A Review of Selection strategies in Genetic Algorithm

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Abstract: A genetic algorithm (GA) has several genetic operators that can be modified to improve the performance of particular implementations. These operators include parent selection, crossover and mutation. Selection is one of the important operations in the GA process. There are several ways for selection. This paper presents the different parent selection strategy. This paper also reveals that tournament and proportional roulette wheel can be superior to the rank-based roulette wheel selection for smaller problems only and become susceptible to premature convergence as problem size increases.

Keywords: Genetic algorithm, Selection strategies, conclusion, future work.

I. INTRODUCTION

Basic genetic algorithm (GA) is generally composed of two processes. The first process is selection of individuals for the production of the next generation and the second process is manipulation of the selected individuals to form the next generation by crossover and mutation techniques. The selection mechanism determines which individuals are chosen for mating (reproduction) and how many offspring each selected individual produces. The main principle of selection strategy is “the better is an individual; the higher is its chance of being parent.” Generally, crossover and mutation explore the search space, whereas selection reduces the search area within the population by discarding poor solutions. However, worst individuals should not be discarded and they have some chances to be selected because it may lead to useful genetic material. A good search technique must find a good trade-off between exploration and exploitation in order to find a global optimum [1]. Hence, it is important to find a balance between exploration (i.e. poor solutions must have chance to go to the next generation) and exploitation (i.e. good solutions go to the next generation more frequently than poor solutions) within the mechanism of the selection. The different selection strategy used in the GA process will significantly affect the performance of the algorithm differently. This study is intended to examine the performance of GA when using different selection strategy.

II. PREVIOUS WORK ON SELECTION STRATEGIES

Several researchers have studied the performance of GA using different selection strategy; yet almost none of them tested on TSP problem. The performance of GA is usually evaluated in terms of convergence rate and the number of generations to reach the optimal solution. Jadaan et al. [3] for example compared the results of GA between proportional roulette wheel and rank-based roulette wheel selection method using several mathematical fitness functions and found that rank-based outperformed proportional in number of generations to come out with the optimal solution. He observed that rank-based is steadier, faster, certainty and more robust towards the optimum solutions than proportional roulette wheel. On the other hand, Zhong et al. [4] compared proportional roulette wheel with tournament selection, with tournament size equal 6 at seven general test functions and concluded algorithm with the tournament selection is more efficient in convergence than proportional roulette wheel selection. Julstrom [5] investigated the computing time efficiency of two types of rank-based selection probabilities;
linear ranking and exponential ranking probabilities and compared with tournament selection. He pointed that tournament selection is preferred over rank-based selection because repeated tournament selection is faster than sorting the population to assign rank-based probabilities. In addition, Mashohor et al. [6] evaluated the performance of PCB inspection system using three GA selection method; deterministic, tournament and roulette wheel and discovered that deterministic has the ability to reach the highest maximum fitness with lowest number of generations for all test images. This is then followed by roulette wheel and tournament selection.

Goh et al. [7] in his work entitled sexual selection for genetic algorithms focused on the selection stage of GA and examined common problems and solution methods for such selection schemes. He proposed a new selection scheme called sexual selection and compared the performance with commonly used selection methods in solving the Royal road problem, the open shop scheduling and the job shop scheduling problem. He claimed that the proposed selection scheme performed either on-par or better than roulette wheel selection on average when no fitness scaling is used. The new scheme also performed better on average when compared to tournament selection in the more difficult test cases when no scaling is used. Apart from that, Goldberg and Deb [8] did comprehensive studies on proportional, ranking, tournament and Genitor (steady state) selection schemes on the basis of solutions to differential equations. Their studies have been performed to understand the expected fitness ratio and convergence time. They found that ranking and tournament selection outperformed proportional selection on average when no fitness scaling is used. The new scheme also performed better on average when compared to tournament selection in the more difficult test cases when no scaling is used.

