



Hybrid Genetic Algorithm based Approach for Energy Efficient Routing in Wireless Sensor Networks

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Abstract: *The nodes in Wireless Sensor Networks have limited energy and are seriously constrained by the battery life. An energy aware routing scheme can greatly enhance the lifetime of WSNs. However the conventional mathematical formulations for energy efficient routing are computationally very time consuming and large and they are not suitable for practical sensor networks. In this paper the Elitist genetic algorithm with memory scheme and simulated annealing algorithms are combined to find an optimal energy efficient route for the sensor nodes towards the sink node to prolong the network lifetime. The proposed scheme selects a path which has got maximum of minimum power available among the alternative paths thus is able to find the optimal solution for larger networks. The proposed scheme proves to give a faster and significant solution compared to traditional routing schemes.*

Keywords: *Wireless sensor network; network lifetime; energy efficient; genetic algorithm, simulated annealing*

I. Introduction

A Wireless sensor network consists of randomly/manually deployed sensors that sense the physical or environmental events and send the collected data to the base station. A large number of inexpensive, small and autonomous sensors are generally deployed in an ad hoc manner at remote areas. Sensor nodes in a WSN are constrained in storage capacity, computation power, bandwidth and power supply [1-4]. The routing protocols in WSN aim at reducing the energy consumption and thus prolong the network lifetime. The development of multifunctional low cost and power, sensors is the need of today. Sensor nodes are smaller in size and capable of sensing the events, collecting data and processing it. They also communicate with other sensors in the network, via radio frequency (RF) channel. The application areas of WSNs are in the field of civil, health, military and environment [4]. Different routing schemes have been addressed by researcher for static problems. When the topology changes due to failure of a node these algorithms consider it as a new topology and restart again. Whereas in the case of GA the new individuals are generated in each generation called the immigrants and some useful information is stored in the memory from the last solution before the change occurs. This helps the scheme to adapt to the changing environment as quickly as possible. Thus it allows the algorithm to keep on running even when the topology is changing and avoid the restart which is more time consuming. Thus genetic algorithm with memory scheme can significantly improve the performance of GA for WSN.

II. Review work

Energy Efficient Routing in Wireless sensor networks has gained a lot of attraction from the researchers in the recent years. In [5, 6] summary of recent research results on energy efficient data routing in sensor networks is discussed. To increase the network lifetime, the design of efficient routing protocol for communication is very important. A data centric approach using the existing routing schemes and performance analysis of these schemes is done in [7]. Evolutionary Algorithms can be used effectively to find the energy efficient path in wireless sensor networks [8]. A simple approach to minimize the average path length is proposed in [9] where they considered the wireless network of sensor nodes having known spatial distribution using a GA approach. Each of the nodes consists of a relatively simple transceiver (antennas, a receiver and a transmitter). The goal of the optimization is to minimize the average path length from source to destination to minimize the transmitted power. Further, a method proposed in [10] has used a multipath routing protocol for WSNs to improve the reliability. The technique uses many paths and sends through them the same subpackets. This increases the network traffic (not energy aware), but the reliability of the network is increased but this may reduce the lifetime of the sensor network. The energy awareness in multi path routing is done in [11-14] with consideration of maximizing the lifetime of the network. This protocol uses the idea of routing the packets through path where the nodes have the maximum residual energy. The path is changed whenever a better path is found. By using this approach, the nodes in the primary path will not get their energy exhausted by the continuously using the same path, thus longer lifetime is achieved.

Each the request is forwarded only to the neighbors closer to the source than itself and farther from the destination node to find the optimal path [15]. Ant colony optimization is also used by researchers to check if a node has lower energy, then its probability of being chosen in the route is low [16]. Choosing the lowest energy path is not always best for long term health of the network, because the energy of the optimal path shall quickly deplete [17]. Elitist GA is used in [18] that have inherent advantage whereby it keeps the elite solutions in the next generation so as to quickly converge towards the global optima. Considering the distance between the transmitting node and receiving node and the remaining energy of the nodes to find the energy efficient route is a better approach [19]. The use of GAs for finding the optimal path in changing environment has been shown in [20]. It has been shown how the GAs can use memory to store useful information and can quickly converge towards the solution. A new approach using Elitist genetic algorithm and simulated annealing algorithms are combined to find an optimal energy efficient route for the sensor nodes towards the sink node to prolong the network lifetime in [21]. This technique ensures that the algorithm is able to find the global optima.

Rest of the paper is organized as follows: Section 3 discuss about the GA & SA techniques, section 4 describes the implementation of the proposed GA & SA with memory based scheme for WSN, section 5 discusses the simulation & analysis and section 6 is the conclusion.

