



Guided golden jackal optimization using elite-opposition strategy for efficient design of multi-objective engineering problems

Václav Snášel¹ · Rizk M. Rizk-Allah^{1,2,4} · Aboul Ella Hassanien^{3,4}

Received: 3 January 2023 / Accepted: 30 June 2023 / Published online: 25 July 2023
© The Author(s), under exclusive licence to Springer-Verlag London Ltd., part of Springer Nature 2023

Abstract

Multi-objective optimization (MOO) issues that are encountered in the realm of real engineering applications are characterized by the curse of economically or computationally expensive objectives, which can strike insufficient performance evaluations for optimization methods to converge to Pareto optimal front (POF). To address these concerns, this paper develops a guided multi-objective golden jackal optimization (MOGJO) to promote the coverage and convergence capabilities toward the true POF while solving MOO issues. MOGJO embeds four reproduction stages during the seeking process. Firstly, the population of golden jackals is initialized according to the operational search space and then the updating process is performed. Secondly, an opposition-based learning scheme is adopted to improve the coverage of the Pareto optimal solutions. Thirdly, an elite-based guiding strategy is incorporated to guide the leader golden jackal toward the promising areas within the search space and then promote the convergence propensity. Finally, the crowding distance is also integrated to provide a better compromise among the diversity and convergence of the searched POF. To evaluate the MOGJO's performance, it is analyzed against sixteen frequently utilized unconstrained MOO issues, five complex constrained problems, four constrained engineering designs, and real dynamic economic-emission power dispatch (DEEPD) problem. The experimental results are performed using the generational distance (GD), hypervolume (HV), spacing (SP) metrics to validate the efficacy of the proposed methods, which affirms the progressive and competitive performance compared to thirteen state-of-the-art methods. Finally, the results of the Wilcoxon rank sum test with reference to GD and HV exhibited that the proposed algorithm is significantly better than the compared methods, with a 95% significance level. Furthermore, the results of the nonparametric Friedman test were performed to detect the significant of average ranking among the compared algorithm, where the results confirmed that the proposed MOGJO outperforms the best algorithm among thirteen state-of-the-art algorithms by an average rank of Friedman test greater than 41% while outperforming the worst one, MOALO, by 84% for ZDT and DTLZ1 suits. Additionally, the proposed algorithm saved the overall energy cost and total emission of the DEEPD problem by 1.89%, and 1.48%, respectively, compared with the best existing results and thus, it is commended to adopt for new applications.

Keywords Golden jackal optimization · Opposition · Pareto front · Multi-objective optimization · Design optimization

✉ Aboul Ella Hassanien
aboitcairo@cu.edu.eg
https://www.egyptscience.net
Rizk M. Rizk-Allah
https://www.egyptscience.net

¹ Faculty of Electrical Engineering and Computer Science,
VŠB-Technical University of Ostrava,
70800 Poruba, Ostrava, Czech Republic

² Basic Engineering Science Department, Faculty of
Engineering, Menoufia University, Shebin El-Kom 32511,
Egypt

³ Faculty of Computers and Information, Cairo University,
Cairo, Egypt

⁴ Scientific Research Group in Egypt (SRGE), Cairo, Egypt

1 Introduction

1.1 Overview

Currently, engineering designs have become a global challenge due to the industrial revolution and population growth. In fact, the problems encountered in real life are in the form of multi-benefit and/or multi-cost objectives that need to be handled simultaneously and this type of problem is termed as multi-objective optimization (MOO) problem. Therefore, optimizing this type of problem has become a great challenge for practical engineering fields to maintain reliable design in terms of operability and accuracy. In MOO problems, the difficulty level of the problem likewise rises as the number of conflicts of objective functions increases [1, 2]. Unlike a single solution to the optimization of a single objective (SO) problem, the optimal of the MOO problem is a set of solutions caused by the conflicting nature among the targets or objectives, which is denoted by Pareto optimal set (POS) that is purported in the decision space while its corresponding set in the objective space is denoted by Pareto optimal front (POF). Based on this sense, a solution is termed as POF, if no goal or objective can be advanced without harming one another goal at least [3].

To deal with MOO problems, there are three categories-based approaches on the basis of the perspectives or preferences of decision maker (DM), which are priority, interactive, and posteriorly methods [4]. In a priority method, termed as (decide \Rightarrow search), the DM decide his/her preferences before the beginning of the searching process. This type of preference is formulated using the utility function to aggregate all objective functions into only one function (i.e., for example, weighted sum approach), and then MOO problem can be solved by the SO method. The drawback of this category is the difficulty of articulating the DM's preferences. In the interactive method, termed as decide \leftrightarrow search, the DM elicit s the compromise solution in interactive articulation from the local/partial generated POF. The STEM and Steuer represent the prominent methods for this category [5, 6]. These methods are occupied by shortages such as relying on derivative calculations, initial estimates, and they suffer from local optima stagnation. In a posteriorly method, termed as search \Rightarrow decide, the POF is generated tentatively, and then the DM can select a solution from the POF based on utility function. However, the production of the entire POF requires a significant amount of processing time. Consequently, the aforementioned approaches are not appropriate for handling a wide range of optimization problems [7]. For the three last decades, several attentions have been paid to using the meta-heuristics algorithms (MHAs) to overcome

the shortages of traditional approaches. MHAs have a capability in providing a good coverage and convergence search toward the POF due to stochastic rules associated with their iterative processing. MHAs often imitate effective traits found in nature, especially in biological and swarm systems, and they can offer workable solutions to challenging optimization tasks.

1.2 Literature review

As previously stated, it is desired to meet the two challenges while dealing with the MOO problem which are that the attainable solutions should be well converged and well distributed along the POF. Toward this mission, researchers have proposed several multi-objective MHAs to deal with MOO problem using three groups of methods: (1) MHAs based on Pareto dominance, (2) MHAs based on indicator concept, and (3) MHAs based on decomposition. In the first group, the algorithms employ the Pareto dominance relation (PDR) to guide the search toward the POF. One the popular MHAs based on PDR is the non-dominated sorting genetic algorithm (NSGA) that selects the elite solution based on PDR and then preserves the diversity of the selected solutions using the crowding distance [8]. Also, there are many attentions have been introduced in the field of multi-objective MHAs based on the concept of PDR including the multi-objective (MO) particle swarm optimization (MOPSO) [9], MO ant lion algorithm (MOALA) [10], MO grey wolf optimizer (MOGWO) [11], MO artificial bee colony (MOABC) [12], and MO water cycle optimization (MOWCO) [13], MO slime mould algorithm (MOSMA) [14], and non-sorted moth-flame optimizer (NSMFO) [15], MO equilibrium optimizer (MOEO) [16], MO crow search algorithm-based on orthogonal-opposition strategy (M2O-CSA) [17], MO hurricane optimization (MOHO) [18], and MO ant colony optimization (MOACO) [19]. Other meta-heuristics present a modified aspect of PDR via relaxation to attain well diversity and convergence of solutions. In this context, the epsilon-dominance relation was proposed to extend the dominance region of a solution vector through modulating the related objective values by a small value [20]. This concept of relaxation is employed in many works of multi-objective MHAs whether for improving the solutions' diversity or updating and avoiding the explosion of the archive [21]. Similar to that, some relaxation concepts have been proposed including the alpha-dominance [22], grid dominance [23], cone dominance [24], fuzzy dominance, $(1 - M)$ -dominance [25], and theta-dominance [26]. However, the majority of the suggested dominance relations aim to enhance the convergence of MHAs, they may not provide a reasonable balance among coverage and

convergence capabilities while dealing with MOO problem.

The second group is the multi-objective MHAs based on indicator concept. In this sense, the performance metrics have been proposed to reach a good compromise among the diversity and convergence, where these metrics include inverted generational distance (IGD) indicator, hypervolume indicator (HV), and S-metric. For example, HV metric and new HV have been introduced to guide the optimization operation toward the Pareto front [27, 28]. Recently, there are some MHAs that have employed the distance indicators, IGD metric, and R-metric to guide the searching toward the POF [29]. The advantage of these indicators is that can provide a good balance among coverage and convergence abilities.

The third group is the decomposition-based algorithm in which the main problem is decomposed into sub-problems, and they are optimized simultaneously through using the scalarizing functions and weight vectors. The frequently used scalarizing functions are the weighted sum, Tchebycheff method, vector angle distance scaling, and the boundary intersection. One of the most well-known MO evolutionary algorithms (MOEAs) algorithms based on decomposition is MOEA/D [30]. It performs the exploration of the candidate search region using a set of scalar subproblems. Also, there are some algorithms that are presented based the decomposition such as NSGA-III [31], MOEA based on dominance and decomposition (MOEA/DD) [32], and MOEA/D-DE [33], etc. The MHAs based on decomposition can provide an effective manner in solving MOO problem. However, the selection of the scalarizing function affects each of these strategies differently.

