International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 / https://doi.org/10.14445/22315381/IJETT-V71I3P218
Volume 71 Issue 3, 175-183, March 2023
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Review Article

Comparison of Meta-Heuristic Optimization Algorithms for Solving Optimized Task Scheduling Problems in Fog Environment

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Received: 21 September 2022 Revised: 09 February 2023 Accepted: 12 March 2023 Published: 25 March 2023

Abstract - *These days, the most popular kind of algorithm being utilized is called a meta-heuristic algorithm. Because the search space in such an algorithm can only be constrained by the best answer, the resulting searching domain is poor, which in turn leads to a long searching process. The reason for this study is to provide a comparative examination of a meta-heuristic optimization approach that may be used to address difficulties with task scheduling. When using the recently created and effective swarm intelligence algorithms, determining the solution for the Optimized task scheduling issue in Fog Environment is a tough challenge. An overwhelming number of challenges need to be tackled, including mixed decision variables; diversified restrictions; inherent mistakes; competing aims; and various locally optimum solutions. The behavior of various meta-heuristic algorithms, such as the Multiverse Optimizer(MVO), Improved Multi-Objective Multi-Verse Optimizer (IMOMVO), Moth-Flame Optimizer(MFO), Atom Search Optimization (ASO), Ecogeography-based Optimization (EBO), Queuing Search Algorithm (QSA), and the equilibrium optimizer, is investigated in this work. In earlier research activities, IMOMVO was developed as a solution to address the shortcomings that were discovered in the original MVO as well as its most recent improved version, MVP. This category of approaches is capable of resolving the issue of the avg positioning by improving equations for updating AP based on the best & second-best solutions currently available. The creators of IMOMVO employed many datasets scenarios with various jobs and virtual machines (Vms) to assess the capabilities of the technique while doing an evaluation. The findings of the IMOMVO approach have been validated with the use of standard evaluation criteria, including Vms processing power, task execution time, and throughput. During the task scheduling process, IMOMVO got better outcomes according to the assessment metrics than other methods that are considered to be state-of-the-art.*

Keywords - *Fog environment, Optimized task scheduling, Meta heuristic optimization technique, MVO, IMOMVO, MFO, ASO, EBO, QSA.*

1. Introduction

An architecture known as fog computing or fog networking, often referred to as fogging, is one that uses edge devices to perform a significant amount of computing, storage, and communication locally, with the results transmitted across the Internet's main infrastructure. Large data centers, which may be anywhere from a few hundred to a few thousand kilometers distant from client devices, comprise the backbone of the cloud's centralized design. Fog architecture is decentralized and made up of millions of tiny nodes that are strategically placed near client devices.

1.1. Task Scheduling in a Cloud-Based Fog Environment

It is a relatively new kind of computing platform that has become prevalent as a result of Internet technologies and the development of virtualization [1]. The term "cloud computing" refers to a certain kind of distributed system that is made up of a network of virtualized computers that are associated with one another and whose resources are allocated on demand. It makes available aggregated computing resources by SLA that have been made between consumers & service providers [2]. The uses of this presented some difficulties. These issues are security, performance, resource management, along with dependability. The scheduling of tasks is a problem that arises in the context of resource management. When discussing cloud computing, the term "task scheduling" refers to the process of assigning users' tasks to the various resources that are available to enhance the execution of tasks and boost resource utilization [3].

One of the most crucial measures of a task scheduling algorithm's effectiveness is its execution cost [5]. This is because SLA dictates how Cloud resources are divided up.

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However, the task scheduling method's difficulty comes from the need to squeeze a high number of activities into a finite set of resources. Yet, while designing a work scheduling algorithm, there are several considerations to bear in mind. Some of these criteria are critical to consider from the point of view of a cloud user, such as the reaction time, cost, and compilation time of tasks. Other metrics, such as resource usage, fault tolerance, and power consumption, are significant from the standpoint of the cloud provider [4]. "Fog computing" refers to the practice of extending cloud-based services to the network's periphery. In such a situation, deciding where applications should be processed to fulfill their quality-of-service needs is crucial. Therefore, an efficient task scheduler is necessary for a cloud-fog system to decide where applications should run. Integer linear programming-based task schedulers have been developed via previous research. Schedulers vary from a previous paper by selecting processing components on which tasks should be done based on the class of services[5]

