Study Of The Genetic Algorithm – Parameters In Telecommunications Network Planning Process

Aleksandar Tsenov[1]

Abstract: **The Genetic Algorithm is a heuristic approach witch is being used in wide areas of optimization works. In the last years this approach is also widely implemented in Telecommunications Network Planning. In order to solve less or more complex planning problem it is important to find the most appropriate parameters for initializing the function of the algorithm.**

There are six important parameters of the Genetic Algorithm witch define the normal and successful function and the obtaining of optimal decisions of the problem – Number of individuals in the initial population, number of populations in the process, usage of mutation, usage of additional local search, type of selection and type of replacement of the individuals. The variation of each of them causes different results.

The goal of this work is to define the optimal values of the parameters in dependence of the problem witch must be solved.

I. INTRODUCTION

The problem of optimally designing a network in order to meet a given set of specifications (such as prescribed traffic requirements, achieving a desired level of reliability, respecting a given maximum transit time), while minimizing total cost, arises in a wide variety of contexts: computer networks, telecommunications networks, transportation networks, distribution systems.

Network design algorithms draw an increasing amount of attention nowadays. Considering the complexity, high cost factor and fast deployment times of today's communications systems (such as IP and ATM backbones, optical networks, numerous types of access structures etc.), network operators can benefit a lot from the use of network design tools.

These tools can help speeding up and 'automating' the design process, ensuring superior quality (i.e. lower cost and/or better Quality of Service) and more justifiable solutions. Network design tools typically incorporate a wide range of functionality, such a geographical database handling, traffic estimation, link dimensioning, cost calculation, equipment configuration databases etc.

The real benefit of using these tools, however, comes from the possibility of using the algorithmic network optimization approaches. In this way, there arises a possibility for finding solutions of better quality in much shorter time, as compared to the manual network design.

II. PARAMETERS OF THE GENETIC ALGORITHM

Initial Population

The genetic algorithm begins by creating a random initial population. There is very important to obtain the optimal number of individuals in the initial population in order to:

- give the algorithm enough genetic material for creating "fit" offsprings;
- reduce the working time by finding the optimal solution of any problem.

The number of the individuals depends in most cases of the representation of the problem and of the number of the genes in the chromosome.

Number of Populations

The number of populations in the algorithm is also important for finding the best solution of a definite problem. This number must be large enough to obtain the optimal solution, and at the same time it must be not too large, because of the computing time and the production of too many unused solutions. The number of population depends of the complexity of the problem.

Selection

The selection method determines how individuals are chosen for mating. If you use a selection method that picks only the best individual, then the population will quickly converge to that individual. So the selector should be biased toward better individuals, but should also pick some that aren't quite as good (but hopefully have some good genetic material in them).

In selection the individuals producing offspring are chosen. The first step is fitness assignment. Each individual in the selection pool receives a reproduction probability depending on the own objective value and the objective value of all other individuals in the selection pool. This fitness is used for the actual selection step afterwards.

The most popular selection schemes are:

- rank – based assignment;
- roulette wheel selection;
- tournament selection;
- stochastic remainder sampler;
- stochastic uniform sampler.

Some of the more common methods include roulette wheel selection (the likelihood of picking an individual is proportional to the individual's score), tournament selection (a number of individuals are picked using roulette wheel selection, then the best of these is (are) chosen for mating), and rank selection (pick the best individual every time). Threshold selection can also be effective.

Replacement

Replacement schemes are used by genetic algorithms with overlapping populations to determine how the new individuals will be assimilated into the population. Replace-worst and replace most-similar are the only really useful replacement schemes. Sometimes replace-parent can be effective, but usually when the parents are similar to the offspring, and this is just replace-most-similar.

[1]Aleksandar Tsenov is with Telecom Department at Technical University of Sofia, "Kliment Ohridsky Blvd 8, 1756 Sofia, Bulgaria, E-mail: akz@tu-sofia.bg

The most popular replacement schemes are:

- replace worst;
- replace best;
- replace parent;
- replace random;
- replace most similar (crowding).

Mutation

The mutation is the recombination operator, which randomly changes the value of a separate gene in the chromosome. This appears with a low probability. The probability of the mutation must be chosen very carefully because of two reasons: if too high the algorithm will operate with non stabile genetic material, and if too low – the algorithm will achieve too rapidly a limited decision, without using the whole genetic material in the generations.

