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REVIEW ARTICLE

Multi-verse optimizer algorithm: a comprehensive survey of its results, variants, and applications

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Abstract
This review paper presents a comprehensive and full review of the so-called optimization algorithm, multi-verse optimizer algorithm (MOA), and reviews its main characteristics and procedures. This optimizer is a kind of the most recent powerful nature-inspired meta-heuristic algorithms, where it has been successfully implemented and utilized in several optimization problems in a variety of several fields, which are covered in this context, such as benchmark test functions, machine learning applications, engineering applications, network applications, parameters control, and other applications of MOA. This paper covers all the available publications that have been used MOA in its application, which are published in the literature including the variants of MOA such as binary, modifications, hybridizations, chaotic, and multi-objective. Followed by its applications, the assessment and evaluation, and finally the conclusions, which interested in the current works on the optimization algorithm, recommend potential future research directions.

Keywords Multi-verse optimizer algorithm · Meta-heuristic optimization algorithms · Optimization problems · Nature-inspired algorithms

1 Introduction

Several optimization techniques have been established in numerous different domains in order to solve an optimization problem, such as data mining, engineering applications, test functions, energy, parameters control, networks, economics, and medical [1]. It is mainly applied in a domain to find several optimal solutions (decisions or values) to address the underlying problem effectively. Usually, the optimal solution for any optimization problem is accomplished by considering the value (i.e., minimization or maximization) of a potential decision that making an algorithm ordinarily adjusted. The final result of the enhancement processes (optimization) is selected the best decision or position value from all given decisions. Best word refers to a satisfactory solution, which is the best option to address the given optimization problem. Moreover, the achievable better solution over a series of processes may be estimated as a satisfactory solution [2].

Lately, researchers in optimization fields have survived active and achieved promising results due to its near real life to all problems that belong to the class of NP-hard optimization problems in nature. In general, optimization problems are classified into four main sections: section one, constrained problems or unconstrained problems; section two, continuous problems or discrete problems; section three, single-objective problems or multi-objective problems; and section four, static problems or dynamic problems. The saleability of these algorithms in solving the problems is attractive because of their powerful and robust search ability, and its results in tackling the high-dimensional problems are better enough than other methods (i.e., calculus-based methods). Normally, optimization techniques are introduced based on studying the natural phenomena of life when some species or living organisms are seeking for a better life. The general categories of these algorithms are (1) local search-based algorithms, (2) evolutionary search-based algorithms, (3) swarm search-based algorithm, and (4) hybrid algorithms [3, 4].

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The first category, local search-based optimization algorithms, runs iteratively with one candidate solution until the termination criteria are reached in order to enhance its performance (increase its fitness function), for example random optimization [5], tabu search [6], *B*-hill climbing [7], and hill climbing [8]. The second category, evolutionary search-based optimization algorithms, works with a population strategy (collection of randomly generated solutions), which iteratively mixes the solutions until the acceptable solution (optimal) is reached in order to get new and better solutions in terms of its fitness function. Examples include genetic programming [9], cuckoo optimization algorithm [10], artificial bee colony algorithm [11], firefly algorithm [12], ant colony optimization algorithm [13], genetic algorithm [14], and harmony search algorithm [15]. The third category (swarm search-based algorithm), the swarm search-based algorithm, works with a population-based technique, and at each iteration, the current solutions are normally produced based on historical information obtained by prior generations. Several algorithms in this section are multi-verse optimizer algorithm [16], krill herd algorithm [17], flower pollination algorithm [18], artificial bee colony algorithm [19], wind-driven optimization [20], intelligent water drop [21], particle swarm optimization algorithm [22], bacterial foraging algorithm [23], biogeographical-based optimization [24], and other related studies can be found in [2]. Finally, the fourth category, hybrid algorithms, these algorithms usually are combined of two algorithms together such as the hybrid whale optimization algorithm with local search strategy [25], a hybrid particle swarm optimization-generic algorithm [26], the hybrid genetic wind-driven heuristic optimization algorithm [27], and the hybrid firefly and particle swarm optimization algorithm [28].

The main aim of this review paper is to carry a comprehensive consideration for all perspectives of multi-verse optimizer algorithm in the computer science field, and how the researchers in that field are attracted and motivated to implement this algorithm to address different optimization problems in different applications. Further, this review paper highlighted and call attention to the robustness of the multi-verse optimizer algorithm and the modification versions proposed in the literature to overwhelm the algorithm weaknesses. Besides, the review indicated to all of the past studies that examined the multi-verse optimizer algorithm by leading to the various well-known publishers (i.e., IEEE, Springer, Elsevier, Taylor and Francis, Hindawi, Inderscience, and others publishers). Figure 1 presents the number of published papers (i.e., journal papers, chapter books, conference papers, and others), which are classified based on the publisher of the multi-verse optimizer algorithm publications. Figure 2 shows the classified of these papers based on the variety of applications (problems).

This review presents and explains the multi-verse optimizer algorithm (MOA) based on two main groups:

- Theoretical aspects of multi-verse optimizer algorithm include the multi-verse optimizer algorithm versions of binary, modifications, hybridizations, chaotic, and multi-objective. Figure 3 shows the classification of the theoretical aspects in perspective to the multi-verse optimizer algorithm based on the classes of modifications.
- Applications of multi-verse optimizer algorithm involve benchmark test functions, machine learning applications, engineering applications, network applications, parameters control, and other applications of multi-verse optimizer algorithm. Figure 1 presents the number of published papers, which are categorized based on the groups of applications.

This rest of this review paper is arranged as follows. The main procedures of the multi-verse optimizer algorithm and its description are shown in Sect. 2. In Sect. 3, the theoretical aspects of the multi-verse optimizer algorithm and its variants are summarized. In Sect. 4, applications of multi-verse optimizer algorithm are outlined and highlighted. Section 5 discusses theoretical aspects and evaluation of multi-verse optimizer algorithm. Section 6 shows experiments and results for the multi-verse optimizer algorithm compared with other similar algorithms. Assessment and evaluation of multi-verse optimizer algorithm are shown in Sect. 7. Finally, in Sect. 8, the conclusion, possible future works, and potential research trends of the multi-verse optimizer algorithm are presented.

2 Multi-verse optimizer

These following subsections present the multi-verse optimizer algorithm, which is introduced by Mirjalili et al. [16], and describe its essential operations. As well as, it presents the descriptions of the convergence, exploitation/intensification (local) search, and exploration/diversification (global) search of this algorithm.

2.1 Inspiration

The Big Bang theory in [29] explains that the universe begins with a large burst. Related to this assumption, the Big Bang is the foundation of all things in this nature, and there was nix happened prior that. The multi-verse notion is a new and common notion among physicists [16].

There are three major notions chosen in the multi-verse assumption as the revelation for the multi-verse optimizer

