SEXUAL SELECTION WITH COMPETITIVE/CO-OPERATIVE OPERATORS FOR GENETIC ALGORITHMS

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ABSTRACT
In a standard genetic algorithm (GA), individuals reproduce asexually: any two organisms may be parents in crossover. Gender separation and sexual selection here inspire a model of gendered GA in which crossover takes place only between individuals of opposite sex and the GA's evaluation, selection, and mutation strategies depend on gender. Consequently, a pattern of cross-gender co-operation and intra-gender competition emerges. A symbiotic relation between the selection and crossover operators also arises. Experimental results prove this strategy to be advantageous, significantly outperforming the standard GA, both in number of generations required and in the quality of solutions.

KEY WORDS
Genetic Algorithms, Sexual Selection, Evolutionary Computation

1 Introduction

Genetic Algorithms are one approach of Evolutionary Computation. Although GAs were conceived by modelling key elements of natural evolution, one of those elements, and perhaps one of the most crucial, was left out, namely *gender* [13, 23]. Gender is not only responsible for preserving diversity in genes and maintaining a successful genetic pool by means of selection, crossover and mutation, but is also responsible for the optimisation of the different tasks vital to survival. There is much evidence that the specialisation of individuals is mainly by gender group [20].

Through gender came the developing of sexual selection, a component of natural selection where reproductive success depends on interaction with a partner of the opposite sex to produce offspring [23]. Sexual selection originates the observed differences between males and females in the phenotypic traits of many species, as well as complex behavioural patterns like competitiveness inside a gender group and co-operativeness between the two sex groups.

Some attempts to formulate GAs featuring gender have already been proposed [2, 21, 22, 25]. However, in most cases, these simulations simply consist of adding an extra attribute of gender to the chromosome, and defining a constraint preventing crossover between individuals of the same sex. Similarly, approaches including competitive/co-operative operators and natural selection derived strategies [11, 1] omit key elements of the sexual evolution strategy, such as sexual selection, mutation variations between gender and the competitive/co-operative patterns of individuals (in the same and opposite gender groups respectively) [10, 23, 13, 8, 3, 15].

The gendered GA proposed here integrates two well known components: the standard GA [16, 18, 12], and the theory of sexual selection [8, 23, 13]. A competition co-operation dynamic is simulated based on an adaptation of Hamilton's definition of *inclusive fitness* [17], and the incorporation of differing mutation rates for each gender as observed in biological systems [10]. Hamilton pointed out that an individual's fitness can be partitioned into two components, namely the *Direct fitness* resulting from personal reproduction, and which we shall adapt to our model as the individual's *Competitive fitness*, and the *Indirect fitness* which results from additional reproduction by relatives that is made possible by an individual's actions, adapted to our model as the individual's *Co-operative fitness* (for further reading on Hamilton's work, see [13, 23, 15]).

The organisation of this paper is as follows: Section 2 provides a brief description of the proposed model, Section 3 discusses some experimental results on the TSP and includes a comparison with the non-gendered standard GA performance, finally the conclusions and some recommendations for further work are presented in Section 4.

2 The Gendered GA

To the complex task of survival, organisms have responded with adaptation. It is believed that life on earth began some 3.8 billion years ago and it first developed in an asexual scenario [23]. Around two billion years ago, environmental pressure triggered a response of a simple yet powerful nature, namely *sex*. According to standard evolution theory, this newly acquired feature must have represented an advantage for individuals, and indeed a very useful one, for it has not disappeared since then.

Sexual attractors are very common in nature, and although their exact functions are still unclear, they have passed the tests of evolution. Consequently, applying the time honoured Evolutionary Computation practice of “if it works for nature, it is worth trying it" [2], the proposed model intends to integrate in a single approach some of the principal strategies observed in gendered societies. More precisely, it involves the simulation of patterns of competitive and co-operative behaviour derived from sexual selection [15], as well as recent discoveries on how male and female mutation rates differ [10].

