Research Article
Volume 12:1, 2021

Global Journal of Technology and Optimization

ISSN: 2229-8711 Open Access

Comparative Analysis of Multi-Verse Optimizer with Time Freeze Effect and basic Multi-Verse Optimizer

Ameer Khan*

Ameer Khan Research and Development Center, Gujranwala, Pakistan

Abstract

In this paper an improvement of a well-known nature inspired meta-heuristic algorithm is compared with the original algorithm i.e. Multi-Verse Optimizer (MVO). Multi-Verse Optimizer with Time Freeze Effect (MVOTFE) is compared with original MVO in terms of optimization performance, time taken and convergence behavior. MVOTFE is first tested with same 19 benchmark test problems that are used by MVO. MVOTFE uses same mathematical model as used by MVO with only addition of time freeze effect in the algorithm. Comparative analysis suggests that MVOTFE not only outperforms original MVO in 16 out of 19 test problems but also provides faster convergence in lesser time. As indicated by convergence curves, it also effectively escapes from local optima present in the search space.

Keywords: Optimization • Genetic Algorithm • Meta-Heuristic • Multi-verse optimizer • Swarm based algorithm • Computational intelligence • Benchmark

Introduction

In recent years, a number of nature inspired meta-heuristic algorithms have been proposed for optimization that claims to mimic behaviors of natural organisms or phenomenons by mathematically modeling their traits. A variety of swarm based approaches have proven to provide relatively better and faster results using lesser resources [1]. These swarm based algorithms belong to Computational Intelligence (CI) area of Artificial Intelligence (AI) in which collective behavior of birds, animals and other species is modeled; another approach belonging to CI is Genetic Algorithms in which concepts of reproduction, natural selection and mutation are adopted [2,3]. Particle Swarm Algorithm (PSO) [4] is one of the most famous swarm based algorithms which is inspired by the behavior of birds flying in a flock.

There are a few common things that are considered by all the algorithms in this area e.g. exploration and exploitation. All these algorithms strive to maintain balance between exploration (searching the whole search space thoroughly) and exploitation (converging to the best solution or global optimum). Numbers of search agents or swarm size and iterations or numbers of generations are two important tuneable variables.

In this paper, a variation of Multi-Verse Optimizer is presented and comparative analysis is performed with original algorithm. Multi-Verse Optimizer is another meta-heuristic algorithm that is inspired by the concept of multi-verse in cosmology. MVO has modeled three major concepts of multi-verse theory i.e. black hole, white whole and wormholes [5]. Multi-Verse Optimizer with Time Freeze Effect (MVOTFE) utilizes the concept of time freeze effect which is also regarded as freezing effect in cinematography. In Time Freeze Effect, time seems to stop for all the characters and screen is frozen except for one character. MVOTFE utilizes this concept to freeze the motion of all the search agents except for one agent which is at the best known position and allows it to explore its vicinity [6]. After that time starts again and all the agents start working, as they were before, following the original algorithm of MVO.

***Address for Correspondence:** *Ameer Khan, Ameer Khan Research and Development Center, Gujranwala, 52250, Pakistan, E-mail: ceo@akrndc.com*

Received 05 January 2021; **Accepted** 15 February 2021; **Published** 25 March 2021

Distribution of this paper is as follows: section 2 provides literature review of MVO, including the recent improvements and applications of MVO. Section 3 provides basic understanding of the working of original MVO. Section 4 discusses improved version i.e. Multi-Verse Optimizer with Time Freeze Effect. Section 5 provides comparative analysis of MVOTFE and MVO on benchmark functions. Section 5 concludes the research and suggests future directions.

Literature Review

In recent years a variety variants have been proposed for MVO and it has been applied for a number of applications. In 2020 and 2019, following improvements and applications have been proposed: In [7], K-Means MVO (KMVO) has been proposed for code storage of DNA, using recent theories of wormholes and clustering. In [8] Parallel Multi-Verse Optimizer (PMVO) is presented that uses new communication mechanism and is applied for multilevel image segmentation. It was also tested for CEC2013 benchmark functions. In [9] another improvement of MVO namely Link Based multi-verse optimizer was proposed that utilized a concept called Neighborhood Selection Strategy (NSS) and it was applied to text documents clustering. In [10] authors have used multi-objective MVO for gray scale image segmentation.

