International Journal of Modern Science and Technology
http://www.ijmst.co/
Vol. 1, No. 4, July 2016. Page 115-120.
ISSN: 2456-0235

Research Article

Effective Optimization of Network Reliability using New Adaptive Genetic Algorithm

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Abstract

To search the optimal route is a complex task in wireless sensor network because high optimization depends upon a number of parameters. Most of the multimedia applications require the *k* shortest paths during the communication between a single source and multiple destinations. This problem is known as multimedia multicast routing and has been proved to be NP-complete. In this paper proposes a genetic algorithm to determine the *k* shortest paths with bandwidth constraints from a single source node to multiple destinations nodes. The algorithm uses the connection matrix of a given network, and the bandwidth of the links to obtain the *k* shortest paths. The success of Genetic Algorithm depends upon the number of operators such as selection, mutation and crossover. Needless to say crossover is most innovative. The performance of the proposed approach has been compared with k shortest path algorithm and improvement has been observed.

Keywords: Optimization; Neural Networks; Evolutionary Algorithm; Genetic Algorithms.

Introduction

A wireless sensor network (WSN) consists of spatially distributed autonomous sensors to monitor physical or environmental conditions, such as temperature, sound, pressure, etc. and to cooperatively pass their data through the network to a main location. The more modern networks are bi-directional, also enabling control of sensor activity. The development of wireless sensor networks was motivated by military applications such as battlefield surveillance; today such networks are used in many industrial and consumer applications, such as industrial process monitoring and control, machine health monitoring, and so on. The WSN is built of "nodes" – from a few to several hundreds or even thousands, where each node is connected to one (or sometimes several) sensors. Each such sensor network node has typically several parts: a radio transceiver with an internal antenna or connection to an external antenna, a microcontroller, an electronic circuit for interfacing with the sensors and an energy source, usually a battery or an embedded form of energy harvesting. The WSN is built of "nodes" – from a few to several hundreds or even thousands, where each node is connected to one (or sometimes several) sensors. Each such sensor network node has typically several parts: a radio transceiver with an internal antenna or connection to an external antenna, a microcontroller, an electronic circuit for interfacing with the sensors and an energy source, usually a battery or an embedded form of energy harvesting. Size and cost constraints on sensor nodes result in corresponding constraints on resources such as energy, memory, computational speed and communications bandwidth. The topology of the WSNs can vary from a simple star network to an advanced multi-hop wireless mesh network. The propagation technique between the hops of the network can be routing or flooding.

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Received: 12.06.2016; Received after Revision: 30.07.2016; Accepted: 30.07.2016; Published: 03.08.2016
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unacceptably high computational complexity for communication involving rapidly changing network topologies and involvement of other routing metrics like path reliability, delay, bandwidth etc. for computation of optimal path from source to destination [3-5]. The selection of routes in large-scale computer communication networks is extremely complex network optimization problems. Such problems belong to the class of nonlinear combinatorial optimization problems most of which are NP-hard [6].

The problem can be formulated as finding a minimal cost path with greater path fitness that contains the designated destination and source nodes [7-9]. The Shortest and reliable Path routing problem is a Classical combinatorial optimization problem. Evolutionary algorithms such as, genetic algorithms, neural networks, ant colony optimization etc. promise the solution for such problems, as these have been used successful in many practical applications. Neural Networks and Genetic Algorithms may also not be promising candidates for supporting real-time applications in networks because they involve a large number of iterations in general but will be able to provide the adequate solution. In literature GA is the most popular technique to solve complex multi objective optimization problems. Researchers have applied GAs to the Shortest Path routing problem, multi casting routing problem, ATM bandwidth allocation problem, capacity and flow [10-11].

K Shortest path algorithm

The *k* shortest paths problem has several applications in others network optimization problems. One of them is the restricted shortest path, where the shortest path that verifies a specified condition is searched. This research will attempt to apply a genetic algorithm to solve this problem based on a real world system. This is based on the analogy of finding the shortest path (i.e., the shortest possible bandwidth) between two nodes in the communication networks (assuming that each edge in the network has the bandwidth value) [6]. So, applying a genetic algorithm is an interesting idea. This is clearly different from traditional algorithms that try to compare every possibility to find the best solution, which might be a time consuming algorithm for a network containing a large number of nodes and edges [12].