Apart from the previously mentioned approaches, the scientific literature is highly rich with several applications of multi-objective MHAs. For example, in [34] the authors introduced a MO bee swarm optimization (MOBSO) to deal with the harmonic loss problem that occurs in power system operation. Study [35] analyzed the performance of designing a semi-active Fluid Viscous Damper (SAFWD) system using the NSGA-II on the basis of MOO problem with the purpose of lowering the seismic reaction of nonlinear frames. Authors applied an improved variant of the NSGA-II for tractor electromechanical drive system [36]. In [37] a hybrid algorithm based on MO artificial bee colony and differential evolution (HABC-DE) was applied to deal with the Next Release Problem (NRP) to identify the best demand set with the aim to boost the value of software release. Study [38] applied the teaching learning-based optimization (TLBO) to solve the MOO of TI-6Al-4 V micro-EDM with the aim to reach the best combination of program parameters. In [39] the authors applied an adaptive MO artificial immune algorithm (MOAIA) to solve the reactive power model with the aim to improve the

stability aspect of power grid voltage. In addition, some practical MOO tasks have been solved, such as power generation problem based on renewable energy technologies using MOO methodology [40], designing and improving the network of maritime protected areas [41], automobile hood problem [42], volatility index prediction problem based on deep learning system and MOO [43], biogas systems [44], biomedical field [45], and computerized tomography diagnosis [46]. Most of the world's issues acquire different natures, finite or infinite, continuous, discrete. Some works show that for more complicated issues with nonlinear and indiscernible concerns, methods such as the use of equality constraints to address these issues is often ineffective [47]. Therefore, the MHAs are designed and employed as an effective tool because of their convenience and ability [48].

2 Research gap and contributions

Although the recent advances in the field of MOO, there is still room for improvement to emphasize the quality of final results as well as finding well-distributed solutions regarding the POF. For example, the use of the normal algorithmic updating steps may lead to poor spread performance on MOO problems associated with irregular and non-smooth POFs. Moreover, ignoring the experience-based elite guiding strategy through the iterative process may degrade the convergence performance of the algorithm toward the POF. Besides, there is always inquiry ‘‘might a novel algorithm provide a better outcome?’’ The answer is ‘yes’ according to perspective of the No-Free-Lunch (NFL) theorem [49] that says, no optimization algorithm can address all natures of optimization tasks with reaching the global optimal solutions. Meanwhile, the main challenge in the MOO using optimization algorithms is the coverage and convergence features which are in conflict nature. In this sense, the coverage will be poor if an algorithm merely focuses on enhancing the accuracy of non-dominated solutions. By contrast, the accuracy of the non-dominated solutions is negatively impacted by the simple consideration of the coverage. Notwithstanding numerous alternatives as per the above-mentioned to reach the POF of the MOO designs with ensuring well-distributed solutions along the POF, and once again, still always there are room of improvements to precisely address two conflicting perspectives in dealing with MOO designs, convergence (i.e., that refers to the process of finding approximations very close to the true POF) and coverage (i.e., that refers to the process of improving the distribution of the solutions to cover the entire true POF). Therefore, scientists continue to be motivated to develop novel methods wishing to address a wider variety of

difficulties or specific unsolved optimization challenges while fulfilling the convergence and coverage perspectives. Thus, this study aims to fill this research gap by proposing a novel multi-objective algorithm. It involves finding an accurate and reliable solution for MOO issues. In this sense, a Golden Jackal Optimization (GJO) [50] based on multi-objective strategy, opposition-based learning concept, and elite-based guidance strategy, named MOGJO, is developed to deal with MOO problems. The incorporation of these strategies into the single objective GJO aims to provide better convergence and more uniform coverage solutions toward the true POF. Hence, the major's contributions regarding the present work are listed as follows:

- *Prospective of the multi-objective GJO* A new version of GJO, named MOGJO, is developed for the first time. MOGJO incorporates the guided archive to store and retrieve the generated Pareto front so far, and crowding distance is to manage the archive size while surviving the best non-dominated solutions during the iterative process.
- *Integration of improvement strategy* The MOGJO embeds the concept of opposition and elite learnings to enhance the diversification and identification searches, respectively. By this conception, the convergence and coverage processes toward the POF can be realized.
- *Validation and performance analysis* The performance of the MOGJO is rigorously validated and analyzed on eleven well-known problems, five constrained problems, four engineering designs and real dynamic economic-emission power dispatch (DEEPD). Also, graphical representation, performance metrics, Wilcoxon test, and Friedman test are conducted to statistically compare and realize the performance of the proposed algorithm with other methodologies.

The novelty and effectiveness of the MOGJO lie behind the intelligent exploration of golden jackals during the hunting strategies and management the movement of the male and female jackals using archive population. Furthermore, opposition and elite strategies can enrich exploration and exploration toward promising regions, thereby reaching a good balance among the coverages and convergence patterns. Besides, the best of our information, no attempts to suggest the MOGJO version in solving the MOO designs and DEEPD problem have been recorded in the literature.

2.1 Paper organization

Following Sect. 1 that has offered the introduction, the remainder sections of the paper are outlined as follows. Section 2 offers the basic concepts of MOO and briefly

overviews the framework of classical GJO. Section 3 provides the proposed multi-objective variant of GJO. The experimental simulations and results are addressed in Sect. 4. Lastly, Sect. 5 offers the conclusion and delivers some worth directions for future works.

3 Background

This section exhibits background information regarding the formulation of MOO problem, solution concepts, and a brief overview regarding the original GJO concept.

3.1 Multi-objective optimization (MOO): problem statement

In the single objective (SO) task, usually there is only one alternative or solution that wants to be regarded, due to the unitary nature of the objective and the existence of a single global optimal solution. It is relatively simple to compare alternatives when a target is taken into account, which is typically done using relational operators. This type of problem's characteristics makes it simple to assess potential solutions and ultimately identify the best one. However, in real-world engineering problems, it is common for optimization problems to have multiple objectives that may conflict with each other. Such optimization problems are called MOO problems [3, 4]. Generally, a MOO can be modeled as follows.

$$\begin{aligned} & \text{Minimize: } F(\theta) \{f_1(\theta), f_2(\theta), \dots, f_M(\theta)\}, \\ & \theta = \{\theta_1, \theta_2, \dots, \theta_n\} \in R^n \\ & \text{Subject to: } \begin{cases} g_j(\theta) \leq 0 & j = 1, 2, \dots, P \\ h_l(\theta) = 0 & l = 1, 2, \dots, Q \\ \theta_i^{Lb} \leq \theta_i \leq \theta_i^{Ub} & \forall i = 1, 2, \dots, n \end{cases} \quad (1) \end{aligned}$$

where $F(\theta)$ contains M conflicting objectives, P defines the number of inequality constraints, Q denotes the number of equality constraints, and n stands for number of control variables. Here, $f_m(\theta)$, $g_j(\theta)$, and $h_l(\theta)$ define m th objective function element, the j th inequality constraint, and the l th equality constraint, respectively, and θ_i^{Lb} , θ_i^{Ub} define the lower and upper bounds of i th decision variable (θ_i). $\mathbb{C} = \prod_{i=1}^n [\theta_i^{Lb}, \theta_i^{Ub}] \subseteq R^n$ defines the decision space of n decision variables. It is clear that relational operators are ineffective for addressing MOO issues, so multi-objective Pareto regulations are utilized to resolve such issues, and the Pareto optimal formulas can be provided as follows [3].

Definition 1 Pareto-dominance regulation: A solution θ_i is said to dominate the solution θ_j , (termed as $\theta_i \succ \theta_j$) if two rules are hold:

$$\begin{aligned} f_i(\theta_i) &\leq f_i(\theta_j), \quad \forall i \in 1, 2, \dots, M \\ f_j(\theta_i) &< f_j(\theta_j), \quad \exists j \in 1, 2, \dots, M \end{aligned} \tag{2}$$

If neither θ_i nor θ_j dominates each other, then the solutions θ_i and θ_j are said to be equivalent or incomparable (termed as $\theta_i \sim \theta_j$).

Definition 2 Solution feasibility: The presence of constraints prospective on \mathbb{C} leads to the necessity of defining the feasibility concept in terms of the overall constraint violation $\phi(\theta)$ of a solution θ which is expressed as follows:

$$\phi(\theta) = \sum_j \max\{g_j(\theta), 0\} + \sum_l |h_l(\theta) - \gamma| \tag{3}$$

where γ defines a tiny real-value threshold ($\gamma = 10^{-6}$ for the studied problems in this work). When $\phi(\theta) = 0$, θ is defined as a feasible solution, otherwise, it is denoted as an infeasible solution. The set of all feasible solutions is expressed by $\Psi = \{\theta \in \mathbb{C} | \phi(\theta) = 0\}$.

Definition 3 Pareto optimality regulation. A solution θ_i is termed as Pareto-optimal solution, if and only if:

$$\nexists \theta_j \in \Psi \mid \theta_j \succ \theta_i \tag{4}$$

Each solution with the set Ψ is compared with everyone in this set according to Pareto dominance (given in Def. 1). Then, if there is not a solution θ_j prevails over solution θ_i , then θ_i is a Pareto-optimal solution.

Definition 4 Pareto optimal set (POS). The collection of all Pareto-optimal solutions is defined as POS and is expressed as follows:

$$PS = \{\theta_i \in \Psi \mid \nexists \theta_j \in \Psi \wedge \theta_j \succ \theta_i\} \tag{5}$$

Definition 5 Pareto optimal front (POF): The set of solutions in the objective functions space is defined as POF and can be expressed as follows:

$$PF = \{F(\theta_i)\} : \forall \theta_i \in POS \tag{6}$$

For every MOO issue, there is a POS, which illustrates the optimal trade-off among the multiple objectives. The POS's projection into the target space is known as POF. However, because the POF contains several solutions, and the fronts of various MOO problems have different natures (convex, concave, separated, discrete, linear), it is very challenging to reach the POF with uniform distribution for each nature. If the optimization algorithm is employed to find a uniformly distributed POF, two prospectives (convergence and coverage) should be realized. The former's ultimate goal is to identify an approximation that closely

matches the true POF. In the latter scenario, the algorithm should attempt to broaden the distribution of non-dominated solutions to fully cover the true POF. This is an essential factor in the Pareto reaching process due to the conflict among the convergence and coverage being the main challenge to MOO issue. In this sense, the coverage will be decreased if an algorithm concentrates primarily on enhancing the accuracy of non-dominated solutions. Contrarily, focusing only on coverage has a detrimental effect on the precision of non-dominant solutions. Most of the present optimization methods can balance convergence and coverage regularly to discover the POF spread uniformly along all targets.

