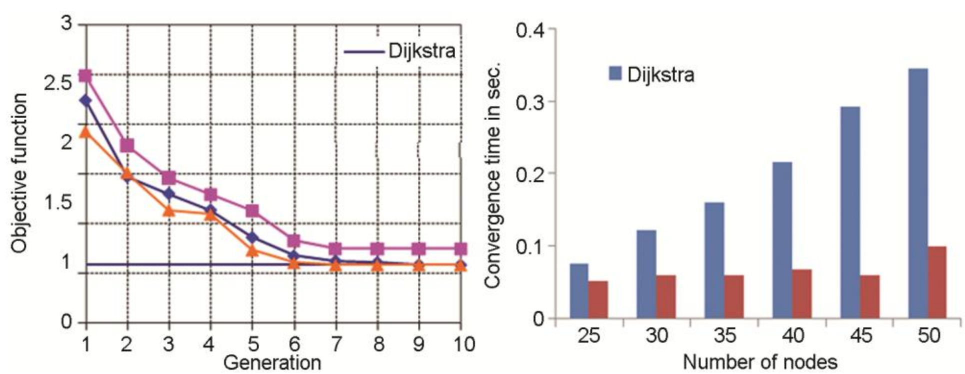

Fig.3—Comparison of Results and Convergence diagram for Dijkstra and proposed

Table 1—Comparison of Objective Function Values

Generation / Algorithm	1	2	3	4	5	6	7	8	9	10
Dijkstra	0.578	0.578	0.578	0.578	0.578	0.578	0.578	0.578	0.578	0.578
Munemoto	2.49	1.786	1.464	1.294	1.131	0.824	0.748	0.748	0.748	0.748
Ahn	2.241	1.47	1.298	1.132	0.856	0.668	0.618	0.602	0.578	0.578
Proposed GA	1.924	1.507	1.132	1.09	0.729	0.602	0.578	0.578	0.578	0.578

Dijkstra's algorithm is given in figure 3. The computation time of the proposed GA does not increase significantly with the network size while it does in case of Dijkstra's algorithm.

Conclusion

This paper presents a near optimal based SP routing for solar powered WSNs. A three phase hybrid genetic algorithm for solving the SP routing problem was demonstrated. From the literature, it was found that solar energy is an efficient alternate energy source for WSNs. By using efficient clustering and routing concepts the battery and computation overhead will be reduced. The simple clustering like k-means clustering proved to be effective as it was able to group the nodes into clusters in an optimal manner with reduced convergence time. The basic solution algorithm provided the initial population. The crossover and the mutation operations work on variable-length chromosomes. Consequently, the algorithm can search the solution space in a very effective manner. Simulation results show that the algorithm is indeed insensitive to variations in network topologies in respect of both route optimality and convergence speed. The convergence performance of the proposed GA was better than the Dijkstra's algorithm. GA routing introduces the concept of using sub-optimal paths randomly at times to reduce and distribute energy consumption in routing thus increasing the lifetime of the network. These algorithms provide fast computation of the shortest path for WSNs irrespective of topologies.

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