Problem description

A network is usually represented as a weighted digraph, Now $G=(N, E)$,where $N = \{1, \dots , n\}$ denotes the set of nodes and $E = \{e_1, \dots , e_m\}$, denotes the set of communication links connecting the nodes. Let $M = \{n_0, u_1, u_2, \dots , u_m\} \subseteq N$ be a set of form source to destination nodes, where n_0 is source node and $U = \{u_1, u_2, \dots , u_m\}$ denotes a set of destination nodes.$P(n_0, u_i)$ is a path from source node n_0 to destination node u_i € U. The path P is the shortest path if the bandwidth of that path is equal to constant value B (this value is determined from the user or is a required value of the bandwidth). The bandwidth of P ($Band(P)$) is the minimum value of link bandwidth ($Band(e)$) in P. i.e.,

$$\boldsymbol{Band(Path) = min\,(Band(e), e \in Ep}$$

Hence, the problem of bandwidth constrained *k* shortest path is to find all the paths from source node to each destination node which satisfy:

$$\boldsymbol{Band(Path) \geq Bandwidth}$$

New adaptive genetic algorithm

Genetic algorithms, as powerful and broadly applicable stochastic search and optimization techniques, are the most widely known types of evolutionary computation methods today. In general, a genetic algorithm has five basic components as follows: (1) an encoding method that is a genetic representation (genotype) of solutions to the program. (2) A way to create an initial population of chromosomes. (3) The objective function. (4) The genetic operators (crossover and mutation) that alter the genetic composition of offspring during reproduction.

Encoding method

Given a network G (N, E) with N nodes and E is the set of communication links connecting the nodes. Also, we consider the source node n_0 and destination nodes set $U = \{u_1, u_2 \dots , u_m\}$. The chromosome can be represented by a string of integers with length N. The genes of the chromosome are the nodes between the source node n_0 and destination node u_i. Each chromosome in population denotes the shortest path. Obviously, a chromosome represents a candidate solution for the *k* shortest path problem since it guarantees the shortest path between the source node and any of the destination nodes.

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Initial population

The initial population is generated according to the following steps:

1. A chromosome x in the initial population can be generated in a form as indicated in below mentioned Figure 1.

n_0	n_i	n_j	n_k	….	….	n_m	d

   Figure 1. A chromosome form (where n_i, n_j, n_k, …, n_m are the nodes between the source node n_0 and destination node d).
2. If the generated chromosome in Step 1 fails to meet 2-connectivity conditions, discard it and go to Step 1.
3. Repeat Steps 1 to 2 to generate population size number of chromosomes.

Objective function

The objective function is to find the shortest paths from the source node to the destination nodes which satisfy.

$$\mathrm{Band(Path)} = \min\,(\mathrm{Band}(e), e \in Ep \geq B$$

Crossover operation

The crossover operation is performed by one-cut point. In the proposed approach, the crossover operation will perform if the crossover ratio (P_c) is verified. The value of P_c is 0.9. The cut point is selected randomly [13-15]. The offspring generated by crossover operation is shown in Figure 2.

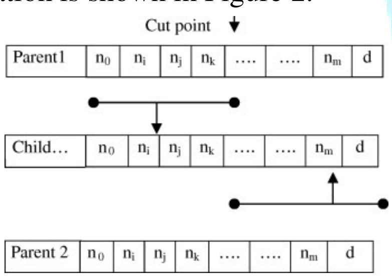

Figure 2. Crossover operation

Mutation operation

The mutation operation is performed on bit-by-bit basis. In the proposed approach, the mutation operation will perform if the mutation ratio (P_m) is verified. The mutation ratio, P_m in this approach is 0.2. The mutated bit is selected randomly. The offspring generated by mutation is shown in Figure 3.

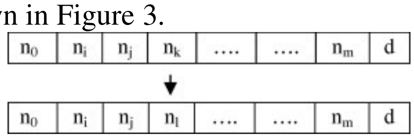

Figure 3. Mutation operation

Proposed algorithm

New Adaptive Genetic Algorithm is section proposed for solving the k shortest paths problem. The steps of this algorithm are as follows:

Algorithm: The New Adaptive Genetic algorithm for finding the k shortest path.
Input: pop_size, maxgen, Pm, Pc, n0, the destination nodes U, B.
Output:
1. Generate the initial population
2. gen ← 1.
3. While (gen ≤ maxgen) do
4.P ← 1
5.While (p ≤ pop_size) do
6.Obtain chromosomes of the new population, select two chromosomes from the parent population according to Pc.Apply crossover, and then mutate the new child according to Pm parameter.
7.Compute the bandwidth of the new child (Band(P)) according to Eq. (1).
8.If B(P) ≥ B then
Save this child as a candidate solution.
9.P ← p+1.
10.End if
11.End
12.Print all obtained solutions.
13.End.

