# GENDER SPECIFIC GENETIC ALGORITHMS 

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#### Abstract

In this paper we propose to incorporate gender in genetic algorithms. Existing genetic algorithms are gender-neutral. Every genetic algorithm which is gender-neutral can be easily constructed as a gender-specific genetic algorithm. We compared the performance of the gender-neutral and its gender-specific counterpart on four optimization problems and found that the gender-specific algorithm exhibits superior performance. A statistical analysis allows this conclusion to be stated with $99.5 \%$ confidence.


## INTRODUCTION

Genetic algorithms, first suggested by Holland [7], have become in recent years a popular metaheuristic method for solving optimization problems. Borrowed from the natural sciences and Darwin's law of natural selection and survival of the fittest, genetic algorithms are based on the premise that, like in nature, successful matching of parents will tend to produce better, improved offspring. For a review see [6].
Unlike natural processes, the basic tenet of genetic algorithms is that the "pool" of candidate parents for mating is gender-neutral. In nature, the pool of candidates is gender-specific. Mating of two males or two females will not produce an offspring. The "pool" of possible mates is therefore reduced by one half and the gender of the offspring is randomly determined. Only two manuscripts that mention gender in conjunction with a genetic algorithm were found in the literature and both deal with multiobjective optimization problems $[1,8]$.
In this paper we introduce a version of genetic algorithms, which simulates natural processes, one that distinguishes between the sexes. Mating takes place only between a male and a female and the gender of the offspring is randomly determined.

## GENETIC ALGORITHMS

To use a genetic algorithm we need to define a solution by a chromosome consisting of genes and an objective function to be minimized or maximized. The objective function is sometimes referred to as a "fit function". When a pair of parents is selected, they generate an offspring by some merging rule. the most popular merging rules are based on a "crossover" point which sets apart the genes taken from the first parent and the genes taken from the second one. A population (usually of a constant size) is maintained. Parents are selected to produce offspring, and these offspring can be fitter (in terms of the value of the objective function) than the parents or other population members. By adding better offspring to the population and removing inferior ones (survival of the fittest) the population members keep improving. When the process is stopped according to some stopping criterion, the best population member is selected as the solution. The general framework of a genetic algorithm (whether gender-neutral or gender-specific) is: (i) An initial population of solutions is randomly generated. (ii) In each generation: (a) Pairs of population members are matched to produce offspring by a crossover operator. In hybrid genetic algorithms
(sometimes called memetic algorithms) a local search is applied on the offspring before considering it for inclusion in the population. (b) A new population for the next generation is formed by replacing some of the existing population members by some of the newly generated offspring. In the genetic algorithms tested in this paper the new offspring replaces the least fit population member as long as it is fitter than the least fit population member and is not identical to an existing population member. (iii) The procedure is stopped according to some stopping rule. In our applications the number of generations is pre-specified. (iv) The best solution found throughout the process (the fittest population member when the algorithm terminates) is the result of the algorithm.
Mutations of population members or offspring can also be considered. A mutation of a solution is a random perturbation of the solution.

## THE GENDER PRINCIPLE

We propose to add a gender attribute to population members. A gender-specific genetic algorithm is similar to a gender-neutral genetic algorithm with one exception, namely, the solutions (population members) are assigned a gender. By using gender we promote an increase in diversity and thus expect to obtain better solutions. Each population member is assigned a gender (either male or female) that is not changed throughout the procedure, and mating is allowed only between opposite sexes. The following three modifications are applied to any gender-neutral algorithm in order to convert it to its gender-specific counterpart:
(i) When generating the starting population, each population member is arbitrarily assigned a gender. Half of the starting population members are arbitrarily classified as males and the other half as females.
(ii) When selecting a pair for mating it is ensured that the mating is between a male and a female.
(iii) The gender of the offspring is randomly determined with equal probability for each.

## COMPUTATIONAL EXPERIMENTS

For our experiments we selected four problems: The Golf Scramble Problem (Golf) [3], the Distance Dependent Unreliable Multifacility Location Problem (DDUMLP) [2], the Network Design Problem (NDP) [5], and the Quadratic Assignment Problem (QAP) [4, 9]. We compared the solutions obtained by the gender-neutral genetic algorithms proposed for various instances of these problems with their gender-specific counterparts.
Two measures were used to compare the two algorithms for each of the 46 instances:
(i) The average value of the objective function obtained in all runs.
(ii) The minimal value of the objective function obtained in all runs of the respective algorithm. If there is a tie in the minimal value, the tie is broken by the number of times this minimum is obtained.
These measures lead to 46 comparisons of average values, and 46 comparisons of minimal values, for a total of 92 comparisons. Table 1 depicts the comparison of the results. The comparison between the two algorithms clearly shows that the gender-specific algorithm is superior to its genderneutral counterpart. The superiority of the gender-specific algorithm is statistically significant as demonstrated below.
We applied three "two-related samples" non-parametric tests: Wilcoxon Signed Ranks Test, The Sign Test, and McNemar Test, using SPSS. When all 92 comparisons were included, the genderspecific algorithm was better than the gender-neutral one in 43 cases, inferior in only 16 cases,

Table 1: Summary of Results

| Problem <br> Name | Gender-Neutral <br> is Better | Gender-Specific <br> is Better |
| :--- | :---: | :---: |
| Golf | 1 | 8 |
| DDUMLP | 3 | 12 |
| NDP | 7 | 10 |
| QAP | 5 | 13 |
| Total | 16 | 43 |

and tied in 33 cases. The significance levels for the three tests were $p=0.00044,0.00071$ and 0.00071 , respectively. This proves the superiority of the gender-specific algorithm with over $99.9 \%$ confidence. We also compared only the 46 means. The gender-specific algorithm outperformed the gender-neutral one in 24 cases, was inferior in only 7 cases, and tied in 15 cases. The significance levels of the three tests were $0.00226,0.00406$, and 0.00406 , respectively. When only the mean performances were compared, the superiority of the gender-specific algorithm is proven with more than $99.5 \%$ confidence.

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