4 Multi-objective golden jackal optimization (MOGJO)

This section addresses the basics of GJO regarding the updating procedures and then these procedures are adapted to introduce the multi-objective GJO (MOGJO) variant through embedding the relevant strategies of multi-objective nature.

4.1 Single-objective golden jackal optimization

GJO is a recent nature-inspired optimization algorithm, that describes the jackals' cooperative foraging and hunting mechanism [50]. In GJO, jackals run in parallel to their prey and surpass it. The jackals mainly include three foremost stages during the hunting process: (1) looking for and proceeding toward the prey; (2) encircling, and troubling the victim until it stops moving, and pouncing on the victim. This behavior was modeled mathematically to design the GJO which was performed on 23 benchmark functions and seven engineering design problems. The results and comparisons have been proved the effective performance of GJO in dealing with the diverse set of benchmark problems. Generally, the mathematical formulation of the GJO approach is summarized below.

4.1.1 Initialization

Like many other optimization algorithms, GJO starts its iterative searching by a population of jackals that are generated using the uniform distribution as follows.

$$\begin{aligned} \theta_{ij} &= \theta_j^{Lb} + U(0, 1) \cdot (\theta_j^{Lb} - \theta_j^{Ub}), \\ i &= 1, 2, \dots, N, \quad j = 1, 2, \dots, n \end{aligned} \tag{7}$$

where $U(0, 1)$ denotes a random number ranged from 0 to 1, N number of jackals, and n number of variables. This

initialization generates initial positions which are considered as the initial Prey’s matrix as follows.

$$\text{Prey} = \begin{bmatrix} \theta_{11} & \theta_{12} & \dots & \theta_{1n} \\ \vdots & \vdots & & \vdots \\ \theta_{N1} & \theta_{N2} & \dots & \theta_{Nn} \end{bmatrix} \tag{8}$$

where θ_{ij} denotes the i th jackal in the j th dimension.

Afterward, each position is evaluated using the fitness function ($f_i(\theta_i)$), where male jackal is referred to be the fittest, and the female jackal is the second fittest.

4.1.2 Searching the prey: exploration phase

In this phase, the exploration phase is carried out. The jackal’s nature allows them to observe and pursue the prey, yet occasionally the prey escapes or cannot be caught easily. Consequently, the jackals wait and look for new prey. The hunting process during this phase is driven by male jackal which is followed by a female jackal.

$$\theta_1(t) = \theta_M(t) - E \cdot |\theta_M - rl \cdot \text{Prey}(t)| \tag{9}$$

$$\theta_2(t) = \theta_{FM}(t) - E \cdot |\theta_{FM}(t) - rl \cdot \text{Prey}(t)| \tag{10}$$

where $\text{Prey}(t)$ denotes the position of prey, t denotes the current iteration, and θ_{FM} and θ_M define, respectively, the positions of the male and female jackals. θ_1 and θ_1 define, respectively, the renewed positions of male and female jackals.

The evading energy (E) regarding the prey defiance is expressed as:

$$E = E_0 \cdot E_1 \tag{11}$$

E_0 defines the initial energy, and E_1 defines the reducing energy of the prey when it is exhausted.

$$E_0 = 2 \cdot r - 1 \tag{12}$$

$$E_1 = 1.5 \cdot (1 - t/T) \tag{13}$$

where r denotes an arbitrary value within $[0,1]$, and T defines the maximum restrict of iterations.

Over the course of iteration, the defense energy E decreases. So, when $|E| \geq 1$, the jackal pairs perform the searching in different areas for exploring prey, while when $|E| < 1$, then perform the exploitation phase and then attack the prey.

Here rl represents a vector of arbitrary numbers generated based on Levy distribution to simulate the prey’s movement according to Levy search and is expressed as follows.

$$rl = 0.05 \cdot \text{LF}(\theta) \tag{14}$$

LF denotes the levy flight function, that is considered as follows.

$$\text{LF}(\theta) = 0.01 \cdot (\mu \cdot \sigma) / |v^{(1/\beta)}|; \tag{15}$$

$$\sigma = \left\{ \frac{\Gamma(1 + \beta) \sin\left(\frac{\pi\beta}{2}\right)}{\beta \cdot \Gamma\left(\frac{1+\beta}{2}\right) \cdot 2^{\frac{\beta-1}{2}}}\right\}^{1/\beta}$$

where μ , v represent random numbers within $(0,1)$ and β is default parameter which is set to 1.5. Finally, the jackal renewed its position in terms of mean positions as follows.

$$\theta(t + 1) = \frac{\theta_1(t) + \theta_2(t)}{2} \tag{16}$$

4.1.3 Encircling and pouncing the prey: exploitation phase

When jackals harass the prey, the prey loses some of its ability to flee, and the jackal pairs and then encloses the prey they had previously detected. After encircling, they pounce on the victim or prey and eat it. The mathematical expression for this cooperative hunting behavior regarding the male and female jackals is as follows:

$$\theta_1(t) = \theta_M(t) - E \cdot |rl \cdot a\theta_M(t) - \text{Prey}(t)| \tag{17}$$

$$\theta_2(t) = \theta_{FM}(t) - E \cdot |rl \cdot \theta_{FM}(t) - rl \cdot \text{Prey}(t)| \tag{18}$$

After this update, the jackal positions are again renewed by Eq. (16). The pseudo-code regarding the GJO is illustrated in Fig. 1.

4.2 The proposed multi-objective GJO (MOGJO)

The MOGJO was established based on three features to deal with MOO natures. (1) An external archive is embedded with GJO to save and retrieve the Pareto optimal solutions during the searching process. (2) Crowding distance is used to manage the archive size during the exploration phase; (3) Opposition and elite strategies are integrated to MOGJO to enrich the convergence and coverage capabilities.

4.2.1 Initialization

Typically, random initialization is used to start the MOGJO population. To enhance the diversity of the solutions, logistic map is adopted as the one of the prominent and simplest chaotic maps [51]. This map offers more diversified solutions than the random aspects, and it has a lower likelihood of convergence’ stagnation dilemma [51]. Therefore, this map is adopted in this work which is expressed as follows.

$$z_{k+1} = \Delta \cdot z_k(1 - z_k), \quad k = 0, 1, \dots, N - 1 \tag{19}$$

where z_k stands for the k th number in the chaotic sequence and k denotes as the chaotic sequence’ index of z ; z_{k+1}

Fig. 1 The working steps of GJO

```

1: Inputs: invoke size of population ( $N$ ), Max. iteration number ( $T$ )
2: Create initial population of  $N$  preys at random
3: while ( $T$  not reached) do
4:     Evaluate the fitness of each prey
5:     Obtain the male jackal  $\theta_1$  (the position of best prey)
6:     Obtain the female jackal  $\theta_2$  (the position of second best prey)
7:     Update the evading energy ( $E$ ) by Eq. (11)
8:     Update the levy vector ( $rl$ ) by Eq. (14)
9:     for  $i = 1: N$  do
10:         If  $|E| \geq 1$  then                                % Exploration phase
11:             Update the position of prey by Eqs.(9), (10), and (16)
12:         If  $|E| < 1$  then                                % Exploitation phase
13:             Update the position of prey by Eqs.(17), (18), and (16)
14:         end if
15:     end for
16: end for
17:      $t = t + 1$ 
18: end While
19: Output: return  $\theta_M$ 

```

defines the next chaotic number in the sequence. z_0 denotes the initial point for the chaotic map, $z_0 \in (0, 1)$, $z_0 \notin \{0, 0.25, 0.75, 0.5, 1\}$; and Δ is a control parameter that is set to 4.0. Then the new population is generated as follows.

$$\theta_{ij} = \theta_j^{Lb} + z_{k+1} \cdot (\theta_j^{Lb} - \theta_j^{Ub}), \quad i = 1, 2, \dots, N, \quad (20)$$

$$j = 1, 2, \dots, n$$

4.2.2 Evaluation and updating the archive

After obtaining the solutions or positions of jackals, the non-dominated set of solutions are evaluated and stored in the archive (AR_θ) which is updated with growth of iteration until it may become full. In this sense, a solution is not prevented from storing in the archive, if it is non-dominated by all stored solutions in the archive. Also, the solution removes some of stored Pareto solutions in the archive, if it dominates them, and then it becomes a member of the archive. If a solution is dominated by at least one member of the archive, then it is not becoming a member of the archive. In order to provide some room for new solutions in the archive when it becomes full, at least one solution must be deleted from the most occupied portions. To effectively choose the solution that is leaving the archive, the worst (most overcrowded) hyper-sphere should be chosen to prevent the jackals from searching around unproductive crowded places. The selection of this solution is performed using the roulette-wheel mechanism associated with the subsequent probability (P_s) as follows.

$$P_s = \frac{M_s}{\delta} \quad (21)$$

where δ defines a non-negative number greater than one (i.e., δ is adopted as 10), and M_s defines the number of non-dominated solutions within the archive in the s th segment.

4.2.3 Mechanisms of hunting tactic of jackals

4.2.3.1 Elite jackals

This step is vital for selection of leader of male jackal during the hunting process. The elite jackals (EJ_θ) aim to save the best positions that previously searched by jackals during each iteration, and this can facilitate the generation of non-dominated solutions. The step firstly constitutes an elite population with the initial population in first iteration. Afterward, during the growth of iteration, the trial solution $\theta_s(t+1)$ is assessed by the comparison with the target solution $\theta_s(t)$ that is stored in the current elite population according to the dominance concept. If the target solution can be dominated by the trial solution, then it replaces the target solution. During the growth of iteration, the elite members are presented to renew the archive members.

