Determining the global minima of a set of functions using Genetic Algorithms

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1 Introduction

This paper will compare different selection and crossover methods for a genetic algorithm applied to a set of functions in trying to determine their global minimum. Genetic algorithms are an alternative to trajectory methods as are more flexible with their parameters.

2 Experimental setup

2.1 Representation

A genetic algorithm works with a collection of candidate solutions called *population*. Each candidate solution is called an *individual* or a *chromosome* and is represented using a bitstring which represents a point in the domain space. It is composed of smaller bitstrings concatenated. Each one is called a *component* and represents a point in a single dimension of the domain. Each bit of a bitstring is called a *gene*. Using this representation, a genetic algorithm works with data and not with numbers.

- Let a and b be the extremes of interval on which the function is defined and precision being the decimal precision.
- The length of a component is given by the formula $\log_2 (10^{precision} \cdot (b-a))$. Let this length be l.
- The bitstring represents numbers in the $[0, 2^l 1]$ interval. Let this number be B
- Let S be $\frac{B}{2^l-1}$. It represents the number in the [0, 1] interval.
- By multipying with (b-a) and adding a, B gets transported into the [a,b] interval.

2.2 Selection methods

For this experiment, there have been used 3 selection methods.

2.2.1 Roulette Wheel

It is also knows as **Fitness proportionate selection**. It is a genetic operator which selects potentially useful solutions for recombination. It uses the fitness levels of the individuals to associate a probability of selection with each individual. [20]

Let f_i be the fitness level of the chromosome i, then the probability of selecting the i chromosome out of the **N** chromosomes is:

$$p_i = \frac{f_i}{\sum_{i=1}^N f_i}$$

A portion of the wheel is assigned to each of the possible selections based on their fitness value.

The analogy to a roulette wheel can be envisaged by imagining a roulette wheel in which each candidate solution represents a pocket on the wheel; the size of the pockets are proportionate to the probability of selection of the solution. Selecting N chromosomes from the population is equivalent to playing N games on the roulette wheel, as each candidate is drawn independently. [20]

2.2.2 Tournament

Tournament selection is a method of selecting an individual. It involved running several "tournaments" among a few chromosomes chose at random from the population. The winner of each tournament will be slotted into the new population. In a tournament of size k, the best individual is chosen with a probability p, the second best with probability $p \cdot (1-p)$, the third best with the probability $p \cdot (1-p)^2$ and so on. Deterministic tournaments selection selects the best individual in any tournament, p = 1.[24]

There are two variants of the tournament selection: with replacement and without replacement. In the former, an individual who participated in a tournament can be re-elected to compete in another one. In addition, the same individual can compete with itself thus producing noise with this variant. In the latter, an individual who has been selected for a match cannot be selected again for the next match and no same individual participates in a match, so that each individual has the same opportunity to be selected for a match. [23]

The tournament selection procedure follows two steps which are repeated until the population size desired is satisfied[25]:

- a group of k individuals are chosen at random from the current population
- the best individual is selected for the mating pool

Commonly used tournament sizes are: 2,4 and 7[26]. These sizes are used to illustrate how the tournament size affects the selection behaviour. As the size of the tournament grows the selection pressure grows as well. With more individuals in a tournament, it is less likely for a less fit individual to be selected as the winner of a tournament.

For this experiment, the deterministic tournament selection with replacement has been used and the tournament size k belongs in $\{2,7\}$. In this experiment, the selection for the tournament is done this way:

- let *popSize* be the size of population
- let r be a random integer belonging in [1,popSize]

- the r^{th} individual is selected to participate in the tournament
- repeat until the desired size of the tournament is achieved

2.2.3 Elitist

Introduced by Ken De Jong(1975), elitism is an additional scheme to any selection method. It keeps the k best individuals at each generation to be transferred into the next generation[19].

For this experiment, at any generation, the 20 best individuals of the current population are selected to perform a crossover operation resulting in an additional 20 individuals added to the current population. From the new population, a percentage p is selected to be kept in the new population. To fill the population back to its original size, a **Roulette Wheel selection** is performed on the individuals that have not been selected.

For this experiment, $p \in \{4, 10\}$.

2.3 Crossover methods

It is a probability-based crossover selection. Let p_{cx} be the general crossover probability.

For each individual a random number $r_i \in [0,1)$ is assigned representing the crossover probability. The population is sorted based on this probability. All individuals that have a lower probability than p_{cx} are selected for the crossover operation. If the number of participants is odd, then there is a 50% chance that the last individual will perform a crossover with the next one.

2.3.1 Replacement

This crossover operation is applied on 2 individuals. Let cp be a random integer representing a single cut point around which the operation will be performed on. The crossover operation is applied on the 2 individuals and their offspring replace them in the population.

2.3.2 Elitist

The crossover operation is applied on the 2 individuals resulting in 2 offspring. Between the 4 of them, the 2 best fit individuals are kept in the population.

3 Experiment

For the experiment, a set of functions was selected for the genetic algorithm to be applied to determine the global minimum of each function. To measure the accuracy and the amount of time it takes to arrive at a result we've tested the algorithm with different number of dimensions. The precision of the values that was used is 10^{-5} . The mutation probability 1%. The crossover probability is 20%. These probabilities are constant across the experiment. The sample size is 30.

The following functions were tested with a population size equal to 100 and 200. They have also been tested with 1000 and 10000 generations. Roulette Wheel will be referred as **W**, Tournament as **T** and Elite as E. Replacement will be referred as **R** and Elitist as **E**. Let δ be the notation for the time measured in seconds and

let CX be the notation for the crossover method. Let G be the notation of the number of generations. Let D be the number of dimensions.

The experiment has been benchmarked on an AMD Ryzen 5 3600x.

3.1 De Jong's function 1

It is also known as the sphere model. It is continuous, convex and unimodal.

$$f(x) = \sum_{i=1}^{n} x_i^2$$
 $x_i \in [-5.12, 5.12]$

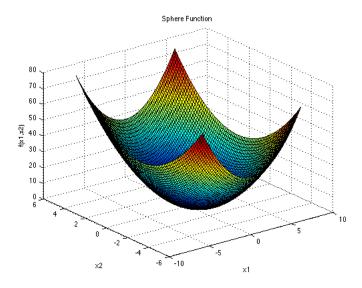


Figure 1: De Jong's function 1[7]

Dimensions	Global minimum
5	0
10	0
30	0

Table 1: De Jong's sphere function known global minima[3]

3.1.1 Fitness function

Let f_1 be De Jong's function and D_1 its fitness function.

$$D_1(x) = (f_1(x))^{-8}$$
 ; $x \in [-5.12, 5.12]^n$, $n \ge 1$

De Jong's sphere function has values in \mathbb{R}_+ and its global minimum is 0. Because of this, the fitness function is De Jong's function raised to a negative value. This means that values that are far from 0 will be less fit while values near 0 will be more fit. Because of hardware limitation, it is extremely unlikely that 0 will be reached thus avoiding the $\frac{1}{0}$ case.