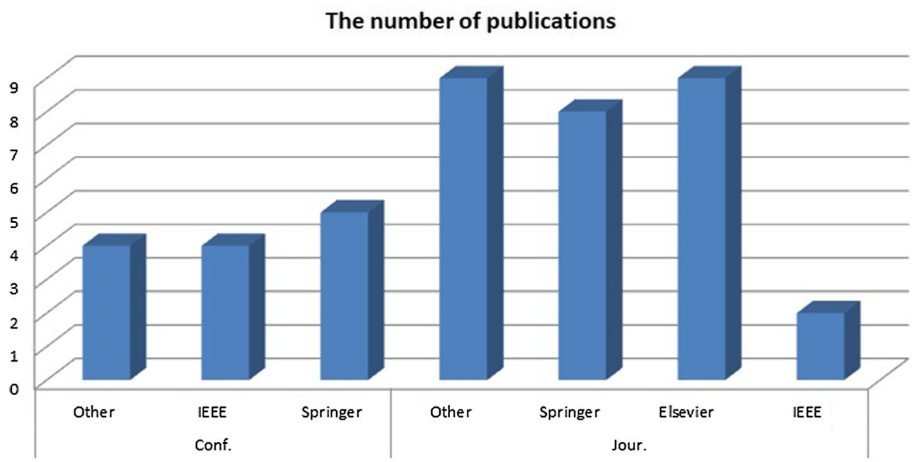

Fig. 1 Number of publications of multi-verse optimizer algorithm per publisher

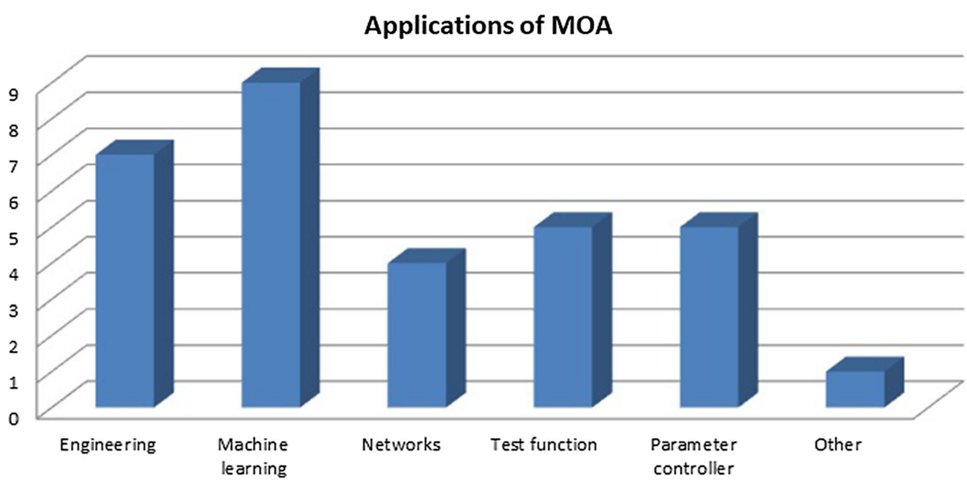

Fig. 2 Applications of the multi-verse optimizer algorithm

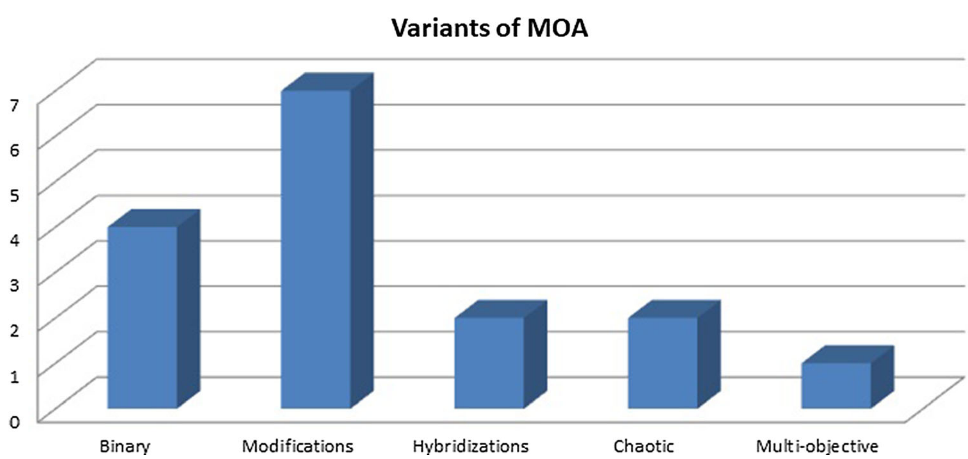

Fig. 3 Variants of the multi-verse optimizer algorithm

algorithm: black holes, white holes, and wormholes. Black holes have been recognized repeatedly, which act completely indifference to white wholes. They engage involving beams of light with their notably large attraction strength [30]. A white hole has had never observed in this universe; however, physicists assume that the Big Bang may be analyzed as a white hole and can be the major element for the beginning of a universe. It is additionally discussed in the cyclic paradigm of the multi-verse method that Big Bangs/white holes are produced when the marriage among parallel universes happening. Wormholes are those cells that combine various components of a universe concurrently. The wormholes in the multi-verse system behave as time/space travel holes while aims are capable of moving forthwith (without delay) among any edges of a universe [16, 31]. Conceptual paradigms of these three essential parts of the multi-verse system are shown in Fig. 4.

Each universe owns an extension rate (eternal extension) that triggers its extension through the available space [32]. The rising rate of a universe is quite essential in regard to creating stars, planets, asteroids, physical laws, black holes, white holes, wormholes, and suitability for real life. It is presented in a cyclic of multi-verse patterns that many solutions (universes) communicate through white, black, and wormholes to give a well-built position. This is the accurate revelation of the multi-verse optimizer algorithm, which is mathematically and conceptually illustrated in the next subsection [16].

2.2 Multi-verse optimizer algorithm

As explained in the previous part, a population-based optimization algorithm distributes the search procedure into main two stages: exploration contra exploitation. The theories of a white hole and black hole are used with a view to investigate the available search spaces of the multi-verse optimizer algorithm. In opposition, the wormholes help multi-verse optimizer algorithm in taking advantage of the search spaces. It assumed that a single solution (row) is similar to a universe in the multi-verse optimizer algorithm and each position in the row is an object (position) in that universe (solution) [33]. Moreover, each solution is assigned to an increased ratio, which is equivalent to its value of the fitness function in the universe (solution). The term time is utilized rather than the iteration since it is a popular standard term in multi-verse assumption and cosmology [16].

Through the improvement process (optimization process), the below commands are employed to the universes of the multi-verse optimizer algorithm [34, 35]:

1. The larger the inflation speed, the greater the prospect of owning a white hole.
2. The larger the inflation speed, the smallest the prospect of owning black holes.
3. Solutions with a greater inflation speed lead to transfer objects via white holes.
4. Solutions with a smaller inflation speed lead to win more objects via black holes.
5. The objects in all universes may meet random motion across the best universe through wormholes despite the inflation speed.

The conceptual design of the proposed multi-verse optimizer algorithm is presented in Fig. 5.

Figure 5 explains the objects how they are supported to run among various universes by black/white hole holes. When a black/white hole is discovered among two universes (two solutions), the universe with a greater inflation speed/time is supposed to have a white hole, whereas the solution with small inflation speed/time is allowed to own black holes. The objects are next shifted from the white holes of the original solution to black holes of the target solution. This method enables the solutions to simply replace objects. For enhancing the whole distension speed/time of the universes, it is observed that the solutions with high inflation speed/time are extremely feasible to own white holes. In contrast, the solutions with small inflation speed/time own a large possibility of owning black holes. Consequently, there is constantly a large possibility to transfer objects from a solution with a large inflation speed/time to a solution with a small inflation speed/time. This can assure the development of the average distension speed/time of the whole universes over the repetitions [16, 36].

In order to build the mathematically presentation of the black/white holes and replace the objects of solutions, a roulette wheel selection method is used. At every repetition, the solutions based on their distension degrees are sorted and one of them by this mechanism is selected to own a white hole [37]. The following procedures are performed to accomplish that:

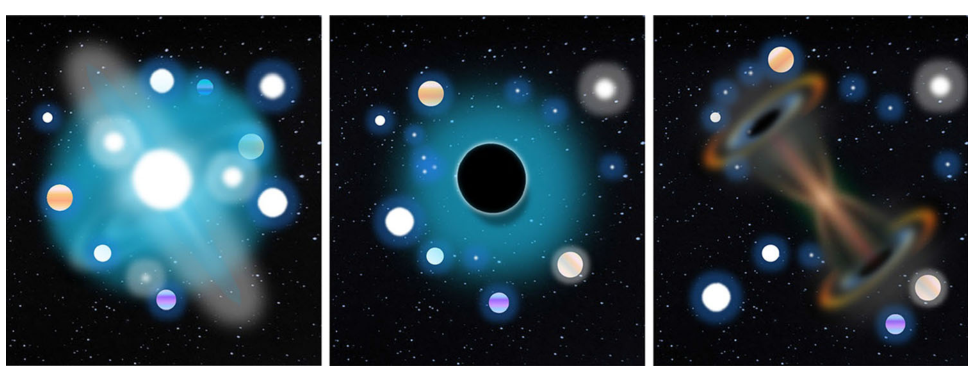

Fig. 4 White, black, and worm holes [16]

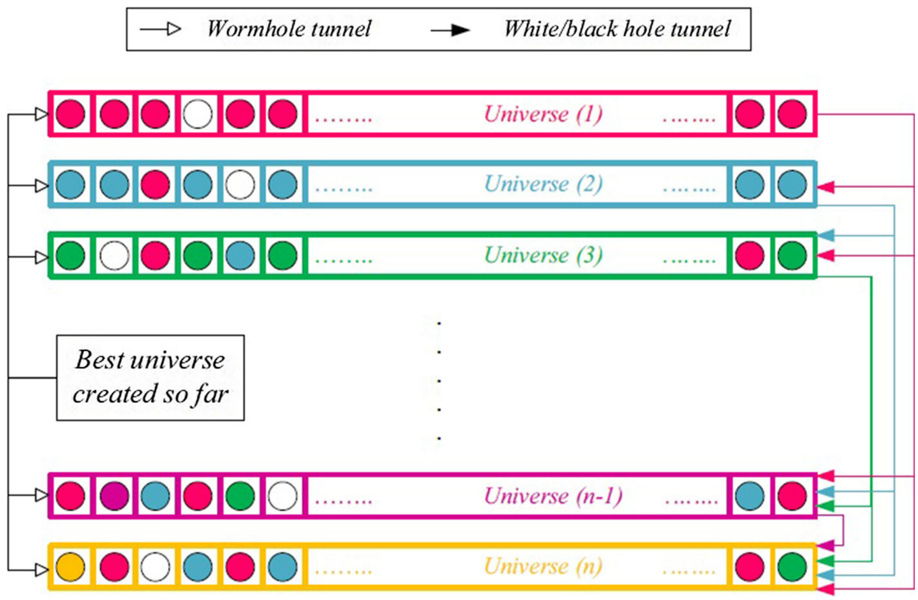

Fig. 5 Conceptual model of the proposed multi-verse optimizer algorithm [16]

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

where d presents the number of the solution values (each one is a variable for a position) and n is the number of current solutions. The value of each position is updated using Eq. (2) which is as follows:

$$x_i^j = \begin{cases} \text{if } r1 < NI(U_i) = x_j^k \\ \text{if } r1 < NI(U_i) = x_j^i \end{cases} \tag{2}$$

where x_j^i presents the jth parameter of ith solution, U_i presents the ith solution, $NI(U_i)$ is normalized inflation speed/time of the jth solution, $r1$ presents a random value between [0, 1], and x_j^k presents the jth parameter of kth solution chosen by the selection method (i.e., roulette wheel selection mechanism).

The pseudo-codes of this section are (see Algorithm 1) as follows:

Algorithm 1 The procedure in the first part of the multi-verse optimizer algorithm.

```
SU=Sorted solutions (universes)
NI=Normalize fitness function of the solutions
for each solution indexed by i do
    Black_hole_index=i;
    for each position indexed by j do
        r1=random value ([0,1]);
        if r1¡NI(U_i) then
            White_hole_index= Roulette Wheel Mechanism(-NI);
            U(Black_hole_index,j)= SU(White_hole_index,j);
        end if
    end for
end for
```

As observed in this pseudo-code and Eq. (2), the selection of white holes is specified by the roulette wheel selection method according to the normalized inflation scale. The smaller inflation scale, the greater the probability of conducting objects in black/white holes. Note that the $-NI$ is transferred to NI for the maximization problems. The global search can be assured by utilizing this mechanism of selection while the solutions are needed to change objects and handle unexpected fluctuations in order to examine (explore) the search space efficiently [16].