Local search

The local search by applying the genetic algorithms includes an estimation if the effect of small changes over the decision – if a change leads to a better result, it will be accepted, if not – the change will be rejected. There are two possible strategies for realizing the local search in the network planning:

- exchange of customers between nodes;
- exchange of the node, serving a group of customers.

III. EXPERIMENTAL METHOD

In order to find the most appropriate application values of the parameters two experiments were made. The planning problem is to find the optimal topological solution for a real town area by applying the following initial requirements:

- the network is a Passive Optical Network;

- the network to be optimized is a three level network – primary nodes, secondary nodes (splitters) and end nodes (customers);

- the problem is of type UCPL (Uncapacitated Concentrator Plant Location) – the splitters have unlimited capacity;

- two primary nodes, located on fixed positions;

- 12 secondary nodes (as a result obtained in [7]), located on positions in the terrestrial infrastructure equipment - ducts;

- 63 end nodes;

The experiments were fulfilled using a application, developed by the author and called PonOpt.

Experiment 1

The experiment includes 8 test by using the following initial conditions:

- Individuals in the initial population – 20, 50, 100, 200, 250, 500;
- Number of populations – respectively 20, 50, 100, 200, 250, 500 for every number of individuals;
- The algorithm were started 50 times for every combination;
- The algorithm was started 50 times for every combination of the algorithms parameters;

The tests performed in this experiment are:

- Test 1 – mutation, random selection, local search, replace parent;
- Test 2 – mutation, random selection, local search; replace – worst (50%);
- Test 3 – no mutation, random selection, local search, replace parent;
- Test 4 – no mutation, random selection, local search, replace worst (50%);
- Test 5 – mutation, best selection (rank-based assignment), local search, replace parents;
- Test 6 – mutation, best selection (rank-based assignment), local search, replace worst;
- Test 7 – mutation, random selection, no local search, replace parent;
- Test 8 – mutation, random selection, no local search, replace worst (50%);

Figure 1 represents the optimal solution obtained with the application PonOpt for experiment 1.

Fig. 1: The optimal topological decision for experiment 1

Table 1 shows the computational results for all the tests. The dark grey fields contain the lower price of the network.