The approach is based upon the following fundamental factors being included in the model:

- A clear distinction between the two gender groups, with the possibility of embedding different tasks for each one, such as the determination of what a "good" partner is (for mating and crossover).
- The inclusion of the principle of co-operation between elements of different gender to optimise the chances of survival for the following generations.
- The inclusion of the principle of competition in each gender group to ensure that the co-operative entities will be fit individuals.
- The simulation of mutation biased on the group's gender, as observed in nature.
- The inclusion of a relation between age, fertility and fitness as in biological systems affecting the selection process.

In the literature, many successful genetic operators have been proposed for the GA [16, 7, 24, 19, 1, 4], however, although these methods can be included in the proposed strategies here, our concern is to assess the improvement these strategies may represent over the standard GA, therefore, we have kept the standard variation operators such as roulette wheel selection and a one-point crossover. From this, tests will be run on both standard GAs with and without the sexual selection strategies and the results will be compared on the basis of the strategies and not on the advantages of the operators.

The elements of the proposed model may be described as follows: Let P be the population of the GA, and let X and Y be two proper subsets of P representing each gender (females and males respectively), such that $P = X \cup Y$ and $X \cap Y = \emptyset$:

$$X, Y \subset P \tag{1}$$

$$\forall a \in P, \;\; a \in X \Longleftrightarrow a \notin Y \tag{2}$$

A parameter γ_Y denotes the fraction of individuals in set Y, so at any given time, the probability of an individual $a \in P$ being in set Y or X is

$$p(a, Y) = \gamma_Y \quad , \quad p(a, X) = 1 - \gamma_Y \tag{3}$$

Procreation/crossover is permitted only between individuals of opposite gender, and only two offspring are created, one of each gender. This keeps the male:female ratio constant throughout the evolution of the system.

Figure 1 represents the implementation of the gendered population. As this Unified Method Language Diagram [5, 6] shows, individuals in the population each have their own methods of evaluating a "good" partner and their mutation. Their similar characteristics are contained within the meta-class which represents the species.

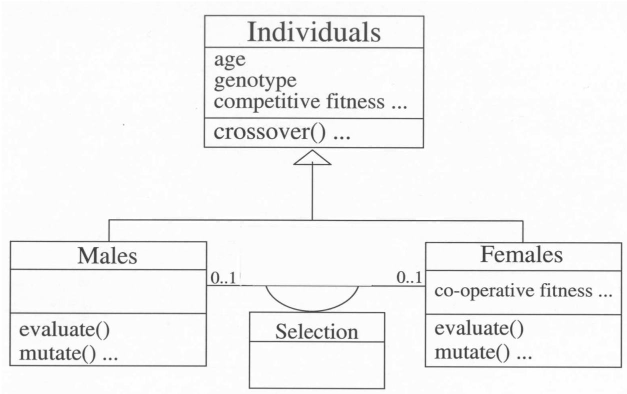

Figure 1. The structure of the population. A species class defines similar attributes. Polymorphic methods are embedded in each gender group.

For practical purposes and clarity in the evaluation of the strategies, the selection method used for procreation was the 'roulette wheel' model in which the probability of selection is in linear proportion to each individual's fitness [16]. We usually work with a fixed population size, so the number of individuals remaining from one generation to the next will depend on the chosen degree of elitism and the procreation probabilities. An extra attribute of *age*, measured in generations, enables us to model males' preferences over females' fertility derived from sexual selection.

Sexual selection simulation consisted of implementing different partner assessment functions for individuals in contrasting gender groups. Males were selected based on the direct outcome of the quality or fitness function applied to the individual's genotype, denoted by f and defined as its *Competitive Fitness*. Females however, were subject to a different evaluation scheme, that also involves the differential in competitive fitness between male parent and offspring that she makes possible by means of crossover. Using the age attribute, the longevity and fertility parameters (see [11]) were also able to be included in the assessment of her fitness. Combining these factors gives the *Co-operative Fitness* for female individuals. We shall now specify these ideas more precisely.