3.1.2 Results

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	0	0	0	0.715
5	11	10000	0	0	0	0	7.229
	Е	1000	0	0	0	0	0.718
		10000	0	0	0	0	6.784
	R	1000	0	0	0	0	1.408
10	11	10000	0	0	0	0	14.162
	Е	1000	0	0	0	0	1.397
	127	10000	0	0	0	0	12.948
	R	1000	6e-5	6.5e-4	2.1e-4	1.2e-4	4.178
30	E	10000	6e-5	2.2e-3	3e-4	3.8e-4	39.264
		1000	5e-5	4e-4	1.68e-3	1.7e-4	4.182
	12	10000	1e-5	3.6e-4	1.5e-4	8e-5	38.49

Table 2: De Jong's function. Population 100. Roulette Wheel Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	\mid R \mid	1000	0	0	0	0	1304
5	11	10000	0	0	0	0	13.561
	Е	1000	0	0	0	0	1.335
	12	10000	0	0	0	0	13.949
	R	1000	0	0	0	0	2.543
\parallel_{10}	10	10000	0	0	0	0	27.246
10	Е	1000	0	0	0	0	2.547
	12	10000	0	0	0	0	27.673
	R	1000	0	3e-5	1e-5	0	7.69
30	10	10000	0	3e-5	1e-5	0	79.694
30	E	1000	0	1e-5	0	0	7.514
	127	10000	0	1e-5	0	0	83.160

Table 3: De Jong's function. Population 200. Roulette Wheel Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	e-5	0	0	0.978
5	10	10000	0	3e-5	0	0	9.42
3	Е	1000	0	0	0	0	0.98
	Е	10000	0	0	0	0	9.487
	R	1000	1.685e-2	9.122e-2	4.065e-2	1.771e-2	1.863
\parallel_{10}	10	10000	1.118e-2	9.047e-2	4.083e-2	2.027e-2	18.308
10	E	1000	7.9e-4	1.06e-2	4.29e-3	2.18e-3	1.84
	15	10000	1.22e-3	2.697e-2	5.54e-3	4.7e-3	18.443
	R	1000	14.5845	30.4525	21.68601	4.06314	5.4431
30	10	10000	0	0	0	0	0
\parallel 30	E	1000	7.91	21.1193	14.79087	3.41132	5.502
		10000	8.506	19.907	13.97039	3.10695	54.534

Table 4: De Jong's function. Population 100. Tournament Size 2 Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	0	0	0	1.917
\parallel 5	10	10000	0	1e-5	0	0	18.852
	E	1000	0	0	0	0	1.909
		10000	0	0	0	0	18.721
	R	1000	3.14e-3	4.099e-2	2.104e-2	7.89e-3	3.665
\parallel_{10}	10	10000	5.56e-3	3.84e-2	1.772e-2	6.99e-3	36.595
10	E	1000	01.14e-3	6.47e-3	2.53e-3	1.18e-3	3.644
		10000	8.1e-4	5.87e-3	2.35e-3	1.28e-3	37.014
	\mathbb{R}	1000	11.879	26.4213	18.20133	3.25344	10.884
30	E	10000	11.0076	28.6056	18.6056	3.78328	108.9419
		1000	6.736	14.531	10.32632	1.89222	10.6424
	12	10000	5.93929	16.4262	11.04394	2.42318	109.650

Table 5: De Jong's function. Population 200. Tournament Size 2 Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	0	0	0	1.021
5	Ι 1	10000	0	0	0	0	10.255
	Е	1000	0	0	0	0	1.073
	15	10000	0	0	0	0	10.192
	R	1000	0	0	0	0	1.928
\parallel_{10}	10	10000	0	0	0	0	19.137
10	E	1000	0	0	0	0	1.913
	15	10000	0	0	0	0	19.4878
	R	1000	0.12245	0.40119	0.23063	6.4103e-2	5.444
30	E	10000	0.10284	0.31039	0.21611	4.649e-2	55.476
		1000	7.638e-2	0.18912	0.12073	0.02856	5.535
	15	10000	8.491e-2	0.2012	0.13241	3.041e-2	55.590

Table 6: De Jong's function. Population 100. Tournament Size 7 Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	0	0	0	2.081
5	11	10000	0	0	0	0	20.719
	E	1000	0	0	0	0	2.044
	12	10000	0	0	0	0	20.805
	R	1000	0	0	0	0	3.9128
10	10	10000	0	0	0	0	39.006
	E	1000	0	0	0	0	3.852
	127	10000	0	0	0	0	39.0868
	R	1000	7.725e-2	0.25618	0.15159	3.840e-2	11.037
\parallel_{30}	E	10000	0.10011	0.22638	0.15183	3.572e-2	111.934
30		1000	3.631e-2	0.10897	7.446e-2	1.982e-2	11.2769
	II)	10000	3.329e-2	0.13918	7.039e-2	2.582e-2	111.702

Table 7: De Jong's function. Population 200. Tournament Size 7 Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	0	0	0	0.963
5	11	10000	0	0	0	0	9.386
'	Е	1000	0	0	0	0	0.9164
	12	10000	0	0	0	0	9.4124
	R	1000	0	0	0	0	1.784
10	10	10000	0	0	0	0	18.292
10	Е	1000	0	0	0	0	1.830
	12	10000	0	0	0	0	18.426
	R	1000	0.11496	0.31613	0.19630	3.875e-2	5.365
30	11	10000	0.14341	0.25242	0.19137	3.433e-2	55.384
30	Е	1000	4.772e-2	0.13081	9.056e-2	1.898e-2	5.444
	12	10000	4.799e-2	0.12531	8.772e-2	1.819e-2	55.251

Table 8: De Jong's function. Population 100. Elitist 4% Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	0	0	0	1.8865
5	1ι	10000	0	0	0	0	18.996
	E	1000	0	0	0	0	1.860
	1 12	10000	0	0	0	0	18.9344
	R	1000	0	0	0	0	3.544
\parallel_{10}	10	10000	0	0	0	0	37.056
10	Е	1000	0	0	0	0	3.550
	1 12	10000	0	0	0	0	37.350
	R	1000	3.547e-2	0.19841	9.702e-2	9.702e-2	3.12e-2
30	11	10000	5.414e-2	0.16107	8.289e-2	2.112e-2	112.264
30	E	1000	2.614e-2	5.330e-2	3.737e-2	5.64e-3	11.006
		10000	2.492e-2	4.341e-2	3.447e-2	5.13e-3	111.152

Table 9: De Jong's function. Population 200. Elitist 4% Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	0	0	0	0.916
5	16	10000	0	0	0	0	9.495
	Е	1000	0	0	0	0	0.926
	נ	10000	0	0	0	0	9.347
	R	1000	0	3e-5	0	0	1.810
\parallel_{10}	11	10000	0	0	0	0	18.506
10	E	1000	0	0	0	0	1.863
	Ľ	10000	0	0	0	0	18.737
	R	1000	1.11611	2.19555	1.59099	0.26148	5.409
30	16	10000	1.10619	2.22242	1.67441	0.28846	55.320
30	Е	1000	0.55377	0.97561	0.80212	0.10142	5.435
		10000	0.60634	1.03441	0.78544	0.12994	55.728