TABLE 1
COMPUTATIONAL RESULTS FOR EXPERIMENT 1

		Mutatiom	NoMutatiom	RandSelection	BestSelection	LocalSearch	NoLocalSearch
Replace Parents	20-20	2818.10	2593.98	2818.10	2906.16	2818.10	3838.33
Replace Worst	10	3322.55	2988.13	3322.55	3322.27	3322.55	3973.31
Replace Parents	50-20	2492.76	2214.84	2492.76	2391.93	2492.76	3792.37
Replace Worst	25	2855.21	2413.41	2855.21	2838.81	2855.21	3750.71
Replace Parents	100-20	2436.86	2145.78	2436.86	2445.79	2436.86	3835.41
Replace Worst	50	2458.00	2130.64	2458.00	2409.52	2458.00	3877.40
Replace Parents	200-20	2495.15	2142.16	2495.15	2446.67	2495.15	3820.05
Replace Worst	100	2430.00	2126.39	2430.00	2383.00	2430.00	3739.68
Replace Parents	250-20	2399.72	2140.12	2399.72	2159.17	2399.72	3794.41
Replace Worst	125	2470.89	2086.66	2470.89	2330.00	2470.89	3799.59
Replace Parents	500-20	2332.21	2129.00	2332.21	2106.82	2332.21	3837.88
Replace Worst	250	2349.74	2046.67	2349.74	2277.00	2349.74	3773.53
Replace Parents	20-50	2564.91	2293.60	2564.91	2550.00	2564.91	3569.47
Replace Worst	10	3090.00	2907.84	3090.00	3190.00	3090.00	3627.52
Replace Parents	50-50	2166.04	2021.42	2166.04	2020.33	2166.04	3625.71
Replace Worst	25	2465.00	2224.50	2465.00	2640.00	2465.00	3534.71
Replace Parents	100-50	2030.48	1989.54	2030.48	2004.74	2030.48	3570.57
Replace Worst	50	2109.50	2081.70	2109.50	2203.64	2109.50	3650.02
Replace Parents	200-50	2035.85	1989.54	2035.85	2058.00	2035.85	3593.16
Replace Worst	100	2052.46	2006.44	2052.46	2076.00	2052.46	3660.85
Replace Parents	250-50	2038.85	1989.54	2038.85	2006.77	2038.85	3663.22
Replace Worst	125	2050.84	2014.93	2050.84	2019.77	2050.84	3657.35
Replace Parents	500-50	2024.42	1989.54	2024.42	1990.72	2024.42	3603.02
Replace Worst	250	2016.14	1991.15	2016.14	1989.54	2016.14	3667.54
Replace Parents	20-100	2359.13	2315.27	2359.13	2762.19	2359.13	3281.27
Replace Worst	10	2996.00	3036.31	2996.00	3296.40	2996.00	3457.83
Replace Parents	50-100	2060.33	2044.41	2060.33	2029.34	2060.33	3286.49
Replace Worst	25	2533.86	2354.35	2533.86	2694.07	2533.86	3281.27
Replace Parents	100-100	1992.29	1991.15	1992.29	2030.28	1992.29	3385.00
Replace Worst	50	2080.75	2036.82	2080.75	2096.65	2080.75	3278.06
Replace Parents	200-100	2002.52	1989.54	2002.52	1996.28	2002.52	3362.00
Replace Worst	100	2003.97	2051.59	2003.97	2005.67	2003.97	3375.45
Replace Parents	250-100	1995.82	1989.54	1995.82	2004.96	1995.82	3523.42
Replace Worst	125	2008.37	1989.54	2008.37	2015.47	2008.37	3570.10
Replace Parents	500-100	1998.63	1989.54	1998.63	1993.89	1998.63	3434.00
Replace Worst	250	2001.07	1989.54	2001.07	1990.71	2001.07	3448.16
Replace Parents	20-250	2339.00	2234.00	2339.00	2604.23	2339.00	3179.60
Replace Worst	10	2957.00	2944.31	2957.00	3295.00	2957.00	3541.86
Replace Parents	50-250	2015.01	2030.47	2015.01	2027.47	2015.01	3214.02
Replace Worst	25	2494.61	2445.41	2494.61	2535.46	2494.61	3472.11
Replace Parents	100-250	2000.94	1989.54	2000.94	1999.98	2000.94	3005.65
Replace Worst	50	2009.57	2065.00	2009.57	2121.46	2009.57	3366.99
Replace Parents	200-250	1989.54	1989.54	1989.54	1989.54	1989.54	3112.98
Replace Worst	100	2006.68	2036.97	2006.68	2022.75	2006.68	3232.86
Replace Parents	250-250	1989.54	1989.54	1989.54	1989.54	1989.54	3256.65
Replace Worst	125	1989.84	2015.88	1989.84	1999.55	1989.84	3335.78
Replace Parents	500-250	1989.54	1989.54	1989.54	1989.54	1989.54	3185.96
Replace Worst	250	1989.54	1989.54	1989.54	1989.54	1989.54	3102.45
Replace Parents	20-500	2315.14	2220.00	2315.14	2706.46	2315.14	3291.48
Replace Worst	10	2933.97	3144.50	2933.97	3317.00	2933.97	3581.36
Replace Parents	50-500	2006.65	2008.62	2006.65	2035.38	2006.65	3001.01
Replace Worst	25	2483.53	2551.72	2483.53	2460.20	2483.53	3476.22
Replace Parents	100-500	1989.84	1989.54	1989.84	1989.54	1989.84	3111.22
Replace Worst	50	2004.00	2018.54	2004.00	2122.21	2004.00	3302.56
Replace Parents	200-500	1989.54	1989.54	1989.54	1989.54	1989.54	2999.89
Replace Worst	100	2008.61	2007.97	2008.61	2011.32	2008.61	3105.00
Replace Parents	250-500	1989.54	1989.54	1989.54	1989.54	1989.54	2845.23
Replace Worst	125	1989.54	1995.85	1989.54	1998.98	1989.54	2962.30
Replace Parents	500-500	1989.54	1989.54	1989.54	1989.54	1989.54	2781.94
Replace Worst	250	1989.54	1989.54	1989.54	1989.54	1989.54	2889.31

Figures 2 to 9 show the graphical results for all the tests in experiment 1 – the left side of each figure shows the cost dependence of the number of populations, and the right side – of the number of individuals in the populations.