Experimental Results

In this section, we show the effectiveness of the above algorithm by applying it on two examples as follows.

First example

A network with eight nodes as shows in Figure 4 was considered. Each link has a corresponding bandwidth.

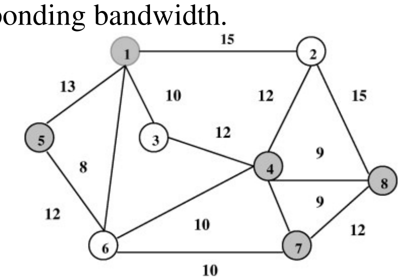

Figure 4. Sample network

The parameters setting in this algorithm are: pop_size = 20, P_m=0.2, P_c = 0.9, maxgen = 600. The source node n_0 is the node No. 1 and the destination nodes are U = {4, 5, 7, 8}, and the objective value of B is equal to 10 (Figure 5).

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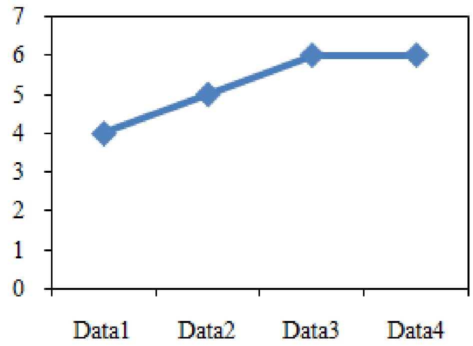

Figure 5. Shortest path obtained by using NAGA

The k shortest paths which obtained by the proposed genetic algorithm are shown in table 1. These results indicate that the proposed algorithm is finding the k shortest paths with bandwidth constraints from a single source node to multiple destinations nodes for any given network topology.

Second example

Second example with 20 nodes was considered. The connection matrix of that example is shown in table 2. The corresponding bandwidth of each link is shown in table 3. The parameters setting in this algorithms: pop_size = 25, $P_m = 0.1$, $P_c = 0.9$, maxgen = 2000,000. The source node n_0 is the node No. 1 and the destination nodes are $U = \{9, 11, 12, 14, 16, 17, 19, 20\}$, and the objective value of B is equal to 10.

The k shortest paths for each destination node at N generations are shown in the table 4.

Table 1. NAGA bandwidth iteration

The k shortest paths which obtained by the proposed new adaptive genetic algorithm.									
Destination node	The shortest paths							k	Band (P)
4	1	2	8	7	6	4		5	10
1	3	4					10		
1	5	6	4				10		
1	2	4					13		
1	5	6	7	8	2	4	10		
5	1	5						4	13
1	2	4	6	5			10		
1	2	8	7	6	5		10		
1	3	4	6	5			10		
7	1	3	4	2	8	7		6	10
1	3	4	6	7			10		
1	2	4	6	7			10		
1	2	8	7				12		
1	5	6	7				10		
1	5	6	4	2	8	7	10		
8	1	5	6	4	2	8		6	10
1	3	4	2	8			10		
1	3	4	6	7	8		10		
1	5	6	7	8			10		
1	2	8					15		
1	2	4	6	7	8		10		

Table 2. The connection matrix of the network (20 nodes)