Table 10: De Jong's function. Population 100. Elitist 10% Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	0	0	0	1.861
5	10	10000	0	0	0	0	18.949
	Е	1000	0	0	0	0	1.8875
		10000	0	0	0	0	19.051
	R	1000	0	2e-5	0	0	3.649
10	10	10000	0	0	0	0	36.8938
10	E	1000	0	0	0	0	3.672
		10000	0	0	0	0	37.94
	R	1000	0.66148	1.30247	0.97214	0.15807	11.079
30	E	10000	0.58611	1.12637	0.84575	0.14369	111.360
30		1000	0.29507	0.61002	0.411524	6.664e-2	10.894
	12	10000	0.28803	0.46076	0.36483	4.212e-2	111.283

Table 11: De Jong's function. Population 200. Elitist 10% Selection.

3.2 Schwefel's function

Schwefel's function is deceptive in that the global minimum is geometrically distant, over the parameter space, from the next best local minima. Therefore, the search algorithms are potentially prone to convergence in the wrong direction.

$$f(x) = \sum_{i=1}^{n} -x_i \cdot \sin\left(\sqrt{|x_i|}\right)$$
 $x_i \in [-500, 500]$

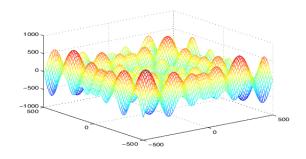


Figure 2: Schwefel's function[8]

Dimensions	Global minima
5	-2094.9145
10	-4189.829
30	-12569.487

Table 12: Schwefel's function known global minima[4]

3.2.1 Fitness function

Let f_2 be Schwefel's function and S_7 its fitness function. For this paper two fitness functions have been used. Let these functions be S'_7 and S''_7 .

$$\begin{cases} S_7'(x) = \left(\frac{\arctan(f_2(x)) + \frac{\pi}{2}}{\pi}\right)^{-25} \\ S_7''(x) = 1.015^{\sqrt{\left(\frac{\arctan(f_2(x)) + \frac{\pi}{2}}{\pi}\right)^{-2}}} \end{cases}, x \in [-500, 500]^n, \quad n \ge 1 \end{cases}$$

Because Schwefel's function has values in \mathbb{R} , it was necessary to find a function that is defined on \mathbb{R} and has a restrictive codomain. The found function was arctan as its domain is \mathbb{R} and codomain is $\left(-\frac{\pi}{2}, \frac{\pi}{2}\right)$. It is known that for this from of Schwefel's function, the global minimum is a negative value and by applying the arctan function the function will get mapped to arctan's codomain in such a way that the minimum will be close to $-\frac{\pi}{2}$ and positive values will be above 0. The fitness function is a positive function so $\frac{\pi}{2}$ was added and then it was divided by π to get a restrictive interval to raise the selection pressure. Now the global minimum is a value close to 0. To get high values of fitness for a function with values belonging to (0,1), the result is raised to a negative power. The exponent was found empirically. This is the S_7' fitness function.

Through multiple experiments it was observed that this fitness function doesn't have a high enough selection pressure. Because of this, there was used an exponential function for which the exponent was initially S'_7 but due to hardware limitations it couldn't be tested. While S''_7 is mathematically equivalent to

$$1.015^{\left(\frac{\arctan(f_2(x)+\frac{\pi}{2}}{\pi}\right)^{-1}}$$

due to hardware limitation, S_7'' yielded better results than the function above. The base of the exponential function was found empirically.

Because S'_7 didn't have great results, its data was not included in this paper but it is still mentioned as it is the base of the fitness function that was used.

3.2.2 Results

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-2094.8	-2059.85	-2093.03166	6.27556	1.328
\parallel 5	10	10000	-2094.78	-2093.48	-2094.4353	0.29200	9.604
	Е	1000	-2094.88	-2094.21	-2094.58266	0.16606	1.345
		10000	-2094.79	-2094.17	-2094.586	0.16397	9.50606
	R	1000	-4188.87	-4153.2	-4186.06233	6.27485	2.580
\parallel_{10}	10	10000	-4189.17	-4186.05	-4187.70166	0.90815	18.795
	E	1000	-4189.41	-4069.64	-4184.077	21.62934	2.694
	Ľ	10000	-4189.38	-4187.02	-4188.54866	0.61963	18.90926
	R	1000	-12463.1	-11840.4	-12241.81333	148.76857	7.929
\parallel_{30}	10	10000	-12551.7	-12500.4	-12535.113	9.349	56.81526
	E	1000	-12458.1	-11894.3	-12307.58666	124.160	7.956
	1	10000	-12554.8	-12522.3	-12540.94333	6.65772	56.561

Table 13: Schwefel's function. Population 100. Roulette Wheel Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-2094.87	-2094.02	-2094.45733	0.18902	1.904
5	11	10000	-2094.89	-2094.34	-2094.70266	0.15242	19.022
	Е	1000	-2094.89	-2094.37	-2094.591	0.14905	1.859
	Ľ	10000	-2094.9	-2094.2	-2094.6493	0.15065	19.249
	\mathbb{R}	1000	-4188.68	-4186.53	-4187.93	0.62240	3.811
\parallel_{10}	10	10000	-4189.53	-4187.24	-4188.39533	0.66385	37.94773
	E	1000	-4189.43	-4187.56	-4188.67633	0.43201	3.744
		10000	-4189.43	-4188.22	-4188.75866	0.31439	38.070
	R	1000	-12501.6	-12102.5	-12321.23666	93.06507	11.206
30	10	10000	-12556.8	-12535.7	-12548.61666	5.05958	113.375
	E	1000	-12520	-11986.4	-12337.64666	107.303	11.324
		10000	-12560.2	-12537.4	-12551.22	5.30714	113.7873

Table 14: Schwefel's function. Population 200. Roulette Wheel Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-2094.91	-2094.29	-2094.64433	0.13348	0.977
5	11	10000	-2094.91	-2094.4	-2094.65166	0.1573	9.724
	Е	1000	-2094.91	-2060.57	-2093.5166	6.22422	0.964
	ப்	10000	-2094.91	-2094.37	-2094.67366	0.11885	9.680
	R	1000	-4187.15	-4019.22	-4156.124	35.68590	1.903
\parallel_{10}	11	10000	-4183.28	-4142.39	-4169.15233	8.75971	19.222
10	Е	1000	-4188.56	-4110.15	-4175.50266	20.83982	1.894
		10000	-4187.68	-4177.16	-4184.175	2.813	19.149
	R	1000	-10035	-8495.86	-9177.82133	395.63129	5.717
30	10	10000	-10289.6	-8834.29	-9383.55433	310.95300	57.129
	Е	1000	-10848.1	-9073.86	-9962.037	373.61167	5.705
	12	10000	-11042.2	-9149.34	-10062.935	407.690	57.044