Following are the improvements and applications proposed till 2018. In [11] authors have used chaotic maps are used to improve MVO and applied it for feature selection. In [12] MVO is hybridized with random walk and is applied on Network on chip scheduling problem. In [13] Stud Selection and Crossover (SSC) is used to improve MVO and is tested on benchmark functions. In [14] multi-objective version of MVO was proposed and compared with other multi-objective algorithms on benchmark functions. In [15] authors improved MVO by introducing exponential function inflation size and improvement in efficiency and convergence rate was reported. In [16] concepts from quantum theory were used and in [17] chaotic maps were used with MVO to apply on engineering optimization problems. In [18] authors introduced binary version of MVO using percentile binary operator.

As for the applications, [19] used MVO and ANN for intrusion detection, [20] formulated binarization process of images, [21,22] trained multi-layer perceptron neural network, [23] optimized parameters of Support Vector Machine (SVM) and [24] adopted MVO for clustering problems. Above are the most recent (2019-20) and till 2018 improvements and applications proposed for MVO algorithm. Most of these focused on the improvement of efficiency of original algorithm, trying to overcome deficiencies and apply original or enhanced MVO for specific applications. A book [25] was also published about nature inspired algorithms including MVO that provides description and survey of MVO variants and applications.

Materials and Methods

Multi-Verse Optimizer

Multi-Verse Optimizer is inspired by cosmological theory of multi-verse that indicates the existence of multiple universes created by multiple big bangs. Three concepts that are adopted by MVO from multi-verse theory are white holes, black holes and wormholes. Black holes and white holes are used to explore the search space while main purpose of wormholes is to exploit the optimum. To control the explore and exploit ratio, inflation rate is introduced that controls the frequency of appearance of black holes and white holes.

In MVO, a solution is represented as a universe and its variables are components or objects inside that universe. Each universe has its own inflation rate, which entails the probability of having white holes and black holes. Objects can travel from one universe to another through a portal created by white hole and a black hole or through a wormhole. Following are the basic rules followed in the process of MVO [5]:

- High inflation rate indicate high probability of presence of white holes and low probability of presence of black holes
- Higher inflation rate universes will send objects through white holes and low inflation rates universes will receive objects through black holes
- Objects can travel towards best universe through worm holes which is independent of inflation rates

However, based on [26] black hole and white hole tunneling has been a misconception because in cosmological multi-verse theory, anything that gets swallowed by a black hole is likely to emerge from a connected white hole (making the transportation from black hole towards white hole), whereas, in MVO, white holes are senders and black holes are receivers of the objects. Nevertheless, this does not effect the efficiency or performance of MVO.

At every iteration, universes are sorted and one universe is selected to have a white hole based on roulette wheel selection. It is done as follows:

$$U = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^d \\ x_2^1 & x_2^2 & \cdots & x_2^d \\ \vdots & \vdots & \vdots & \vdots \\ x_n^1 & x_n^2 & \cdots & x_n^d \end{bmatrix}$$

Where 'd' is the number of variables and n is the number of universes in the population.

$$x_i^j = \begin{cases} x_k^j & r1 < NI(Ui) \\ x_i^j & r1 \geq NI(Ui) \end{cases} \quad (1)$$

Where x_i^j represents j^{th} object of i^{th} universe, *NI*(*UI*) is normalized inflation rate of *Ui* i.e. i^{th} universe and r1 is a random number between 0 and 1. x_k^j is selected with roulette wheel selection which is j^{th} object of k^{th} universe.