A male parent is selected first. We can define our selection function to be $Sel(\phi(a))$ which returns one chosen individual from the set of all competing individuals a with fitness function ϕ. So our chosen male parent y_{sel} will be selected from all $y \in Y$ according to

$$y_{sel} = Sel(f(y)) \tag{4}$$

After a male parent is selected, his female partner is chosen from all $x \in X$ according to their co-operative fitness that depends on their competitive fitness f, her Age, and the improvement Δf in fitness of her son compared to her chosen mate. Clearly Δf will have a value of zero for the initial generation. After the offspring are evaluated, Δf will be computed for that female in the next selection process. This is not a disadvantage to the oestrogenic individuals due to the sexual selection scheme, where competition is not present in contrasting gender groups. This can be expressed as

$$x_{sel} = Sel\left(\frac{w_1 f(x) + w_2 \Delta f(y) + w_3 g(Age(x))}{w_1 + w_2 + w_3}\right) \quad (5)$$

in which we have the fitness change

$$\Delta f(y) = f(y_{son}) - f(y_{sel}) \quad (6)$$

and $g(Age(x))$ is a scaling function that determines the effect of age on the chances of being selected. A simple triangular function of width σ around the age of maximum fertility μ proves adequate for our purposes

$$g(Age(x)) = \begin{cases} 1 - \frac{|Age(x)-\mu|)}{\sigma} & : \quad Age(x) < \mu + \sigma \\ 0 & : \quad Age(x) \geq \mu + \sigma \end{cases} \quad (7)$$

For practical purposes we can take $\mu + \sigma$ to be the given individual's life-span. The w_i are a set of fixed weighting parameters that we must choose to specify appropriate relative importance to the three components.

The combination of this selection scheme and the crossover operator steadily evolve to a symbiotic relationship. The rationale for this is that each gender specialises on a substring of the genome. For instance, in a one-point crossover, females may contribute to the trailing part of the genome string (by means of crossover). Thus, the better her contribution is to the offspring's fitness, the better her fitness will also be (by means of the *Indirect fitness scheme*), and hence the better her chance to get selected again. Such co-operative patterns between opposite genders allows the selection and crossover operators to "adapt" to each other.

As with all GAs, the individuals $a \in P$ will each be specified by a chromosome that represents the given problem solution as a string of length L in some generalised alphabet. We then have to define appropriate mutation and cross-over operators on those chromosomes.

The mutation process is simulated with different mutation rates for each gender group (as is found in nature [23, 10, 13]). These rates are fixed throughout the evolution process, and are set as initial input parameters. We can define these mutation probabilities to be

$$m_X \quad \forall a \in X \quad , \quad m_Y \quad \forall a \in Y \quad (8)$$

and following biological systems have

$$m_X < m_Y \quad (9)$$

Therefore, the total effective mutation rate of the population P is

$$m_P = \gamma_Y m_Y + (1 - \gamma_Y) m_X \quad (10)$$

Clearly the details of the mutation when it occurs will depend on the problem and the specification of the chromosome.

This mutation scheme depicts two different groups of individuals: males with a more dynamic or "active" genetic pool given higher mutation rates, and females with lower mutation rates and hence with a more static or "passive" genetic material, providing a balancing element in crossover.

The crossover operator is implemented using one split point for each parental chromosome, s_f and s_m for father and mother respectively. These are chosen at random and thus divide the two parental chromosomes in four segments (two segments each) with probability

$$p_{(4\_segments)} = \left(1 - \frac{2}{L}\right)^2 \quad (11)$$

Figure 2 shows the one-point crossover operator, in which F_i and M_i represent the genes of the father and mother respectively. The son inherits the trailing part of his mother's genes starting after position s_f, and the rest is taken from the father's chromosome starting with the first gene F_1. Similarly, the daughter inherits her mother's trailing genes in the same way as her sibling, however, the rest of her chromosome is obtained by copying her mother's heading genes in inverted order. Generation of infeasible individuals (e.g. those with a chromosome that transgresses a constraint) is avoided by employing a repair algorithm [4]. If a gene F_i is found to produce an illegal individual when copying the father's gene to the son, the next one F_{i+1} is considered instead, and so on. In the case of the daughter, this crossover operator does not yield illegal individuals for the test problem used here.

