



## Optimum Path Routing in Networks Using Genetic Algorithms

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**Abstract—** *In packet switching networks, routing directs packet forwarding, the transit of logically addressed packets from their source toward destination through intermediate nodes, typically hardware devices called routers, bridges, gateways, firewalls, or switches. The routing process usually directs forwarding on the basis of routing tables which maintain a record of the routes to various network destinations. Thus, constructing routing tables is very important for efficient routing, which are held in the router's memory. Most routing algorithms use only one network path at a time, but multipath routing techniques enable the use of multiple alternative paths.*

*The objective of our study will be to find the optimal path in the network routing. As we have in the biological principle of survival of the fittest, together with the biological evolution, leads to better adaptation of the species to their environment. Genetic algorithms combine survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair. Genetic algorithms efficiently exploit historical information to speculate on new search points with expected improved performance.*

**Keywords—** *Roulette wheel, chromosome, fitness function, crossover, mutation, optimized path*

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### I. INTRODUCTION

Routing is a process of finding paths between nodes. There are mainly two types of routing policies viz., static routing and dynamic routing. In static routing, the routes between the nodes are pre-computed based on certain factors and are stored in routing table. All packets between any two nodes follow the same path. If topology of the network changes, then the path between two nodes may also change, and hence in dynamic routing policy, the routes are not stored but are generated when required. The new routes are generated based on the factors like traffic, link utilization etc which is aimed at having maximum performance. Routing policy may be centralized or distributed. In the case of centralized routing, only centralized node generates routes between any pair of nodes. In distributed routing, each node generates routes independently between pair of nodes as and when required. Other classification of routing policy is optimal routing (global routing) and shortest path routing (local routing). Some of the shortest path algorithms are distance vector algorithm and link state algorithm. Characteristics of routing policy are distributed-ness, stochastic and time varying, multiobjective and multiconstraint.

Genetic Algorithm (GA) is a programming technique that depicts the biological evolution as the problem solving technique. GA works on the search space called population. Each element in the population is called as chromosome. GA begins with randomly selecting set of feasible solution from population. Each chromosome is a solution by itself. Each chromosome is evaluated for fitness and this fitness defines the quality of solution. GA uses adaptive heuristic search technique which finds the set of best solution from the population. New offsprings are generated /evolved from the chromosomes using operators like selection, crossover and mutation. Most fit chromosomes are moved to next generation. The weaker candidates get less chance for moving to next generation. This is because GA is based on the principle of Darwin theory of evolution, which states that the “survival is the best”. This process repeats until the chromosomes have best fit solution to the given problem. The summary is that the average fitness of the population increases at each iteration, so by repeating the process for many iterations, better results are discovered.

The most important feature of genetic algorithms is that they are parallel in nature. They explore solution space in multiple directions at once. GA is well suited for solving problems where the solution space is huge and time taken to search exhaustively is very high. They perform well in problems with complex fitness. If the function is discontinuous, noisy, changes over time or has many local optima, then GA gives better results. GA has ability to solve problems with no previous knowledge. The performance of GA is based on efficient representation, evaluation of fitness function and other parameters like size of population, rate of crossover and mutation and the strength of selection.

Genetic Algorithms work with a set of individuals, representing possible solutions of the task. The selection principle is applied by using a criterion, giving an evaluation for the individual with respect to the desired solution. The Section I give the introduction, Section II represents the proposed algorithm, Section III represents the results and analysis and finally Section IV concludes the work done.

### II. PROPOSED ALGORITHM

Real values for genes are used in the coding for this problem. The chromosome size is variable for each chromosome and each chromosome represents a probable rout having some distance and total congestion in the path. Number of nodes is

fixed in the network with each node having a congestion factor associated to it having value between 0 and 1; 0 represents a totally free node while a 1 represents a totally congested node.

The following algorithm is used to encode the proposed GA for this problem:

1. Select the nodes with their x and y coordinates and associated congestion factors.
2. Designate initial and final nodes.
3. Initialize the initial population having each chromosome, with its first gene as the starting node and last gene as the terminating node, so as each chromosome represents a probable path with varying number of nodes encountered in each path.
4. Evaluate the fitness of the population by the objective function, which calculates the distances between nodes from the starting node to terminating node and also sums up the congestion factors of all the nodes in the path. Objective function assigns fitness to each chromosome by way of calculating the total path distance and the total congestion factor of the path represented by the chromosome.
5. Perform Roulette Wheel selection on the population.
6. Perform crossover on the new population obtained after selection, with a probability of crossover 0.8, which may be increased or decreased for faster convergence of GA.
7. Perform Mutation with a probability of mutation between 0.001 to 0.003. Probability of mutation may be varied for faster convergence of GA.
8. Evaluate the fitness of the population by the objective function.
9. Check convergence of GA, stopping criterion may average fitness or predefined number of runs for the GA. If stopping criterion is met, Stop the GA Else GOTO 4, Iterations continued till stopping criterion is met.
10. Display the optimum path with coordinates and corresponding congestion factors of the nodes.