Other than this, objects can also travel from one universe to another through wormholes, independent of inflation rates. To mathematically model this phenomenon, following equations have been proposed:

$$x_i^j = \begin{cases} \begin{cases} X_j + TDR \times ((ub_j - lb_j) \times r4 + lb_j) & r3 < 0.5 \\ X_j - TDR \times ((ub_j - lb_j) \times r4 + lb_j) & r3 \geq 0.5 \end{cases} & r2 < WEP \\ x_i^j & r2 \geq WEP \end{cases} \quad (2)$$

Where X_j is the j^{th} object of best universe, TDR and WEP are coefficients, ub_j and lb_j are upper and lower bounds respectively, r2, r3 and r4 are random numbers between 0 and 1. WEP and TDR are calculated using following equations:

$$WEP = \min + l \times \left(\frac{\max - \min}{L} \right) \quad (3)$$

Where min is 0.2 and max is set to 1, *l* is current iteration and *L* is maximum iterations.

$$TDR = 1 - \frac{l^{1/p}}{L^{1/p}} \quad (4)$$

Where *p* is equal to 6 and it controls exploitation.

Following above equations, MVO starts with random potential solutions inside the search space and then during the course of iterations, universes with higher inflation rates tend to send objects to the universes with lower inflation rates. Apart from that, wormholes also send objects from different universes towards best universe.

Multi-Verse Optimizer with Time Freeze Effect

Multi-Verse Optimizer with Time Freeze Effect follows all the features of MVO except for introducing the novel time freeze effect. Time freeze effect or freezing effect is adopted from cinematography, in which a frame is frozen including all the objects and characters in the frame except for one character who is allowed to move around in the frozen frame [6]. It gives out the effect that time has stopped for everything except that character and only that character is aware of this change. This effect is introduced for MVO where the entire universes act as characters of a frame and the best universe is the character that is allowed to witness this effect.

During time freeze effect, none of the universes except for the best universe notices any difference in the normal working of the algorithm. However, best universe gets an opportunity to get the best out of this short freeze, where it looks around its current location to find a better location with better fitness value. Five random points inside the vicinity of best universe's location are generated and evaluated with objective function. As a result, best universe is faced with two options:

1) Move to the best of five newly generated locations if it is better than current position

2) Stay at current position if none of newly generated locations is better than current position

To model the operations during time freeze effect, following mathematical model has been proposed:

$$XT_j = 2 \times r5 \times (X_j) \quad (5)$$

Where XT_j is the j^{th} object of a newly generated potential position of the best universe X_j is the j^{th} object of the best universe and r5 is a random number between 0 and 1. Five independent distinct locations are generated using equation eq.5 and their fitness value is computed in order to decide if the best universe will change its location or retain previous one. After this process, time freeze effect ends and the normal flow continues.

Frequency of introducing time freeze effect is optimize-able and impacts the convergence speed and exploitation efficiency. However, for this paper the frequency is set to be five, which implies that time freeze effect is applied during every fifth iteration.

Algorithm of MVOTFE: Initialize random population of universes

Run original MVO algorithm

After certain number of iterations do

Generate five random universes using eq.5

Compute objective value for these five universes

If objective value of any newly generated universe is better

Update the best universe

Continue the normal flow of MVO

Time freeze effect has proven to effectively improve convergence speed and exploitation efficiency of MVO owing to its ability to allow the best universe to avoid local optima faster and better. It also enables the best universe to hold a better position within its vicinity in lesser time and exploit it using original algorithm.

Results and Comparative Analysis

Same 19 test functions [5] have been used to test the performance of MVOTFE as used by MVO. Details of test functions have been provided in Table 1. These test functions can be divided into three major categories based on their surface i.e. uni-modal, multi-modal and composite functions [5]. In uni-modal functions, there is one optimum and they are used to test the exploitation abilities of an algorithm, whereas, multi-modal functions have one or more than one local optima, in addition to one global optimum and these are used to test the exploration abilities of an algorithm because it involves the search of entire space. Composite functions are even more complex to provide near to reality problem space and these are used to test both exploration and exploitation abilities.

During testing on benchmark functions, all the parameters are kept same as MVO to make a fair comparison. However, to compensate the time taken during the time freeze effect, population size has been reduced which ensures that less time is being taken by MVOTFE when compared to original MVO.