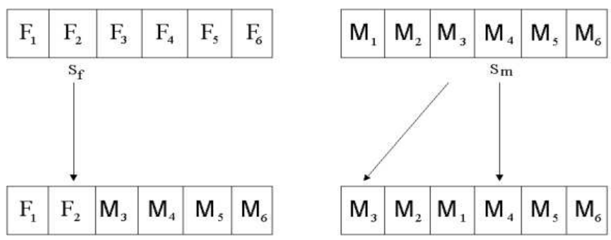

Figure 2. Details of the crossover process. Split points, s_f and s_m in father and mother respectively, denote the cut-points for chromosome inheritance. In this case, the son inherits his father's genes $F_1 \ldots F_2$ in positions $1 \ldots s_f$, and mother's genes $M_3 \ldots M_6$ in $s_f + 1 \ldots L$. The daughter inherits $M_4 \ldots M_6$ in $s_m \ldots L$, and $M_3 \ldots M_1$ in $1 \ldots s_m - 1$

It is clear that the approach described includes new features for the GA. Female selectiveness is reflected in the males' competition by means of the competitive fitness and higher mutation rates, while males' preferences for fertility and capacity to rear fit offspring in females, are intrinsically included in the co-operative fitness model.

3 Experimental Results

As a first test of the approach, the performance was explored using the Travelling Salesman Problem (TSP), the reason being the exponential nature of the problem, its solution landscape, and the available resources to compare results against other GA models featuring diverse and more complex variation operators. The TSP is a classic combinatorial problem that has been widely used to study different optimisation algorithms in the past. The task is for an agent (the salesman) to complete a circuit of all the nodes (the cities) in a fully connected graph, with the constraint that no node is permitted to be visited more than once. Clearly, as the number of nodes in the graph increases, the number of possible circuits or tours increases exponentially. The aim is to get the salesman to complete the circuit while travelling the least total distance possible.

The TSP chromosome is the usual representation of this problem: the list of cities in order of visit, so a chromosome (1 4 2 5) represents the tour $1 \rightarrow 4 \rightarrow 2 \rightarrow 5 \rightarrow 1$. A mutation simply swaps two cities in that list and the fitness is the minimum possible tour distance D, divided by the actual tour distance. To be sure of the global optimum and to give an intuitive idea of fitness, the cities were laid out on the circumference of a circle. Starting at any node on the circumference, the global optimum will be a tour corresponding to a cycle through consecutive cities around the circumference. Thus, with $C_{m,n}$ representing the link cost, i.e. the distance between m and n, the fitness function $\forall a \in P$ is defined as:

$$f(a) = \frac{D}{\sum_{i=1}^{L-1} C_{m_i,m_{i+1}} + C_{m_L,m_1}} \qquad (12)$$

The results presented are a comparison of matched runs of the standard and gendered genetic algorithms, so the same parameter configurations were used for all the simulations. Good parameters proved to be a population size $|P| = 200$, crossover probability of 0.75, and an elitism proportion of 0.07. For the gendered GA, there were several additional parameters to specify. For the sexual selection, good co-operative fitness parameters were found to be $w_1 = 0.75$, $w_2 = 0.55$ and $w_3 = 0.18$. The perceived fertility function $g(Age(x))$, defined in Equation 7, had parameter values $\mu = 2$ and $\sigma = 4$, leading to the age factor influence on fitness shown in Table 1. The chosen gender dependent mutation rates were $m_X = 10^{-3}$ and $m_Y = 10^{-1}$, with the fraction of male individuals in the population $\gamma_Y = 0.5$ (see equation 3). Thus, following from equation 10, the mutation rate selected for the standard GA was 0.0505, in order to equate the total number of mutations in both algorithms.