With the used improvement method, the solutions continue exchanging its positions without disturbances. In order to keep the variety of solutions and produce exploitation, each solution has wormholes is considered to encourage its objects by random space. In Fig. 1, white points express carried objects by the wormholes [38]. It recognized that the wormholes randomly replace the objects of the solutions without taking into account their inflation degrees. To provide exploitation (local) switches for each solution and own a large prospect of enhancing the inflation scale using wormholes, it is assumed that wormholes are regularly organized among a solution and the obtained best solution so far [16]. The mathematical formulation of this procedure is (see Eq. (3)) as follows:

$$x_i^j = \begin{cases} \text{if } (r2 < \text{WEP}) & \begin{cases} \text{if } (r3 < 0.5) & X_j + \text{TDR} \times ((ub_j - lb_j) \times r4 + lb_j) \\ \text{if } (r3 \geq 0.5) & X_j - \text{TDR} \times ((ub_j - lb_j) \times r4 + lb_j) \end{cases} \\ \text{if } (r2 \geq \text{WEP}) & x_i^j \end{cases} \tag{3}$$

where X_j presents the jth parameter value of the best current solution, TDR and WEP (wormhole existence prospect and traveling distance value) are variables (coefficients) and lb_j and ub_j present the lower and upper bounds of jth position, respectively. x_j^i presents the jth parameter value of jth solution, and r2, r3, r4 are random numbers between [0, 1]. The pseudo-codes are (see Algorithm 2) as follows (assuming that lb_j and ub_j present the lower and upper bounds of jth position):

where the min variable is the minimum value (in the original proposed paper, approximate value is 0.2), the max variable is the maximum value (in the original proposed paper, approximate value is 1), l presents the number of the current iteration, and L presents the termination criteria (the maximum number of iterations).

Algorithm 2 The procedure in the second part of the multi-verse optimizer algorithm.

```
for each universe indexed by i do
  for each object indexed by j do
    r2=random([0,1]);
    if r2 < Wormhole_existance_probability then
      r3= random([0,1]);
      r4= random([0,1]);
      if r3¡0.5 then
        U(i,j) = Best_universe(j) + Travelling_distance_rate * ((ub(j) − lb(j)) * r4 + lb(j));
        U(i,j) = Best_universe(j) − Travelling_distance_rate * ((ub(j) − lb(j)) * r4 + lb(j));
      end if
    end if
  end for
end for
```

It may be assumed from the pseudo-codes and mathematical notations that there are a couple of coefficients included; WEP: wormhole existence probability and TDR: traveling distance value (rate). The first variable is for determining the prospect of wormhole's presence in universes. It is needed to grow linearly through the repetitions in order to maintain exploitation as the process of optimization. The second coefficient is for determining the variation scale that an object can be transported by a wormhole nearby the best-obtained universe so far. In opposition to WEP, TDR is raised through the repetitions to own extra accurate exploitation/local search nearby the best-obtained universe [16, 39]. Wormhole existence and traveling distance values are explained in Fig. 6. The mathematical equations for the two variables are (see Eqs. (4 and 5)) as follows:

$$\mathrm{WEP} = \min + l\left(\frac{\max - \min}{L}\right) \tag{4}$$

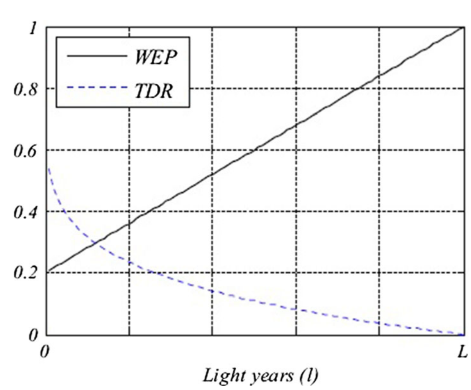

Fig. 6 WEP: Wormhole existence probability versus TDR: traveling distance rate [16]

$$\mathrm{TDR} = 1 - \frac{l^{1/p}}{L^{1/p}} \tag{5}$$

where p (in the original proposed paper, the approximate value is 6) presents the exploitation rate through the iterations. The larger p, the earlier and more precise exploitation/local search. Note that these two coefficients (WEP and TDR) can be examined as unchanging factors (constants) as well, but the adaptive evolution values are recommended based on the obtained results experimentally.

In the multi-verse optimizer algorithm, the optimization method begins with generating a group of random solutions (universes). At each improvement stage (iteration), positions in the solutions with large inflation values head for going to the solutions with small inflation values via white/black holes. Meantime, each solution faces random teleportations in its aims by wormholes toward the best solution. This procedure is repeated until the termination criteria are reached (the maximum number of iterations) [40].

2.3 Analysis of the multi-verse optimizer

The computational complication of the multi-verse optimizer algorithm (i.e., its complexity) is based on the max number of iterations, number of solutions, the selection mechanism (roulette wheel selection method), and solutions sorting method. Sorting solution is performed in every improvement repetition, and the Quicksort algorithm is employed because its complexity, which is O(n log n) in the best case and O(n^2) in the worst case. The selection mechanism is worked for every position in every solution over all the iterations and is of O(n) or O(log n) based on the execution [16]. Hence, the general computational complexity for the overall procedures is as follows:

$$O(\mathrm{MVO}) = O(l(O(\mathrm{Quick}_{\mathrm{sort}}) + n * d * (O(\mathrm{roulette}_{\mathrm{wheel}})))) \tag{6}$$

$$O(\mathrm{MVO}) = O(l(n^2 + n * d * \log n)) \tag{7}$$

where n presents the number of solutions, l presents the maximum iterations, and d presents the number of objects. To recognize how the multi-verse optimizer algorithm theoretically owns well possibility to address various optimization problems, some comments are as follows [16, 41]:

- White holes are also potential to be generated in the solutions with high inflation (fitness) values, so they could transfer positions to other solutions and help them to increase their fitness values.
- Black holes are also possible to have presented in the solutions with small fitness values, so they own a greater prospect to obtain positions from other solutions. This again improves the likelihood of increasing inflation values for the solutions with small inflation values.
- Black/white holes lead to move prospect from solutions with large inflation values to those with small inflation values, so the average inflation value of all solutions is enhanced across the number of iterations.
- Randomly, wormholes lead to rising in any solution of the inflation value, so the diversity of solutions could be kept over the number of iterations.
- While/black holes need solutions to abruptly replace, so this can ensure the exploration (global) of the available search space.
- Abrupt replacements also help to determine exploitation (local) optima stagnation.
- Wormholes randomly re-stretch part from the positions of solutions nearby the obtained best solution so far across the number of iterations, so this can ensure local nearby the more encouraging area of the search area.
- Acclimate WEP values easily improve the existence of wormholes in solutions. Hence, exploitation is maintained through the optimization process.
- Acclimate TDR values reduce the traveling range of variables nearby the best solution, a method for enhancing the precision of exploitation strategy (local search) across the iterations.
- The convergence rate of the multi-verse optimizer algorithm is proved by emphasizing the symmetric of the local search to a specific number of iterations.

2.4 Open-source software of multi-verse optimizer algorithm

However, the earlier simulations and investigations illustrated the effectiveness of the multi-verse optimizer algorithm in determining the optimal global agent in a search area [16]. Note that the free code of the multi-verse optimizer algorithm is available at http://www.alimirjalili.com/MVO.html.

3 Variants of multi-verse optimizer algorithm

This algorithm, the multi-verse optimizer, is introduced in 2015. It is a recent optimization algorithm in likening with other algorithms such as krill herd algorithm, firefly algorithm, harmony search algorithm, particle swarm optimization algorithm, and ant colony optimization algorithm introduced in 2012, 2008, 2001, 1995, and 1992, respectively. But, the multi-verse optimizer algorithm has been redesigned for various modifications developed by researchers to face and solve wide range optimization problems. Most of these modifications will be extensively but not exhaustively represented. A short summary of the main variants of the multi-verse optimizer algorithm is summarized in Table 1.

3.1 Binary multi-verse optimizer algorithm

Several problems such as combinatorial optimization problems and NP-hard kinds are solved in the operational research domain. Consequently, producing binary search algorithms for continuous problems based on swarm intelligence meta-heuristics is a field of interest in the operational research domain. A global binarization strategy is introduced and tested in [30] based on the percentile theory. This theory, percentile concept, is used in the multi-verse optimizer algorithm to address the problem of a set covering. Experiments are produced to show the efficiency of the binarization version of the proposed algorithm based on the percentile concept in addressing the mentioned problem. Moreover, the effectiveness of the proposed multi-verse optimizer algorithm is verified through benchmark test function instances. The results revealed that binary multi-verse optimizer algorithm achieved satisfactory results assessed against other comparative state-of-the-art algorithms.