III. Genetic Algorithm and Simulated Annealing

Genetic algorithm (GA) [22] is an optimization technique which is based on process of natural selection. GA can obtain satisfactory results for NP hard search problems. GA does well at global search; it does not get trapped in local minima when following in a rapid descending direction. It can compute the result fast as it is a parallel search, but poor at local search.

Simulated annealing (SA) [23] simulates the physical annealing process of a molten particle starting from a high temperature and then gradually cooling it down, to solve the optimization problem. During the search for the optimal solution, SA not only accepts good or optimal solutions, but also accepts the degraded or poor solutions to certain extent determined by a parameter called temperature at a particular instant in the algorithm. SA is a more powerful local search algorithm, but it depends more on parameter (temperature).

Genetic Algorithm Simulated Annealing (GASA) is a combination of the two optimization algorithms. A special feature of GASA is the integration of SA with GA which improves the solution quality, consistency and speed of convergence of GA. Such combination of methods [24, 25] have been shown to exploit the solution search space using the convergence properties of SA at the same time maintains the recombinative power of GA. Such a strategy helps the technique to seek out the global optimum without getting stuck in any local optimum. In this paper, based on GASA, a routing protocol is introduced which prevents the low-energy nodes to exist in the data gathering route and the energy load balancing of the network can be achieved. The proposed model ensures that if the energy of a particular node in the routing reaches below a predefined level, the node is replaced in the routing chain based on some probability. This is done to distribute the energy consumption on the nodes in routing so that the overall lifetime of the network is prolonged.

IV. GA based routing with memory scheme

The performance of genetic algorithms for Dynamic Optimization problems can be enhanced by memory based GA schemes. It stores some useful information about the routing from the current environment like the alternate paths between nodes i to j . This information is stored in an extra memory [26-28]. This information is used later when the topology changes occur due to node energy depletion or failure. When the topology changes (due to energy of a sensor falling low), old solutions which are previously stored in memory and fit the changed topology can be reactivated, and as a result the performance of GA can be improved [20].

a. Encoding Scheme

The individual/chromosome is represented as a string containing node numbers as genes. The length of each chromosome is equal to the number of sensor nodes. The routing scheme with a base station and 6 nodes, is shown in Figure 1(a) and the corresponding individual is shown in Figure 1(b). In this example, the value of the gene in position 1 is 2, indicating that node 1 transmits to node 2. Similarly, the gene value at position 3 is 8, which means that the node 3 transmits to node 8 (base station).

b. Fitness Function

Each chromosome represents a valid route. The routing thus developed is based on the respective positions of the nodes in the network. The base station creates a list, $N_i, 1 \leq i \leq n$, that contains all the nearest one-hop neighbors j , of i , such that the link $i \rightarrow j, \square \square j \in N_i$ can be used to route data from i towards the base station through j . For example, node 1, from figure 2, will have $N_i = \{2, 4\}$ (where $i=1$) which are one hop neighbors of node 1.

Based on this information, the greedy approach is used to generate the routes for the initial population, by randomly picking up the neighboring node $j \in N_i$ for each source node i . The problem's search space is enormous. If each node has d valid neighbors (which are one-hop away), then the number

of paths/routes for a network with n nodes is $O(d_n)$. In order to select an optimal energy efficient route, from a large number of possible valid solutions, within an optimum amount of time, a non-conventional search technique, such as GA, is needed [29]. The energy dissipation of different nodes in the network is usually different. When the network has operated for some time, the nodes in the networks will be having different residual energy levels at any particular instance. This variation in energy may also occur due to changing network operating conditions e.g. when some of the nodes in the network fail. The networks lifetime can be prolonged by computing a new routing that takes into account the nodes available in the network and the residual energy of the nodes at any given instance of time. The route along which the minimum Power Available (PA) of any particular node in the routing is larger than the

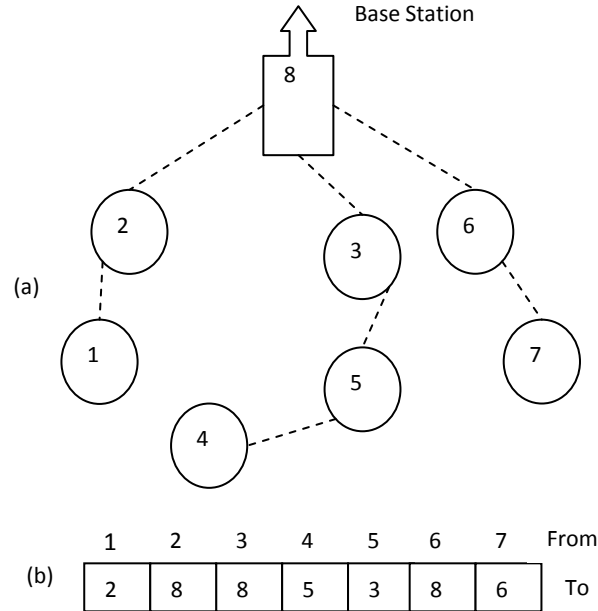


Figure 1: Representation of network graph as chromosome

minimum PAs of the other routes is preferred [30] as shown in the Figure (2) the routing from source node T to the sink path via node D has the maximum of minimum PA along the path $T-G-D-Sink$, so it is selected for routing the data packets.