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III. SELECTION STRATEGIES FOR REPRODUCTION

The selection strategy addresses on which of the chromosomes in the current generation will be used to reproduce offspring in hopes that next generation will have even higher fitness. The selection operator is carefully formulated to ensure that better members of the population(with higher fitness) have a greater probability of being selected for mating or mutate, but that worse members of the population still have a small probability of being selected, and this is important to ensure that the search process is global and does not simply converge to the nearest local optimum. Different selection strategies have different methods of calculating selection probability. The differing selection techniques all develop solutions based on the principle of survival of the fittest. Fitter solutions are more likely to reproduce and pass on their genetic material to the next generation in the form of their offspring. There are five major types of selection schemes will be discussed, tournament selection, roulette wheel, and rank-based roulette wheel selection, Boltzmann and SUS. The subsequent section will describe the mechanism of each strategy. A more detailed of selection method can be found in [8, 11, 12, 13].

A generic selection procedure may be implemented as follows:

1. The fitness function is evaluated for each individual, providing fitness values, which are then normalized. Normalization means dividing the fitness value of each individual by the sum of all fitness values, so that the sum of all resulting fitness values equals 1.

2. The population is sorted by descending fitness values.

3. Accumulated normalized fitness values are computed (the accumulated fitness value of an individual is the sum of its own fitness value plus the fitness values of all the previous individuals). The accumulated fitness of the last individual should be 1 (otherwise something went wrong in the normalization step).

4. A random number \( R \) between 0 and 1 is chosen.

5. The selected individual is the first one whose accumulated normalized value is greater than \( R \).
There are different types of selection strategies:

A) Tournament Selection

B) Proportional Roulette Wheel Selection

C) Rank-Based Roulette Wheel Selection

D) Boltzmann Selection

E) Elitism

F) Stochastic Universal Sampling

A. Tournament Selection

Tournament selection is probably the most popular selection method in genetic algorithm due to its efficiency and simple implementation [8]. In tournament selection, \( n \) individuals are selected randomly from the larger population, and the selected individuals compete against each other. The individual with the highest fitness wins and will be included as one of the next generation population. The number of individuals competing in each tournament is referred to as tournament size, commonly set to 2 (also called binary tournament). Tournament selection also gives a chance to all individuals to be selected and thus it preserves diversity, although keeping diversity may degrade the convergence speed. Fig. 2 illustrates the mechanism of tournament selection while Fig. 3 shows the procedure for tournament selection. The tournament selection has several advantages which include efficient time complexity, especially if implemented in parallel, low susceptibility to takeover by dominant individuals, and no requirement for fitness scaling or sorting [8, 12].

In the above example, the tournament size, \( Ts \) is set to three, which mean that three chromosomes competing each other. Only the best chromosome among them is selected to reproduce. In tournament selection, larger values of tournament size lead to higher expected loss of diversity [12, 14]. The larger tournament size means that a smaller portion of the population actually contributes to genetic diversity, making the search increasingly greedy in nature. There might be two factors that lead to the loss of diversity in regular tournament selection; some individuals might not get sampled to participate in a tournament at all while other individuals might not be selected for the intermediate population because they lost a tournament.
Tournament selection is the most popular selection method in genetic algorithm. In tournament selection binary selection (k=2) is probably most popular.

**Binary tournament selection**

![Fig.3 Binary selection method](image)

**Pseudocode:**

- choose k (the tournament size) individuals from the population at random
- choose the best individual from pool/tournament with probability p
- choose the second best individual with probability p \((1 - p)\)
- choose the third best individual with probability p \((1 - p)^2\)
Efficient implementation, easy to adjust.

B. Proportional Roulette Wheel Selection

In proportional 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.

1. Imagine a roulette wheel where all the chromosomes in the population are placed.

2. The size of the section in the roulette wheel is proportional to the value of the fitness function of every chromosome - the bigger the value is, the larger the section is.

3. A marble is thrown in the roulette wheel and the chromosome where it stops is selected. Possible problems if there is a large difference of fitness from the best to the worst, which could hardly be selected.

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[4].

