

**Memetic Algorithm with Multi-Parent Crossover (MA-MPC) for
Multi-Objective Network Design**

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Abstract

In many Evolutionary Algorithms (EAs), a crossover with two parents is commonly used to produce offsprings. Interestingly, we need not restrict ourselves to two-parent crossover since EA allows us to emulate natural evolution in a more flexible fashion. There are experimental results in the literature which show that multi-parent crossover operators can achieve better performance than traditional two-parent versions. However, most of these experimental results are based on common test functions. Experimental studies involving real-life, NP-hard problems such as network design problem are very rare. This paper presents Memetic Algorithm with Multi-Parent Crossover (MA-MPC) with a view to providing a case study of multi-parent crossover within the framework of MA for network topology design problem. Results show that MA-MPC does not always outperform MA. It depends on the size of the problem and the number parents (be it 3, 5, 7, or any other).

Keywords: Evolutionary Algorithms, Multi-Parent Crossover, NP-hard problems, Memetic Algorithm, network design

1.0 Introduction

Memetic Algorithm (MA) is known to be one of the highly effective meta-heuristic approaches for solving a large number of constraint satisfaction and optimization problems [1]. One of the key features of a MA is the crossover operator for generating offspring solutions. Generally, meaningful crossover operators enhance healthy diversification in the population and prevent premature convergence of the population. In many Evolutionary Algorithms (EAs), a crossover operation with two parents is commonly used to produce offsprings. However, we need not restrict ourselves to two-parent crossover only as EAs allow us to emulate natural evolution in a more flexible fashion. Several attempts studying the use of more than two parents for crossover in EAs have been reported [1, 2, 3, 4]. In fact, there are experimental results in the literature which show that multi-parent crossover operators can achieve better performance than their two-parent versions. Elsayed et al [5] showed that the efficiency of genetic algorithm (GA) can be enhanced by using multi-parent crossover with a randomized operator. Ting and Buning [6] proposed a tabu multi-parent genetic algorithm (TMPGA) and observed from their computational experiments that TMPGA achieved faster convergence and better solution quality than the classic two-parent GA. Eiben [7, 8] provides excellent overview of multi-parent crossovers. These researchers and a host of others have demonstrated the effectiveness of multi-parent crossover on functional optimization problems as well as multi-objective problems. However, computational experiments involving real-life, NP-hard problems such as network design problem are very rare.

In this paper, we provide a case study of (diagonal) multi-parent crossover operator within memetic algorithm for multi-objective network design problem.

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Breadth First Search (BFS) is used for routing. The metric used for this purpose is the length of the link. The following assumptions were made in the problem formulation

- The location of each network node is given
- Each C_{ij} is fixed and known
- Each link is bidirectional i.e. a path can be traversed in either direction
- There is no redundant link in the network

2.0 Algorithm design and Implementation Details

2.1 MA-MPC

The template of MA-MPC used in this paper is as follows:

- 1 Initialization: generate a population of N chromosomes
- 2 Fitness: calculate the fitness of each chromosome
- 3 Create a new population:
 - a. Selection: select m chromosomes from the population ($m \geq 3$)
 - b. Crossover: produce m offsprings from the m selected chromosomes
 - c. Local Search: apply local search to each offspring
 - d. Mutation: perform mutation on each offspring.
 - e. Local search: apply local search to each offspring.
- 4 Replace: replace the current population with the new population
- 5 Evaluation: compute the objective vector of each chromosome
- 6 Termination: Test if the termination condition is satisfied. If so stop. If not, go to step 2

2.2 Implementation Details

This presents relevant details concerning the implementation of MA-MPC

3.0 Encoding Scheme

The chosen encoding scheme is such that every chromosome codes a possible network, which corresponds to an individual in a set of feasible solutions of the problem. This set of feasible solutions constitutes a population. The chromosome is represented by a constant length integer string representation. The chromosome consists of two parts, the first part contains details of NE's at the nodes and the second part consists of details of the links. For example, if there are H types of nodes, then $\log_2 H$ bits are required to encode a node. Therefore the first part of the chromosome consists of $N \cdot \log_2 H$ bits, where N is the number of nodes in the network. If a link exists between nodes 1 and 2 then the first bit position in the link part is set to 1. Hence the second part of the chromosome consists of $(N(N-1))/2$ bits.