1.2. Optimization Strategies

On the other hand, meta-heuristic methods may be applied to problems regardless of whether or not the underlying function is differentiable, continuous, convex, etc. Algorithms treat optimization issues as a black box, only evaluating the objective function at a set of choice variables. Three main types of algorithms may be used to solve many problems. The idea of evolution is the foundation for evolutionary algorithms. This group includes such diversity. Algorithms that take cues from physical principles or events make up the second group, physics-based algorithms. Numerous algorithms have been developed to aid in the search for charged systems. Algorithms inspired by swarm intelligence are motivated by the idea of foraging behavior seen in swarms of animals such as ants, fish, and birds. Together with other species, they discussed the best spots to go to get food. Researchers and optimization algorithms have detected this very sophisticated behavior. Numerous metaheuristic optimization approaches have been developed to solve the structural design issues that arise in machining applications. Despite metaheuristics' shown efficacy in a wide variety of engineering applications, they have received very little research attention for mechanical design problems. In this study, we evaluate nine alternative metaheuristic algorithms and analyze how well they perform on problems with a wide range of restrictions and search areas. Solution quality and convergence rate analyses are performed at various stages of the search operation to evaluate the search performances of each algorithm used [19].

1.3. Need for Research

It has been determined that the issue of scheduling tasks is an NP-Complete one. As a result, optimization strategies might be used to find a solution to the problem by taking into account various performance criteria (such as the amount of money spent, the amount of time needed to complete the task, etc.). [4]. The purpose of this study is to conduct a comparative examination of several meta-heuristic optimization algorithms for use in the fog environment for work scheduling algorithms. These optimization algorithms provide support for the task scheduling algorithm when independent tasks are being allocated and carried out. Because of this, the amount of time it takes to do a job may improve, the cost of execution may go down, and resource utilization may be increased.

1.4. Literature Review

The present section presents existing research in task scheduling, cloud computing, fog computing, and meta-heuristic optimization techniques. S. H. Jang [1] did a study on genetic algorithms. They focused on task scheduling in cloud computing. T. Goyal [2] made a research on the Host Scheduling Algorithm. The author used a Genetic Algorithm and provided a scalable solution.R. Kaur [3] introduced an enhanced Genetic Algorithm. The objective of their work was to contribute to task scheduling over the cloud platform. J. W. [4] researched cloud computing task scheduling algorithms. Their research was also based on an improved genetic algorithm. Mouradian [5] surveyed fog computing and considered issues and challenges in the fog environment. Ren Z [6] conducted research on resource scheduling. Their research was for delay-sensitive application, which was applicable over three-layer fog-to-cloud architecture. Guevara [7] introduced a task-scheduling mechanism for cloud-fog computing systems. Wang S [8] proposed a reliability-aware task scheduling mechanism. Their research was based on the replication of heterogeneous systems. Mapetu [9] did work for low-time complexity along with low-cost binary PSO. The author used the PSO mechanism to perform task scheduling with load balancing. They implemented task scheduling in cloud computing. Abualigah [10] proposed a novel hybrid antlion optimization algorithm. The research was used to resolve multi-objective task scheduling issues that have been found in cloud computing environments. Oyelade [11] researched the Ebola optimization searching mechanism. This mechanism is a new nature-inspired meta-heuristic optimization technique. Sreenu [12] proposed a task-scheduling mechanism that makes use of whale optimization. Abualigah [13] did work on Reptile Search Algorithm. This is a nature-inspired meta-heuristic optimization mechanism. Shayanfar [14] introduced a recent meta-heuristic algorithm. This mechanism was introduced to solve issues related to continuous optimization. Abd Elaziz [15] proposed an advanced optimization technique. Their technique has been applied for scheduling IoT operations in cloud-fog environments. Arunarani [16] introduced a task scheduling mechanism used in the cloud environment. Otair [17] focused on optimized task scheduling. The author did work in the cloud environment and used an enhanced multi-verse optimizer. Shubham Gupta [18] did the comparative analysis. The author considered meta-heuristic optimization algorithms in their work.

