ISSN 2278-3091
Volume 9, No.1.4, 2020
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse8391.42020.pdf
https://doi.org/10.30534/ijatcse/2020/8391.42020

Performance Evaluation of Multiplying Factor on Multiple Mitosis Genetic Algorithm

K. Kamil[1], K.H. Chong[2], H. Hashim[3], H. Mansor[4]
[1]Universiti Tenaga Nasional, Malaysia, Karmila@uniten.edu.my
[2]Universiti Tenaga Nasional, Malaysia, KHChong@uniten.edu.my
[3]Universiti Tenaga Nasional, Malaysia, Halimatun@uniten.edu.my
[4]Universiti Tenaga Nasional, Malaysia, MHelmi@uniten.edu.my

ABSTRACT
This paper presents the performance of Multiple Mitosis Genetic Algorithm to solve Rosernbrock's test function for different multiplying factor. Multiplying factor in Multiple Mitosis Genetic Algorithm is introduced by the author to improve convergence rate to find final optimum. To compare with simple Genetic Algorithm, this method promotes productive parents to produce greater number of kids in one generation where it increases the possibilities to have good quality of individuals and prevent premature convergence. Result shows that as the factor increases, the final answer converge approaching global optimum and the result is comparable with other methods proposed by other researchers.

Key words: genetic algorithm, premature convergence, genetic algorithm

1. INTRODUCTION

Nowadays, the application of optimization technologies is emerging in various industries to promotes user friendly, efficient, smart, fast and many more added values in wide range of area such as engineering, financial, medical, education and many more [1] – [7]. For example, higher quality medical images can be generated with faster processing time which can help medical practitioners for diagnosis purpose and traffic can be controlled with the intelligence of emerging optimization technique in traffic management [8] – [10].

Because of that, optimization techniques evolved from time to time by many researchers to improve the performance of current techniques and fulfil the needs of current needs. There are many approaches introduced such as development of new optimization techniques, hybrid different techniques together, modification on the flow of the algorithm, manipulation of operator of certain algorithm and many more techniques done by researchers [11] – [15].

Particle Swarm Optimization (PSO) is another metaheuristic method was introduced by Kennedy and Eberhart in 1995 to solve optimization problem. PSO is an algorithm inspired by the foraging behaviors of birds. Innovation of this method also emerging from time to time as it is known as one of powerful optimization algorithm [16] – [17].

Whale Optimization Algorithm (WOA) was introduced by Mirjalili & Lewis in 2016. There are three operators introduced which are encircling prey, bubble-net foraging in exploitation phase and search for prey in exploration phase. This method was developed inspired by the behavior of humpback whales in hunting activity [18].

Genetic Algorithm (GA) is one of the pioneer algorithms in metaheuristic optimization technique introduced by John Holland in 1988. It is a method based on genetic evolution that has several operators: mutation, crossover, and selection processes [19] – [20]. Many researchers improved the performance of classical GA by doing modification on these operators which results outstanding performance in solving optimization problems [21] – [25].

Abid Hussain in [26] proposed the idea of Best-Worst Selection (BWS) criteria for Genetic Algorithm as a new selection scheme which separates healthy parents and unhealthy parents to reduce the effect of premature convergence. It has simple scheme and results proved the method help to improve the performance of simple GA. David in [27] promotes chaotic induced genes into normal GA to improve the accuracy of the best fitness found using GA techniques. The proposed idea shows that the influence of chaos theory improves the performance of GA.

This paper study the impact of changing multiplying factor on the performance of Multiple Mitosis Genetic Algorithm (MMGA). As the factor increased, the proposed idea improves the diversity of high-quality individuals by producing higher number of children which also helps to improve the performance of simple GA from premature convergence.

Rosernbrock's test function has been used as the test function because it is challenging to find out the global optimum of the function and it has been used continuously as a benchmark to test the performance of new optimization algorithm. The global optimum lies inside a narrow, long, parabolic shaped flat valley, and to find a minimum point is trivial [28]. Result shows that as the factor increases, the final answer converge approaching global optimum and the result is comparable with other methods proposed by other researchers.