4.2.3.2 Leader (male jackal) selection

In the construction of the MOGJO, an archive is embedded into GJO in order to store and retrieve the closest matches to the true POF throughout iterative optimization in order to find a widely distributed Pareto-front, an elite population member must be located in the area of least populated within the attained POF. This area is detected by segmenting the search space through obtaining the ideal and anti-ideal (i.e., best, and

worst objective values) of the attained POF, defining N_{grid} cells that include all solutions, as well as splitting the hyper-spheres in each iteration into equal sub-hyper-spheres. After generating the segments, the selection is performed by the roulette-wheel mechanism along with the subsequent probability (PL_s) for each segment as follows.

$$PL_s = \frac{\delta}{M_s} \tag{22}$$

Equation (22) increases the likelihood that MOGJO will select the population’s elite member from less-populated segments. Therefore, the jackals’ population are encouraged to roam through this area, which improves their distribution throughout the entire POF.

4.2.3.3 Movement of jackals In this step, the exploration phase is carried out using the concept of archive population (AR_{θ}) and elite jackals. The population of elite jackals denoted by EJ_{θ} and the stored solutions in the archive denoted by AR_{θ} are used to perform this tactic of hunting process for male jackal and female jackal as follows.

$$\theta_1(t) = AR_{\theta_{M,h}}(t) - E \cdot |AR_{\theta_{M,h}}(t) - rl \cdot EJ_{\theta}(t)| \tag{23}$$

$$\theta_2(t) = AR_{\theta_{FM,h1}}(t) - E \cdot |AR_{\theta_{FM,h1}}(t) - rl \cdot EJ_{\theta}(t)| \tag{24}$$

where $AR_{\theta_{M,h}}$, $AR_{\theta_{FM,h1}}(t)$ are positions of the male and female jackals that are chosen from the archive according to the roulette-wheel mechanism with random indices h and $h1$, respectively. EJ_{θ} defines the elite positions of jackals; θ_1 and θ_2 define, respectively, the renewed positions of male and female jackals.

Similarly, the encircling, and pouncing on the prey during hunting process are simulated according to the concept of archive and elite jackals as follows:

$$\theta_1(t) = AR_{\theta_{M,h}}(t) - E \cdot |rl \cdot AR_{\theta_{M,h}}(t) - EJ_{\theta}(t)| \tag{25}$$

$$\theta_2(t) = AR_{\theta_{FM,h}}(t) - E \cdot |rl \cdot \theta_{FM}(t) - rl \cdot EJ_{\theta}(t)| \tag{26}$$

After this update, the jackal positions are again renewed by Eq. (16).

4.2.4 Improving diversity of population

Learning based on opposition (LBO) strategy is presented to improve the diversity of solutions due to its effectiveness as it has been attracted much considerable attentions in the past decade [52]. In this sense, LBO can enable the population to jump at new enrich search space. It is carried out

herein if $\text{rand} < t/T$, then the corresponding opposition solution carried out as follows.

$$\theta_i^{op} = U(0, 1) \cdot (\theta_j^{Lb} - \theta_j^{Ub}) - \theta_i, \quad i = 1, 2, \dots, N \tag{27}$$

where θ_i^{op} defines the opposite of the i th solution θ_i .

4.2.5 Eliciting the compromise solution

For most engineering problems, the designer preferred to apply its design with a single operating point rather than a set of solutions. In this sense, the concept of compromise solution (CS) can be evident. Fuzzy technique (FT) presents one of most decision-making methods for selecting the CS [53]. Therefore, FT is presented in this work with a membership value (γ_i) and it is modeled for each objective f_i of the i th solution as follows.

$$\gamma_i = \begin{cases} 1 & f_i \leq f_i^{\min} \\ (f_i^{\max} - f_i) / (f_i^{\max} - f_i^{\min}) & f_i^{\min} \leq f_i \leq f_i^{\max} \\ 0 & f_i \geq f_i^{\max} \end{cases} \tag{28}$$

For the stored non-dominated solutions in the archive, the normalized value of all membership functions is denoted by γ^k and it is defined by:

$$\gamma^k = \frac{\sum_{i=1}^M \gamma_i^k}{\sum_{k=1}^Q \sum_{i=1}^M \gamma_i^k} \tag{29}$$

where Q defines the size of non-dominated solutions in the archive, and M is the number of objectives. The maximum of γ^k is termed as the best compromise point.

All the MOGJO’s parameters are typical of the GJO’s initial work, though a new parameter for indicating archive size has been added. Moreover, the framework of the proposed MOGJO is illustrated by the flowchart as depicted in Fig. 2.

5 Experimental simulation and discussion

In this section, the performance of the MOGJO is evaluated and analyzed on sixteen well-known problems, five constrained problems, four engineering designs and real dynamic economic-emission power dispatch (DEEPD) [17, 53]. In this regard, some successful multi-objective optimizers, including MOPSO [9], NSMFO [15], MSSA [54], MOSMA [14], and MO bonobo optimizer (MOBO) [55], are presented to assess the performance of MOGJO variant. As these metaheuristic algorithms have stochastic characteristics and may yield some fluctuation regarding the optima [17], each algorithm was carried out 20 independent runs for each benchmark problem to avoid any stochastic discrepancy. In regard to the hardware, a laptop

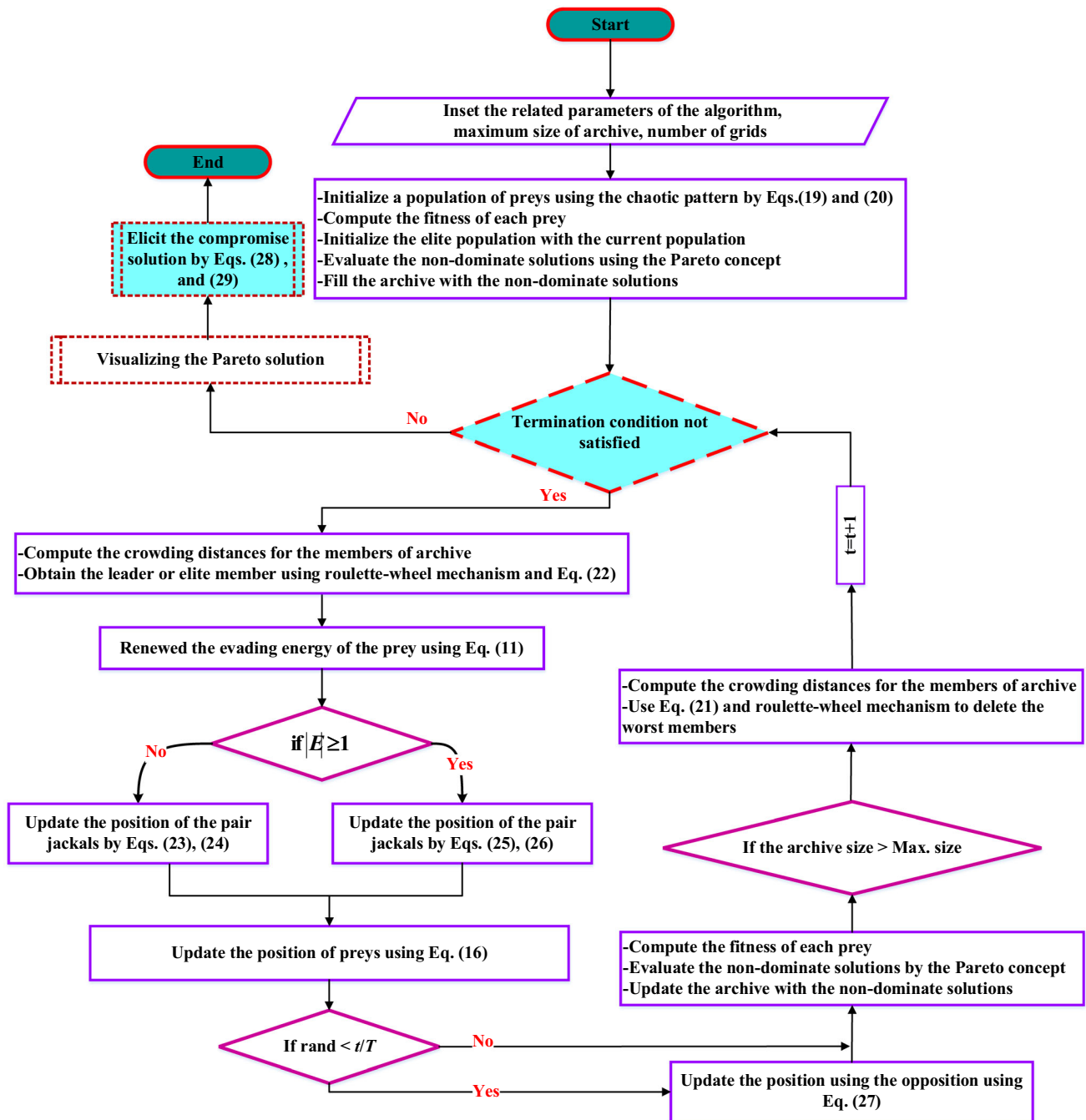


Fig. 2 Framework of the proposed MOGJO

with the following specifications, AMD Ryzen 5 5600u CPU, @ 2.30 GHz, 16 GB RAM, and Windows 10 with 64-bit OS. MATLAB_R2021a is used for the implementation issue.