Table 1. Existing Research

Citation	Author/year	Objective	Methodology	Limitations
[1]	S. H. Jang/ 2012	To make the study of genetic algorithm-depending on task scheduling	Genetic algorithm	No work in the area of the fog system
[2]	T. Goyal/ 2013	To host scheduling Algorithm by making use of a genetic algorithm	Genetic algorithm	No work in the area of optimization along with fog
[3]	R. Kaur/ 2014	With the goal of introducing a better genetic algorithm for scheduling tasks.	Genetic algorithm	No work in the area of the fog system
[4]	J. W. Ge/ 2013	Improved genetic algorithm-based job scheduling algorithm implementation.	Genetic algorithm	No work in the area of the fog system
[5]	Mouradian/ 2018	To make the survey on fog computing	Fog computing	To schedule, a mechanism has been applied.
[6]	Ren Z/ 2020	Performing Resource scheduling for delay-sensitive application	Resource scheduling mechanism	Need to improve the solution by the optimizer
[7]	Guevara/ 2021	Performing Task scheduling	Task scheduling mechanism	Need to integrate a high-accuracy solution.
[8]	Wang S/ 2017	To provide a work scheduling technique that takes dependability into account for distributed systems	Replication-based task scheduling	Lack of scalability
[9]	Mapei/ 2019	In order to develop a load-balancing and task-scheduling system that is low-cost and low-complexity in terms of time	PSO	Need to consider a meta-heuristic approach.
[10]	Abualigah/ 2021	To propose a novel hybrid approach for multi-objective task scheduling issues.	Hybrid Antlion optimization	Lack of meta-heuristic approach
[11]	mOyelade/ 2022	Making use of advanced nature-inspired meta-heuristic optimization	Ebola optimization	Limited scope
[12]	Sreenu/ 2019	Making use of whale optimization to perform task scheduling	Whale optimization	Lack of flexibility
[13]	Abualigah/ 2022	To get optimum solution	Reptile searching algorithm	Lack of reliability
[14]	Shayanfar/ 2018	To resolve optimization problems	Metaheuristic algorithm	Need to do more work on performance
[15]	Abd Elaziz/ 2021	Tasks related to the Internet of Things (IoT) must be scheduled, and cloud-fog situations provide a	Optimization technique	Need to update optimization technique
[16]	Arunarani/ 2019	To implement task scheduling over the cloud	Task scheduling mechanism	Scope of work is limited
[17]	Otair/2022	Performing optimized task scheduling.	IMOMVO	Complexity of work
[18]	Shubham Gupta/2021	To perform a comparative analysis of metaheuristic optimization algorithms	MVO, MFO, ASO, EBO, QSA,	Need to do more work on MVO
[19]	K. M. Mak/ 2014	Circularly polarized patch antenna for future 5G mobile phones	5G	Lack of security and accuracy
[20]	S. Bitam/ 2018	Fog computing job scheduling optimization based on bees' swarm	scheduling, optimization technique	There is lack of performance
[21]	B. Jamil/ 2020	A job scheduling algorithm for delay and performance optimization in fog computing	optimization technique, scheduling algorithm	Lack of technical work
[22]	M. Ghobaei-Arani/2020	An efficient task scheduling approach using moth-flame optimization algorithm for cyber-physical system applications in fog computing	scheduling, optimization technique	Research is limited to traffic flow
[15]	M. Abd Elaziz/ 2021	Scheduling Internet of Things jobs in cloud-fog computing systems requires an advanced optimization method.	Internet of Things, optimization technique	There is less technical work
[24]	S. Ghanavati/ 2017	Fog computing: an energy-aware task scheduling model with ant-mating optimization	Optimization technique, Task scheduling	There is not performed in future
[25]	Z. Movahedi/ 2021	The use of a population-based, multi-objective scheduling method in fog computing systems.	Fog computing, scheduling	Lack of efficiency