2. METHODOLOGY

Traditionally, Simple Genetic Algorithm (SGA) can be presented in following pseudocode [29-30]:

```
START
Generate the initial population
Compute fitness
REPEAT
    Selection
    Crossover
    Mutation
    Compute fitness
UNTIL population has converged
STOP
```

SGA have potential to eliminate good quality individuals in the new generation while the population going through the process of crossover and mutation and finally the process brings the problem of slow convergence. To improve the performance of SGA in improving convergence rate, this paper proposed following modification on SGA, namely Multiple Mitosis Genetic Algorithm (MMGA).

```
START
Generate the initial population
Compute fitness

Selection

Set Multiplying Factor of MMGA, M
REPEAT

Multiple Mitosis Crossover
Mutation
Compute fitness
UNTIL number of individuals in new generations = M
STOP
```

In MMGA, selection process is not conducted in every generation. After the multiplying factor, M setup either randomly or preset by the user, selected parents will generate a number of children on the same amount of M value. If the value of M is 10 means that 1 parent will produces 10 number of children at one time and 1 parent can produce children more than one time. This is done by the multiple mitosis crossover and mutation process. Again, the children will be evaluated and compared to find the best solution of its generation.

It is expected that this method can improve the existence of high fitness individual in increment of the multiplying factor even though the number of populations is small as it is productive to produce number of children. Experiments are conducted to optimize a mathematical problem for different value of multiplying factor, M using Multiple Mitosis Genetic Algorithm.

Experiments are conducted to observe the quality of the new offspring in solving Rosernbrock's test function as in Equation 1.

$$f(x) = 100(x_1^2 - x_2) + (1 - x_1)^2 \qquad (1)$$

$$-2.048 \leq x_1, x_2 \leq 2.048$$

This function has "0" global optimum value at (1, 1). Variables x_1 and x_2 are encoded in binary where the number of bits for each variable are 29 bits to maintain the precision to eight places after the decimal point.

In this experiment, the following parameter are set to find the global minimum of Rosernbrock's function using Multiple Mitosis Genetic Algorithm.

Number of generations: 1

Population size: 50

Probability of crossover: 1.0

Probability of mutation: 0.01

Multiplying factor, M = [10, 30, 50, 70, 90]

Chromosome length = 29 bits, binary representation.

3. RESULTS AND DISCUSSIONS

Figure 1 shows the fitness distribution of the individuals at the initial population. The fitness of the initial population generated are scattered up to more than *f(x)* =2000 where the global optimum *f(x)* = 0.

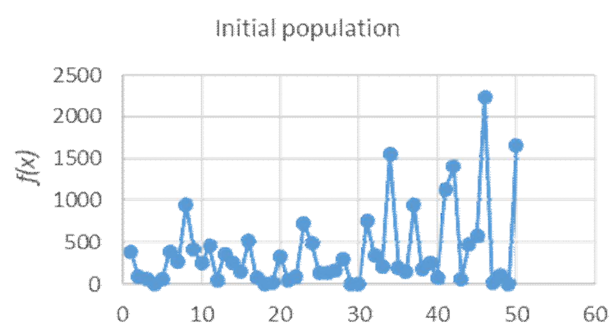

Figure 1: Best Fitness for Individuals at Initial Population

The same function and parameter are now tested by setting the number of multiplying factor, M to 10 where it is expected that the fitness of the individuals is improved. Figure 2 shows that the fitness of the individuals is now scattered below *f(x)* =

120 where it shows 90 percent improvement on the fitness to achieve global solution.

To observe the performance of multiplying factor on increasing the convergence rate, again the value of multiplying factor is now increased to M=30. Now, the fitness of the individuals is more converging from *f(x)* = 120 in previous figure to *f(x)* = 6 in Figure 3 where it shows 95 percent improvement of the quality of the fitness.