The possible optimum path is one which is having minimum distance as well as the congestion factor is to be minimized through the path, a path with less congestion but having relatively larger distance may be selected as per the objective function, which takes care of both distance as well as the congestion in the path. Figure 1 represents the flowchart for genetic algorithm used.

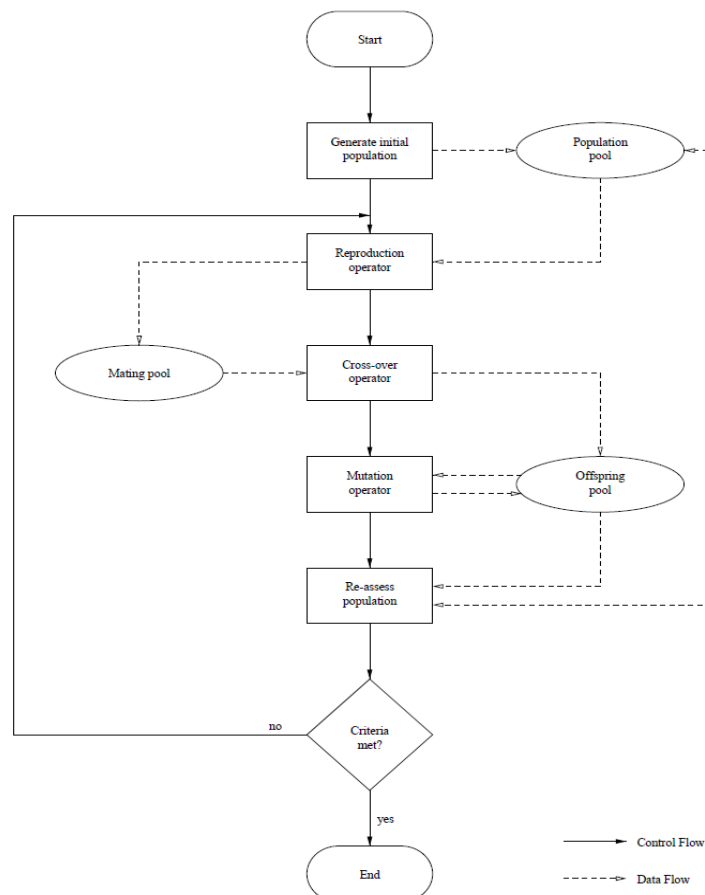


Figure 1: Flow Chart for Genetic Algorithm

### III. RESULTS AND ANALYSIS

Real coding with variable length chromosomes is performed in Matlab. The chromosome size is variable for each chromosome and each chromosome represents a probable route having some distance and total congestion in the path. Number of nodes is fixed in the network with each node having a congestion factor associated to it having value between 0 and 1; 0 represents a totally free node while a 1 represents a totally congested node. All the work can be performed in the following three processes used by the proposed GA for this problem:

**(i) Initialization of Population**

In the first step a network of 56 nodes is taken, which are assigned a congestion factor. Number of nodes is fixed in the network with each node having a congestion factor associated to it having value between 0 and 1; 0 represents a totally free node while a 1 represents a totally congested node. Select the nodes with their x and y coordinates and associated congestion factors to form a path. Consider the initial and final nodes of each path same as the starting node and the terminating node. Initialize the initial population in this way, having each chromosome, with its first gene as the starting node and last gene as the terminating node, so as each chromosome represents a probable path with varying number of nodes encountered in each path.

Also in this step, Evaluate the fitness of the population by the objective function which assigns fitness to each chromosome by way of calculating the total path distance and the total congestion factor of the path represented by the chromosome.

The starting node (S) and the ending node (E) are represented as:

$$S = [0.0, 5.0, 0.1]$$

$$E = [10.0, 2.0, 0.1]$$

Table 1 represents 56 nodes taken alongwith its congestion factor used in the Network:

Node No.	x-coordinate	y-coordinate	Congestion factor
1	0.0	5.0	0.10
2	0.0	0.0	0.15
3	0.0	1.0	0.83
4	0.0	2.0	0.25
5	0.0	8.0	0.62
6	1.0	0.0	0.78
7	1.0	1.0	0.98
8	1.0	4.0	0.99
9	1.0	8.0	0.97
10	1.0	10.0	0.87
11	2.0	0.0	0.88
12	2.0	3.0	0.98
13	2.0	4.0	0.99
14	2.0	5.0	0.97
15	2.0	7.0	0.02
16	3.0	1.0	0.43
17	3.0	3.0	0.92
18	3.0	4.0	0.99
19	3.0	9.0	0.75
20	4.0	0.0	0.65
21	4.0	4.0	0.13
22	4.0	6.0	0.91
23	4.0	7.0	0.95
24	4.0	8.0	0.76
25	4.0	9.0	0.83
26	4.0	10.0	0.43
27	5.0	0.0	0.68
28	5.0	1.0	0.88
29	5.0	2.0	0.96
30	5.0	7.0	0.67
31	6.0	2.0	0.28
32	6.0	3.0	0.97
33	6.0	5.0	0.09
34	6.0	6.0	0.98
35	6.0	8.0	0.74
36	7.0	0.0	0.98
37	7.0	1.0	0.99
38	7.0	2.0	0.97
39	7.0	3.0	0.87
40	7.0	6.0	0.78
41	7.0	7.0	0.98
42	7.0	8.0	0.99
43	8.0	1.0	0.64
44	8.0	3.0	0.93

45	8.0	5.0	0.97
46	8.0	7.0	0.92
47	8.0	8.0	0.83
48	9.0	0.0	0.98
49	9.0	2.0	0.99
50	9.0	3.0	0.07
51	9.0	8.0	0.57
52	9.0	9.0	0.78
53	9.0	10.0	0.08
54	10.0	2.0	0.10
55	10.0	7.0	0.25
56	10.0	9.0	0.03

Figure 2 represents the network consisting the above mentioned 56 nodes of network.

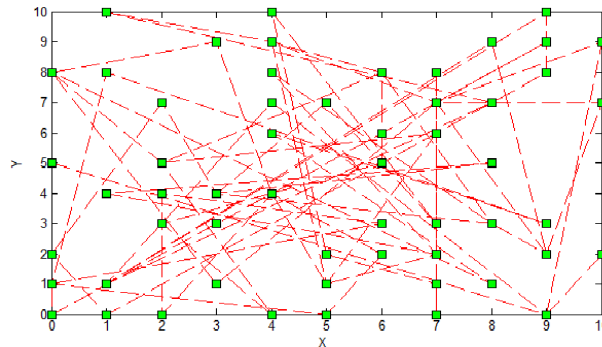


Figure 2: Network consisting of 56 nodes

Initial population is as given below (comprises of 10 chromosomes of variable lengths)

Chromosome 1:

[0.0, 5.0, 0.10], [0.0, 5.0, 0.10], [4.0, 10.0, 0.43], [3.0, 4.0, 0.99],[7.0, 1.0, 0.99], [8.0, 8.0, 0.83], [9.0, 9.0, 0.78], [10.0, 2.0, 0.10].

Chromosome 2:

[0.0, 5.0, 0.10], [1.0, 1.0, 0.98], [2.0, 5.0, 0.97], [4.0, 7.0, 0.95], [9.0, 0.0, 0.98], [10.0, 2.0, 0.10].

Chromosome 3:

[0.0, 5.0, 0.10], [1.0, 10.0, 0.87], [2.0, 0.0, 0.88], [4.0, 9.0, 0.83], [5.0, 0.0, 0.68],[10.0, 2.0, 0.10].

Chromosome 4:

[0.0, 5.0, 0.10], [0.0, 8.0, 0.62], [1.0, 0.0, 0.78], [2.0, 7.0, 0.02], [3.0, 1.0, 0.43], [6.0, 8.0, 0.74], [7.0, 0.0, 0.98], [10.0, 2.0, 0.10].

Chromosome 5:

[0.0, 5.0, 0.10], [2.0, 4.0, 0.99], [3.0, 3.0, 0.92], [4.0, 8.0, 0.76], [5.0, 1.0, 0.88], [9.0, 10.0, 0.08], [10.0, 7.0, 0.25], [10.0, 2.0, 0.10].

Chromosome 6:

[0.0, 5.0, 0.10], [0.0, 2.0, 0.25], [1.0, 4.0, 0.99], [4.0, 6.0, 0.91], [5.0, 2.0, 0.96], [8.0, 1.0, 0.64], [10.0, 2.0, 0.10]

Chromosome 7:

[0.0, 5.0, 0.10], [2.0, 3.0, 0.98], [3.0, 9.0, 0.75], [5.0, 7.0, 0.67], [6.0, 2.0, 0.28], [8.0, 7.0, 0.92], [9.0, 2.0, 0.99], [10.0, 2.0, 0.10].

Chromosome 8:

[0.0, 5.0, 0.10], [0.0, 1.0, 0.83], [1.0, 8.0, 0.97], [4.0, 4.0, 0.13], [6.0, 3.0, 0.97], [7.0, 8.0, 0.99], [8.0, 3.0, 0.93], [9.0, 3.0, 0.07], [10.0, 2.0, 0.10].