Table 15: Schwefel's function. Population 100. Tournament Size 2 Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-2094.91	-2094.46	-2094.74633	0.14172	1.947
5	10	10000	-2094.91	-2094.56	-2094.74733	0.090665	19.354
'	Е	1000	-2094.91	-2094.49	-2094.7356	0.11681	1.941
	15	10000	-2094.81	-2094.39	-2094.70033	0.09901	19.628
	R	1000	-4184.86	-4148.65	-4173.143	7.68670	3.792
\parallel_{10}	10	10000	-4184.5	-4163.56	-4175.577	5.18554	38.337
10	E	1000	-4189.09	-4183.91	-4187.076	1.32482	3.816
	L	10000	-4189.52	-4185.67	-4187.685	1.0396	38.4745
	R	1000	-10452.8	-9233.94	-9855.716	300.94153	11.386
30	10	10000	-11370.8	-9391.27	-10035.93	418.56131	114.702
	E	1000	-11210.1	-9967.85	-10624.11	300.93115	11.393
	ניו	10000	-11222.2	-10042.8	-10534.21666	298.60231	114.55746

Table 16: Schwefel's function. Population 200. Tournament Size 2 Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-2094.81	-2094.5	-2094.673	0.08009	1.04896
5	11	10000	-2094.81	-2094.5	-2094.637	0.08867	10.312
3	E	1000	-2094.91	-2094.4	-2094.614	0.11037	1.048
	E	10000	-2094.81	-2094.5	-2094.62366	0.10736	10.504
	R	1000	-4189.72	-4070.75	-4184.23233	22.31005	1.982
\parallel_{10}	11	10000	-4189.62	-4188.89	-4189.257	0.20463	19.750
10	Е	1000	-4189.52	-4154.84	-4187.01866	8.7167	1.955
		10000	-4189.62	-4188.89	-4189.267	0.17620	19.940
	R	1000	-12142.9	-11401.9	-11815.1	202.49877	5.723
30	10	10000	-12506.6	-12385.6	-12448.87666	32.83440	57.458
30	E	1000	-12259.7	-11515.1	-11904.90666	236.70704	5.728
	12	10000	-12522.3	-12441.5	-12489.48	21.77849	57.556

Table 17: Schwefel's function. Population 100. Tournament Size 7 Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-2094.91	-2094.4	-2094.67166	0.12830	2.069
5	10	10000	-2094.91	-2094.4	-2094.67333	0.11336	21.062
	E	1000	-2094.91	-2094.5	-2094.682	0.11801	2.097
		10000	-2094.81	-2094.4	-2094.63766	0.10711	21.072
	R	1000	-4189.62	-4188.79	-4189.27366	0.204475	3.954
10	10	10000	-4189.52	-4189	-4189.28533	0.12266	39.764
10	Е	1000	-4189.62	-4189	-4189.28766	0.16424	3.962
		10000	-4189.62	-4189.1	-4189.29633	0.14135	39.686
	R	1000	-12383.5	-11862.8	-12202.22666	131.349	11.504
\parallel_{30}	10	10000	-12512.2	-12440.4	-12479.49333	11.72006	115.421
	E	1000	-12443.2	-12026.4	-12218.49666	125.69742	11.539
	12	10000	-12530.7	-12494.1	-12511.123333	9.42742	115.848

Table 18: Schwefel's function. Population 200. Tournament Size 7 Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-2094.91	-2094.49	-2094.733	0.09494	1.214
5	10	10000	-2094.91	-2094.49	-2094.707	0.1221	12.468
	Е	1000	-2094.91	-2094.5	-2094.70633	0.10216	1.2111
	15	10000	-2094.91	-2094.5	-2094.70933	0.14205	12.452
	R	1000	-4189.61	-4120.11	0-4175.379	21.11138	2.485
\parallel_{10}	10	10000	-4189.59	-4188.33	-4188.84633	0.29463	24.768
10	Е	1000	-4189.45	-4146.51	-4183.227	13.54196	2.463
	12	10000	-4189.56	-4188.65	-4189.173	0.21719	25.137
	R	1000	-11355.2	-9806.81	-10637.4733	387.789	7.369
30	10	10000	-12336.5	-11686	-12045.44666	190.54121	74.592
	E	1000	-11637.6	-10223.9	-10970.48666	334.92574	7.259
	12	10000	-12487.3	-11908.2	-12314.55	131.42920	74.581

Table 19: Schwefel's function. Population 100. Elitist 4% Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-2094.91	-2094.5	-2094.72066	0.09310	2.447
\parallel 5	10	10000	-2094.91	-2094.6	-2094.77466	0.10941	25.124
	E	1000	-2094.91	-2094.5	-2094.72433	0.105460	2.43213
		10000	-2094.91	-2094.5	-2094.75533	0.10318	25.257
	R	1000	-4189.76	-4155.03	-4187.99833	6.23309	4.867
\parallel_{10}	11	10000	-4189.76	-4188.66	-4189.20766	0.242468	50.476
	E	1000	-4189.57	-4188.88	-4189.271	0.17786	5.052
	12	10000	-4189.66	-4188.8	-4189.25833	0.20525	50.131
	R	1000	-11341.1	-9575.88	-10574.42966	407.55289	14.797
\parallel_{30}	10	10000	-12297	-11218	-11944.963333	238.08588	150.735
	E	1000	-11331.2	-9631.03	-10681.253	394.62144	14.825
	12	10000	-12461	-11700.2	-12105.84666	207.18577	151.620

Table 20: Schwefel's function. Population 200. Elitist 4% Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-2094.91	-2094.49	-2094.72	0.12884	1.269
\parallel 5	11	10000	-2094.91	-2094.49	-2094.72166	0.10728	12.788
	Е	1000	-2094.91	-2094.39	-2094.647	0.13610	1.233
		10000	-2094.91	-2094.5	-2094.64333	0.11090	12.312
	R	1000	-4189.09	-4012.95	-4161.80166	43.32211	2.422
10	10	10000	-4189.31	-4187.36	-4188.40733	0.54486	24.670
	E	1000	-4189.55	-4120.35	-4185.621	13.81011	2.455
	l E	10000	-4189.65	-4188.42	-4189.10366	0.27577	24.976
	R	1000	-11168.7	-9486.87	-10250.788	411.99165	7.441
30	10	10000	-12123.4	-11075.1	-11676.3533	276.783675	73.775
	E	1000	-11687.2	-9521.37	-10502.56366	499.54363	7.398
	12	10000	-12157.8	-11255.4	-11796.76	229.78904	74.320

Table 21: Schwefel's function. Population 100. Elitist 10% Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-2094.91	-2094.6	-2094.766	0.10457	2.484
5	10	10000	-2094.91	-2094.6	-2094.80866	0.09365	25.291
"	Е	1000	-2094.91	-2094.5	-2094.73166	0.09255	2.411
	10	10000	-2094.91	-2094.6	-2094.77566	0.09038	25.167233
	R	1000	-4189.41	-4154.66	-4187.48166	6.23637	4.746
\parallel_{10}	10	10000	-4189.48	-4188.08	-4188.69666	0.32958	50.194
10	Е	1000	-4189.66	-4188.74	-4189.19033	0.26827	4.846
	L	10000	-4189.63	-4188.56	-4189.18266	0.25392	49.149
	R	1000	-11228.4	-9791.59	-10562.40133	379.48162	14.962
30	10	10000	-12138.8	-10957.6	-11562.3666	263.68360	0150.128
30	E	1000	-11308.6	-10026.1	-10705.14333	321.08802	14.835
	L	10000	-12050.8	-11172.3	-11172.3	250.34544	146.582

Table 22: Schwefel's function. Population 200. Elitist 10% Selection.