3.1 Initial Population

The two algorithms start by creating an initial population. There are two ways of generating initial population namely heuristic process and random process. A random process of generating initial population is adopted.

3.2 Fitness Evaluation

Fitness of a chromosome is evaluated based on principle of Pareto ranking. Pareto-rank of each individual is equal to one more than the number of individuals dominating it. All non-dominated individuals are assigned rank one. Network cost and average delay are used to evaluate the rank of an individual chromosome using the principle of Pareto dominance. The fitness of an individual as defined in [9] is given by

$$\text{Fitness} = \frac{1}{\text{Rank}^2} \quad (12)$$

3.3 Selection

Roulette Wheel Selection Process is used. In roulette wheel, individuals are selected with a probability that is directly proportional to their fitness values i.e. an individual's selection corresponds to a portion of a roulette wheel. The probabilities of selecting a parent can be seen as spinning a roulette wheel with the size of the segment for each parent being proportional to its fitness. Obviously, those with the largest fitness (i.e. largest segment sizes) have more probability of being chosen. The fittest individual occupies the largest segment, whereas the least fit have correspondingly smaller segment within the roulette wheel. The circumference of the roulette wheel is the sum of all fitness values of the individuals. The proportional roulette wheel algorithm procedure is depicted by the algorithm below. Let $f_1, f_2, \dots, f_n$ be fitness values of individuals 1, 2, ..., n . Then the selection probability, P_i , for an individual i , is given as

$$P_i = \frac{f_i}{\sum_{j=1}^n f_j} \quad (13)$$

For 10-node network, it is evident from Table 1 that the use of multi-parent crossover will always enhance the efficiency of MA since MA has the highest CPU time (410 seconds). It could also be observed that quality of results is either degraded as it is the case with MA-MPC with 3 and 5 parents or not affected at all by multi-parent crossover as it is the case with MA-MPC with 7 parents.

For 21-node network, Table 2 shows that multi-parent crossover will reduce computation time of MA whenever it is used. Results quality is however either reduced or left unaffected by multi-parent crossover.

In the case 36-node network, Table 3 depicts that multi-parent crossover can either improve or impede the efficiency of MA depending on the number of parents involved. Results also reveal that when the efficiency of MA is improved owing to the use of multi-parent crossover, its effectiveness is equally hampered and vice versa. The table also shows that multi-parent crossover will either improve solution quality as it is the case with MA-MPC (with 5 parents) or degrade solution quality as it is the case with MA-MPC (with 3 and 7 parents)

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In this paper, the impact of multi-parent crossover on a Memetic Algorithm applied to solve real-life problem is investigated. In particular, MA-MPC is designed and tested for a multi-objective network design problem whose size ranges from small (10-node network), medium (21-node network) to large (36-node network). The results obtained show that, while multi-parent crossover will certainly improve the efficiency of MA for small and medium networks, it is not the case for large networks. For large networks, multi-parent crossover will either improve or impede the efficiency of MA depending on the number of parents used.

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Table 1: Table of Results for 10-node network problem

Number of Parents	Cost	AvDelay	Rank	CPU Time
2 (MA)	619.6	0.05	1	410
3	934.9	0.045	3	150
5	758	0.03	2	142
7	689.6	0.03	1	185

Table 2: Table of Results for 21-node network problem

Number of Parents	Cost	AvDelay	Rank	CPU Time
2 (MA)	1167.4	0.04	1	5665
3	1354.3	0.07	4	2899
5	1293.8	0.03	1	5390
7	1350.4	0.03	2	990

Table 3: Table of Results for 36-node network problem

Number of Parents	Cost	AvDelay	Rank	CPU Time
2 (MA)	1167.4	0.05	2	5673
3	1258.9	0.055	3	4744
5	1163.8	0.04	1	6455
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10-NODE NETWORK

Node Details (Node Type, C_i) = { (01,42) ,(0, 78) ,(10,33) ,(00,53) ,(01,42) ,(00,13) ,(10,9) ,(11,23) ,(10,57) ,(10,25) }

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