We now turn to the simulation results, for which each case is averaged over 100 experimental runs. To assess and

Table 1. Age dependence of perceived fertility

Age(x)	0	1	2	3	4	5	6+
g(Age(x))	0.5	0.75	1.0	0.75	0.5	0.25	0

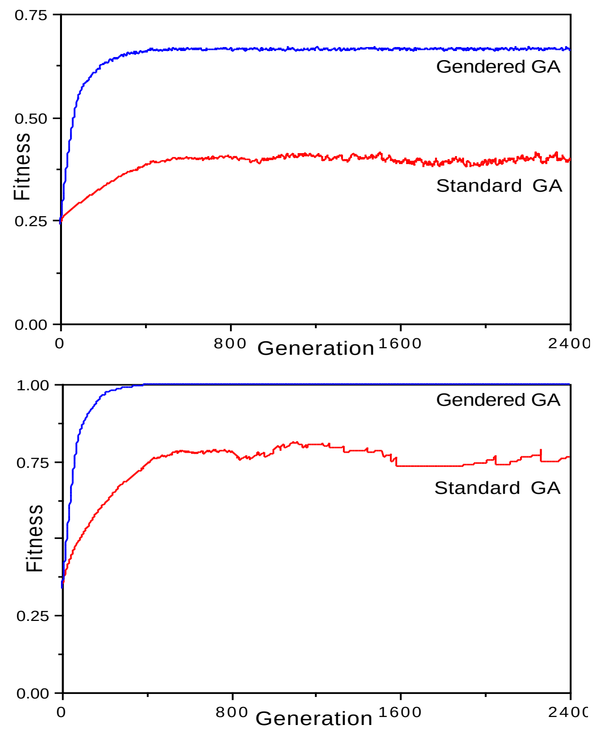

Figure 3. Results from the TSP experiment for the gendered GA and standard GA with 20 cities. The fitness averages of the population (above), and average best individual fitness (below).

compare the performance of the algorithms, we used the De Jong's off-line measure [9] defined as

$$X_e^*(h) = \frac{1}{T}\sum_{t=1}^{T} f_e^*(t) \qquad (13)$$

where $f_e^*(t) = best\{f(a_1), f(a_2), \ldots, f(a_{|P|})\}$ at generation t, and T is the total number of generations. This measure is thus the average of the best individuals over all the generations iterated in the algorithm. Since all our experiments were based on 100 trials, our off-line measure is then averaged over 100 runs.

In Figure 3, for 20 cities, we can see that the population's mean fitness in the gendered approach has a much steeper evolution towards a higher asymptotic state. It also shows a similar advantage in terms of speed of evolution for the best individual fitness, achieving the optimal fitness of 1.0, whereas the standard approach only achieves around 0.75.

Figure 4 reveals how the results differ for runs with

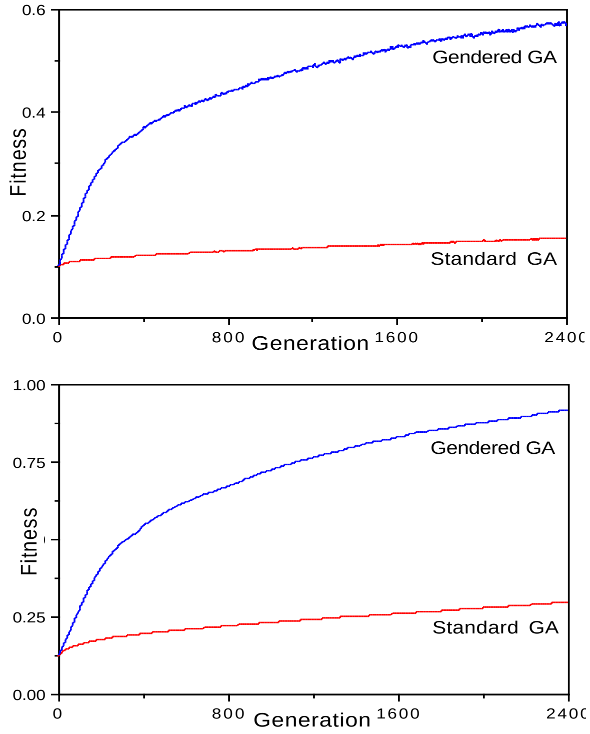

Figure 4. Results from the TSP experiment for the gendered GA and standard GA with 50 cities. The fitness averages of the population (above), and average best individual fitness (below).