Population size is set to be 20, in contrary to MVO that has used population size of 30. It effectively reduces the time taken by the algorithm to complete optimization process. Maximum iterations are limited to 500 and frequency of time freeze effect is set to be after every five iterations. Apart from these, no tuneable parameter was altered to ensure fair and significant analysis. All the results are reported after doing 30 independent runs of MVOTFE for each test function. Results of MVOTFE are stated in Table 2 and compared with MVO and other famous swarm based algorithms on benchmark test functions (as reported in [5]).

It can be gathered from the results that MVOTFE provides superior results in most of the benchmark test functions. Highly significant improvements in functions f1-f6 show that MVOTFE has better exploitation abilities. Improvements in functions f7-f13 show that MVOTFE has better exploration abilities too. Lastly, functions f14-f19 indicates that MVOTFE effectively balances between exploration and exploitation, giving better results when compared to other algorithms. Functions, for which MVOTFE showed state of the art results, among given algorithms, are given in bold face.

Convergence Analysis

Convergence curves of both MVOTFE and MVO are given in Figure 1. Blue colored plots represent MVOTFE whereas red colored plots represent MVO. It can be deduced from convergence curves that MVOTFE has relatively faster convergence speed when compared to MVO. Furthermore, the functions where MVO gets stuck, MVOTFE effectively keeps on improving on most of the test functions. Highly superior exploitation abilities are exhibited by MVOTFE in uni-modal test functions f1-f6. In multi-modal benchmark functions, in addition to showing better optimization results, MVOTFE also shows faster convergence.

Conclusion

An enhancement of a meta-heuristic algorithm Multi-Verse Optimizer has been proposed in this paper, i.e. Multi-Verse Optimizer with Time Freeze Effect. It was tested on same 19 benchmark test functions as MVO. MVOTFE showed significant improvements in exploitation efficiency, giving improved results on 16 out of 19 benchmark functions. Comparative analysis also indicated that MVOTFE provides faster convergence. In future, its application on real life problems is planned.

Declarations

Funding

Authors declare that no funding was received for this project.

Conflict of interest

Authors declare no conflict of interest.

Availability of data

Data is available for this research.

Code Availability

Code is available for this research.

References

1. Aghdam MH, Heidari S. "Feature Selection Using particle Swarm Optimization In Text Categorization." *J Artif Intell Soft Comput Res*. 5 (2015): 231-238.
2. Aljarah I, Faris H, Mirjalili S, Al-Madi N, Sheta A, et al. "Evolving Neural Networks Using Bird Swarm Algorithm For Data Classification And Regression Applications." *Clust Comput*. 22 (2019): 1317-1345.
3. Aljarah I, Ludwig SA. Towards a scalable intrusion detection system based on parallel pso clustering using mapreduce. In Proceedings of the 15th Annual Conference Companion on Genetic and Evolutionary Computation. 2013: 169-170.
4. Kennedy J and Eberhart R. Particle swarm optimization. In Proceedings of ICNN'95-International Conference on Neural Networks. 1995: 1942-48.
5. Mirjalili S, Mirjalili SM and Hatamlou A. Multi-verse optimizer: A Nature-Inspired Algorithm for Global Optimization. *Neural Comput Appl*. 27 (2016): 495-513.
6. Deren M. "Cinematography: The Creative Use of Reality." *Daedalus 89*. 1960: 150-167.
7. Cao B, Zhao S, Li X and Wang B. K-means Multi-Verse Optimizer (KMVO) Algorithm to Construct DNA Storage Codes. *IEEE Access*. 8(2020): 29547-29556.
8. Wang X, Pan JS and Chu SC. "A Parallel Multi-Verse Optimizer for Application in Multilevel Image Segmentation." *IEEE Access*. 8(2020): 32018-30.
9. Abasi AK, Khader AT, Al-Betar MA, Naim S, Makhadmeh SN et al. Link-Based Multi-Verse Optimizer for text documents clustering." *Appl Soft Comput*. 87(2020): 106002.
10. Elaziz MA, Oliva D, Ewees AA and Xiong S. Multi-Level Thresholding-Based Grey Scale Image Segmentation using Multi-Objective Multi-Verse Optimizer. *Expert Syst Appl*, 125(2019): 112-129.
11. Ewees AA, El Aziz MA and Hassanien AE. Chaotic Multi-Verse Optimizer-Based Feature Selection. *Neural Comput Appl*. 31(2019): 991-1006.
12. Hu C, Li Z, Zhou T, Zhu A and Xu C. "A Multi-Verse Optimizer with Levy Flights for Numerical Optimization and its Application in Test Scheduling for Network-On-Chip." *PloS one*. 11(2016): 1-22.
13. Meshkat M, Parhizgar M. Stud multi-verse algorithm. 2nd Conference on Swarm Intelligence and Evolutionary Computation (CSIEC) (2017): 42-7.
14. Mirjalili S, Jangir P, Mirjalili SZ, Saremi S and Trivedi IN. Optimization of Problems with Multiple Objectives using the Multi-Verse Optimization Algorithm. *Knowl Based Syst*. 134(2017): 50-71.
15. Pan W, Zhou Y and Li Z. An Exponential Function Inflation Size of Multi-Verse Optimization Algorithm for Global Optimization. *Int J Comput Sci Math*. 8(2017): 115-128.
16. Sayed GI, Darwish A and Hassanien AE. Quantum multiverse optimization algorithm for optimization problems. *Neural Comput Appl*. 31(2019): 2763-2780.
17. Sayed GI, Darwish A and Hassanien AE. A New Chaotic Multi-Verse Optimization Algorithm for Solving Engineering Optimization Problems. *J Ex Theor Artif Intell*. 30(2018): 293-317.