In addition, some metric indices are presented to assess the quality of outcomes obtained by the implemented algorithms such as generational distance (GD) metric, the hypervolume (HV), and spacing (SP) metric [4] where the superiority of results are evaluated with respect to the

minimum values of the GD, SP, and the maximum value of the HV metric.

5.1 Descriptions of the studied benchmark functions and engineering designs

Some of challenging and well-known benchmark functions with different landscape shapes regarding the Pareto front are collected from the literature, where these benchmark

functions contain two or three objectives, namely ZDT and DTLZ suits. They also bear up to 30 dimensions (control variables). These benchmark suits along with related characteristics of POFs such as nonconvex or convex, discontinuous or continuous, and non-uniform or uniform distribution are summarized in Table 1. To confirm applicability of the proposed MOGJO, its performance is applied and realized on some engineering designs including welded beam design (WBD) problem, speed reduced design (SRD), disk brake design (DBD), and four bar truss design (FBTD).

5.2 Parameters settings

In this subsection, the parameter values of the compared algorithms (MOPSO, NSMFO, MSSA, MOSMA, and MOBO) are suggested based on the found values in the original works. To make sure that the algorithms are fairly compared, the maximum number of iterations and the population size are adjusted after some trails and they are set to 1000, and 100, respectively. Each test problem was performed for 20 independent runs to mitigate the haphazardness situation. For a fair comparison among the presented algorithms (MOPSO, NSMFO, MSSA, MOSMA, and MOBO), and proposed MOGJO, they start with same population generated randomly per run.

5.3 Performance assessments

As the discovered set of solutions by multi-objective optimization methods represent an approximated POF, therefore their convergence and coverage behaviors must be assessed. In this sense, the popular employed assessment indices include the following [4]. (1) Convergence: implies that the best non-dominated solutions are those that most closely match the true POF. (2) Uniformity: implies that the good non-dominated alternatives are those evenly distributed along the true POF. (3) Distribution: implies that the POF should be fully covered by the searched non-dominated solutions. In this sense, some performance metrics can be adopted as follows.

5.3.1 Hypervolume (HV) index

HV index refers to the volume in the objective space that is occupied by the alternations of the non-dominated set (AR) [4]. Mathematically, for each member of archive ($i \in AR$), the hypercube v_i is constructed in terms of the reference point (RP). The RP can be obtained by forming a vector of the worst values of the objective functions. The HV values of the discovered hypercubes are produced by Eq. (30).

$$H = \text{Volume} \left(\bigcup_{i=1}^{AR} v_i \right) \tag{30}$$

Table 1 The characteristic and nature of the studied multi-objective functions

Name	M	n	Nature	Characteristics
ZTD1	2	30	UC	CF
ZTD2	2	30	UC	NCF
ZTD3	2	30	UC	DF
ZTD4	2	30	UC	MF with 2^{21} local Pareto-optimal fronts
ZTD6	2	30	UC	NU
DTLZ1	3	7	UC	Linear POF
DTLZ2	3	12	UC	Spherical POF
DTLZ4	3	12	UC	POF involves dense set of alternatives to exist near the $f_M - f_1$
DTLZ5	3	12	UC	Aims to verify the ability of multi-objective optimizer to converge to a degenerated curve
DTLZ6	3	12	UC	Acquires 2^{M-1} disconnected POF
DTLZ7	3	22	UC	POF is a combination of a straight line and a hyper-plane
SRN	2	2	CO	CC
BNH	2	2	CO	CC
KIT	2	2	CO	CC
TNK	2	2	CO	D
CONSTR	2	2	CO	CCA

CC continuous concave, *CCA* continuous concave, *D* discrete, *UC* unconstrained, *CO* constrained, *CF* convex front, *NCF* non-convex front, *DF* discontinuous front, *MF* multi-modal front, *NU* non-uniformity, *POF* Pareto-optimal front, M No. of objectives, n No. of variables

HV exhibits information about both the diversity and convergence of set AR, where larger HV values denote a superior algorithm.

5.3.2 Generational distance (GD) metric

The GD index was provided by Veldhuizen [17] as a convergence index to clarify the distance between the reached POF and the true POF. The GD index is expressed mathematically as follows [17]:

$$GD = \frac{\sqrt{\sum_{i=1}^{n_{PF}} d_i^2}}{n_{PF}} \quad (31)$$

where n_{PF} denotes the number of reached Pareto optimal solutions and d_i defines the Euclidean distance among a solution from the reached Pareto front and the corresponding true solution on POF. $GD = 0$ stands for the reached solutions are the true solutions.

5.3.3 Spacing (SP) metric

SP represents an index to measure the distribution of searched solution vectors throughout the whole nondominated vectors reached so far [17]. It is expressed as follows.

$$SP = \sqrt{\frac{1}{n_{PF} - 1} \sum_{j=1}^{n_{PF}} (\bar{d} - d_j)^2} \quad (32)$$

where $d_j = \sum_{i=1}^M |f_i^j - f_i^k|$, $j \neq k$, $k \in$ obtained POF, n_{PF} defines the number of obtained solution vectors in the archive, while \bar{d} denotes the average of all d_j . SP defines the standard deviation regarding the distance among two consecutive solutions on the reached POF. A smaller value of the SP denotes that obtained solutions have better distribution. Also, a zero value of SP implies that all members of the reached POF are equidistantly spaced.

5.4 Results on ZDT and DTLZ suits

In this subsection, the performance of the proposed MOGJO and the compared counterparts (MOPSO, NSMFO, MSSA, MOSMA, and MOBO) is evaluated on the ZDT and DTLZ test suits. Each algorithm was carried out 20 times, and the statistical measures of assessment metrics (HV, and GD) are reported as in Tables 2 and 3. In Table 2, the GD values for proposed MOGJO and other counterparts are recorded. Based on the GD best values, it can be observed that MOGJO is better than MOPSO, NSMFO, MSSA, MOSMA, and MOBO, in 10/11, 11/11, 11/11, 11/11, 11/11 test functions, respectively, illustrating that MOGJO provides better approximate solutions compared to other competitors. Moreover, the results of HV values are reported in Table 3, which exhibits that the

MOGJO is better than MOPSO, NSMFO, MSSA, MOSMA, and MOBO, in 11/11, 10/11, 11/11, 10/11, 11/11 test functions, respectively, illustrating that MOGJO achieves higher diversity and convergence than the other algorithms. Also, in terms of mean values of HV and GD, the proposed MOGJO provides superior and affirms the stability of the proposed algorithm. The best result among the compared algorithms is highlighted in boldface. Moreover, the searched POFs by the proposed MOGJO and the other peers on ZDT and DTLZ test suits are depicted in Figs. 3 and 4, respectively. Inspecting these figures, it is observed that MSSA offers the poorest convergence while the proposed MOGJO exhibits good convergence and coverage results with respect to the true POFs. On the other hand, the NSMFO and MOBO offer provide a competitive edge with the proposed MOGJO algorithms, especially for ZDT suit. The most interesting features behind the superior performance of the proposed MOGJO are contained in chaotic initialization and opposition strategies that help in preserving the diversity of solutions as well as the concept of elite strategy that helps in enhancing the convergence behavior during the iteration searching. For clarity, the overall best values among the compared optimization methods are highlighted in boldface.

5.5 Pair-wise Wilcoxon rank sum test

In this subsection, the Wilcoxon rank sum test (WRST) [56] is carried out to further assess the significance of the searched results of POF. WRST is presented with a statistical significance value ($\alpha = 0.05$). Also, WRST aims to affirm that the obtained results did not occur by chance, i.e., caused by the stochastic nature of metaheuristic algorithms. WRST is carried out based on the null hypothesis H_0 regarding this test states that no difference among the medians of two solutions searched by algorithm A and B. To regulate whether algorithm A achieved statistically better results than B, or if not, the alternative hypothesis is valid. Thus, the superiority can be guaranteed if the p value is below significance value ($\alpha = 0.05$). In this context, the results of GD and HV metrics obtained by compared algorithms are examined using the WRST and the obtained results of p values are reported in Table 4. Based on these results, it is obvious that the obtained p values are below a significance value, and this can validate the superiority of the proposed MOGJO over the implemented competitors.