![Fig.4. Roulette wheel selection](image)

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 mechanism and the algorithm procedure are depicted in Fig. 4 and Fig. 5 respectively. In Fig. 4, when the wheel is spun, the wheel will finally stop and the pointer attached to it will point on one of the segment, most probably on one of the widest ones. However, all segments have a chance, with a probability that is proportional to its width. By repeating this each time an individual needs to be chosen, the better individuals will be chosen more often than the poorer ones, thus fulfilling the requirements of survival of the fittest. Let $f_1, f_2, \ldots, f_n$ be fitness values of individual 1, 2, \ldots, n. Then the selection probability, $P_i$ for individual $i$ is define as,

$$ P_i = \frac{f_i}{\sum_{j=1}^{N} f_j} $$

The basic advantage of proportional roulette wheel selection is that it discards none of the individuals in the population and gives a chance to all of them to be selected. Therefore, diversity in the population is preserved. However, proportional roulette wheel selection has few major deficiences. Outstanding individuals will introduce a bias in the beginning of the search that may cause a premature convergence and a loss of diversity. For example, if an initial population contains one or two very fit but not the best individuals and the rest of the population are not good, then these fit individuals will quickly dominate the whole population and prevent the population from exploring other potentially better individuals. Such a strong domination causes a very high loss of genetic diversity which is definitely not advantageous for the optimization process. On the other hand, if
individuals in a population have very similar fitness values, it will be very difficult for the population to move towards a better one since selection probabilities for fit and unfit individuals are very similar[5].

Moreover, it is difficult to use this selection scheme on minimization problems whereby the fitness function for minimization must be converted to maximization function. In general there are two types of such non-proportional selection operators: tournament based selection techniques which already been described in the previous section, and the rank-based selections that assign the probability value depending on the order of the individuals according to their fitness values, which will be discussed in the following section.

Fig. 5. Selection strategy with roulette wheel mechanism

**Procedure**: Roulette Wheel selection

**While** pop_size < pop_size do

Generate pop_size random number(r)

Calculate cumulative fitness, total fitness($p_i$) and sum of proportional fitness(Sum)

Spin the wheel pop_size times

If Sum < r then

Select the first chromosomes, otherwise select the jth chromosomes

End If

End While

Return chromosomes with fitness value proportional to the size of selected wheel selection

End Procedure

**Procedure for Roulette Wheel selection**

**C. Rank-based Roulette Wheel Selection**

Rank-based roulette wheel selection is the selection strategy where the probability of a chromosome being selected is based on its fitness rank relative to the entire population. Rank-based selection schemes first sort individuals in the population according to their fitness and then computes selection probabilities according to their ranks rather than fitness values. Hence rank-based selection can maintain a constant pressure in the evolutionary search where it introduces a uniform scaling across the population and is not influenced by super-individuals or the spreading of fitness values at all as in proportional selection. Rank-based selection uses a function to map the indices of individuals in the sorted list to their selection probabilities. Although this
mapping function can be linear (linear ranking) or non-linear (non-linear ranking), the idea of rank-based selection remains unchanged. The performance of the selection scheme depends greatly on this mapping function[5].

Rank-based selection schemes can avoid premature convergence and eliminate the need to scale fitness values, but can be computationally expensive because of the need to sort populations. Once selection probabilities have been assigned, sampling method using roulette wheel is required to populate the mating pool. Rank-based selection scheme helps prevent premature convergence due to “super” individuals, since the best individual is always assigned the same selection probability, regardless of its objective value. However this method can lead to slower convergence, because the best chromosomes do not differ so much from other ones[14]. The different between roulette wheel selection with proportionate fitness and rank-based fitness is depicted in Fig. 6a and Fig. 6b

![Fig.6a. Situation before ranking (graph of fitness)](image1)

![Fig.6.b Situation after ranking (graph of order numbers)](image2)

**Procedure**: Rank – based roulette wheel selection

**While** population size < pop_size **do**

Sort population according to rank

Assign fitness to the individual according to rank function

Generate pop_size random number(r)

Calculate cumulative fitness, total fitness($p_i$) and sum of proportional fitness($Sum$)

Spin the wheel pop_size times

If $Sum < r$ then

Select the first chromosomes, otherwise select the jth chromosomes

End If

End While

Return chromosomes with fitness value proportional to the size of selected wheel selection

End Procedure

**Procedure for rank based roulette wheel selection**
Possible problems: slow convergence, due to small difference between best and worst parents.