Traveling salesman problem (ATSP) is known as an NP-hard problem (optimization problem). In this problem, there is a salesman who wants to begin the trip from the first point (home) to other points. The multi-verse

Table 1 Variants summary of the multi-verse optimizer algorithm

Category	Problem	Year	Author (References)
Binary MOA	Binary classification problems	2016	Faris et al. [39]
	The set covering problem	2017	Valenzuela et al. [30]
	Traveling salesman problem	2018	Gunardi et al. [31]
	0–1 multi-dimensional knapsack problems	2019	Abdel-Basset et al. [32]
Modifications of MOA	Test scheduling for network-on-chip	2016	Hu et al. [42]
	SVM parameters optimization	2016	Ying et al. [43]
	Data feature selection and classification	2017	DIF et al. [44]
	Test function	2018	Liu et al. [45]
	LabVIEW	2018	Vivek et al. [46]
	IoT smart agriculture monitoring	2018	Abdel-Basset et al. [47]
	0–1 multi-dimensional knapsack problems	2018	Abdel-Basset et al. [32]
Hybridization of MOA	Global numerical optimization problem	2017	Jangir et al. [48]
	Annual peak load forecasting	2018	Zhao et al. [37]
Chaotic MOA	Feature selection	2017	Ewees et al. [33]
	Network intrusion detection	2018	Liuet al. [34]
	Engineering optimization problems	2018	Sayed et al. [49]
Multi-objective of MOA	Image segmentation	2019	Elaziz et al. [50]

optimizer algorithm is proposed in [31] to address the traveling salesman problem. This meta-heuristic optimizer stimulated life events of infinite numbers of verse in-universe in nature. In the multi-verse optimizer algorithm, a universe has white and black holes and wormholes. The targets in a universe will describe a city in traveling salesman problems, and hence, a universe will describe a route that needs to be attended by a salesman. Multi-verse optimizer algorithm is performed on three traveling salesman problems benchmark utilizing eight various parameter values. Three examined parameters are investigated. The proposed algorithm is tested against several other algorithms published in that domain. The results proved the superiority of the proposed multi-verse optimizer algorithm to solve that problem (the travel salesman problem).

A novel version of the modified multi-verse optimization algorithm is proposed in [32] for addressing the problems of 0–1 knapsack (0–1 KP) and multi-dimensional knapsack. The proposed algorithm, modified multi-verse optimization algorithm (MMVO), includes two separate steps to improve the control strategy for managing constraints. Additionally, a check function is applied for specifying negative charges to the infeasible solutions. Hence, its fitness function cannot exceed the fitness of the possible ones. Modified multi-verse optimization algorithm averts the stuck in local optima by re-initializing the solutions every predetermined number of generations while maintaining the current best solution achieved so far. For separating the solutions, the proposed modified multi-verse optimization algorithm uses the transfer function (i.e., V-shaped). The proposed method is applied to solve various knapsack case studies. The results proved the effectiveness of the modified multi-verse optimization algorithm in addressing two kinds of optimization problems (i.e., binary test problems and real-world problems.

3.2 Modifications of multi-verse optimizer algorithm

The multi-verse optimizer algorithm is recently proposed, motivated by the multi-verse ideas, to address hard optimization problems. Despite the efficiency of the multi-verse optimizer algorithm and its capacity to produce a good balance between the search strategies (i.e., exploration and exploitation), further enhancements can be investigated. Like all other meta-heuristic optimization algorithms, the multi-verse optimizer algorithm needs to be modified to the domain of the application. An enhanced multi-verse optimizer algorithm is proposed [44] to enhance the exploitation of the multi-verse optimizer algorithm in addressing the problem of gene selection, especially for the microarray dataset, as well as to enhance the performance of the classifier (support vector machine). The comparison between the original multi-verse optimizer algorithm and the enhanced multi-verse optimizer algorithm proved that the proposed enhanced approach achieved the best results, particularly in dimension decrease in all samples, except one, and it is competitively better than the other comparative methods. The comparison revealed that the results of the enhanced multi-verse optimizer algorithm are the best results for two datasets.

A new modified version of mutational multi-verse optimizer algorithm with Lévy flight is proposed in [45]. The random operations of Lévy flight improve the experience of the individual exploration to avert the stuck in local optimum and make a balance between the search strategies (i.e., exploration and exploitation) for the proposed algorithm (the modified version of mutational multi-verse optimizer algorithm with Lévy flight). To examine the performance of the proposed modified version, the basic multi-verse optimizer algorithm and other four well-known optimization algorithms are used to compare with it using eight different test functions. Moreover, the proposed algorithm is tested in solving the cantilever beam design problem. The obtained final results confirmed that the proposed modified version of mutational multi-verse optimizer algorithm with Lévy flight has a satisfying balance between the search strategies and excellent convergence accuracy.

LabVIEW is a many-sided tool with multiple in-built toolkits to make different measurement and leading tasks. Therefore, it is utilized in almost all areas of engineering. However, it does not present enough enrichment to the area of optimization which is the main concern. It has just one optimization technique based on differential evolution (DE) algorithm. Even though differential evolution is a very powerful global optimization technique, its performance highly relies on parametric contexts. Differential evolution includes the big number of pre-defined parameters; hence, it is heavy for the user to get the best parametric values for the used optimization problem. Lately, different nature-inspired optimization algorithms are introduced in the literature with a decreased number of adjustment parameters to achieve optimum solutions while addressing difficult black-box optimization problems. Consequently, to modernize the LabVIEW in the area of optimization, there is a demand for continuous improvement of other useful global optimizers. Multi-verse optimizer algorithm is recognized as one of the modern optimization techniques but a powerful nature-inspired algorithm with only two adjustment parameters. The multi-verse optimizer algorithm with the toolkit is proposed in [46] for LabVIEW podium, and the effectiveness of the proposed method (the multi-verse optimizer algorithm with the toolkit) is investigated by five standard benchmark functions. The statistical analysis revealed that the obtained results of the proposed method are better in comparison with other well-known methods.

3.3 Hybridizations of multi-verse optimizer algorithm

A big number of renewable powers and uncertain energy load obtaining electric energy usage make the energy load predicting more complex and meet also unusual difficulties. A new hybrid yearly peak load predicting model, namely MVO-DGM (1, 1), which uses the recent optimization algorithm (multi-verse optimizer algorithm) is proposed in [37] to find the optimal two parameters of DGM (1, 1) model, and then utilizes the selected DGM (1, 1) model to predict yearly peak load. The yearly peak load of Shandong region in China from the years 2005 to 2014 is chosen as the experimental example, and the investigation results illustrated that the multi-verse optimizer algorithm has notable superiority for adjusting the parameters' values of DGM (1, 1) model compared the least square evaluation technique, fruit fly optimization algorithm, and particle swarm optimization algorithm in regard to yearly peak load predicting. Moreover, the proposed multi-verse optimizer algorithm for DGM (1, 1) peak load predicting model has superior predicting performance compared with other non-optimized predicting procedures and other optimized DGM (1, 1) procedures because of its rise local optima escape and excellent convergence rate. The proposed hybrid multi-verse optimizer algorithm for DGM (1, 1) is possible and effective in yearly peak load predicting, which enhanced the predicting accuracy values.

The modern trend of research is to hybridize (individuals of two different species or varieties) two and more algorithms components to achieve a better solution in the area of optimization problems. A new hybridization technique using particle swarm optimization algorithm and multi-verse optimizer algorithm is used in [48] to solve two different problems: Several unconstraint benchmark functions are tested using the proposed hybrid particle swarm optimization algorithm and multi-verse optimizer algorithm, and the most well-known problem of the common energy system named optimal reactive power dispatch is tested using the novel hybrid particle swarm optimization algorithm and multi-verse optimizer algorithm. The main purposes of the proposed hybrid algorithm are an integration of particle swarm optimization algorithm used for the exploitation phase and multi-verse optimizer algorithm for the exploration phase in an unstable environment. Positions and speed of solutions in particle swarm algorithm are improved according to the position of creations in each iteration. The proposed hybrid algorithm has a high-speed convergence ratio because of the performance of a roulette wheel selection process. For the optimal reactive power dispatch solution, standard IEEE-30 bus test scheme is utilized. The proposed hybrid algorithm is executed to address the proposed problem. The results achieved with the proposed hybrid algorithm are analyzed and matched with other methods original methods such as particle swarm optimization and multi-verse optimizer algorithm. The results confirmed the effectiveness of the proposed algorithm compared with other comparative methods.

3.4 Chaotic multi-verse optimizer algorithm

The multi-verse optimizer is a new meta-heuristic optimization algorithm motivated by the ideas of the multi-verse system, namely the black/white holes, which expresses the cooperation and communication between the universes. But, the multi-verse optimizer algorithm, called MVO, has some weaknesses, similar to other optimization algorithms, such as late convergence, slow motion, and getting trapped in local optima (i.e., maximum or minimum). A new chaotic multi-verse optimizer algorithm, called CMVO, is proposed in [33] to avert these weaknesses, where chaotic theories are employed to enhance the effectiveness of multi-verse optimizer algorithm. The chaotic multi-verse optimizer algorithm is employed to tackle a machine learning problem (the feature selection problem). Experiments are conducted on various five benchmark test function datasets to assess the effectiveness of the proposed chaotic multi-verse optimizer algorithm. The results are analyzed and compared with the original multi-verse optimizer algorithm and other two optimization algorithms. The experimental results confirmed that the logistic chaotic theory is the best map in chaotic theories, which improves the performance of the multi-verse optimizer algorithm, and also the multi-verse optimizer algorithm got better results in comparison with other optimization algorithms.

Low accuracy of detection has occurred when the support vector machine (SVM) is applied in the encroachment discovery because of the big volume and high dimensionality of data. The principal component technique is incorporated with chaotic multi-verse optimizer algorithm and support vector machine in [34], which is modified to increase the accuracy ratio of intrusion discovery. Among them, the principal component technique is utilized for feature extraction and dimensionality reduction on encroachment data and the optimal parameter selection of the support vector machine is selected by chaotic multi-verse optimizer. The performance of the proposed chaotic multi-verse optimizer algorithm is examined on KDD CUP99 common test dataset. The results showed that the proposed algorithm obtained better results in terms of high accuracy of intrusion detection, low false alarm value, and low false negative value.