3.3 Rastrigin's function

This function has many local minima thus this test function is multimodal. The location of the minima are regularly distributed.

$$f(x) = 10 \cdot n + \sum_{i=1}^{n} (x_i^2 - 10 \cdot \cos(2 \cdot \pi \cdot x_i)) \qquad x_i \in [-5.12, 5.12]$$

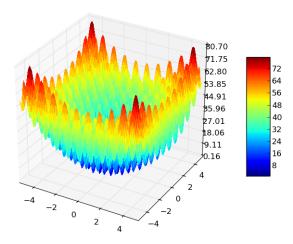


Figure 3: Rastrigins's function[9]

Dimensions	Global Minimum
5	0
10	0
30	0

Table 23: Rastrigin's function known global minima[5]

3.3.1 Fitness function

Let f_6 be Rastrigin's function and R_6 its fitness function.

$$R_6(x) = (f_6(x))^{-15} \; ; \; x \in [-5.12, 5.12]^n \; ; \; n \ge 1$$

Similar to De Jong's function, Rastrigin's function only has positive values and its global minimum is 0. Because of this a similar strategy was applied as the concepts applied for De Jong's function also apply to this one. The absolute value of the exponent was raised in trying to raise the selection pressure.

3.3.2 Results

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	12.3714	3.13256	2.76663	0.716
5		10000	0	2.4834	0.78437	0.889900	7.201
	E	1000	0	6.16358	1.27744	1.39421	0.721
		10000	0	2.47297	0.94794	0.77404	7.135
	R	1000	1.24144	19.9523	6.254917	4.38606	1.420
10	10	10000	0	6.18413	2.455547	1.51920	14.1819
	Е	1000	0	12.3958	4.55714	3.43295	1.397
		10000	0	8.66267	2.23845	1.735	14.125
	R	1000	24.7944	49.3061	34.76536	7.10413	4.209
30	10	10000	1.60464	26.6147	12.745215	6.47888	42.165
	Е	1000	13.5127	53.0354	31.74513	9.8899	4.16386
	127	10000	4.35842	34.1293	15.80399	7.24689	42.207

Table 24: Rastrigin's function. Population 100. Roulette Wheel Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	6.16986	2.02250	1.82264	1.391
5	10	10000	0	1.23786	0.20622	0.46901	14.465
	E	1000	0	3.70997	1.730831	0.89514	1.448
	l E	10000	0	1.23648	0.37081	0.57610	14.507
	R	1000	0	11.1945	4.27408	2.95424	2.768
10	10	10000	0	3.7387	1.4517	0.9856	28.221
10	Е	1000	0	12.3623	4.17227	2.93762	2.833
		10000	0	02.4863	0.9922	0.9443	28.451
	\mathbb{R}	1000	10.0644	45.115	28.76103	7.47784	8.41883
30	10	10000	4.23932	19.3346	10.2431	3.915104	84.324
	E	1000	9.28699	48.8435	25.06786	9.507925	8.324
	12	10000	4.00942	17.4161	10.11461	3.81334	84.331

Table 25: Rastrigin's function. Population 200. Roulette Wheel Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0.000226762	2.4838	0.66190	0.77964	0.868
5		10000	4e-5	1.23757	0.08405	0.31349	9.564
	E	1000	0	2.47201	0.7827	0.8878	0.879
	15	10000	0	2.47167	0.28837	0.62286	9.539
	R	1000	4.24688	13.8916	8.2276	2.699	1.829
10	11	10000	3.10801	12.2861	6.62671	2.43623	18.649
10	Е	1000	0.7369	11.3394	4.77417	3.04361	1.773
		10000	0.213861	3.48877	1.242717	0.79220	18.413
	R	1000	149.012	213.559	178.094	16.6952	0
30	10	10000	151.219	217.571	179.5222	017.21008	54.279
	Е	1000	129.49	178.498	153.7466	12.8095	5.374
	L	10000	125.353	179.814	153.4707	11.4841	55.162

Table 26: Rastrigin's function. Population 100. Tournament Size 2 Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	2e-5	4.96153	0.45425	1.00239	1.873
5	10	10000	2e-5	1.23739	0.04165	0.22583	18.991
'	E	1000	0	1.2378	0.32962	0.55595	1.850
	E	10000	0	1.23584	0.04119	0.2256	18.931
	R	1000	2.17334	8.84327	4.896658	1.62609	3.780
10	10	10000	1.07972	6.53882	3.77150	1.27174	37.573
	Е	1000	0.19927	8.70614	2.8665	2.2099	3.632
	177	10000	0.18295	0.96521	0.50493	0.19816	36.550
	R	1000	123.213	189.285	156.50936	14.103721	10.717
30	10	10000	124.624	0202.596	0163.8809	018.382	109.60
30	E	1000	94.107	164.206	132.166	15.70035	11.013
	II)	10000	118.05	157.246	136.3946	10.5377	108.771

Table 27: Rastrigin's function. Population 200. Tournament Size 2 Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	4.92341	1.3999	1.28542	1.063
5	10	10000	0	2.47165	0.82388	0.87886	10.242
	Е	1000	0	3.70747	1.27701	1.1466	1.057
	E	10000	0	3.70747	1.02985	1.17390	10.412
	R	1000	0	12.3185	4.14596	2.90730	1.91
10	10	10000	0	6.17926	2.47166	01.45142	19.492
	Е	1000	0	11.0827	4.67151	3.01899	1.91856
		10000	0	6.17914	2.1420	1.51993	19.244
	R	1000	38.1732	64.8228	51.4465	7.16074	5.536
30	10	10000	33.8836	59.572	42.8753	6.4801	55.424
	Е	1000	28.969	67.6087	44.42737	8.3098	5.477
	127	10000	20.0223	44.1675	29.44718	5.677646	55.845