18. Valenzuela M, Peña A, Lopez L and Pinto H (2017) A binary multi-verse optimizer algorithm applied to the set covering problem. In 2017 4th International Conference on Systems and Informatics (ICSAI): pp. 513-518.

19. Benmessahel I, Xie K, Chellal M and Semong T. "A New Evolutionary Neural Networks Based on Intrusion Detection Systems using Locust Swarm Optimization." *Evol Intell*, 12(2019): 131-146.

20. Elfattah MA, Hassanien AE, Abuelenin S and Bhattacharyya S (2019) Multi-Verse Optimization Clustering Algorithm For Binarization Of Handwritten Documents. In Recent Trends in Signal and Image Processing: 165-175. Springer, Singapore.

21. Faris H, Aljarah I and Mirjalili S (2017) Evolving radial basis function networks using moth-flame optimizer. In Handbook of neural computation: pp. 537-550. Academic Press.

22. Hassanin MF, Shoeb AM and Hassanien AE (2017) Designing Multilayer Feed forward Neural Networks Using Multi-Verse Optimizer. In Handbook of Research on Machine Learning Innovations and Trends: pp. 1076-1093. IGI Global.

23. Rosenberg A and Hirschberg J (2007) V-measure: A conditional entropy-based external cluster evaluation measure. In Proceedings of the 2007 joint conference on empirical methods in natural language processing and computational natural language learning (EMNLP-CoNLL): pp. 410-420.

24. Faris H, Hassonah MA, Ala'M AZ, Mirjalili S and Aljarah I. 2018. A Multi-Verse Optimizer Approach For Feature Selection And Optimizing Svm Parameters Based On A Robust System Architecture. *Neural Comput Appl*, 30(2018): 2355-2369.

25. Mirjalili S, Dong JS and Lewis A (2020) Nature-Inspired Optimizers Theories, Literature Reviews and Applications. Springer Nature Switzerland.

26. Haggard HM and Rovelli C. Black to White Hole Tunneling: An Exact Classical Solution. *Int J Mod Phys A*, 30(2015): 1545015.

How to cite this article: Ameer Khan. "Comparative Analysis of Multi-Verse Optimizer with Time Freeze Effect and basic Multi-Verse optimizer." *Global J Technol Optim* 12 (2021): 246