5.6 Comparison analysis versus some state-of-the-art methods

In this section, the suggested MOGJO is further examined and evaluated against thirteen well-known state-of-the-art optimizers: MO jellyfish (MOJF) [53], MOEA/D [53],

Table 2 Statistical measures for GD metric by the proposed and compared optimizers for ZTD and DTLZ suits

Test function	Statistical metric	MOPSO	NSMFO	MSSA	MOSMA	MOBO	MOGJO
ZTD1	Best	1.1733E−02	4.4553E−03	7.6149E−01	9.3454E−03	9.8633E−03	1.7946E−04
	Mean	5.5836E−02	4.7936E−03	1.0247E +00	9.9714E−03	1.0410E−02	2.0200E−04
	Median	3.0358E−02	4.7874E−03	9.7718E−01	9.6229E−03	1.0208E−02	2.0584E−04
	Worst	1.7062E−01	5.1672E−03	1.2652E +00	1.1527E−02	1.1348E−02	2.1089E−04
	St. Dev	6.6146E−02	2.5280E−04	2.0254E−01	9.0763E−04	5.8000E−04	9.6489E−06
ZTD2	Best	5.6482E−04	1.1742E−04	5.7820E−02	1.1424E−03	1.6586E−04	0.0000E +00
	Mean	4.4460E−01	1.2424E−04	1.0668E−01	1.1944E−03	1.8373E−04	7.5095E−05
	Median	4.0021E−01	1.2169E−04	1.2490E−01	1.2054E−03	1.8241E−04	1.0979E−04
	Worst	9.4681E−01	1.3243E−04	1.4322E−01	1.2723E−03	2.0701E−04	1.4785E−04
	St. Dev	4.5183E−01	7.5553E−06	3.8262E−02	5.3875E−05	1.7245E−05	6.5596E−05
ZTD3	Best	1.2945E−03	1.6749E−04	5.3897E−02	7.2066E−04	1.8747E−04	1.2341E−04
	Mean	1.2154E−02	2.1012E−04	8.1522E−02	1.2502E−03	2.0239E−04	1.2925E−04
	Median	1.0747E−02	1.8569E−04	7.0063E−02	1.0285E−03	2.0343E−04	1.2895E−04
	Worst	2.1300E−02	2.7730E−04	1.1466E−01	2.2758E−03	2.1549E−04	1.3646E−04
	St. Dev	8.1149E−03	4.7763E−05	3.0310E−02	6.1436E−04	1.1347E−05	4.5202E−06
ZTD4	Best	1.4096E +01	2.4557E−04	8.6463E−01	1.0445E−03	5.0252E−02	1.1258E−04
	Mean	3.1702E +01	3.6386E−01	2.1500E +00	4.4564E−03	2.3885E−01	1.6517E−04
	Median	2.8609E +01	3.1841E−04	2.4103E +00	2.0990E−03	1.9422E−01	1.7512E−04
	Worst	4.6910E +01	1.5179E +00	2.7477E +00	9.9569E−03	5.6964E−01	1.9333E−04
	St. Dev	1.2895E +01	6.5808E−01	7.6024E−01	4.1608E−03	1.9889E−01	2.3513E−05
ZTD6	Best	1.3848E−02	4.7910E−02	5.5968E−01	2.3629E−02	1.5775E−04	7.2461E−05
	Mean	5.6316E−01	5.2906E−02	5.7425E−01	2.7148E−01	2.3101E−04	1.3077E−02
	Median	4.6981E−01	4.9817E−02	5.6460E−01	3.4392E−01	1.6233E−04	1.3838E−02
	Worst	1.5019E +00	6.4858E−02	6.0903E−01	3.7166E−01	5.0661E−04	2.4239E−02
	St. Dev	5.6965E−01	7.1153E−03	2.0875E−02	1.4701E−01	1.5412E−04	7.6640E−03
DTLZ1	Best	3.6136E +00	3.4364E +00	2.8820E +00	2.9611E +00	4.2834E−02	8.1797E−03
	Mean	3.9936E +00	4.4915E +00	3.3544E +00	3.2466E +00	2.3014E−01	6.6621E−02
	Median	4.1551E +00	4.6924E +00	3.1467E +00	3.0966E +00	9.8937E−02	4.7579E−02
	Worst	4.2408E +00	5.5271E +00	3.9058E +00	3.9418E +00	6.1949E−01	1.7355E−01
	St. Dev	2.9819E−01	8.1160E−01	4.3203E−01	4.0091E−01	2.5052E−01	6.0144E−02
DTLZ2	Best	1.0238E−01	8.6481E−02	4.6614E−01	2.7635E−01	1.1821E−01	1.4205E−02
	Mean	1.0535E−01	9.6692E−02	4.7869E−01	3.5631E−01	1.2410E−01	2.7412E−02
	Median	1.0304E−01	9.2101E−02	4.7460E−01	3.6760E−01	1.2362E−01	2.8289E−02
	Worst	1.1148E−01	1.0969E−01	4.9803E−01	3.9746E−01	1.2950E−01	4.4075E−02
	St. Dev	3.9770E−03	9.4789E−03	1.3546E−02	4.6923E−02	4.9033E−03	9.3542E−03
DTLZ4	Best	5.3487E−03	1.8607E−02	3.9470E−01	2.4852E−02	6.5841E−03	2.6028E−03
	Mean	1.2829E−02	2.5427E−02	7.0995E−01	2.8965E−02	7.2476E−03	1.6691E−02
	Median	1.2343E−02	2.3653E−02	7.7257E−01	2.7504E−02	7.2952E−03	9.2346E−03
	Worst	2.0434E−02	3.6018E−02	9.2914E−01	3.4199E−02	7.8067E−03	3.8549E−02
	St. Dev	5.6275E−03	6.7884E−03	2.4128E−01	4.2258E−03	4.5900E−04	1.4862E−02
DTLZ5	Best	2.4060E−02	2.7440E−03	2.7075E−01	1.8401E−01	1.9336E−02	1.5153E−04
	Mean	3.2208E−02	2.9411E−03	3.1577E−01	2.0133E−01	2.1872E−02	2.7828E−03
	Median	3.0532E−02	2.9456E−03	3.1434E−01	1.9737E−01	2.2013E−02	3.3810E−04
	Worst	4.2943E−02	3.1464E−03	3.8773E−01	2.3231E−01	2.4113E−02	1.5067E−02
	St. Dev	7.3735E−03	1.9564E−04	4.6078E−02	2.0066E−02	1.6998E−03	5.3141E−03
DTLZ6	Best	8.1428E−06	1.4235E−05	3.4513E−02	9.3994E−02	1.3867E−05	8.6040E−06
	Mean	2.3830E−02	1.6151E−05	8.3602E−02	1.1274E−01	1.5223E−05	9.9809E−06
	Median	8.4606E−06	1.5644E−05	7.4867E−02	1.0997E−01	1.5170E−05	9.4282E−06

Table 2 (continued)

Test function	Statistical metric	MOPSO	NSMFO	MSSA	MOSMA	MOBO	MOGJO
DTLZ7	Worst	1.1911E-01	1.8763E-05	1.7375E-01	1.3141E-01	1.7498E-05	1.3268E-05
	St. Dev	5.3266E-02	1.6906E-06	5.7537E-02	1.6376E-02	1.4189E-06	1.4770E-06
	Best	2.7433E-02	4.1216E-03	9.6144E-02	3.7764E-03	3.8728E-03	2.3666E-03
	Mean	1.4974E-01	1.1224E-02	4.0404E-01	4.6602E-03	6.3751E-03	3.0511E-03
	Median	5.5101E-02	1.1061E-02	4.1759E-01	4.7019E-03	7.2364E-03	2.9808E-03
	Worst	5.6533E-01	1.6301E-02	6.3437E-01	5.3225E-03	8.2814E-03	3.5581E-03
	St. Dev	2.3260E-01	4.5980E-03	1.9707E-01	5.9467E-04	2.0111E-03	3.2714E-04

MOPSO1 [53], NSGA-II [53], MO chaos game optimization (MOCGO) [57], MO crystal structure algorithm (MOCryStAl) [58], efficient MOSMA (EMOSMA) [59], MO grasshopper optimization algorithm (MOGOA) [60], MO ant lion optimizer (MOALO) [60], MO lightning attachment procedure optimizer (MOLAPO) [61], MOGWO [61], M2O-CSA [17], and MO moth swarm algorithm (MOMSA) [62]. These algorithms are assessed according to GD index, where lower GD indicates better performance. In this context, the statistical results using the mean (average) and standard deviation (S.D) values of the compared algorithms are recorded in Table 5. The comparisons affirmed that the MOGJO surpasses most of the state-of-the-art counterparts for most ZDT and DTLZ1 suits, where the best result among the compared algorithms is highlighted in boldface. Moreover, a statistical conclusion is drawn based on a nonparametric statistical test named Friedman-test [63] to detect the significant differences among the proposed algorithm and its competitors. In this sense, the compared algorithms are divided to four groups (i.e., G_i symbolizes the group index) according to the availability of reported results. Figure 4 depicts the average ranking of each method on the candidate test suits using Friedman's test. Note that in the Friedman test, the lower the ranking, the better the performance of the algorithm. It is clear from Fig. 4 that the proposed MOGJO ranks first regarding the GD metric among the thirteen-competing methods. The results confirm that the proposed MOGJO outperforms the best algorithm, MOJF, within the thirteen state-of-the-art algorithms by an average rank of Friedman test greater than 41% for ZDT and DTLZ1 suits while outperforming the worst one, MOALO, by 84%. Therefore, the quantitative results along with nonparametric test demonstrate that the MOGJO exhibits better, and more competitive performance compared to the other competitors.

5.7 Results on multi-objective constrained suits

In this section, the effectiveness of the proposed MOGJO is further assessed and clarified using some well-known

multi-objective constrained suits with diverse characteristics regarding the Pareto front including discontinuous and continuous convex natures as illustrated in Table 1 [17].

The results of the proposed MOGJO are compared with the other optimizers using the GD metric. The statistical results are reported in Table 6 for the MOGJO and other counterparts, where the best results are marked with bold font. Based on the best values of the GD metric, it can be concluded that the proposed MOGJO suppresses the other peers. Although it can be noted that the MSSA provides minimum value for GD index, it is not satisfied with the coverage feature as it reaches the set of semi-identical points for POF and can seem to be as single point which may reduce the GD metric. Moreover, the searched POFs by the presented algorithms are illustrated in Fig. 5. It should be observed that the suggested MOGJO offers high coverage and coverage regarding the true POFs for all multi-objective constrained test suits.

5.8 Multi-objective engineering designs

In this subsection, the proposed MOGJO is applied on some popular real engineering designs which are the welded beam design (WBD), speed reduced design (SRD), disk brake design (DBD), and four bar truss design (FBTD) [17]. Furthermore, these designs include some optimization natures such as constraints, discrete variables, and non-convex objectives.