Table 28: Rastrigin's function. Population 100. Tournament Size 7 Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	3.70747	0.90626	0.91411	2.082
5	10	10000	0	2.47165	0.45313	0.75996	20.854
	E	1000	0	4.92341	0.864413	1.26100	2.079
	E	10000	0	2.47165	0.37074	0.66114	20.541
	R	1000	0	6.17912	2.3892	1.652	3.7958
10	11	10000	0	3.70747	1.23582	1.02629	39.070
	E	1000	0	8.63088	2.79987	1.91534	3.84093
		10000	0	4.94329	1.60656	1.26321	38.666
	R	1000	28.1596	54.1222	38.27772	7.44445	11.021
30	10	10000	24.0303	39.3919	30.4737	3.62003	111.634
	Е	1000	23.1432	51.7928	35.4086	06.28163	11.105
		10000	11.5961	27.7319	18.84358	3.60846	110.393

Table 29: Rastrigin's function. Population 200. Tournament Size 7 Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	7.39569	2.14014	1.80004	0.880
5	10	10000	0	4.94393	0.98868	1.14291	9.4290
	E	1000	0	6.15924	1.35807	1.66199	0.92656
	E	10000	0	3.70747	0.8238	1.0432	9.467
	R	1000	1.24461	18.6696	6.63286	3.93677	1.757
\parallel_{10}		10000	0	11.2868	3.44543	2.37900	18.3411
	Е	1000	0	17.6901	5.17721	4.3217	1.805
		10000	0	8.65344	2.76613	1.6466	18.216
	\mathbb{R}	1000	43.115	80.749	64.411	9.2469	5.410
30	10	10000	24.6597	66.6703	43.81157	10.30359	54.8576
	Е	1000	39.0904	71.8314	56.07896	7.693113	5.296
		10000	19.6891	50.0474	34.7075	7.28760	54.767

Table 30: Rastrigin's function. Population 100. Elitist 4% Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	2.47165	0.74149	0.69606	1.842
$\parallel 5$	10	10000	0	1.23582	0.20597	0.468436	19.068
	Е	1000	0	2.47165	0.90626	0.91411	1.831
	E	10000	0	2.47165	0.49432	0.69606	18.918
	\mathbb{R}	1000	0	16.8438	3.26068	3.30798	3.499
\parallel_{10}	10	10000	0	4.96189	2.0656	1.275	36.729
10	E	1000	0	9.88327	2.88446	2.20757	3.628
		10000	0	3.71153	1.31913	1.2550	37.044
	\mathbb{R}	1000	35.7065	74.8751	55.6209	9.33955	10.6573
30	10	10000	22.7985	53.816	36.14355	8.34212	111.326
	Е	1000	32.2477	72.6688	52.8739	10.5313	10.980
	12	10000	19.9112	47.4114	32.730	6.9044	111.028

Table 31: Rastrigin's function. Population 200. Elitist 4% Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	2.47173	0.741502	0.69607	0.942
5	11	10000	0	2.47179	0.576732	0.842178	9.348
	E	1000	0	2.47165	0.94746	0.77370	0.921
	E	10000	0	2.47165	0.61791	0.77822	9.384
	R	1000	1.2589	12.163	6.49084	2.9391	1.754
\parallel_{10}	10	10000	1e-5	7.60593	2.80613	02.07372	18.299
	Е	1000	0	12.1473	4.6141	3.2511	1.8547
		10000	0	6.25973	2.61520	1.7152	18.420
	R	1000	61.8625	117.239	89.45779	12.18508	5.276
30	10	10000	75.4772	124.637	95.19794	11.2647	55.402
	Е	1000	61.8294	107.378	80.68672	10.762879	5.432
		10000	61.3818	98.3481	79.79041	9.84086	55.613

Table 32: Rastrigin's function. Population 100. Elitist 10% Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	0	2.47191	0.53553	0.7737	1.836
5	10	10000	0	1.23594	0.24717	0.502793	18.602
	E	1000	0	1.23582	0.3295	0.55584	1.862
	E	10000	0	1.23582	0.28835	0.531628	18.814
	R	1000	0.001768	9.27334	3.86537	2.0534	3.628
\parallel_{10}	10	10000	5e-5	6.2222	2.196520	1.929	37.147
10	Е	1000	3e-5	9.92494	2.02883	2.174935	3.611
		10000	0	4.98049	1.3667903	1.320420	37.156
	R	1000	61.5287	104.474	80.7117	9.91440	11.084
30	10	10000	52.1792	80.84757	12.75810	78.593	78.1657
30	Е	1000	51.9528	94.6591	71.2116	10.068	10.947
	II.	10000	49.0876	78.6627	64.52396	7.61233	110.703

Table 33: Rastrigin's function. Population 200. Elitist 10% Selection.

3.4 Michalewicz's function

The Michalewicz function is a multimodal test function (n! local optima). The parameter m defines the "steepness" of the valleys or edges. Larger m leads to more difficult search. For very large m the function behaves like a needle in the haystack (the function values for points in the space outside the narrow peaks give very little information on the location of the global optimum).

$$f(x) = -\sum_{i=1}^{n} \sin(x_i) \cdot \left(\sin\left(\frac{i \cdot x_i^2}{\pi}\right)\right)^{2 \cdot m} \qquad x_i \in [0, \pi], \ i = \overline{1, n}, \ m = 10$$

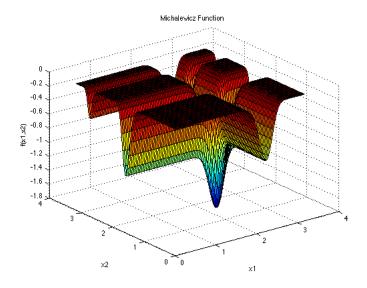


Figure 4: Michalewiczs's function[10]

3.4.1 Fitness function

Let f_{12} be Michalewicz's function and M_{12} its fitness function.

Dimensions	Global minimum
5	-4.68765
10	-9.66015
30	-29.63088

Table 34: Michalewicz's function known global minima[6][13]

$$0.734375^{10 \cdot f_{12}(x)} \; ; \; x \in [0, \pi]^n \; ; \; n \ge 1$$

It is known that Michalewicz's function codomain is \mathbb{R}_{-} . Because of this, the fitness function that was chosen to be an exponential function with a subunit base. The base was found empirically. Through tests it was observed that the selection pressure wasn't big enough, so the exponent of the fitness function was multiplied by a constant which was found empirically.