**E) Elitism**

When creating a new population by crossover and mutation, we have a big chance that we will lose the best chromosome. Elitism is the name of the method that first copies the best chromosome (or few best chromosomes) to the new population. It can rapidly increase the performance, because it prevents a loss of the so–far best found solution[6].

**D) Boltzmann Selection**

In Boltzmann Selection parents are selected with a probability that favors exploration at the beginning of learning and tends to stabilize and select the best solutions as generations proceed[15].

\[
P = e^{-f_{\text{Max}}/T}
\]

\[
T = T_0(1 - \gamma^k), \text{ with } \gamma \in [0, 1], \text{ and } T_0 \in [5, 100]
\]

\[
k = 1 + 100 \gamma g/G,
\]

where \( g \) is the generation number and \( G \) the maximum number of generations

**F) Stochastic Universal Sampling**

Stochastic universal sampling provide zero bias and minimum spread. SUS is an elaborately-named variation of roulette wheel selection. Stochastic Universal Sampling ensures that the observed selection frequencies of each individual are in line with the expected frequencies. So if we have an individual that occupies 4.5% of the wheel and we select 100 individuals, we would expect on average for that individual to be selected between four and five times. Stochastic Universal Sampling guarantees this. The individual will be selected either four times or five times, not three times, not zero times and not 100 times. Standard roulette wheel selection does not make this guarantee.

Stochastic Universal Sampling works by making a single spin of the roulette wheel. This provides a starting position and the first selected individual[4]. The selection process then proceeds by advancing all the way around the wheel in equal sized steps, where the step size is determined by the number of individuals to be selected. So if we are selecting 30 individuals we will advance by 1/30 x 360 degrees for each selection. Note that this does not mean that every candidate on the wheel will be selected. Some weak individuals will have very thin slices of the wheel and these might be stepped over completely depending on the random starting position.

Consider \( N_{\text{Pointer}} \) the number of individuals to be selected, then the distance between the pointers are \( 1/N_{\text{Pointer}} \) and the position of the first pointer is given by a randomly generated number in the range\([0,1/N_{\text{Pointer}}]\). For 6 individuals to be selected, the distance between the pointers is \( 1/6=0.167 \).

Figure of SUS shows the selection for the above example

<table>
<thead>
<tr>
<th>pointer1</th>
<th>pointer2</th>
<th>pointer3</th>
<th>pointer4</th>
<th>pointer5</th>
<th>pointer6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>0.0</td>
<td>0.18</td>
<td>0.34</td>
<td>0.49</td>
<td>0.62</td>
<td>0.73</td>
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<td>0.95</td>
<td>1.0</td>
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</table>

Random number

Fig.7. Stochastic universal sampling

Sample of 1 random number in the range \([0,0.167]:0.1\).

After selection the mating population consist on the individuals,
Stochastic universal sampling ensures selection of offspring that is closer to what is deserved as compared to Roulette wheel selection.

IV. CONCLUSION

In this paper we have described different types of selection strategies with a little pros and cons. All of these selection mechanisms have the same purpose of creating more copies of the individuals with higher fitness than those with lower fitness. However the selection mechanisms differ in the manner in which they allocate copies to the fittest individuals. A selection method has the higher selection measure than the other if it makes more copies of the best individuals thereby eliminating low fit individuals rapidly. A strong selection mechanism reaches equilibrium faster than a weaker method. But it also sacrifices genetic diversity that may be needed to find an adequate solution. Different selection mechanisms work well under different situations. Appropriate method has to be chosen for the specific problem to increase the optimality of the solution.

V. FUTURE WORK

Future work could be evaluated the interaction between selection pressure and selection strategies. For eg. Instead of using binary tournament selection, we could increase the tournament size to increase the selection pressure. Future work could be extending the model to include the selection method or combination of selection method to solve the problem of TSP (travelling salesman problem).

References

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