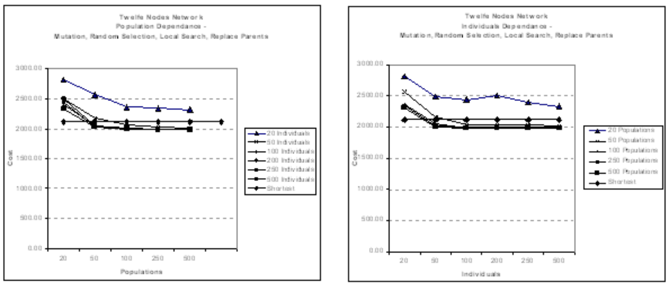

Fig. 2: Experimental results of Test 1

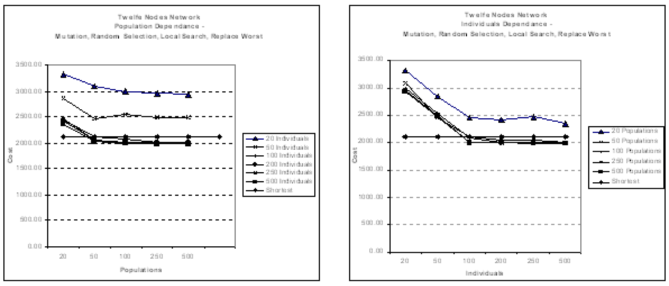

Fig. 3: Experimental results of Test 2

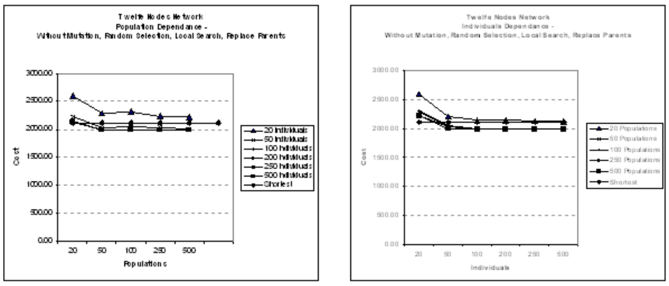

Fig. 4: Experimental results of Test 3

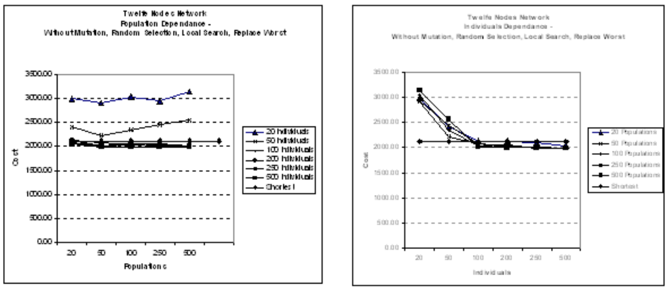

Fig. 5: Experimental results of Test 4

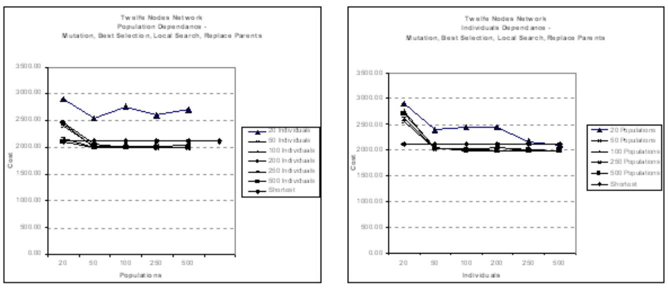

Fig. 6: Experimental results of Test 5

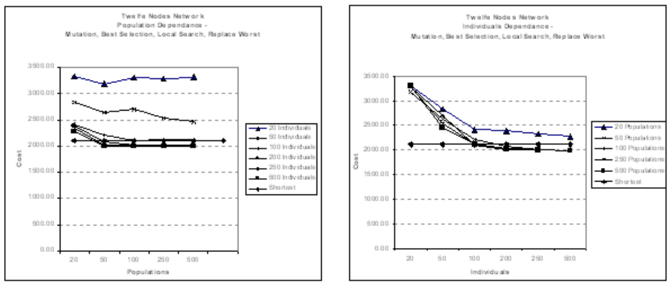

Fig. 7: Experimental results of Test 6

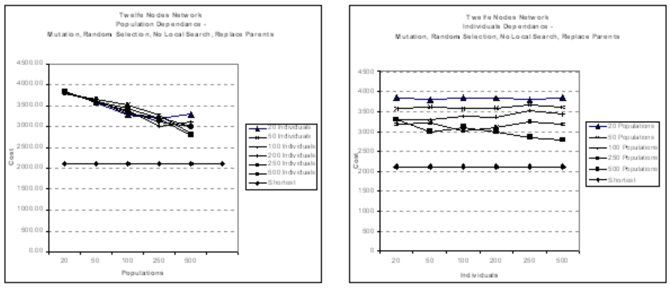

Fig. 8: Experimental results of Test 7

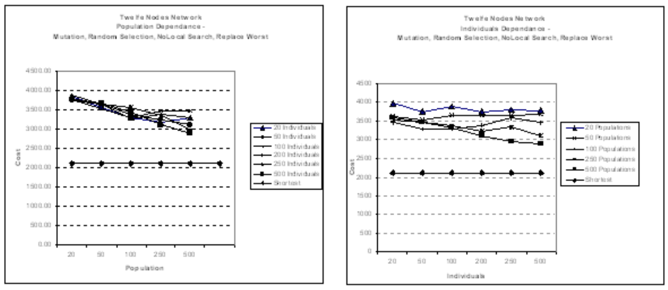

Fig. 9: Experimental results of Test 8

The straight line, presented as “shortest” represents the solution of the problem using the shortest path algorithm. This is shown for a comparison between the algorithms.

The results may be generalized as follows:

- the number of the individuals must be great enough (approximately N*M/2, where N is the number of splitters and M is the number of the end nodes) in order to create a good initial population;
- the number of the populations can be presented by the same mathematical representations – in some cases the algorithm finds the best solution more earlier, but in most cases it needs grater number of populations;
- the local search is very important element of the algorithm – test 7 and test 8 show bed results, especially in cases with small number of individuals;
- the replacement procedure have also an important influence over the results – the parent replacement leads the algorithm a little bit backwards, according to the computational time, the worst replacement makes the algorithm faster, but in some cases not enough reliable – the best solution may be let trough;
- the selection method has no influence on the computational time, but in case of best selection there are too much “bed” solutions in the population.

Experiment 2

The results of experiment 1 give the initial data for experiment 2:

- number of populations – 500;
- number of individuals in the population – 500;
- studied variants:
  - mutation, random selection, local search, replace parents;
  - mutation, random selection, local search, replace worst;
  - mutation, best selection (rank-based assignment), local search, replace parents;
  - mutation, random selection, no local search, replace parents;

The algorithm was started 10 times per variant in order to find the common and the specific characteristics for each case.

The results are graphically represented on figures 10 to 13.