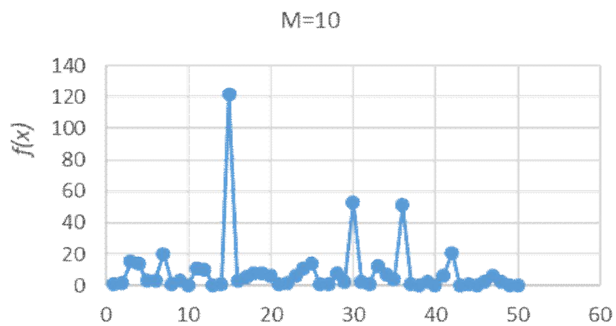

Figure 2: Best Fitness for Individuals at M=10

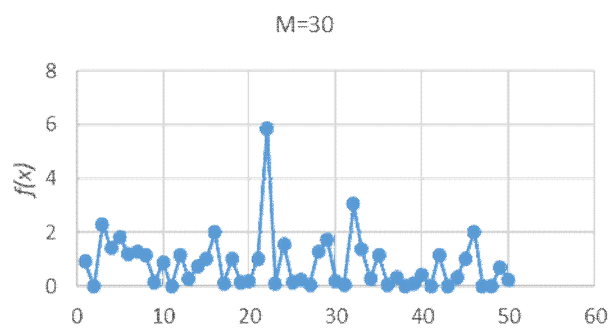

Figure 3: Best Fitness for Individuals at M=30

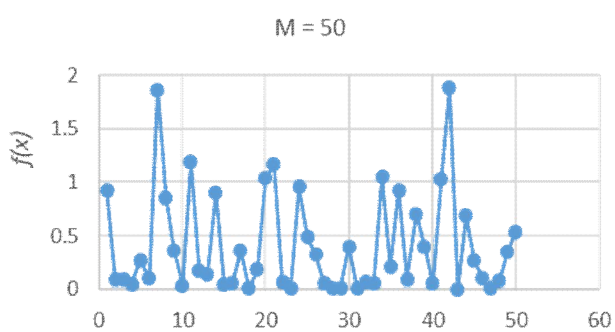

Figure 4: Best Fitness for Individuals at M=50

Figure 4 shows the individuals distribution when M = 50. It shows that the fitness of all individuals is now below *f(x)* = 2.0 which shows 68 percent improvement on the fitness from Figure 3.

Figure 5 and Figure 6 show the distribution of the individuals for multiplying factor, M=70 and M=90. Both of the figure show improvement of the fitness where the fitness of the individuals is now scattered below 1.2. In Figure 7, best individuals with highest fitness for each multiplying factor is taken out to observe the convergence of the solution to achieve global optimum and the summary is listed in Table 1.

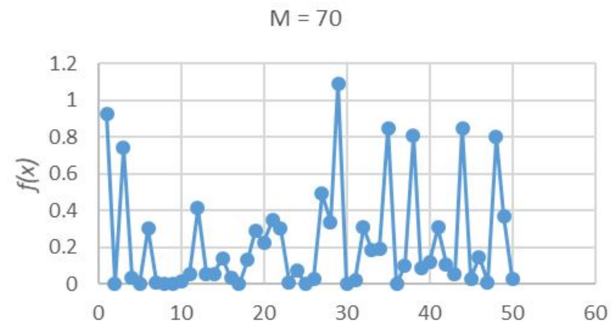

Figure 5: Best Fitness for Individuals at M=70

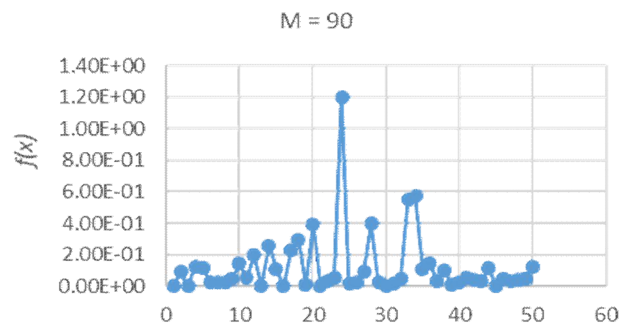

Figure 6: Best Fitness for Individuals at M = 90

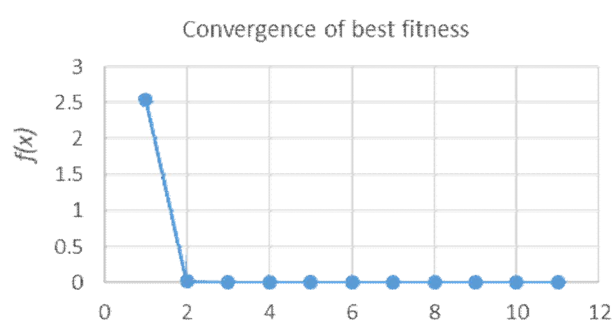

Figure 7: Convergence of Best Fitness for M = 10 to M = 90

Table 1: Best fitness recorded for each multiplying factor

No of Multiplying Factor, M	Best Fitness
10	0.014564
30	0.000103
50	1.64E-05
70	4.89E-05
90	8.16E-07

For benchmarking purpose, the results are compared with other methods to ensure that the proposed method is comparable. Table 2 presents the best fitness of selected methods compared with Multiple Mitosis Genetic Algorithm.