Table 2. Feature Comparison

	Task scheduling	Resource scheduling	Genetic Algorithm	Cloud computing	Fog computing	Optimization based	Meta-heuristic optimization
[1]	Yes	No	Yes	Yes	No	No	No
[2]	Yes	No	Yes	Yes	No	No	No
[3]	Yes	No	Yes	Yes	No	No	No
[4]	Yes	No	Yes	Yes	No	No	No
[5]	No	No	No	No	Yes	No	No
[6]	No	Yes	No	Yes	Yes	No	No
[7]	Yes	No	No	Yes	Yes	No	No
[8]	Yes	No	No	No	No	No	No
[9]	Yes	No	No	No	No	Yes	No
[10]	Yes	No	No	No	No	Yes	No
[11]	No	No	No	No	No	Yes	Yes
[12]	Yes	No	No	No	No	Yes	No
[13]	No	No	No	No	No	Yes	Yes
[14]	No	No	No	No	No	Yes	Yes
[15]	Yes	No	No	Yes	No	Yes	Yes
[16]	Yes	No	No	Yes	No	No	No
[17]	Yes	No	No	Yes	No	Yes	Yes
[18]	No	No	No	No	No	Yes	Yes
[19]	No	No	No	No	No	Yes	No
[20]	No	No	No	No	Yes	Yes	No
[21]	Yes	No	No	No	Yes	Yes	No
[22]	Yes	No	No	No	Yes	Yes	No
[15]	No	No	No	Yes	Yes	Yes	No
[24]	Yes	No	No	No	Yes	No	No
[25]	Yes	No	No	No	Yes	No	Yes

Ka Ming Mak[19] presented a circularly polarized patch antenna for future 5G mobile phones. The proposed antenna covers a wide elevation angle and a complete azimuth range. A parametric study of the effect of the metallic block and the surrounding dielectric substrate on the gain at a low elevation angle and the axial ratio of the proposed antenna are presented. Salim Bitam [20] reviewed fog computing job scheduling optimization based on the bees swarm. To solve the issue of work scheduling in the fog computing setting, they present a novel bio-inspired optimization method they call BLA. Our strategy involves dividing up work amongst all of the fog computing nodes in the most efficient way possible. Bushra Jamil [21] provided a job scheduling algorithm for delay and performance optimization in fog computing. To this end, they offer a new Fog computing scheduler that facilitates service provisioning for the Internet of Things, with the aim of minimising both latency and network consumption. They propose a use case for appropriately scheduling requests from IoE devices on Fog devices and effectively meeting their needs for the available resources on each Fog device. Mostafa Ghobaei-Arani [22] introduced an efficient task-scheduling approach using a moth-flame optimization algorithm for cyber-physical system applications in fog computing. To satisfy the quality-of-service criteria of CPS applications in a manner that minimizes overall execution time, this study introduces a task scheduling method based on the moth-flame optimization process. Mohamed Abd Elaziz [15] focused on advanced optimization techniques for scheduling IoT tasks in cloud-fog computing environments. Based on a variant of AEO, they came up with a new approach to task scheduling for IoT requests in a cloud-fog setting; they named it AEOSSA. By including the operators of SSA, this adaptation aims to improve AEO's exploitation capability while it searches for the best solution to the challenge at hand. Sara Ghanavati [24] researched an energy-aware task scheduling model using ant-mating optimization in a fog computing environment. As a means of decreasing the overall system makespan and energy usage for fog computing platforms, they present and assess a novel job scheduling method. Zahra Movahedi [25][29] presented an efficient population-based multi-objective task scheduling approach in fog computing systems. With time and energy use as two QoS metrics in mind, they tackle the job scheduling issue in the fog environment. To start, they show how a fog-based architecture may handle the ideal options for scheduling tasks. Our second step is to describe the job scheduling issue as an ILP optimization problem, one that takes into account both time and fog energy usage.

Table 2 has classified research on the basis of task scheduling, resource scheduling, cloud-based, fog-based, optimization-based, and research that considered meta-heuristic optimization.

2. Problem Statement

There have been several research works in the area of task scheduling and cloud computing. But limited work has been made in the area of fog computing. Moreover, there is a need to integrate an optimization mechanism to get the best solution during task scheduling. It has been observed that Meta-heuristic approaches such as MVO are performing better than other nature-inspired approaches. Thus, there is a need to do more work in the area of meta-heuristic optimization for task scheduling in a fog environment.