5.8.1 Description of WBD problem

The WBD aims to simultaneously minimize the objectives of the overall fabrication and the end deflection which are subjected to some constraints such as bending stress, shear stress, the buckling load, and weld length. In this sense, four design parameters are needed to be optimized which are the height, the welded joint length, thickness, and the beam width. The mathematical model is presented as follows.

Table 3 Statistical measures for HV metric by the proposed and compared optimizers for ZTD and DTLZ suits

Test function	Statistical metric	MOPSO	NSMFO	MSSA	MOSMA	MOBO	MOGJO
ZTD1	Best	7.0767E−01	7.1910E−01	3.7849E−02	7.1208E−01	7.1436E−01	7.2104E−01
	Mean	6.5098E−01	7.1886E−01	7.5699E−03	7.1097E−01	7.1381E−01	7.2069E−01
	Median	6.8116E−01	7.1881E−01	0.0000E +00	7.1151E−01	7.1402E−01	7.2068E−01
	Worst	5.1097E−01	7.1857E−01	0.0000E +00	7.0846E−01	7.1256E−01	7.2049E−01
	St. Dev	8.1532E−02	2.3330E−04	1.6927E−02	1.4616E−03	7.3335E−04	1.4765E−04
ZTD2	Best	4.3690E−01	4.4364E−01	0.0000E +00	4.2649E−01	4.4148E−01	4.4603E−01
	Mean	1.6059E−01	4.4341E−01	0.0000E +00	4.2569E−01	4.3998E−01	3.0365E−01
	Median	0.0000E +00	4.4339E−01	0.0000E +00	4.2570E−01	4.3983E−01	4.4511E−01
	Worst	0.0000E +00	4.4327E−01	0.0000E +00	4.2486E−01	4.3895E−01	9.0909E−02
	St. Dev	2.2132E−01	1.4428E−04	0.0000E +00	5.9678E−04	1.1073E−03	1.8310E−01
ZTD3	Best	5.8414E−01	6.0012E−01	6.3063E−02	6.0776E−01	5.9870E−01	6.0042E−01
	Mean	5.3138E−01	5.9875E−01	2.1584E−02	6.0013E−01	5.9614E−01	6.0035E−01
	Median	5.2309E−01	5.9928E−01	0.0000E +00	5.9865E−01	5.9559E−01	6.0034E−01
	Worst	4.8654E−01	5.9641E−01	0.0000E +00	5.9749E−01	5.9369E−01	6.0032E−01
	St. Dev	3.7314E−02	1.5003E−03	3.0248E−02	4.2978E−03	2.2754E−03	3.2921E−05
ZTD4	Best	0.0000E +00	7.1870E−01	0.0000E +00	5.2915E−01	4.4936E−01	7.2201E−01
	Mean	0.0000E +00	4.3104E−01	0.0000E +00	3.2566E−01	1.4515E−01	7.2180E−01
	Median	0.0000E +00	7.1823E−01	0.0000E +00	2.8063E−01	9.2068E−02	7.2186E−01
	Worst	0.0000E +00	0.0000E +00	0.0000E +00	1.5186E−01	0.0000E +00	7.2157E−01
	St. Dev	0.0000E +00	3.9349E−01	0.0000E +00	1.4490E−01	1.8644E−01	1.5221E−04
ZTD6	Best	3.8264E−01	3.8727E−01	0.0000E +00	3.6004E−01	3.7468E−01	3.8992E−01
	Mean	7.6528E−02	3.8683E−01	0.0000E +00	1.4474E−01	3.6873E−01	3.8942E−01
	Median	0.0000E +00	3.8694E−01	0.0000E +00	9.0909E−02	3.7413E−01	3.8937E−01
	Worst	0.0000E +00	3.8607E−01	0.0000E +00	9.0909E−02	3.5349E−01	3.8906E−01
	St. Dev	1.7112E−01	4.6175E−04	0.0000E +00	1.2036E−01	9.1023E−03	2.5563E−04
DTLZ1	Best	0.0000E +00	0.0000E +00	0.0000E +00	3.2437E−01	7.9876E−01	7.8722E−01
	Mean	0.0000E +00	0.0000E +00	0.0000E +00	2.5652E−01	4.6717E−01	3.4446E−01
	Median	0.0000E +00	0.0000E +00	0.0000E +00	3.2189E−01	6.6477E−01	2.3345E−01
	Worst	0.0000E +00	0.0000E +00	0.0000E +00	0.0000E +00	0.0000E +00	0.0000E +00
	St. Dev	0.0000E +00	0.0000E +00	0.0000E +00	1.4347E−01	3.9139E−01	3.1805E−01
DTLZ2	Best	4.6882E−01	4.7562E−01	1.4554E−01	1.9323E−01	4.6356E−01	5.2286E−01
	Mean	4.6105E−01	4.3849E−01	1.2959E−01	1.6021E−01	4.4497E−01	5.0082E−01
	Median	4.6274E−01	4.3258E−01	1.2628E−01	1.4863E−01	4.3594E−01	4.9989E−01
	Worst	4.5034E−01	4.1574E−01	1.2038E−01	1.3981E−01	4.3406E−01	4.8975E−01
	St. Dev	6.7782E−03	2.2391E−02	1.0156E−02	2.1951E−02	1.4100E−02	1.0214E−02
DTLZ4	Best	4.9638E−01	5.2822E−01	2.4893E−01	9.0909E−02	4.5130E−01	5.2882E−01
	Mean	4.0388E−01	4.9549E−01	1.2437E−01	9.0879E−02	4.4019E−01	5.1386E−01
	Median	3.9918E−01	4.9040E−01	9.6320E−02	9.0909E−02	4.4582E−01	5.1438E−01
	Worst	3.5200E−01	4.7320E−01	8.1155E−02	9.0760E−02	4.1903E−01	5.0228E−01
	St. Dev	5.7473E−02	2.0547E−02	7.0695E−02	6.6534E−05	1.3061E−02	7.6480E−03
DTLZ5	Best	1.8022E−01	2.0093E−01	6.9229E−02	6.6436E−02	1.8478E−01	1.9866E−01
	Mean	1.7355E−01	2.0044E−01	5.7878E−02	6.5387E−02	1.8260E−01	1.9785E−01
	Median	1.7477E−01	2.0057E−01	6.0221E−02	6.4780E−02	1.8294E−01	1.9794E−01
	Worst	1.6429E−01	1.9979E−01	3.5861E−02	6.4694E−02	1.8007E−01	1.9690E−01
	St. Dev	5.9244E−03	4.2964E−04	1.3417E−02	9.0710E−04	1.7465E−03	6.2290E−04
DTLZ6	Best	1.9743E−01	1.9349E−01	1.8501E−01	1.0053E−01	1.9119E−01	2.0011E−01
	Mean	1.6673E−01	1.9269E−01	1.3325E−01	9.9119E−02	1.8844E−01	1.9997E−01
	Median	1.9692E−01	1.9257E−01	1.5974E−01	9.8527E−02	1.8838E−01	1.9996E−01

Table 3 (continued)

Test function	Statistical metric	MOPSO	NSMFO	MSSA	MOSMA	MOBO	MOGJO
DTLZ7	Worst	4.5177E−02	1.9226E−01	0.0000E +00	9.8424E−02	1.8661E−01	1.9986E−01
	St. Dev	6.7949E−02	4.6835E−04	7.5715E−02	9.4934E−04	1.7618E−03	6.9200E−05
	Best	1.8411E−01	2.4143E−01	9.5453E−03	2.3483E−01	2.5205E−01	2.7062E−01
	Mean	1.1286E−01	2.3140E−01	2.9489E−03	2.3039E−01	2.4036E−01	2.6786E−01
	Median	1.1734E−01	2.3072E−01	0.0000E +00	2.2900E−01	2.3863E−01	2.6782E−01
	Worst	5.2534E−03	2.1627E−01	0.0000E +00	2.2627E−01	2.3378E−01	2.6528E−01
	St. Dev	6.6426E−02	1.0422E−02	4.3204E−03	4.1327E−03	6.8946E−03	1.5623E−03

$$Min : \begin{cases} f_1(x) = 1.10471x_1^2x_2 + 0.04811x_3x_4(14 + x_2) \\ f_2(x) = \frac{4PL^3}{Ex_3^3x_4} \end{cases} \quad (33)$$

Subject to:

$$g_1(x) = -(ta - ta_{max}) \leq 0,$$

$$g_2(x) = -(\sigma - \sigma_{max}) \leq 0,$$

$$g_3(x) = -(x_1 - x_4) \leq 0,$$

$$g_4(x) = -(P - pc) \leq 0,$$

$$[h, l, t, b] = [x_1, x_2, x_3, x_4],$$

where

$$pc = \left(1 - \left(\frac{x_3}{2L}\left(\sqrt{\frac{E}{4G}}\right)\right)\right) \left(\frac{4.013E\sqrt{x_3^2x_4^6/36}}{L^2}\right)$$

$$ta = \sqrt{ta_1^2 + 2ta_1 \cdot ta_2 \cdot (x_2/2R) + ta_2^2}$$

$$Min: \begin{cases} f_1(x) = 0.7854x_1x_2^2(3.3333x_3^2 + 14.9334x_3 - 43.0934) - 1.508x_1(x_6^2 + x_7^2) + 7.4777(x_6^3 + x_7^3) + 0.7854(x_4x_6^2 + x_5x_7^2) \\ f_2(x) = \left(\sqrt{\left(\frac{745x_4}{x_2x_3}\right)^2 + 16.9e6}\right) \left(\sqrt{\left(\frac{745x_4}{x_2x_3}\right)^2 + 16.9e6}\right) / 110x_6^3 \end{cases} \quad (34)$$

$$ta_1 = P/\sqrt{2}x_1x_2, \quad ta_2 = M_pR/J, \quad M_p = P \cdot (L + x_2/2)$$

$$J = 2 \cdot \left(\sqrt{2}x_1x_2 \left((x_2^2/12) + ((x_1 + x_3)/2)^2\right)\right)$$

$$R = \sqrt{(x_2^2/4) + ((x_1 + x_3)/2)^2}$$

$$\sigma = 4PL/x_3^2x_4$$

$$P = 6000, \quad ta_{max} = 13600, \quad L = 14, \quad \sigma_{max} = 30000,$$

$$G = 12e6, \quad E = 30e6$$

$$0.125 \leq x_1, \quad x_4 \leq 5, \quad 0.1 \leq x_2, \quad x_3 \leq 10$$

5.8.2 Description of SRD problem

The SRD aims to simultaneously reduce the gear assembly weight and the transverse deflection for achieving optimized shaft. This design is optimized under some constraints which are the transverse deflections of the shafts, the surfaces stress, bending stress of the gear teeth, and stresses in the shafts. In this regard, seven design parameters are needed to be optimized, the face width, a module of teeth, teeth number in the pinion, the first shaft length between bearings, the second shaft length between bearings, and the first and second shafts’ diameters. This problem is regarded as mixed-integer design as the teeth number in the pinion is an integer while the others are continuous. The mathematical model is expressed as follows.