Chromosome 9:

[0.0, 5.0, 0.10], [0.0, 0.0, 0.15], [4.0, 0.0, 0.65], [6.0, 7.0, 0.89], [7.0, 2.0, 0.97], [8.0, 5.0, 0.97], [9.0, 8.0, 0.57], [10.0, 2.0, 0.10].

Chromosome 10:

[0.0, 5.0, 0.10], [6.0, 6.0, 0.98], [7.0, 3.0, 0.87], [6.0, 5.0, 0.09], [7.0, 6.0, 0.78], [7.0, 7.0, 0.98], [10.0, 1.0, 0.03], [10.0, 2.0, 0.10].

### (ii) Finding the Objective Function

Objective function calculates the distances between nodes from the starting node to terminating node and also sums up the congestion factors of all the nodes in the path. Objective function assigns fitness to each chromosome by way of calculating the total path distance and the total congestion factor of the path represented by the chromosome. GA maximizes the objective function, which is reciprocal of the total sum of distance from starting node to ending node and total congestion factor through this path.

$$T.D = \sum_{i=S}^E \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2}$$

$$T.DF = \sum_{i=S}^E \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2} + w. \sum_{i=S}^E C_i$$

$$ObjFun = 1/ \sum_{i=S}^E \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2} + w. \sum_{i=S}^E C_i$$

So the objective function calculates the above factors for each and every potential path i.e. the chromosome in a population.

**(iii) Optimized path & Convergence curve for GA**

The starting node is taken as S=[0.0,5.0,0.1]; and the ending node is E=[10.0,2.0,0.1]. The Algorithm selected a path which optimizes the distance between the starting and ending node alongwith minimizing the total congestion on the path. The optimum path found by GA is S=[0.0,5.0,0.1]; [2.0,7.0,0.0]; [4.0,4.0,0.2]; [6.0,5.0,0.1]; [9.0,3.0,0.2]; E=[10.0,2.0,0.1].

The nodes are selected by the algorithm for optimizing the distance along with the congestion on the path. A shorter path with higher congestion may be neglected while longer path with lesser congestion may be selected. The path selected is shown in the figure 3 by bold line.

GA Converges when it reaches to an optimal solution. There may be many criterions to access the convergence of GA. When the average fitness of subsequent generations stops growing then GA either converged to an optimal solution or might have struck at some suboptimal point. A predefined number of runs may be taken as the stopping criterion for the GA. Here we have tested both the stopping criterion. In this particular application fixed number of runs may be used as the optimality of the solution.

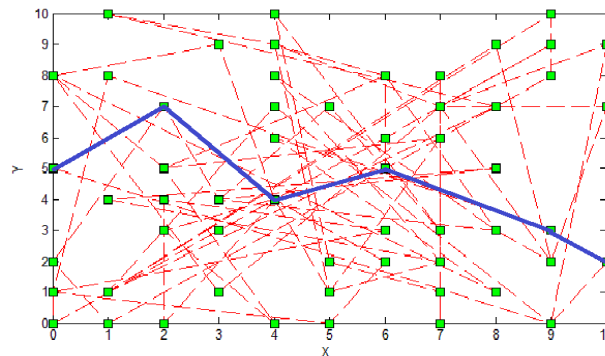


Figure 3: Optimized path

The convergence curve for the GA is shown in figure 4.

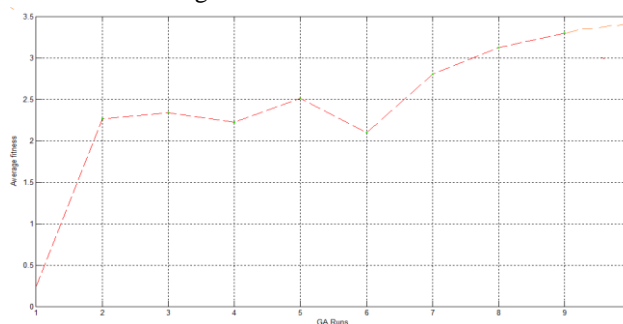


FIGURE 4: CONVERGENCE CURVE FOR GA

**IV. CONCLUSIONS**

The proposed algorithm is simple and can easily be implemented in practice. Not only it is of lower computational complexity, but it can also be theoretically assured to find the optimum path using the genetic algorithms. Coding schemes in Matlab may also be altered for faster convergence and increasing the efficiency of the optimization process. We have initialized the population for 56 nodes and by using the algorithm and formula, the objective function is calculated. It is observed that based on the congestion factor, every node select the minimal rout to the next one only. Then the current node in the routing selects again the minimum rout nearby the existing node. Finally, the minimal or optimum path is traces for the entire network. The most benefit of this technique is that we have no need to find the best or shortest route in advance for the entire network rather every nearest node selects the optimum route everytime, saving the processor time.

Finally, it is found that by using GA in routing, the performance of network has improved even if number of nodes in the network is large. It performs better and effectively even to the changes in the network due to node mobility and topology changes.

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