3.5 Multi-objective multi-verse optimizer algorithm

The image segmentation process is the most well-known tasks utilized in image processing, and several methods have been produced to accomplish this task. A new multi-objective meta-heuristic optimization technique is proposed in [50] based on the multi-verse optimizer algorithm to solve the segment grayscale images through multi-level thresholds. The proposed method includes finding an estimated Pareto-optimal collection by maximizing the values of the objective functions (i.e., Kapur and Otsu). Both of these objective functions are highly utilized for image segmentation technique produced by means of bi-level and multi-level thresholds. But, each of them has specific properties and conditions. Several various meta-heuristic strategies have been suggested in the literature to independently find the optimal values of these objective functions in regard to accuracy, while only some multi-objective methods have examined the advantages of the joint utilization of Kapur and Otsu's functions. The cost of h objective functions (i.e., Kapur and Otsu) is large, and their accuracy rate requires to be developed. The proposed optimization approach, called multi-objective multi-verse optimizer algorithm, averts these restrictions. It was examined using eleven original grayscale images, and its effectiveness was analyzed and matched among three common multi-objective optimization algorithms. The obtained results were investigated based on two collections of measures, one to evaluate the effectiveness of the proposed approach as a multi-objective optimization algorithm, and the other to assess the accuracy rate of the obtained segmented images. As well as, the results confirmed that the proposed approach obtained better results compared with the other optimization algorithms in regard to hyper-volume and spacing. Furthermore, the quality of the resulted segmented image is better also than the other comparative methods in regard to uniformity measures.

4 Applications of multi-verse optimizer algorithm

Many applications of the multi-verse optimizer algorithm have been summarized from various areas. For instance, the multi-verse optimizer algorithm has been employed to address several optimization problems such as benchmark optimization and real-world problems. More details of the multi-verse optimizer algorithm applications are explained below, followed by a short summary of the main applications of the multi-verse optimizer algorithm as shown in Table 2.

4.1 Test functions

A novel nature-inspired algorithm, namely multi-verse optimizer algorithm, is proposed in [16]. The main idea of the inspirations of this proposed algorithm is based on three theories in cosmology: white, black, and worm hole. The mathematical representations of these theories are

Table 2 Applications summary of the multi-verse optimizer algorithm

Category	Date	Author (References)
Test functions	2016	Mirjalili et al. [16]
	2016	Hu et al. [42]
	2017	Ewees et al. [33]
	2017	Jangir et al. [48]
	2018	Trivedi et al. [51]
Machine learning application	2016	Faris et al. [39]
	2017	Hassanin et al. [52]
	2017	DIF et al. [44]
	2018	Shukri et al. [40]
	2018	Liu et al. [53]
	2018	Kolluru et al. [54]
	2018	Faris et al. [38]
	2018	Dif et al. [55]
Engineering applications	2016	Trivedi et al. [51]
	2016	Sulaiman et al. [56]
	2016	Bentouati et al. [35]
	2017	Bentouati et al. [48]
	2018	Wang et al. [57]
	2018	Pei et al. [36]
	2018	Sayedet al. [49]
	2019	Shaheen et al. [58]
Networks application	2016	Hu et al. [42]
	2018	Abdel-Basset et al. [47]
	2018	Liu et al. [34]
	2019	Shaheen et al. [58]
Parameters control application	2016	Ying et al. [43]
	2018	Fathy et al. [59]
	2018	Zhao et al. [37]
	2018	Faris et al. [38]
Other applications	2020	Aljarah et al. [41]

generated to produce intensification, diversification, and local search, respectively. The multi-verse optimizer algorithm is first tested on nineteen tricky test benchmark problems. Thereafter, it is employed to five real-life engineering optimization problems to further validate its ability. To confirm the results, the multi-verse optimizer algorithm is analyzed and compared with four common optimization algorithms: particle swarm optimization algorithm, gray wolf optimizer algorithm, gravitational search algorithm, and genetic algorithm. The obtained results demonstrated that the proposed multi-verse optimizer algorithm is able to produce excellent outcomes and received the best algorithms among the comparative methods in the literature on most of the test cases. The obtained results of the engineering optimization problems also confirmed the potential of the multi-verse optimizer algorithm in tackling real-life optimization problems with wide search area.

A new meta-heuristic optimization algorithm named Levy flights multi-verse optimizer algorithm (LFMVO) is proposed in [42], which combines Levy flights into the original multi-verse optimizer algorithm to address numerical functions and engineering optimization problems. The original multi-verse optimizer algorithm quickly falls into local optima when wormholes stochastically re-spread a number of universes (solutions) around the best solution obtained over the specific number of iterations. Since Levy flights are better in searching unknown space and wide search space, Levy flights are integrated into multi-verse optimizer algorithm to force it out of the local search. This proposed modified algorithm is tested on three sets of twenty-three common benchmark functions and an NP-complete problem of examination schedule for network-on-chip. Experimental results demonstrated that the proposed modified algorithm is more efficient than other comparative algorithms in terms of the solutions quality and high convergence speed.

4.2 Machine learning applications

Support vector machine is a powerful machine training algorithm generally used to analyze tasks and regression problems. Support vector machine was established based on the mathematical training theory and fundamental risk minimization. Regardless of the high forecast ratio of this procedure in a wide variety of real-life applications, the efficiency of support vector machine and its analysis accuracy (classification) extremely rely on the adjusting parameters values as well as the robust subset of selected features [60–62]. A robust approach is introduced in [38] based on a new nature-inspired meta-heuristic optimization algorithm, called multi-verse optimizer algorithm, for solving the problem of selecting an optimal subset of features and finding the optimal parameters values of support vector machine simultaneously. De facto, the multi-verse optimizer algorithm is operated as a tuner to handle the main parameters of support vector machine and find the optimal subset of informative features for this classifier. The proposed method is performed and examined on two various system architectures. Multi-verse optimizer algorithm is analyzed and matched with four classic and recent optimization algorithms using ten different (binary and multi-class) labeled datasets. Experimental results proved that the proposed multi-verse optimizer algorithm can efficiently decrease the number of features while having high accuracy rate.

The newly introduced nature-inspired optimization algorithm, called multi-verse optimizer algorithm, is employed in [39] for training the multilayer neural network. The current training method is assessed utilizing nine various benchmark datasets picked from the repository of UCI machine learning. The results are analyzed and matched with five meta-heuristic optimization algorithms: genetic algorithm, firefly algorithm, particle swarm optimization algorithm, cuckoo search algorithm, and differential evolution algorithm. Moreover, the results are analyzed and matched with two well-respected conventional gradient training approaches: the conventional back-propagation and the Levenberg–Marquardt. The obtained results confirmed that the proposed multi-verse optimizer algorithm is very competitive and got better results than other comparative algorithms in the most datasets in terms of enhanced local optima escape and convergence rate.

Artificial neural network paradigms are included in many purposes in real life due to its excellent computational abilities. Training of multilayer perceptron is the common hard problem through network training. Many various techniques have been proposed to alleviate these problem difficulties. Back-propagation algorithm is a robust method to train multilayer feedforward artificial neural network. But, it suffers from a major drawback (i.e., trapped in local minima). Lately, meta-heuristic optimization methods have proposed to train multilayer perceptron like genetic algorithm, cuckoo search algorithm, particle swarm optimization algorithm, ant colony optimizer algorithm, differential evolution algorithm, social spider optimization algorithm, and gray wolf optimization algorithm. Multi-verse optimizer algorithm is applied in [52] for solving the problem of the multilayer perceptron training. Seven test datasets are utilized to show capabilities of the proposed multi-verse optimizer algorithm as a suitable trainer for multilayer perceptron. Comparisons with other comparative algorithms confirmed that multi-verse optimizer algorithm obtained better results compared with all these optimization algorithms.

Clustering problem, which is based on meta-heuristic optimization algorithms, is known as a field of the quick-growing fields that target to get assist from such optimization algorithms to model the clustering problem as an optimization problem. The search abilities of a modern optimization algorithm called multi-verse optimizer algorithm are employed in [40] to find the optimal clusters in two various methods. The first approach is a static clustering strategy that runs on a pre-defined (known) number of subset clusters. The main aim of this approach is to make as large as possible the distances among various clusters and to make as small as possible the distances between the objects in each cluster. In order to tackle one of the important drawbacks of the common clustering algorithms, the second approach is an effective dynamic clustering method, in which the number of the subset of clusters is automatically recognized without any pre-define data. The proposed methods using the multi-verse optimizer algorithm are tested and evaluated using twelve artificial and real-world benchmark datasets (problems) and matched with several common and nature-inspired optimization algorithms. The results proved that the proposed two approaches, static and dynamic multi-verse optimizer algorithms, achieved better results in comparison with other clustering techniques.

Feature selection problem is an important process in the data mining domain. It is a general technique to assist in decreasing the extreme number of instances also features. The objective of this reduction technique is to reduce the un-informative instances and features to enhance the effectiveness of the classifier. Several related works published in the literature confirmed that meta-heuristic algorithms can tackle the feature selection problem efficiently. A novel feature selection method is proposed in [55] using the multi-verse optimizer algorithm to decrease the computational time and enhance the performance of the nearest neighbor classifier. Experiments are conducted on thirty-one benchmark datasets from the repository of UCI. The obtained results demonstrated that the proposed algorithm is worked better in comparison with other well-known methods.