3. Comparative Analysis of Meta-Heuristic Algorithm

Several meta-heuristic algorithms include MFO, MVO, EBO, ASO, QSA, and equilibrium optimizer. The present section is focused on the elaboration and comparative analysis of these mechanisms.

3.1. MVO

The MVO was developed using the most recent multiverse idea in physics (Mirjalili et al., 2016). In this method, wormholes, white holes, and black holes—three essential features of the multiverse hypothesis—are mathematically represented to create the foundational stages of the multiverse generating set (MVO). Stars, planets, asteroids, white holes, black holes, habitable conditions, and physical laws all depend on the inflation rate of the universe. Because of these problems, the MVO was created. As part of the MVO, wormholes are employed to both exploit and explore space. Each of the MVO's potential solutions within the search space is called a "universe" and is generated randomly. Once the MVO is up and running, it performs updates on each universe as described below:

1. One, the probability of white holes rises while the probability of black holes falls when inflation rates are high.
2. Some items prefer to fall into black holes from white holes, whereas others with a greater inflation rate prefer to acquire new objects via black holes.
3. The most inflamed things, regardless of their origin, may go randomly to the finest possible universe.

3.2. MFO

It is a fresh contribution to the area of metaheuristics along the lines of the MFO created by Mirjalili (2015b). This technique is based on observations of the common moth's navigational habits, known as transverse orientation. In MFO, moths represent candidates for the search operation (either as search agents or as prospective solutions), while flames stand in for the best-obtained locations inside the search space thus far. Because of this, flames are often seen as moths' way of leaving behind a trail of flags as the search progresses. If a moth wants to provide a better response, it will go for warmer environments and improve its perch. The algorithm must always know where to search. Thus, the best flame's coordinates are passed on to subsequent iterations. An initial moth colony is started in the MFO. At each cycle, the following search technique is used to reseed this population:

$$M_i^{t+1} = F_j + D_i \times e^{bl} \times \cos(2\pi t)$$

Where M_i^{t+1} is the position of i^{th} moth at iteration t +1, F_j is the j^{th} flame & D_i is the distance between i^{th} moth & j^{th} flame. b is a constant used to define a form of a logarithmic spiral, whereas l is a random value drawn from the range [r,1]. To hasten convergence towards the fire, this r, the adaptive convergence constant, gradually decreases from -1 to -2 during repetitions.

N_f is the no. of frames during the search procedure:

$$N_f = \text{round}\ (N - t/\ t_{max}) \times (N-1))$$

where N is the maximum number of flames, and t & t_{max} represent the current and maximum iterations, respectively.

3.3. Atom Search Optimization (ASO)

Zhao et al. (2019) created ASO using atomic dynamics. Following the steps below, you will get an equation for the total interaction forces acting on the jth dimension of the ith atom.

$$F^t_{i,d} = \sum_{j\in Kbest} rand_j F^t_{ij,d}$$

where rand is a random value within the interval [0,1], and K_{best} is a subset of the population used for fit testing. In early rounds of ASO, each of them interacts with a large number of atoms with higher fitness ratings in order to undertake more exploration.

3.4. Ecogeography-Based Optimization (EBO)

Zheng et al. modified the BBO algorithm to produce the EBO algorithm (2014). This approach treats the population of islands/solutions as a distributed ecosystem. The EBO is built in a way that is similar to the BBO, with a few key differences. To update island x_i, EBO introduces a new global migration operator in which a non-neighbor x_{far} is chosen in addition to the neighbor x_{nb}.

$$x_{i,d} = x_{far,d} + \beta\cdot(x_{nb,d} - x_{i,d}) \text{ if } fit_{xfar} > fit_{xnb}$$
$$x_{i,d} = x_{nb,d} + \beta\cdot(x_{far,d} - x_{i,d}) \text{ if } fit_{xfar} \leqslant fit_{xn}$$