Table 2: Comparison of best fitness for different optimization technique

Algorithm	Best fitness
PSO	8.2E-02
WOA	7.18E00
GA	5.92 E01
SGA	0.0000100
BWS	0.0013
Chaotic Induced Genes (CGA)	3.83E-07
MMGA	8.16E-07

Best fitness using PSO, WOA, GA, SGA, BWS, Chaotic Induced Genes (GA) and MMGA are listed in the tables. Best fitness is taken from the best performance of each methods to find global optimum. Compared with other optimization technique, MMGA shows that the best fitness found using this method is comparable and has stronger search ability for global optimum compared to normal GA. However Chaotic Induced GA shows the improvement of 4.33×10^{-7}on the best fitness compared to MMGA.

4. CONCLUSIONS

This paper presents the performance of Multiple Mitosis Genetic Algorithm to solve Rosenbrock's test function for different multiplying factor. Multiplying factor in Multiple Mitosis Genetic Algorithm is introduced by the author to improve convergence rate to find final optimum. To compared with simple Genetic Algorithm, this method promotes productive parents to produce greater number of kids in one generation where it increases the possibilities to have good quality of individuals and prevent premature convergence. Result shows that as the factor increased, final answer converges approaching global optimum and the result is comparable with other methods proposed by other researchers.

REFERENCES

1. N. Chakraborti, **Genetic Algorithms In Materials Design and Processing**, *Journal of International Material Reviews*, Vol. 49, pp. 246-260, 2013.
2. Sam Mahfoud, Ganesh Mani, **Financial Forecasting Using Genetic Algorithm**, *Journal of Applied Artificial Intelligence*, pp. 543-565, 1996.
3. Timmy Manning, Roy D Sleator, and Paul Walsh, **Naturally Selecting Solutions The Use of Genetic Algorithms In Bioinformatics**, *Journal of Bioengineered*, pp. 266-278, 2013.
4. Hsin-Pin Fu, Cheng-Yuan Ku, Tsung-Sheng Chang, **A Decision Support System Based On A Genetic Algorithm for The Utilization of Leftovers**, *International Journal of Computational Intelligence*, vol. 9, pp. 483-496, 2016.
5. José Alberto Salinas-Pérez, Maria Luisa Rodero-Cosano, Carlos Ramon García-Alonso & Luis Salvador-Carulla, **Applying an Evolutionary Algorithm for the Analysis of Mental Disorders in Macro-urban Areas: The Case of Barcelona**, *Spatial Economic Analysis,* pp. 270-288, 2015.
6. Min-Yuan Cheng,Doddy Prayogo,Yi-Hsu Ju,Yu-Wei Wu & Sylviana Sutanto, **Optimizing Mixture Properties of Biodiesel Production Using Genetic Algorithm-Based Evolutionary Support Vector Machine**, *Intenational Journal of Green Energy*, pp. 1599-1607, 2016.
7. Reali F, Priami C and Marchetti L, **Optimization Algorithms for Computational Systems Biology**, *Front. Appl. Math. Stat*. Vol. 3, pp. 1-12, 2017.
8. Kergaye, Cameron & Stevanovic, Aleksandar & Martin, Peter, **Comparative Evaluation of Adaptive Traffic Control System Assessments Through Field and Microsimulation**, *Journal of Intelligent Transportation Systems*, vol. 14, pp.109-124, 2010.
9. P. Zhou, Z. Fang, H. Dong, J. Liu and S. Pan, **Data analysis with multi-objective optimization algorithm: A study in smart traffic signal system,** *IEEE 15th International Conference on Software Engineering Research, Management and Applications (SERA)*, pp. 307-310, 2017.
10. Nur 'Afifah Rusdi, Zainor Ridzuan Yahya, Nurshazneem Roslan, and Wan Zuki Azman Wan Muhamad, **Reconstruction of Medical Images Using Artificial Bee Colony Algorithm,** *Mathematical Problems in Engineering*, 2018.
11. Wen Wan and Jeffrey B. Birch, **An Improved Hybrid Genetic Algorithm with a New Local Search Procedure,** *Journal of Applied Mathematics*, pp. 1-10, 2013
12. Tumuluru, Jaya Shankar, and Richard McCulloch. **Application of Hybrid Genetic Algorithm Routine in Optimizing Food and Bioengineering Processes**, *Foods (Basel, Switzerland)*, Vol. 5, pp. 1-13, 2016.
13. Li Hongru, Hu Jinxing, Jiang Shouyong, **A Hybrid PSO Based on Dynamic Clustering for Global Optimization,** *IFAC-PapersOnLine*, Vol. 51, 2018.
14. Ajay Shrestha and Ausif Mahmood, **Improving Genetic Algorithm with Fine-Tuned Crossover and Scaled Architecture,** *Journal of Mathematics*, pp. 1-10, 2016.
15. Raju, M., Gupta, M.K., Bhanot, N. et al. J Intell Manuf, **A hybrid PSO–BFO evolutionary algorithm for optimization of fused deposition**