3.4.2 Results

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-4.68665	-4.04753	-4.52338	0.16452	0.682
\parallel 5	10	10000	-4.68697	-4.37131	-4.56984	0.100284	6.864
	E	1000	-4.68716	-4.28968	-4.539941	0.1184	0.695
	E	10000	-4.68732	-4.33184	-4.618409	0.09218	6.860
	R	1000	-9.54396	-8.45847	-9.003703	0.256	1.3220
\parallel_{10}	10	10000	-9.60795	-9.05704	-9.34292	0.1508	13.226
	E	1000	-9.53408	-8.58867	-9.14373	00.2455	1.3223
	177	10000	-9.64323	-8.8229	-9.3521	0.18416	12.970
	R	1000	-27.4044	-25.3344	-26.4533	0.5097	3.954
30	10	10000	-28.3188	-26.6559	-27.661	0.4234	38.595
	E	1000	-27.7212	-25.7594	-26.55502	0.45451	03.897
	בנו	10000	-28.2843	-26.1553	-27.61295	0.49726604	38.261

Table 35: Michalewicz's function. Population 100. Roulette Wheel Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-4.68646	-4.20071	-4.58536	00.11489	1.326
5	10	10000	-4.68606	-4.37135	-4.608637	0.08860	13.050
	E	1000	-4.68756	-4.28938	-4.54350	0.1263	1.352
	E	10000	-4.68746	-4.3746	-4.6063	0.0989	13.461
	R	1000	-9.46672	-8.69141	0-9.17246	0.2047	2.578
10	11	10000	-9.65301	0-9.01823	-9.45302	0.14242	025.749
10	Е	1000	9.56896	-8.6616	-9.162	0.21955	2.592
		10000	-9.65496	-9.12065	-9.447157	0.1420	26.0911
	R	1000	-27.905	-26.3003	-27.05574	0.4134	7.587
\parallel_{30}	10	10000	-28.9833	-27.2146	-27.941	0.4218	76.550
30	Е	1000	-27.9482	-25.6845	-27.03641	0.58822	7.730
	II)	10000	-28.6328	0-27.3921	-28.15292	0.29416	76.130

Table 36: Michalewicz's function. Population 200. Roulette Wheel Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-4.68765	-4.21297	-4.557588	0.12792	0.838
5	10	10000	-4.68766	-4.53322	-4.647280	0.06315	9.186
'	E	1000	-4.68766	-4.34584	-4.554782	0.106554	0.888
	L L	10000	-4.68766	-4.52099	-4.6437736	0.067308	9.217
	R	1000	-9.39885	0-8.73731	-9.08253	0.2013	1.7639
10		10000	-9.47251	-8.87158	-9.295978	0.13707	17.460
10	Е	1000	-9.5514	-8.59084	-9.236962	0.221073	1.728
		10000	-9.60014	-8.89786	-9.4298	0.1431	17.930
	R	1000	-18.0847	-15.4588	-16.7429	0.688116	5.209
30	10	10000	-19.6651	-14.9498	-16.9432	0.94686	52.800
30	E	1000	-20.5018	-16.3653	-18.22425	0.96598	5.155
	LL I	10000	-19.972	-17.0553	-18.51653	0.7554	52.713

Table 37: Michalewicz's function. Population 100. Tournament Size 2 Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-4.68766	-4.49589	-4.65043	0.06114	1.750
\parallel 5	10	10000	-4.68766	-4.53765	-4.656352	0.06040	18.609
	Е	1000	-4.68766	-4.44861	-4.622058	0.072588	1.820
		10000	-4.68766	-4.53325	-4.66610466	0.051781995	18.507
	R	1000	-9.4939	-8.45033	-9.265648	0.196594	3.490
\parallel_{10}		10000	-9.60844	-9.23095	-9.42838	0.09293	35.539
10	Е	1000	-9.56956	-9.15147	-9.37648	0.11064	3.506
		10000	-9.61866	-9.35563	-9.521280	0.0752699	35.648
	R	1000	-19.6246	-16.5844	-18.1107	0.819287	10.358
\parallel_{30}	10	10000	-18.787	-16.8849	17.96740	0.499602	105.336
30	Е	1000	-21.9677	-18.3116	-19.73194	0.836456	10.483
	ן בו	10000	-21.4766	-18.0099	-19.5414	0.667850	105.464

Table 38: Michalewicz's function. Population 200. Tournament Size 2 Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-4.68759	-4.00497	-4.54115	0.14663	1.004
5	11	10000	-4.68766	-4.3749	-4.619496	0.08532	10.108
	E	1000	-4.68259	-4.22532	-4.519671	0.10882	1.009
	E	10000	-4.68766	-4.49147	-4.627467	0.07495	10.125
	R	1000	-9.64816	-8.73776	-9.17288	0.216054	1.828
\parallel_{10}		10000	-9.57622	-9.06254	-9.38931	0.12583	18.712
	Е	1000	-9.5154	-8.64455	-9.1223	0.2199	1.827
		10000	-9.6174	-9.31319	-9.479513	0.08147	18.750
	R	1000	-26.6512	-23.6535	-25.11856	0.792054	5.348
$\begin{vmatrix} 1 \\ 30 \end{vmatrix}$	10	10000	-26.3926	-24.4237	-25.4352	0.52070	53.557
	Е	1000	-27.2871	-23.229	-25.4666	0.8267	5.278
	Ľ	10000	-26.9416	-24.2861	-25.8696	0.6014	53.591

Table 39: Michalewicz's function. Population 100. Tournament Size 7 Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-4.68766	-4.46386	-4.625177	0.073633	1.953
5	10	10000	-4.68766	-4.51659	-4.6387	0.07057	20.255
	E	1000	-4.68766	-4.35636	-4.5853	0.102367	1.996
	E	10000	-4.68766	-4.53325	-4.65361	0.0599974	20.379
	R	1000	-9.62079	-8.74605	-9.331547	0.2154	3.662
10		10000	-9.66015	-9.3137	-9.5138	0.088501	37.583
	Е	1000	-9.6152	-8.78137	-9.30714	0.22576	3.666
		10000	-9.6584	-9.21681	-9.475173	0.1115605	37.763
	R	1000	-27.2777	-24.7643	-26.1514	0.6079	10.656
30	10	10000	-27.0252	-25.5022	-26.35791	0.46883292	107.670
	Е	1000	-27.4986	-25.3341	-26.377	0.5779	10.677
	L	10000	-27.7044	-26.2039	-26.99839	0.423504	107.657

Table 40: Michalewicz's function. Population 200. Tournament Size 7 Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-4.68766	-4.3452	-4.57914	0.1103	0.8911
5	10	10000	-4.68766	-4.37489	-4.63899	0.0843	9.076
	Е	1000	-4.68765	-4.28955	-4.57317	0.10611	0.89566
	E	10000	-4.68766	-4.3749	-4.62988	0.0842	9.078
	R	1000	-9.54987	-8.59083	-9.145465	0.21174	1.751
10		10000	-9.61339	-8.72356	-9.285025	0.193184	17.501
10	E	1000	-9.52844	-8.56709	-9.128245	0.2367390	1.756
		10000	-9.56823	-8.98266	-9.32155	0.171135	17.531
	R	1000	-26.0674	0-22.8548	-24.3669	0.727903	5.149
30	10	10000	-25.8179	-23.1063	-24.66749	0.654818	52.512
	Е	1000	-25.979	-23.0792	-24.7661	0.6905	5.136
	Ľ	10000	-25.9973	-24.2793	-25.1664	0.487865	52.5813