The Connection Matrix of the Network																			
0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	1	1	1	0
0	0	1	1	1	0	0	0	0	0	1	1	0	0	1	1	1	1	1	1
0	1	0	0	1	1	0	0	0	0	1	0	1	1	0	0	1	1	0	0
0	1	0	0	0	1	1	1	1	0	0	0	1	0	0	1	0	1	0	0
0	1	1	0	0	0	1	0	1	0	0	0	0	0	1	1	0	1	1	0
0	0	1	1	0	0	1	1	0	0	0	1	0	1	1	1	1	0	0	1
0	0	0	1	1	1	0	1	1	1	0	1	1	1	0	0	0	1	0	1
0	0	0	1	0	1	1	0	0	1	0	1	0	1	1	1	1	0	0	0
0	0	0	1	1	0	1	0	0	1	1	0	1	1	0	0	1	0	1	0
1	0	0	0	0	0	1	1	1	0	0	1	0	1	1	1	0	1	1	1
0	1	1	0	0	0	0	0	1	0	0	0	0	1	1	1	0	0	0	0
1	1	0	0	0	1	1	1	0	1	0	0	1	1	1	0	1	0	0	0
1	0	1	1	0	0	1	0	1	0	0	1	0	1	0	1	0	0	0	1
0	0	1	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	1	1
0	1	0	0	1	1	0	1	0	1	1	1	0	0	0	1	0	0	1	0
0	1	0	1	1	1	0	1	0	1	1	0	1	0	1	0	1	0	1	0
1	1	1	0	0	1	0	1	1	0	0	1	0	0	0	1	0	0	0	0
1	1	0	1	1	0	1	0	0	1	0	0	0	0	0	0	0	0	1	1
1	1	0	0	1	0	0	0	1	0	0	0	0	1	1	1	0	1	0	0
0	1	0	0	0	1	1	0	0	1	0	0	1	1	0	0	0	1	0	0

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Table 3. The bandwidth value of the given network

The Bandwidth value of the given network (For 20 Nodes)																			
0	0	0	0	0	0	0	0	0	13	0	9	13	0	0	0	12	3	3	3
0	0	8	13	9	0	0	0	0	0	3	2	0	0	4	13	9	6	8	2
0	8	0	0	7	9	0	0	0	0	1	0	9	13	0	0	10	1	0	0
0	13	0	0	0	15	13	16	10	0	0	0	1	0	0	12	0	6	0	0
0	9	7	0	0	0	3	0	12	0	0	0	0	0	16	9	0	2	2	0
0	0	9	15	0	0	8	14	0	0	0	0	15	0	9	2	3	5	0	7
0	0	0	13	3	8	0	10	13	11	0	7	14	2	0	0	0	11	0	3
0	0	0	16	0	14	10	0	0	9	0	6	0	12	6	5	15	0	0	0
0	0	0	10	12	0	13	0	0	4	6	0	6	5	0	0	11	0	9	0
13	0	0	0	0	0	11	9	4	0	0	11	0	0	2	2	0	8	1	13
0	3	1	0	0	0	0	0	6	0	0	0	0	0	10	12	0	0	0	0
9	2	0	0	0	15	7	6	0	11	0	0	11	1	7	0	5	0	0	0
13	0	9	1	0	0	14	0	6	0	0	11	0	3	0	14	0	0	0	6
0	0	13	0	0	9	2	12	0	1	1	1	3	0	14	0	0	0	12	10
0	4	0	0	16	2	0	6	5	2	10	7	0	0	0	5	1	0	7	0
0	13	0	12	9	3	0	5	0	2	12	0	14	0	5	0	7	0	8	0
12	9	10	0	0	5	0	15	11	0	0	5	0	0	1	7	0	0	0	0
3	6	1	6	2	0	11	0	11	8	0	0	0	0	0	0	0	0	5	6
3	8	0	0	2	0	0	0	9	1	0	0	0	12	7	8	0	5	0	0
0	2	0	0	0	7	3	0	0	13	0	0	6	10	0	0	0	6	0	0

Table 4. k shortest paths at N generations

N Generation	k shortest paths for each destination node							
	node 9	node 11	node 12	node 14	node 16	node 17	node19	node 20
1000	3	2	1	1	3	1	1	1
10000	13	8	18	5	19	15	3	9
20000	18	15	24	12	29	20	10	13
30000	24	18	28	17	31	22	7	9
80000	31	27	38	29	39	32	14	19
90000	33	34	34	30	45	34	18	18
120000	35	28	36	34	45	32	16	24
140000	38	30	40	33	50	32	20	19
180000	39	34	41	36	53	35	20	21
200000	40	38	45	37	54	35	23	26

Conclusions

In the present research work, the use of the new Adaptive Genetic Algorithm has been proposed to find out the optimal route in wireless sensor network. The new adaptive genetic algorithm was proposed to determine the k shortest path with bandwidth constraints from a single source node to multiple destinations nodes. The algorithm uses the connection matrix of a given network, and the bandwidth of the links to obtain the k shortest paths. The proposed NAGA has been applied on two examples network topology and the produced results are obtained by a less number of generations. The proposed algorithm is considered to be the first algorithm that uses the genetic algorithms to obtain the k shortest paths from a single source node to multiple destinations nodes.

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