With respect to the loss of the sample of errors in the test of autopilot, a standard model of error diagnosis based on the multi-verse optimizer algorithm is proposed in [53] to tune the parameters of the support vector machine. This technique worked very well in addressing the small samples and nonlinear problem, which is fit for the error diagnosis of autopilot. To address the underfitting and overfitting produced from the improper parameters of support vector machine, the multi-verse optimizer algorithm is employed to find the optimal parameters values of the support vector machine. A model of error diagnosis with excellent performance is produced also. The results proved that the accuracy of the support vector machine based on the multi-verse optimizer algorithm obtained 98% using fifty training samples. But, the accuracy of genetic algorithm with support vector machine achieves 91% and the accuracy of the support vector machine based on gravitational search algorithm obtained 91%. The simulation results demonstrated that the support vector machine based on the multi-verse optimizer algorithm got satisfying performance compared with other methods.

The increasing human community, building foundations, and technology practices have currently produced electric loss to increase significantly. Subsequently, some of the dynamic tools for more power saving and improvement are effective power management and predicting power loss for buildings. Additionally, dynamic power control and active restructuring can enhance power performance in diverse areas. Given that power is the chief form of energy that is spent in suburban buildings, predicting the electrical power loss in a building will yield important benefits to the building and business owners. All these lead to getting accurate power predicting to make the optimal decisions. Recently, artificial intelligence methods and machine learning methods have been operated to determine building power consumption and productivity. The main aim of [63] is to forecast power consumption with high precision and decrease computational time. The main parameters of the support vector machine are adjusted utilizing the multi-verse optimizer algorithm. The proposed multi-verse optimizer algorithm with support vector machine is presented for predicting power consumption in residential structures. The proposed method is tested using a dataset from the UCI repository. The experimental results showed that the multi-verse optimizer algorithm can definitely reduce the number of features while maintaining a great forecasting accuracy.

4.3 Engineering applications

Multi-verse optimizer algorithm was employed in different optimization problems, where most of these optimization problems are located in engineering applications, such as renewable energy system, scheduling, and control of power systems. The following sections illustrate the effectiveness of multi-verse optimizer algorithm in engineering applications.

The most well-known problem in the common power system is how to optimize the optimal power flow. This problem is solved in [51] by utilizing the novel meta-heuristic optimization algorithm called multi-verse optimizer algorithm. The main motivations of this optimizer are based on three theories in cosmology: white and clack, and wormhole. The multi-verse optimizer algorithm has a quick convergence time. In order to address the mentioned problem (the optimal power flow), common standard IEEE-30 bus examination system is utilized. The multi-verse optimizer algorithm is performed to achieve the optimal solution that can solve the problem efficiently. The problems analyzed in terms of the optimal power flow problem which is the fuel price decrease, voltage variation minimization, and voltage balance enhancement. The results obtained by the proposed multi-verse optimizer algorithm is analyzed and matched with other algorithms such as particle swarm optimization algorithm and flower pollination algorithm. Results proved that the multi-verse optimizer algorithm obtained better results values as compared with other comparative methods well-known.

A new optimization algorithm, namely the multi-verse optimizer algorithm, is used [56] to address the optimal reactive power dispatch problem. This algorithm is motivated by the three principal theories in cosmology (i.e., white, black, and wormholes). These theories are presented mathematically to produce exploration (global) and exploitation (local) search strategies. The proposed multi-verse optimizer algorithm is employed to get the best collection of controllers values such as dynamo voltages, draw changing transformer’s rates, reactive payment devices, and real energy production. To investigate the performance of the proposed multi-verse optimizer algorithm to address the optimal reactive power dispatch problem, IEEE30 bus test arrangement with twenty-five control variables is used and compared with well-known optimization algorithms published in the literature. The result of this investigation proved that the proposed multi-verse optimizer algorithm is efficient in producing smaller power waste than the other comparative algorithms.

A new meta-heuristic optimization technique, the multi-verse optimizer algorithm, is proposed in [35] to optimize the most universal problem of the current energy system (optimal power flow). IEEE 30-bus and IEEE 57-bus test arrangements are utilized to address the optimal power flow problem. There are several various problems that are considered in the problem of the power flow such as fuel price decrease, energy stability improvement, and energy profile enhancement. The achieved results are analyzed and matched with recent well-known meta-heuristic optimization algorithms. The obtained results showed the superior and the speed of the proposed multi-verse optimizer algorithm in addressing the problem of the optimal power flow.

Fundamental energy performs a risky role in the socioeconomic improvement of China, and precise power loss forecasting can benefit the government to express energy strategies and policies. To solve this problem, the multi-verse optimizer algorithm is proposed in [57] to find the optimal parameters values of the support vector machine. It applies a rolling cross-validation system to forecast China’s primary power loss in which the self-governing variables are the gross domestic output per capita, community, the urbanization degree, the share of the management in gross domestic output, and coal’s share of primary power loss. The results showed that the hybrid multi-verse optimizer algorithm with support vector machine model produced better results than other techniques in terms of precision values. Eventually, the hybrid multi-verse optimizer algorithm with support vector machine is employed to forecast the power loss of China between the years of 2017 and 2030 through five testing scenarios. In the reference scenario, China’s initial power consumption will equal 4839.3 and 5656.2 Mtce in 2020 and 2030, respectively.

The non-sinusoidal state and high-filled magnetic field in a turned unwillingness machine perform its design so hard. Popular design techniques are complicated and need a professional experience which creates it hard to achieve an optimal design. A novel exploration search algorithm called multi-verse optimizer is introduced in [36] to solve the switched reluctance motor design. Experiments are conducted and compared the optimal results with a genetic algorithm. Results revealed that the multi-verse optimizer algorithm achieved better results using the equal number of iterations and it averted early convergence and falling into local search compared to genetic algorithm. As well as, the results demonstrated that the multi-verse optimizer algorithm method is fit for solving the switched reluctance motor design.

4.4 Network applications

Wireless sensor networks are the vertebral column in the several modern Internet of Things (IoT) smart applications covering the mechanical control, monitoring, forest fire discovery, etc. One of the more critical applications is smart agriculture in the Internet of Things. The released of wireless sensor networks in agricultural manners can forecast crop yield, soil temperature, water level, air nature, crop cost, and the fit time for market distribution which will assist to enhance productivity. A modified meta-heuristic optimization algorithm, called multi-verse optimizer algorithm, is proposed in [47] with overlapping discovery phase for finding the optimal percentage of the coverage area of wireless sensor networks. The proposed algorithm is analyzed and examined on many standard datasets with various standards, and it is compared with other well-known optimization algorithms including the original multi-verse optimizer algorithm, particle swarm optimization algorithm, and flower pollination algorithm. The experimental results are investigated with a one-way ANOVA statistical test. Moreover, the overlapping detection stage is employed to the Internet of things intelligent agriculture in East Oweinat field in Egypt and matched with krill herd algorithm. Moreover, the obtained results are examined with the Wilcoxon ranking test. The statistical results demonstrated the success and consistency of the proposed multi-verse optimizer algorithm.

Transmission network expansion planning is an essential effect in electrical energy systems. It is a different entity, nonlinear, non-convex optimization problem which proposes to the optimal range of the routs, kinds, and the number of the added loops to handle the demanded future forecasting load at smallest costs. The application of the multi-verse optimizer algorithm is proposed in [58] to address the transmission network expansion planning with protection restrictions. The multi-verse optimizer algorithm has several benefits of being an easy structure, having adaptive handle parameter, and operating with full energy to avoid the local optima stagnation. The multi-verse optimizer algorithm has been produced and utilized to address the transmission network expansion planning problem for two practical transmission Egyptian arrangements of West Delta System and 500 kV of Extra High Voltage System. The load forecasting up to 2030 is analyzed based on the adaptive neuro-fuzzy inference system. The simulation results for the two schemes proved the ability of the proposed multi-verse optimizer algorithm to address efficiently the transmission network expansion planning problem. The proposed multi-verse optimizer algorithm superiority is demonstrated to generate economic planning and safe transmission paths.

4.5 Parameters control

Parameters of photovoltaic are important factors in examining its execution under various atmospheric and loading requirements. In a normal application, parameters of photovoltaic datasheets normally declare 3 points on current-voltage (*I*–*V*) character of the presented parameters of the photovoltaic design at standard test requirements. The five adjustment parameters of the single diode design of parameters of photovoltaic cells are obtained in [41] by using the multi-verse optimizer algorithm. A traditional approximate mathematical approach is first utilized to find fundamental values of the five foreign parameters. At this time, the multi-verse optimizer algorithm is employed to create the optimal values of the adjustment parameters of the photovoltaic solar cell. The optimal selected five parameters received are utilized to mimic the behavior of parameters of photovoltaic cells following different requirements including temperature changes and solar irradiance. The effectiveness of the proposed multi-verse optimizer algorithm is validated by comparing its obtained numerical results to an estimated mathematical system and recent meta-heuristic optimization approaches. Recognized parameters produced by the proposed multi-verse optimizer algorithm-based method are well compared with real test data and the given terms by vendor’s datasheets which indicates the proposed methodology.

In order to address the parameters problem in support vector machine, which is difficult to select and determine, a new optimization algorithm, namely the multi-verse optimizer algorithm, is proposed in [43]. The slow speed of the time domain refractometry (reduced speed) causes increase in travel distance; a developed multi-verse optimizer algorithm is introduced, which is employed to find the optimal parameters values of support vector machine. Moreover, the numerical simulation analysis is carried out with the datasets from the repository of the University of California Irvine (UCI). The achieved results revealed that the developed multi-verse optimizer algorithm for finding the optimal parameters values of support vector machine parameter optimization has powerful optimization ability and better production.