Table 2. Comparison of performance for the Standard and Gendered GA

Nodes	Routes	Standard GA		Gendered GA	
		DeJong's X	Optima	DeJong's X	Optima
20	10^{18}	0.7389	96	0.9826	100
50	10^{64}	0.2379	0	0.7180	44
200	10^{374}	0.0356	0	0.1006	0
500	10^{1133}	0.0123	0	0.0264	0

50 cities, which obviously represents a much larger solution space. They show that the gendered GA again results in steeper slopes than the standard GA, reaching better solutions in fewer iterations (generations) and less computing time.

The averages in the figures do not tell us how often we achieve the optimal routes in each case. Table 2 shows the number of optimal routes achieved out of 100 experimental runs for the two GA types, and for different numbers of TSP nodes. It also provides a performance comparison for both algorithms, running on different problems, based on the De Jong's off-line measure (equation 13). For all the test cases, the gendered GA clearly outperforms the standard GA on these measures.

Table 3 shows the De Jong off-line measure for different total levels of mutation (noise) for both algorithms. For the gendered approach we maintained the initial male:female mutation rates ratio. The comparison is based on the 50 nodes TSP instance. As in Table 2, the gendered GA outperforms the standard GA, keeping a better measure at higher noise levels. Intuitively, this robustness is due to the different mutation rates for each gender group, where the embedded sexual selection strategy helps maintain a more "stable" population by means of competition only between individuals of the same gender.

Table 3. Noise/mutation tolerances of the Standard and Gendered GA

GA	Mutation 10%	Mutation 30%	Mutation 50%
Standard	0.180	0.162	0.155
Gendered	0.513	0.458	0.458

4 Conclusions

A Genetic Algorithm with sexual selection and competitive/co-operative operators has been presented. This approach models the competitive behaviour observed in many species amongst males using standard selection models. However, it also includes a new selection policy, based on *co-operative fitness*, for the female selection. The mutation rates also involved gender-based differences. A symbiotic relation emerged between the selection and crossover operators, and these allowed an adaptive scheme with consequent specialisation of each gender in a sub-area of the chromosome.

The results of preliminary experiments on the Travelling Salesman Problem suggest that this is a promising approach that can significantly outperform the standard GA, both in number of generations required and in the quality of solutions. This was found consistently in all the tests runs. Sexual selection by means of different mutation rates and age parameters are likely to keep the algorithm from local optima stagnation and from exponential take-over of strong individuals.

More appropriate recombination operators for the problem discussed have been proposed, however, as mentioned before, by modelling sexual selection on a gendered GA, a better assessment of the strategies may be possible by keeping the variation operators of the standard algorithm. Nevertheless, results proved promising when compared with other more complex genetic algorithms such as [14].

Further research on parameter-tuning and parameter control strategies (e.g. static, dynamic and adaptive control), as well as further study into the nature of the tradeoffs from having different mutation rates between genders, are likely to result in even greater advantages for the gendered approach.

Although there is obvious potential for this approach, there is still much work to be done in pursuing a more solid theoretical basis for it, and in assembling a general framework capable of producing successful implementations for a range of different problems. In particular, research work on the mathematical foundation on the indirect fitness selection model needs to be carried out. This is likely to lead to a more profound understanding of the co-operative operators, and is likely to steer their nature to a more "real-world" arena, and perhaps introduce further new improvements, approaches and state-of-the-art strategies in all aspects of GA research.

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