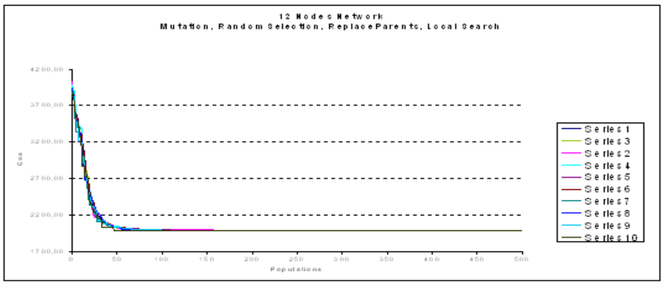

Fig. 10: Experimental results for variant 1 in Experiment 2

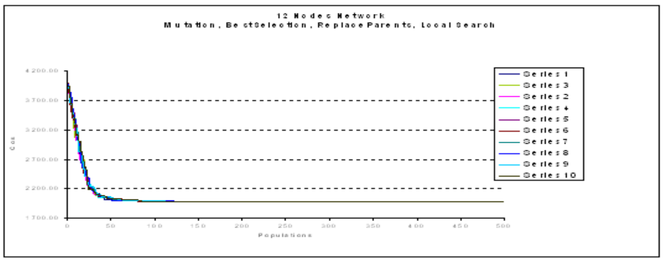

Fig. 11: Experimental results for variant 2 in Experiment 2

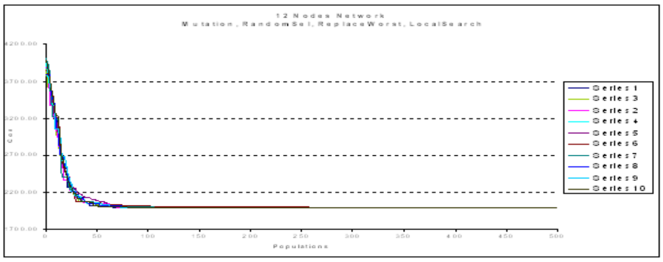

Fig. 12: Experimental results for variant 3 in Experiment 2

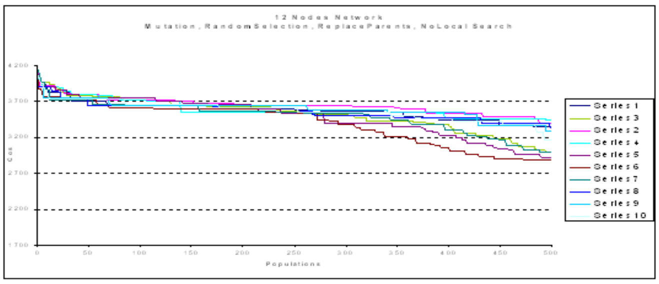

Fig. 13: Experimental results for variant 4 in Experiment 2

IV. Conclusions

The results of this experimental study can be generalized as follows:

- The number of the individuals and the number of the populations must be at least N*M/2. So there are enough initial solutions, which will be used later for producing of next generations. There is enough genetic material available for obtaining more of the possible decisions and at the same time the algorithm has enough possibilities to reach the best solution;
- There is no possibility to find the optimal solution without applying local search. This is so because the first solution for a single point is accepted, independently of other possible solutions by little local changes;
- The best selection approach leads very fast to the lowest price for a problem, but this is not ever the optimal price. This is because of the great number of "bed" individuals which are manipulated;
- The replace worst approach leads to two disadvantages – first: the computational time becomes longer and second: the used genetic material is limited.

The initialization of the genetic algorithm depends also on the capacity of the network to be planed, of the required computational time, of the required price. The results of this work will be used later for future studies in order to increase the performance of the genetic algorithm for solving of most complex network planning problems.

References

[1] Tsenov A., "Presentation of location problems", ICEST 2002, pp. 299 - 302, Nish, Yugoslavia, 2- 4 October 2002

[2] Tsenov A., "Application Of Genetic Algorithms In Access Network Planning", XXXVIII International Scientific Conference ICEST 2003, p. 158-161, Sofia, Bulgaria, (2003)

[3] Routen T., "Genetic Algorithms and Neural Network Approaches to Local Access Network Design", Proceedings of the 2nd International Workshop on Modeling, Analysis and Simulation of Computer and Telecommunications Systems, 1994

[4] Kratica J., V. Filipovitch, V. Ljeljum, D. Toljijg "Solving of the Uncapacitated Warehouse Location Problem Using a Simple Genetic Algorithm", Proceedings of the XIV International Conference on Material handling and warehousing, 3.33-3.37, Belgrade, 1996

[5] Kratica J., "Improvement of Simple Genetic Algorithm for Solving the Uncapacitated Warehouse Location Problem", Proceedings of the 3rd On-line World Conference on Soft Computing (WSC3), 1998

[6] P. Chardaire, A. Kapsalis, J.W. Mann, V.J. Rayward-Smith and G.D. Smith, "Applications of Genetic Algorithms in Telecommunications". In J. Alspector, R. Goodman, T.X. Brown (Eds.), Proceedings of the 2nd International Workshop on Applications of Neural Networks to Telecommunications, pp. 290-299, 1995

[7] Tsenov A., "Concentrator location using Simulated Annealing" , Electronics & Electrotechnics, ISSN 0861-4717, issue 5 -6, p. 10 - 15, 200