Minimum power is computed as in (3)

$$E_{net} = \min(PA_i, \forall i, 1 \leq i \leq n) \quad (3)$$

Where PA_i is the power available for a node in the routing scheme and E_{net} is the minimum power available for a routing path given by the individual, in one data communication round.

Using the first order radio model [25 31], the total energy consumed by a node i , ($1 \leq i \leq n$) to transmit b_i^t bits of data to some other node j , ($1 \leq j \leq n$) is computed as [31]

$$E_i^T(b_i^t, d_{ij}) = \alpha_2 b_i^t + \beta b_i^t d_{ij}^m \quad (4)$$

Euclidian distance between the nodes i and j is d_{ij} , the energy parameter for transmitting energy is α_2 , the amplifier parameter is β and the path loss exponent is m , $2 \leq m \leq 4$. Similarly, the energy consumed by a node i $1 \leq i \leq n$ for receiving data in a round is computed as in [31]

$$E_i^R(b_i^r) = \alpha_1 b_i^r \quad (5)$$

Where b_i^r is the amount of data that a node i is receiving in a round and α_1 is the energy parameter for receiving data. Thus the fitness function for the algorithm is the total energy dissipated by each node i in the network in one round of data gathering is

$$E_i = E_i^T + E_i^R \quad (6)$$

c. Selection

The selection retains the chromosome that have high fitness value to the next generation, thus improving the average fitness of the population.. In this paper, elitist selection and tournament selection are used together. In elitist section the best individuals are not changed and retained for the next generation. Whereas, in tournament selection two individuals are randomly selected and the one having better fitness is included in the mating pool.

When Parent1 and Parent2, produces a new offspring:

$$\Delta E = [Y_c - (Y_2 + Y_1)] * 0.5 \quad (7)$$

Equation (7) represents the energy difference between the two generations. Y_1 , Y_2 , Y_c are the objective values of *Parent1*, *Parent2* and *Offspring* respectively. A negative ΔE means the offspring is better. Whereas a negative ΔE does not always mean that it will be accepted, this eliminates the algorithm to get stuck in local optima so that the global optima can be found. The simulated annealing ensures that an individual with

negative ΔE is accepted with a probability of an acceptance.

d. Crossover

Crossover is used to improve the combinations in chromosomes. A two-point method is used here, in which exchanges of genes occur at any position on the chromosome. For example, consider two parents 4 2 3 1 5 and 5 1 3 2 4, an exchange of gene values takes place at position 2 and 4, then the two offspring produced have the values 4 1 3 2 5 and 5 2 3 1 4. Duplicate genes are deleted. The crossover takes place with a crossover probability P_c ($0 < P_c < 1$).

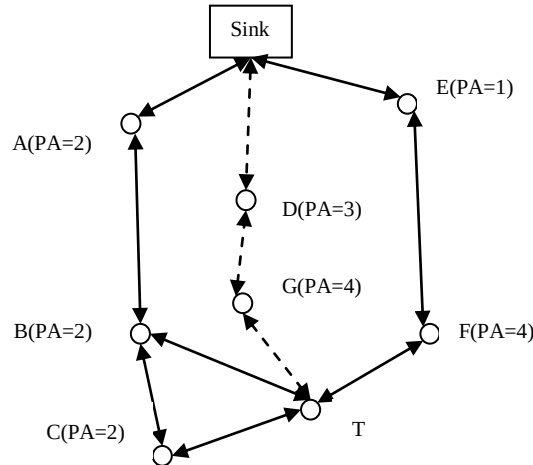


Figure 2: Power efficiency of the routes

e. Mutation

Used to maintain the diversity in the population and avoid trapping into a local optimum. Here, mutation operation changes a gene value with a random number between 1 to N , with a small probability P_m .

V. Simulation and Analysis

The network consists of n sensor nodes which are labeled with node numbers 1, 2, 3, ..., n and a base station. The routing is computed at the base station which has unlimited power supply. The sensor nodes in the network have limited energy.