modelling process parameters, *Journal of Intelligent Manufacturing*, pp. 1-16, 2018.

16. Kennedy, J., & Eberhart, R. (1995), **Particle swarm optimization,** *Proceedings of IEEE international conference on neural networks*, pp. 1942-1948, 1995.
17. Hasan Koyuncu, Rahime Ceylan, **A PSO based approach: Scout particle swarm algorithm for continuous global optimization problems**, *Journal of Computational Design and Engineering*, Vol**.** 6, pp**.**129-142, 2019.
18. Seyedali Mirjalili, Andrew Lewis, **The whale optimization algorithm**, *Advances in Engineering Software,* Vol**.** 95, pp.51-67, 2016.
19. John H Holland., **Adaptation in natural and artificial systems: An introductory analysis with application to biology, control, and artificial intelligence,** *Ann Arbor: University of Michigan Press*, 1975.
20. Çelebi, Mehmed, **A new approach for the genetic algorithm**, *Journal of Statistical Computation and Simulation*, Vol. 79, pp. 275 — 297, 2009. https://doi.org/10.1080/00949650701752939
21. Tengfei Zhang et. al, **Optimization of hazardous POL transportation problem based on simulated annealing genetic algorithm**, *Chemical Engineering Transaction*, Vol. 66, pp. 1471-1476, 2018.
22. Tzung-Pei Hong, Yuan-Ching Peng, Wen-Yang Lin & Shyue-Liang Wang, **Empirical comparison of level-wise hierarchical multi-population genetic algorithm**, *Journal of Information and Telecommunication*, Vol**.** 1, pp.66-78, 2017.
23. P Krist, J Bíla and D Chvátil, **Genetic algorithm-based optimal fuzzy control system for the MT 25 microtron**, *Journal of Instrumentation*, vol. 8, 2013.
24. Demetris et al., **A spatial genetic algorithm for automating land partitioning**, *International Journal of Geographical Information Science,* Vol. 27, pp. 2391-2409, 2013.
25. Chen et. al, **A novel mechanism for efficient the search optimization of genetic algorithm**, *International Journal of Computational Intelligence Systems*, Vol**.** 9, pp. 57 – 64, 2016.
26. Abid Hussain, Yousaf Shad Muhammad, Muhammad Nauman Sajid. **Performance Evaluation of Best-Worst Selection Criteria for Genetic Algorithm**, *Mathematics and Computer Science*, Vol**.** 2, pp. 89-97, 2017.
27. David et. al, **A comparative analysis of various chaotic genetic algorithm for multimodal function optimization**, *Journal of Trends in Applied Sciences Research*, Vol**.** 7, pp. 785-794, 2012.
28. Nagham Azmi, **De Jong's sphere model test for a human community based genetic algorithm model (HCBGA)**, *International Journal of Advanced Computer Science and Applications*, Vol**.** 5, pp. 166-172, 2014. https://doi.org/10.14569/IJACSA.2014.050123
29. Lubna Zaghlul, Rajaa Salih Mohammed Hasan, **Solving banana (Rosenbrock) function based on fitness function**, *World Scientific News,* Vol**.** 6, pp. 41-56, 2015.
30. Payel Ghosh, **Medical Image Segmentation Using a Genetic Algorithm**, *Dissertation of Doctor of Philosophy in Electrical and Computer Engineering*, Portland State University, 2010.