Specifically, the difference$(x_{nb,d} - x_{i,d})$ or $(x_{far,d} - x_{i,d})$ between two islands is considered "ecological differentiation" and is referred to as the "evolutionary force" coefficient when is in the range [0,1]. According to the search equation, people move to island xi from both faraway and nearby islands. This worldwide mobility is especially important during the beginning of the EBO, when species may more easily colonize new environments. The following equation is used to rationalize the pursuit of exploitation or local migration due to the high exploration in the EBO induced by this global migration, which may occasionally lead to divergence 2.

$$(x_{nb,d} - x_{i,d})$$

With the aid of the immaturity index μ, which conducts both local and global migration & is supplied by the following equation, the EBO maintains the balance between exploration & exploitation

$$\mu = \mu_{max} - (t / t_{max}) \times (\mu_{max} - \mu_{min})$$

3.5. Queuing Search Algorithm (QSA)

QSA was created by Zhang et al. to simulate human behavior in a queue (2018). QSA takes into account many broad phenomena, including the fact that customers are served more quickly if they stick to the queue's established order and the fact that each customer is affected differently when the queue's established order is disrupted. The QSA's three "business" stages are designed to strike a balance between resource extraction and discovery. The following are the specifics of each stage:

3.5.1. Business 1

All search agents (or clients in the QSA) are split up across queues Q11, Q12, and Q13. Best-fitting customers A11, A12, and A13 are chosen to serve as team leaders. The QSA tallies the number of people waiting in each line.

3.5.2. Business 2

In this stage, the revised procedures are implemented for a subset of the clientele. Customers are ranked based on their fitness level, and their probabilities are then determined.

3.5.3. Business 3

A subset of customers is used, much as in business2, but this time the mutation probability is applied to the dimensional level of the position update process.

3.6. Equilibrium Optimizer (EO)

Using a simple well-mixed approach, the EO simulates dynamic mass balance on a control volume, making it a unique meta-heuristic. By solving a mass balance equation, we may determine how various sources and sinks contribute to and remove from the final concentration of a nonreactive substance in a controlled volume. When the initialization phase is over, new EO candidate solutions are generated.

$$C_i^{t+1} = C^t_{\theta q} + (C^t_i - C^t_{eq}) \times F^t_i + (1 - F^t_i) \times G^l_i \; / \lambda^t_i v^t_i$$

where C^t_i and C_i^{t+1} are concentration vectors for i^{th} candidate solutions at iteration t and t + 1, respectively. C^t_{eq} is a randomly selected vector from the equilibrium tool.

3.7. Best solutions obtained by the Applied Algorithms

A comparison of the best solution obtained by different meta-heuristic optimization mechanisms has been shown in table 3. Best solutions have been presented for variables d, D, N, and $f_{best.}$

3.8. Comparison of Various Statistical values by Applied Algorithms

A comparison of the best solution obtained by different meta-heuristic optimization mechanisms has been shown in table 4. Best solutions have been presented for mean, best, worst & SD.

Table 3. Best solutions obtained by applied meta-heuristic optimization algorithms for different variables

Variables	MVO	MFO	ASO	EBO	QSA	EO
d	0.051191	0.050858	0.052729	0.053355	0.051688	0.051322
D	0.344817	0.337061	0.382264	0.397653	0.356700	0.347951
N	12.04755	12.54176	9.934610	9.251924	11.28999	11.82200
f_{best}	0.012693	0.012678	0.012684	0.012737	0.012665	0.012667

Table 4. Comparison of various statistical values by meta-heuristic optimization algorithms

Statistics	MVO	MFO	ASO	EBO	QSA	EO
Best	0.012693497334	0.012678015647	0.011588881581	0.012737585662	0.01266523279	0.012667706272
Mean	0.015961898059	0.014306586748	0.014579929867	0.013384405662	0.01266666921	0.013154360934
Worst	0.018075268108	0.017773158078	0.022603040575	0.015001367506	0.01267436276	0.017773158275
Standard deviation	1.8089E-03	1.6344E-03	1.9396E-03	5.1395E-04	2.5895E-06	1.3810E-03