To evaluate the proposed scheme the simulations are performed by writing customized code under MATLAB environment. The sensor fields of 100m x 100m meters is considered ranging from 10 to 85 nodes. Each sensor has a transmitting range of $d_0=40$ m. The initial energy of sensors is 5J. For the simulations described in this paper, the communication energy parameters are set as: $\alpha_1 = \alpha_2=50$ nJ/bit, $\beta=100$ pJ/bit/m², and the path loss exponent m is varied from 2 to 4. Each sensor node generates a packet of fixed size having 1000 bits in each round.

The comparison is made on two traditional techniques, first technique is Minimum Transmission Power [32] where each sensor node i transmits to its nearest neighbor j in such a way that the node j is closer to the destination (base station) than the node i . And the second technique is Minimum Hop Path [33,34] where each sensor node tries to find a path with minimum number of hops towards the base station. For the experiments conducted the lifetime is measured in two cases (i) with the base station located at the lower left corner of the monitoring area (Figure 3) and (ii) with the base station located at the centre of the monitoring area (Figure 4). The results show that the proposed approach has greatly improved the lifetime of the sensor network compared to the traditional routing schemes as it selects the path having maximum of the minimum power (PA) available among the alternative paths to the sink. For networks with less number of nodes the solution can be determined with traditional Integer Linear Programming (ILP) approaches but as the number of nodes is increased the Hybrid GA based solution provides faster solution.

VI. Conclusion

In this paper, the basic Genetic algorithm is improved by combining it with simulated annealing Algorithm. GASA routing delivers a better performance as the number of nodes is increased. Increasing the number of nodes provides more neighbors per node on average. The scheme also considers the routing in which the minimum power available (PA) is maximum among all the other paths available towards the sink node. Therefore proposed GASA routing will have more candidate nodes to choose from to determine a desirable routing path and hence less overall energy consumption. The idea of the proposed scheme is to select the path that have highest minimum Power Available because of which there is significant improvement in the network lifetime.

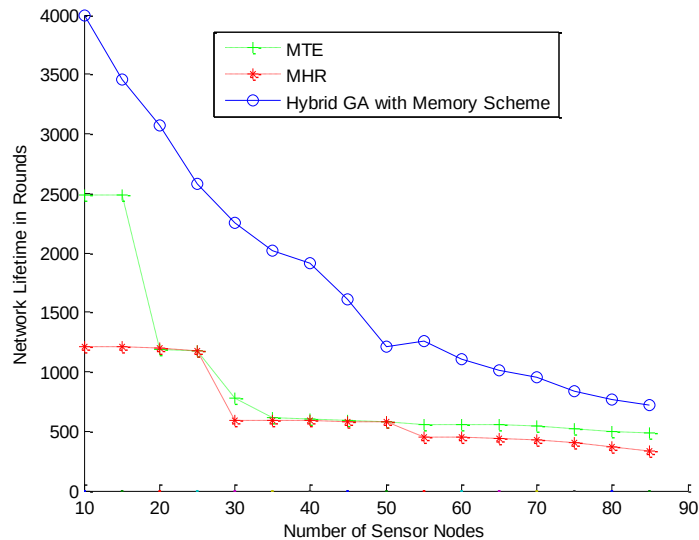


Figure 3: Comparison of the lifetime of WSN by different methods, (base station is located at the corner).

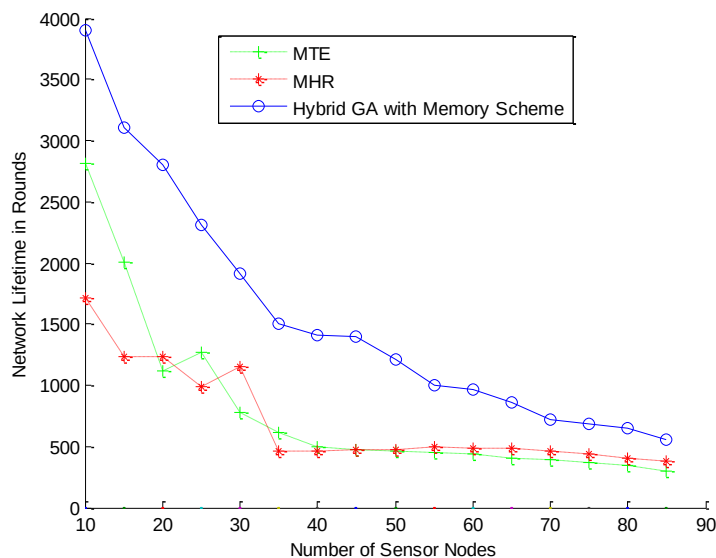


Figure 4: Comparison of the lifetime of WSN by different methods (base station is located at the center).

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