A modern optimization technique, named multi-verse optimizer algorithm, is employed in [59] to recognize the optimal parameters of the proton exchange membrane fuel cell (PEMFC) following specific operating requirements. Seven adjusting parameters are optimized in order to achieve polarization curves closely converged to those achieved in the manufacturer's datasheet. The multi-verse optimizer algorithm is designated by simple configuration, less handling parameters, and demanding less work in the computation process. Four groups of voltage stack experimental are used: Two of them are utilized for the optimization rule while the others are applied for design testing in the behavior of two kinds of parameter restrictions. Comparative studies including analytical adjustment parameters with two kinds of processes are produced: The first systems are published in the literature like SGA, RGA, HABC, HGA, and HADE while the second systems are processed such as gray wolf optimizer algorithm, flower pollination algorithm, artificial bee colony algorithm, and mine blast algorithm. The simulated results showed that the multi-verse optimizer algorithm is a better option among other comparative approaches since it gave less fitness function value and less convergence sped.

4.6 Other applications of multi-verse optimizer algorithm

The multi-verse optimizer algorithm is recognized as one of the recent meta-heuristics optimization algorithms. The multi-verse optimizer algorithm is motivated by the astrophysics theory of the multi-verse in nature life. The theoretical framework, operations, procedures, and main advantages of this algorithm are discussed in [41]. Furthermore, a brief literature review is carried out to present various variants of the multi-verse optimizer algorithm. Moreover, the main applications of the multi-verse optimizer algorithm are further completely explained. As well as, the multi-verse optimizer algorithm is examined on tackling data clustering problems. The proposed algorithm is tested by several datasets and is evaluated qualitatively and quantitatively measures. The obtained results show that the proposed multi-verse optimizer algorithm for tackling the clustering problems obtained better results in comparison with other several similar algorithms published in the literature such as genetic algorithm, particle swarm optimization algorithm, and dragonfly algorithm in regard to clustering purity, clustering correlation, and clustering accuracy.

5 Discussion

Generally, global optimization problems such as benchmark functions are associated with a method of achieving optimal solutions of a numerical operation by defining the minimum/maximum of the assigned objective function. Due to the improved complexity of optimization problems uses in various real-world problems, the improvement of optimization procedures is growing to make the algorithms more valuable, critical, and important than before. Over the earlier decades, several optimization techniques have been employed according to certain characters of biology or nature life.

Generally, as stated before the Introduction part, optimization algorithms are split into two subclasses of special optimization algorithms (runs with one randomly produced solution) and population optimization algorithms (runs with a set of randomly produced solutions). Large gradient data are demanded by the individual optimization algorithms, and they normally run with one single solution, developed fourth a set of a pre-defined number of iterations. The less computation is challenged by these sets of optimization algorithms, and a good plan is implemented to obtain the optimal global solution for simple designs or problems. However, they usually have lacked such as judgment mechanism, agile convergence, and uncertain search in complex problems. Regarding the latter, the optimization rules have a tendency, to begin with, a population of initial random solutions, provided within the available search space and developed repetitively. It would be very important and helpful to operate this set of optimization techniques to avert trapped in local search. Also, the mutual information between the solutions helps the worked algorithm to enhance its solutions over multiple difficulties of complex search spaces [1, 64].

The sets of searching techniques are categorized into two milestones, which are the main character of population methods (i.e., stochastic search methods: exploration search (i.e., diversification/globally) and exploitation search (intensification/locally)) [65]. The above-mentioned exploration search denotes how the population solutions have a tendency to be developed iteratively and explore the promising regions of the search area as far as feasible. In contrast, the search solutions are settled by the exploitation method to converge close the near-optimal solution achieved in that stage.

Usually, the process of exploitation search has ended with a sharp convergence, but escaping the local search is the result of having a variety of solutions. Consequently, a proper procedure should operate to produce a better balance between these search rules. Recently, meta-heuristic optimization approaches have operated successfully in tackling wide sets of real-world optimization problems because of its characteristics: flexibility, homogeneity, privation-free mechanism, and avoid the local optima. That is why these techniques (i.e., population-based algorithms) have utilized to solve complex areas effectively. Scholars have introduced many powerful, successful, and effective optimization techniques driven by nature life.

The benefit of meta-heuristics is portrayed for certain reasons. First reason, the utility of the stochastic framework underpins meta-heuristics to avoid the stuck in nearby optima and unite to the close near-optimum [66]. The point here is not to acquire the definite best solution however to get a close ideal solution with a reasonable computational time. The fundamental factor to give such a point relies upon the regular harmony between the optimization procedures (i.e., exploration and exploitation). Exploration point is to find the empowering spaces in a complex-wide search space by the investigation of search regions adequately. Subsequently, the exploitation search is close by escalated by the investigation technique in a promising zone to discover top optimal solutions [67]. The better accomplishment and execution of a specific meta-heuristic in exchange for these two approaches, the better execution will be accomplished. The present optimization algorithms adjust the balance between these two strategies in a few different ways. They could be additionally balanced by changing it for better exploration or better exploitation search. At least two optimization algorithm parts are connected by mixture meta-heuristics together to take favorable features and ground-breaking of them while maintaining a strategic distance from however much as would be expected their issues and disadvantages [61]. Besides, the achievement of meta-heuristic optimization is because of their guideline, knowledge, usability, and fit in practice.

As previously mentioned, hybridizing meta-heuristics by joining its parts together wins the advantages of the components of them [67, 68]. It very properly may be performed between various optimization procedures in various levels including on the progress of operations inside the two pieces of the algorithms (for example abnormal state hybridization demonstrates low gap among the interior activities of optimization algorithms while low-level hybridization implies that only a meta-heuristic structure is given to another). Through the optimization procedures, the half breed meta-heuristic algorithms may share the data by consolidating more than one operator to introduce a powerful search strategy. Furthermore, the execution sequences of the optimization methods must be considered.

Swarm intelligence procedures, in a theoretical definition, are regularly known as a meta-heuristic enhancement. Meta-heuristics are strong stochastic procedures that lead and attract the search mechanism to iteratively replace the current solutions to improve it. As a rule, the solution is thus grown (accordingly advanced) by comparing to some random potential outcomes and components, in the reason for increasing the abilities to obtain better solutions as far as the solution nature, while the accomplished solutions are acquired from one irregular (stochastic) iteration to the next iteration. Contrary to inescapable standards, meta-heuristics may not be ideal to get the best solution to control an enhancement issue as it has been presented. But, more often than not, they viably produce an acceptable solution (close to the ideal solution) with a good computational time (a fair running time).

Meta-heuristics optimization has been widely applied to handle hard optimization problems. In any case, for complex issues or real problems, the most extreme of the optimization algorithms facing the trapped in local optimum problems fail to reach the near optimum. This is the logic analyzer for the week of exploration (diversification or global search) part (i.e., component) inside the examined algorithm. Several investigation techniques are worked to develop the performance of the algorithms and help in counteracting the disadvantages. These techniques are changing, hybridization, and elitism: the nearness of optimal solutions as a magnificent commanding component in a strategy [69, 70].

MOA has utilized to take care of various optimization problems exponentially and become powerful search method for solving complex problems. It is a cuteness algorithm and keeps running by stochastic computational instruments, which is utilized to locate the close ideal solution for the one-dimensional/multi-dimensional functions dependent on the target of the objective function (minimum or maximum). The MOA has a basic methodology, which can be effectively performed and just applied in various optimization areas. The outcomes condensed in this paper give reliable proof and confirmation of execution achievement of the MOA regarding creation (execution) and the nature of the best-got solution. This assertion is achieved dependent on studying and examining the acquired consequences of comparisons among the MOA and other comparative algorithms.

Like any optimization algorithm, MOA has the two advantages and some decided drawbacks. Even though there is no assembly proof for this algorithm, the outcomes checked on in this paper demonstrates the MOA competitiveness across other algorithms in estimations of the combination running. Table 3 demonstrates the advantages and shortcomings of MOA.

One of the chief problems associated with MOA is how to handle the probabilistic convergence characteristics of MOA, which is needed to fully understand the given algorithm. The problem of fast convergence (premature) in

Table 3 Advantages and disadvantages of the Multi-verse Optimizer Algorithm

Advantages	Disadvantages
- Combining with other algorithms is strangely comforting	- The first version of MOA has been proposed for benchmark optimization problems
- A good convergence speed	- Suffer from early convergence
- The accelerated method of getting high-quality solutions	- No theoretical converging view
- Proper for many sets of difficult optimization problems	- Probability shape changes by generations
- An effective global approach to search	- Several parameter tuning
- Proper for long search space (i.e., continuous and discrete)	
- Powerful neighborhood exploration characteristics	
- Adaptability and robustness are recognized as major characteristics	
- Strong search methods for an extended number of decisions	
- Have a higher possibility and achievement in making global optima	
- Low probabilities to stuck in a local optimum	
- Less dependency on first random solutions	
- MOA is easy in its scheme and implementation compared to other optimization methods	
- Controlled execution time	