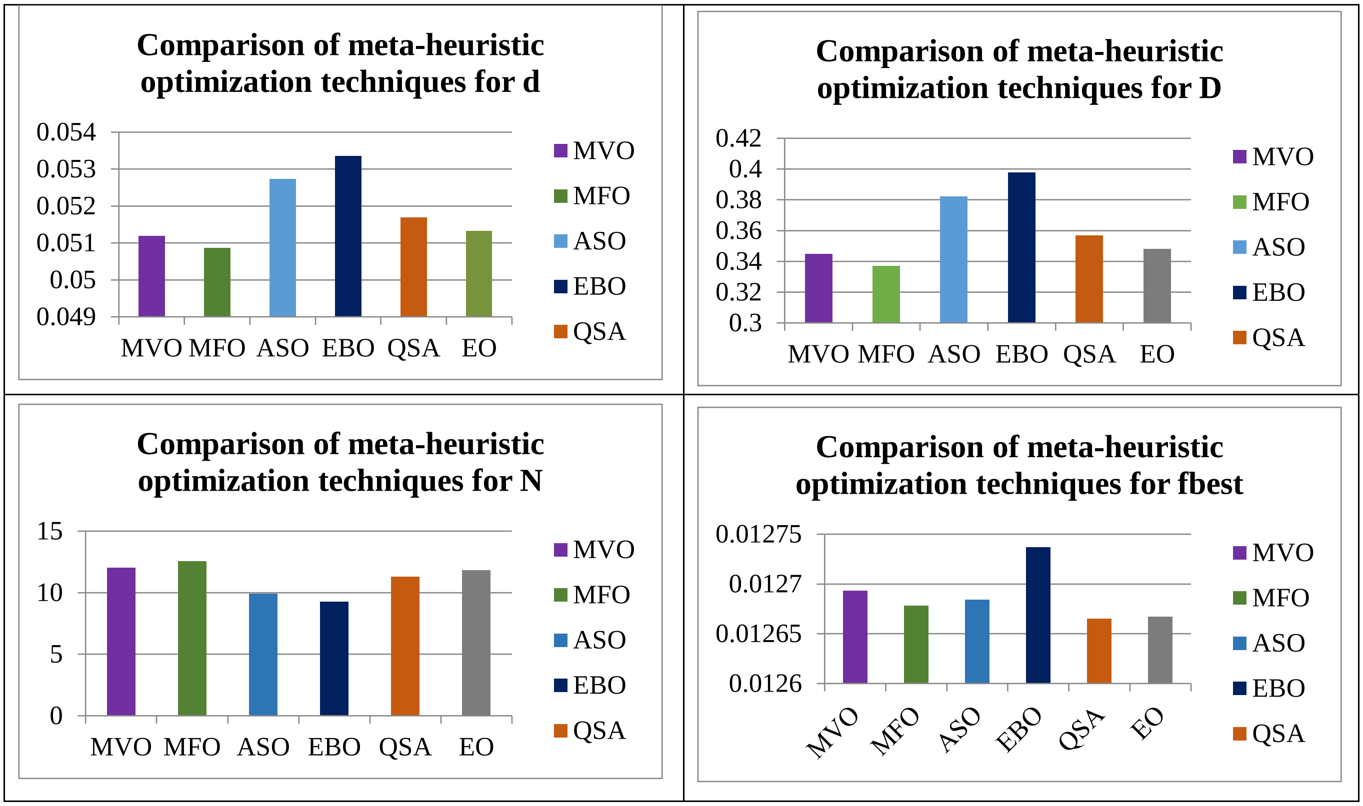

Fig. 1 Comparison of metaheuristic optimization mechanism for best solution obtained