Table 41: Michalewicz's function. Population 100. Elitist 4% Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-4.68766	-4.3749	-4.64517	0.07831	1.750
5	10	10000	-4.68766	-4.53766	-4.6623133	00.05670	17.963
"	E	1000	-4.68766	-4.3749	-4.623556	0.0931	1.833
	E	10000	-4.68766	-4.53766	-4.6576	0.0609	18.052
	R	1000	-9.49366	-8.86034	-9.211764	0.165560	3.563
10		10000	-9.64839	-8.90165	-9.36139	0.16933	35.611
	E	1000	-9.64814	-8.9994	-9.40096	0.1661504	3.482
	L	10000	-9.65964	-9.04659	-9.4806	0.13655	35.201
	R	1000	-26.5284	-23.9703	-25.2395	0.5925	10.443
30	10	10000	-26.5367	-24.7186	-25.5321	0.49315	105.576
	E	1000	-26.3994	-24.3434	-25.442	0.503330	10.502
	נים	10000	-27.2008	-25.0651	-26.17956	0.53231	104.842

Table 42: Michalewicz's function. Population 200. Elitist 4% Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-4.68593	-4.35822	-4.572893	0.094346	0.881
5	10	10000	-4.68766	-4.5249	-4.65609	0.0613781	8.979
	E	1000	-4.68766	-4.3742	-4.586552	0.088089	0.8819
	E	10000	-4.68766	-4.5249	-4.65376	0.0614662	9.034
	R	1000	-9.41675	-8.55575	-9.11505	0.240820	1.711
10	10	10000	-9.5997	-8.97341	-9.3583	0.165	17.440
	Е	1000	-9.55137	-8.77189	-9.19432	0.17644	1.743
		10000	9.61343	-8.94968	-9.337307	0.163135	17.7265
	R	1000	-23.3127	-20.4537	-22.098	0.70315	5.119
30	10	10000	-23.6735	-21.2548	-22.3896	0.67167	52.482
30	Е	1000	-24.215	-21.276	-23.04	0.77027	5.155
	E	10000	-25.5612	-21.9482	-23.24179	0.8585737	52.5155

Table 43: Michalewicz's function. Population 100. Elitist 10% Selection.

D	CX	G	Min	Max	μ	σ	μ_{δ}
	R	1000	-4.68766	-4.5249	-4.66198	0.052928	1.808
5	10	10000	-4.68766	-4.53765	-4.671961	0.045549	18.079
	E	1000	-4.68766	-4.5249	-4.65569	0.0564577	1.770
	Ŀ	10000	-4.68766	-4.53766	-4.6667316	0.0515055	18.182
	R	1000	-9.55143	-8.64583	-9.3231	0.20839	3.4144
10	11	10000	-9.60025	-9.2031	-9.43394	0.110172	35.136
10	Е	1000	-9.63348	-8.88812	-9.39371	0.18163	3.529
		10000	-9.62005	-8.9927	-9.4740	0.1391	35.263
	R	1000	-24.4506	-21.8502	-22.944213	0.652307	10.276
30	10	10000	-24.2357	-22.429	-23.264	0.54137	105.508
30	Е	1000	-24.9792	-22.5553	-23.8291	0.62984	10.469
	E	10000	-24.6402	-22.6449	-23.85566	0.596632	105.788

Table 44: Michalewicz's function. Population 200. Elitist 10% Selection.

4 Observations

A first observation to be made is for the difference of the crossover methods. Throughout the tables, the *elitist* crossover method has gotten better results while maintaining a close execution time to the *replacement* crossover method. The better results come from the fact that after the crossover operation, the population is guaranteed to be at least as fit as it was before the operation. This scenario happens when the offspring have a fitness level lower than their parents. This guarantees that fit individuals are not lost after the operation whereas in the *replacement* method, the offspring always replace the parents which can lead to the loss of well fit individuals.

The different sizes of the population affect the processing time and they also affect the quality of the final result. A higher count of individuals will give the genetic algorithm more chances to escape from a local optimum. This can be seen in the tables 24 and 25. A higher number of individuals results in a higher count of crossover operations between the individuals resulting in the chance of generating better fit individuals. This can be seen in Schwefel's function tables 15 and 16.

For the tournament selection method, the size of a tournament directly affects the selection pressure as in a tournament with many participants, less fit individuals would contest the position in the population with more fit individuals. This behaviour can be seen between the tables with a tournament size of 2 and a tournament size of 7. Size 2 is the minimum size of a tournament and since only tournament winner are selected into the new population, there is a higher chance of less fit individuals to get selected. This is less likely in the opposite case where the size of the tournament is higher. This can be observed easily in Schwefel's function tables 15 and 17.

For the *elitist* selection method, it is built on top of the *Roulette Wheel* selection method. For this experiment, it has been decided that a percentage p of the population would be kept for the crossover operation. The percentage p belongs into $\{4,10\}$ and is used to point that if it is opted in favor of adding elitism to the selection scheme, a low percentage of individuals have to be kept for the new population because a high percentage would guarantee the safety of those chromosomes. Even though they might be in the top p% of the current population they might not be fit enough to support the genetic algorithm towards its goal.

5 Comparison to trajectory strategies

In a previous report[27], I have compared two common trajectory algorithms: Hill Climbing and Simulated Annealing. The latter had a great waiting time compared to the former and it also had better results while being more flexible thanks to the temperature component. Because of it, I concluded that the Simulated Annealing algorithm can be tweaked for even better results. I'll use Schwefel's function to compare the results of the genetic algorithms used in this paper to the results of the Simulated Annealing algorithm. For the comparison, the population count will be 200, the generation count 10000 and the crossover method the elitist one. For the tournament selection method, the size of the tournament will be 7 and for the elitist selection method the percentage will be 4%.

Dimensions	Method	Expected Result	μ_{value}	σ_{value}	μ_{time}
	WoF		-2094.6493	0.15065	19.249
5	T_7	-2094.9145	-2094.62366	0.10736	10.504
9	E_4	-2094.9140	-2094.75533	0.10546	25.257
	SA		-2094.74166	0.09512	29.187
	WoF		-4188.75866	0.31439	38.070
10	T_7	-4189.829	-4189.267	0.17620	19.940
10	E_4		-4189.25833	0.20525	50.131
	SA		-4176.41466	26.67730	43.371
	WoF		-12551.22	5.30714	113.7873
30	T_7	-12569.487	-12489.48	21.77849	57.556
30	E_4		-12105.84666	207.18577	151.620
	SA		-12550.72666	31.07277	81.102

Table 45: Comparison for Schwefel's function

We can observe that the genetic algorithm has better all around results compared to the *Simulated Annealing* algorithm. The genetic has a lower waiting time while being given a high count of individuals and generations.

6 Conclusions

Genetic algorithms have more freedom in regard to finding the optimum of a function compared to trajectory methods. Its parameters can be easily modified to get the desired result. The approach towards the crossover and selection methods has an impact on the quality of the solution.

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