Table 4 The average results for solving benchmark functions

Function	Comparative algorithms					
	PSO	GA	BA	FA	GSA	MOA
F1	0.0003	0.8078	1.0000	0.0004	0.0000	0.0000
F2	0.0693	0.5406	1.0000	0.0177	0.0100	0.0000
F3	0.0157	0.5323	1.0000	0.0000	0.0016	0.0341
F4	0.0936	0.8837	1.0000	0.0000	0.1177	0.0944
F5	0.0000	0.6677	1.0000	0.0000	0.0000	0.0005
F6	0.0004	0.7618	1.0000	0.0000	0.0000	0.0002
F7	0.0398	0.5080	1.0000	0.0009	0.0021	0.0000
F8	1.0000	1.0000	0.0000	1.0000	1.0000	1.0000
F9	0.3582	1.0000	0.4248	0.0190	0.0222	0.0000
F10	0.1045	0.8323	0.8205	0.0000	0.1569	0.3804
F11	0.0521	0.7679	1.0000	0.0074	0.4011	0.0000
F12	0.0000	0.4573	1.0000	0.0000	0.0000	0.0000
F13	0.0000	0.6554	1.0000	0.0000	0.0000	0.0000
F14	0.1816	0.4201	1.0000	0.0000	0.0961	0.3705
F15	0.3016	0.0000	1.0000	0.4395	0.2926	0.0229
F16	0.0427	0.0000	0.3572	0.5298	1.0000	0.0486
F17	0.0294	0.1093	0.8189	0.7093	0.7887	0.0000
F18	0.1772	0.0000	1.0000	0.0723	0.8018	0.0129
F19	0.7727	0.0192	1.0000	0.8176	0.9950	0.0000
Sum	3.2346	9.9634	16.421	3.6134	5.6858	1.8865

the MOA usually influences the search rules to be stuck in the local optimum. Normally, this problem happens when the solutions heterogeneity needs and the solutions cannot avoid the falling in the local optima. Moreover, there are high potentials for scholars to apply and use the advantages of MOA to address the difficult industry and real-world optimization problems.

6 Results and comparisons

This section offers a comprehensive set of benchmark analysis problems with various characters (as shown in Table 4) to study, examine, and prove the effectiveness of the MOA [71] compared to other related optimization algorithms in that domain (i.e., particle swarm optimization (PSO) algorithm [22], genetic algorithm (GA) [72], firefly algorithm (FA) [12], bat algorithm (BA) [73], and gravitational search algorithm (GSA) [74]). The obtained results in this section are normalized between 0 and 1 to explain and compare the results of all benchmark optimization functions. To decide the significance of the obtained results by MOA, a statistical ranking test, called Friedman ranking test, is performed and is shown in Table 5.

As shown in Table 4, the acquired results confirm that the MOA got better and promising results in almost all test cases in these experiments. Firstly, the MOA gives more reliable results (better) on three out of six unimodal benchmark optimization functions. Because of the characteristics of the unimodal test optimization functions, these obtained results proved that the MOA has high exploitation search ability in solving the problems and adjustable convergence rates. Secondly, as shown in Table 4, the results proved that the MOA produced better

Table 5 The results of the Friedman ranking test

Function	Comparative algorithms					
	PSO	GA	BA	FA	GSA	MOA
F1	3	5	6	4	1	1
F2	4	5	6	3	2	1
F3	3	5	6	1	2	4
F4	2	5	6	1	4	3
F5	1	5	6	1	1	4
F6	4	5	6	1	1	3
F7	4	5	6	2	3	1
F8	2	2	1	2	2	2
F9	4	6	5	2	3	1
F10	2	6	5	1	3	4
F11	3	5	6	2	4	1
F12	1	5	6	1	1	1
F13	1	5	6	1	1	1
F14	3	5	6	1	2	4
F15	4	1	6	5	3	2
F16	2	1	4	5	6	3
F17	2	3	6	4	5	1
F18	4	1	6	3	5	2
F19	3	2	6	4	5	1
Summation	52	77	111	44	54	40
Average	2.73	4.05	5.84	2.31	2.84	2.10
Final ranking	3	5	6	2	4	**1**

results matched with all other optimization algorithms used on the multimodal benchmark optimization functions (i.e., F7, F9, F11, and F12). The obtained results proved the MOA benefits from high exploration search and averted from the trapped in neighborhood optima. Eventually, the results of the MOA on the composite benchmark functions confirmed the superiority of MOA in solving the given optimization problems with large search areas.

According to the given normalization results, the overall performance of all comparative optimization algorithms can also be compared. The last row of Table 4 presents the summation of the obtained average results of all comparative optimization algorithms on all benchmark optimization functions. It is observed that MOA gives the minimum average value that MOA reliably overwhelms other relative optimization algorithms. Table 5 shows the summation, average, and final ranking of the ranking results of all given competitor algorithms using all benchmark functions. The ranking results in Table 5 reveal that the performance of the MOA is statistically significant; it achieved the first ranking compared with all comparative algorithms followed by the other algorithms (FA, PSO, GSA, GA, and BA).

7 Assessment and evaluation of multi-verse optimizer algorithm

As reviewed earlier, the multi-verse optimizer algorithm has been generally employed to address various optimization problems since it was proposed. The simple motivation, few parameters, and adaptive global search operation are the essential purposes for the prosperity of this algorithm. In comparison with other proposed meta-heuristic optimization algorithms, however, it has several limitations and suffers from certain drawbacks.

The main limitations and restrictions have occurred because of no-free-lunch theorem in search and optimization domain (NFL theorem), which says no suitable optimization algorithm for solving all various kinds of optimization problems. In other words perfect, the performance of all kinds of optimization algorithms matched over a standard finite set (F) of benchmark test functions is similar iff (if and only if) F is produced under permutation. It means that the multi-verse optimizer algorithm may need modification, adjustment, and changing when addressing real-world optimization problems. Another drawback is the objective function (i.e., single-objective nature) that makes it able to address just single-objective problems kind and the other kind of the objective function (i.e., multi-objective nature) that makes it able to address just multi-objective problems kind. The objective function should be presented with special operators to address various optimization problems such as binary, dynamic, discrete, multi-objective, and continuous.

The foremost drawback of the multi-verse optimizer algorithm is the low powers to manage the complexities of multimodal search procedures, as it considers the adjusting parameters (WEP and TDR) tend to approach to the near-optimal solution. Adding further random sophisticated approach to improve the solutions through the optimization operations will enhance the chance likelihood of finding the optimum solution when addressing complex multi-model problems. The performance of the multi-verse optimizer algorithm increases linked to the number of decisions. This is possible because of the ability of the initial population in a local optimum solution when addressing such problems. Meanwhile, there is no specific procedure or operation to address the failure of local optima in the literature.

The authors of the multi-verse optimizer algorithm executed a sufficient experiment and realized that investigating four collections of results in the best average (outcome) performance on standard benchmark test function problems and a collection of a normal dimensional space real-world problem. More testing collections is required when addressing medium or large scale problems. Last but not least important, the fast convergence speed/rate and stimulated local search method need further investigations to run ahead to find the local optimum solution when addressing difficult optimization problems with a big number of decisions and local solutions. Mechanisms should be arranged to reduce the convergence velocity and exploitations processes if the algorithm is stuck in local solutions. Adaptive methods are considered as beneficial methods/ways in this regard to improving the quality of the convergence acceleration corresponding to the number of maximum iterations of the best solution reached so far.

8 Conclusion and possible future directions

In this review paper, over 50 research articles were collected that have been used the multi-verse optimizer algorithm, studied, and analyzed to highlight the advantages, disadvantages, robustness, and weaknesses of the multi-verse optimizer algorithm for the researchers who are interested in the meta-heuristic optimization algorithms domain. This review comprehensively and exhaustively summarizes references published from the beginning of 2015 (March-2015) until the beginning of 2019 (April-2019). Most of these articles described the variants of the multi-verse optimizer algorithm, where the proposed versions of the multi-verse optimizer algorithm support to improve the ability of the original the multi-verse optimizer algorithm to address variant kinds of optimization problems, for instance binary, modifications, hybridizations, chaotic, multi-objective, and parameterless of the multi-verse optimizer algorithm. Furthermore, introduce the applications of the multi-verse optimizer algorithm in various fields, for instance machine learning (i.e., feature selection and training neural networks), engineering (i.e., scheduling, control of power systems, renewable energy system), image processing, and other applications.

The multi-verse optimizer algorithm is a very promising and interesting algorithm that has already been successfully applied to several problems. The multi-verse optimizer algorithm shares some advantages with other optimization algorithms (i.e., CSA, BA, and FA), such as simplicity, speed in searching, and ease of hybridization with other optimization algorithms. Furthermore, it has a unique advantage which it has only two parameters (WEP and TDR) responsible for balancing between exploration and exploitation [16]. However, multi-verse optimizer algorithm suffers from the problem of the slow convergence [49].

Based on the above discussion, the multi-verse optimizer algorithm is strongly viable for continued employment in the community. This review paper guides researchers who have a present work or planning to work in this field by explaining how the multi-verse optimizer algorithm can be used to deal with the various problems, pointing out its features, weaknesses, and proving its performance. Thus, different research problems can be solved by using the multi-verse optimizer algorithm.

As conclusion, the results obtained by MOA are promising in many areas, and there are still several opportunities to enhance its performance further. The MOA could be extended into various other areas of focus, including hybridization, modification, improvements, and variants based on the problems' needs. Consequently, the results of this survey paper could be beneficial for future interested scholars to explore developments by taking into account the advantages or disadvantages of other suggested methods.

For possible future works, we recommend enhancing the MOA with other meta-heuristic algorithm operators for further improvements and employing the MOA to solve different optimization problems. In future work, we will cover the following perspectives:

- Employing the MOA to solve unsolved optimization problems, especially multi-objective optimization problems.
- Modifying the MOA to deal with real-world optimization problems: NP-hard problems and discrete problems.
- Hybridizing the MOA with other algorithm components such as differential evolution and hill climbing.

Compliance with ethical standards

Conflict of Interest The author declares that there is no conflict of interest regarding the publication of this paper.

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