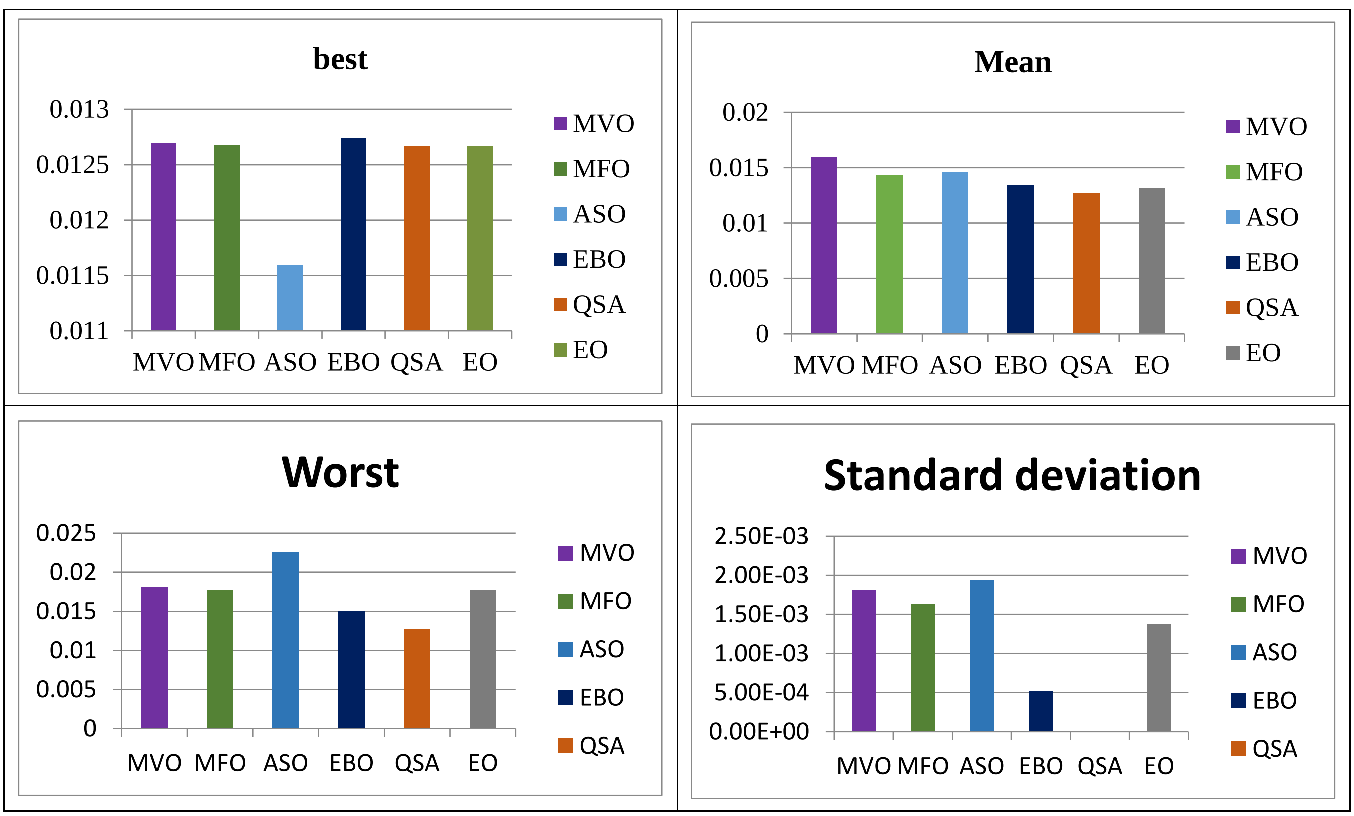

Fig. 2 Comparison of various statistical values by the applied algorithms

4. Conclusion

When trying to find the best answer to genuine design problems, evaluating the searchability and performance of newly presented meta-heuristic algorithms might be difficult. This is made more challenging by the structure of the decision parameters, which comprises continuous and discrete variables, many goals, and different nonlinear restrictions depending on performance operations, manufacturing needs, and kinematic conditions.

In this analysis, we evaluate the meta-heuristic optimization algorithms MFO, MVO, EBO, ASO, QSA, & EO on eight different scenarios, contrasting their results in terms of solution quality, convergence time, success rate, and resilience.

In a comprehensive analysis of the available algorithms, we find that the QSA is head and shoulders above the competition in terms of solution quality, convergence speed, success rate, and resilience. Comparisons of algorithms reveal that the used meta-heuristic algorithms may provide significant alternatives in numerous domains, including task scheduling in a cloud-based fog computing environment, for solving real global optimization issues.

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