Subject to:

$$g_1(x) = 27/x_1x_2^2x_3 - 1 \leq 0,$$

$$g_2(x) = 397.5/x_1x_2^2x_3^2 - 1 \leq 0,$$

$$g_3(x) = 1.93x_4^3/x_2x_3x_6^4 - 1 \leq 0,$$

$$g_4(x) = 1.93x_5^3/x_2x_3x_7^4 - 1 \leq 0,$$

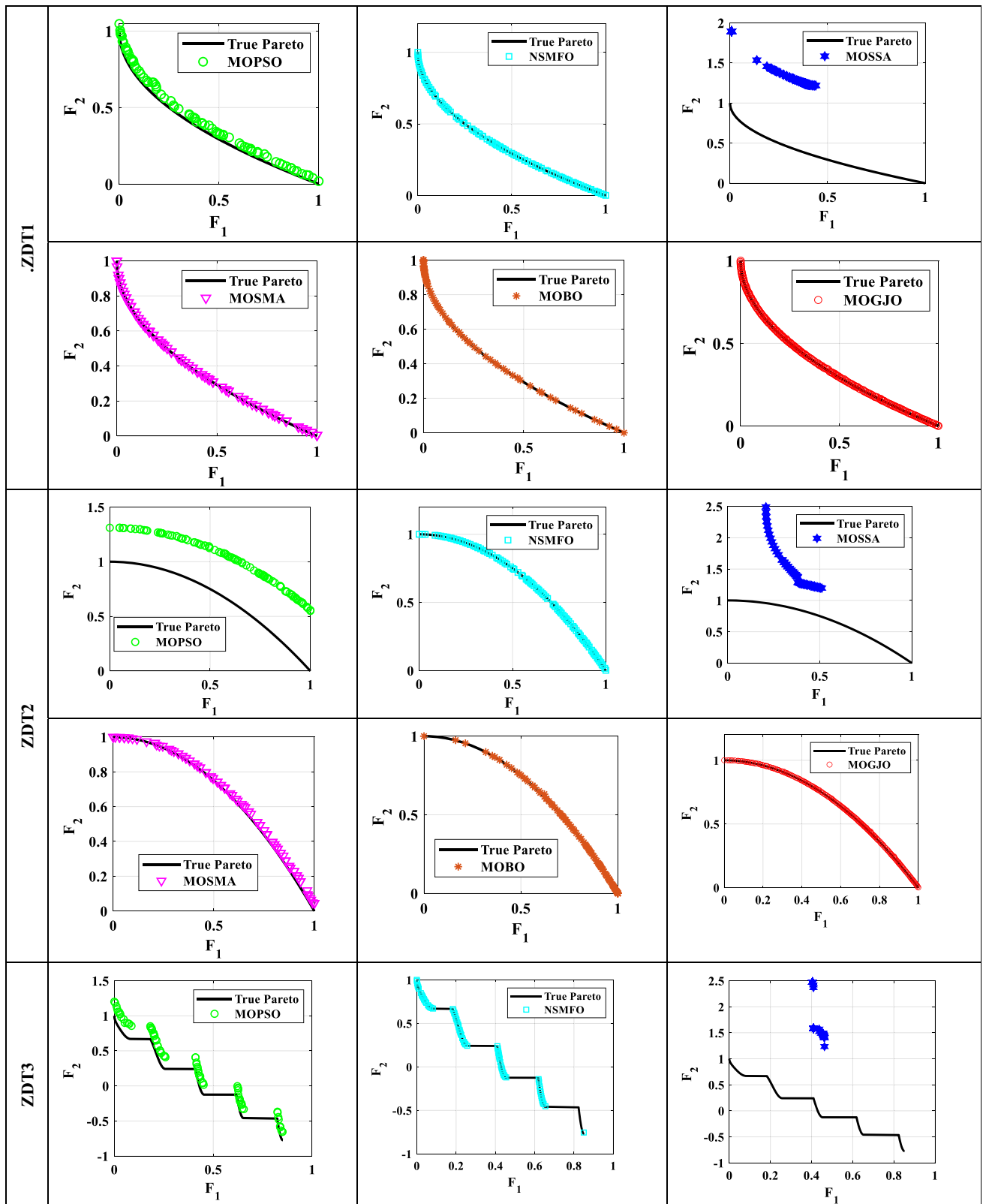


Fig. 3 The obtained POF for DTLZ suits using the proposed MOGJO and compared ones

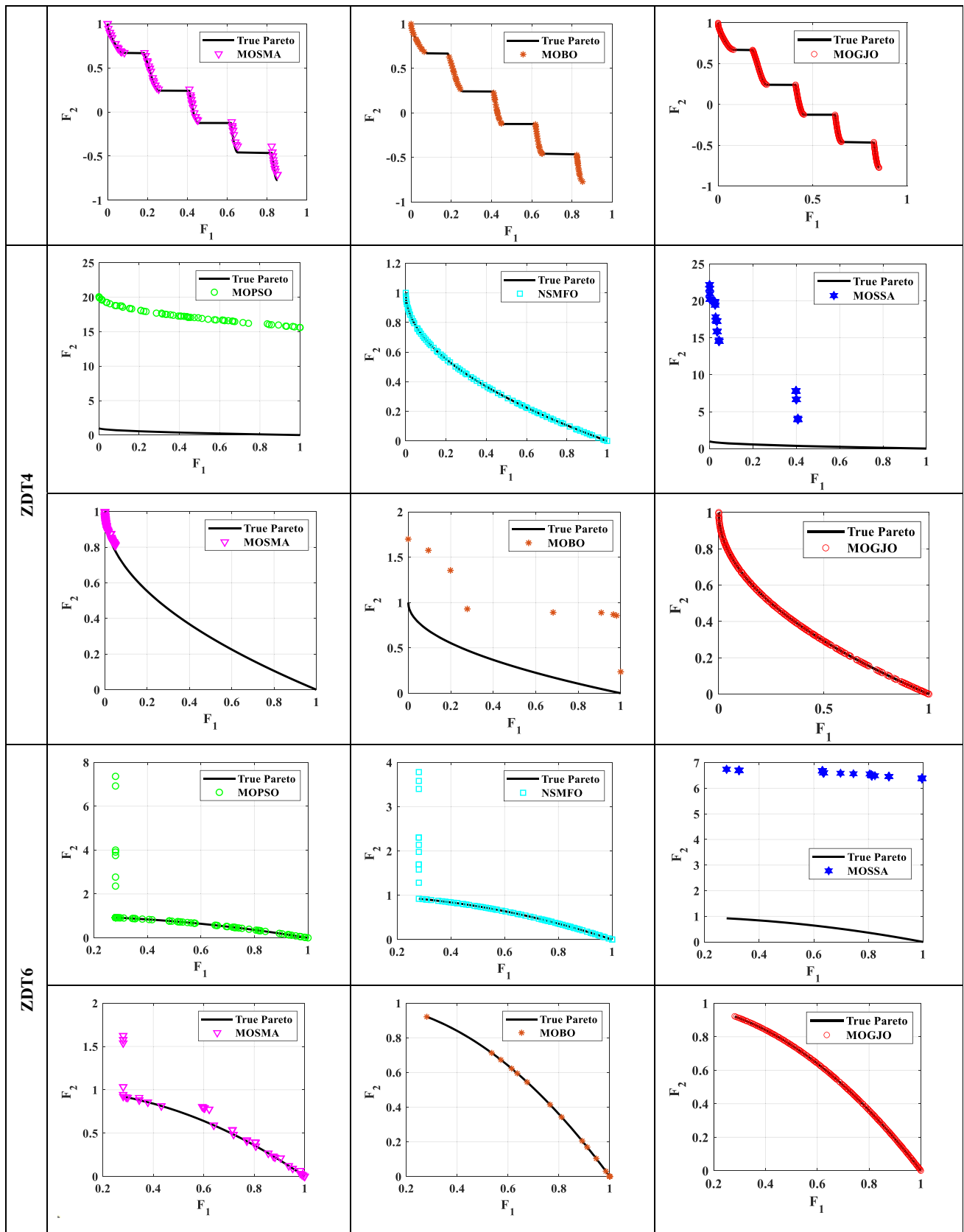


Fig. 3 continued

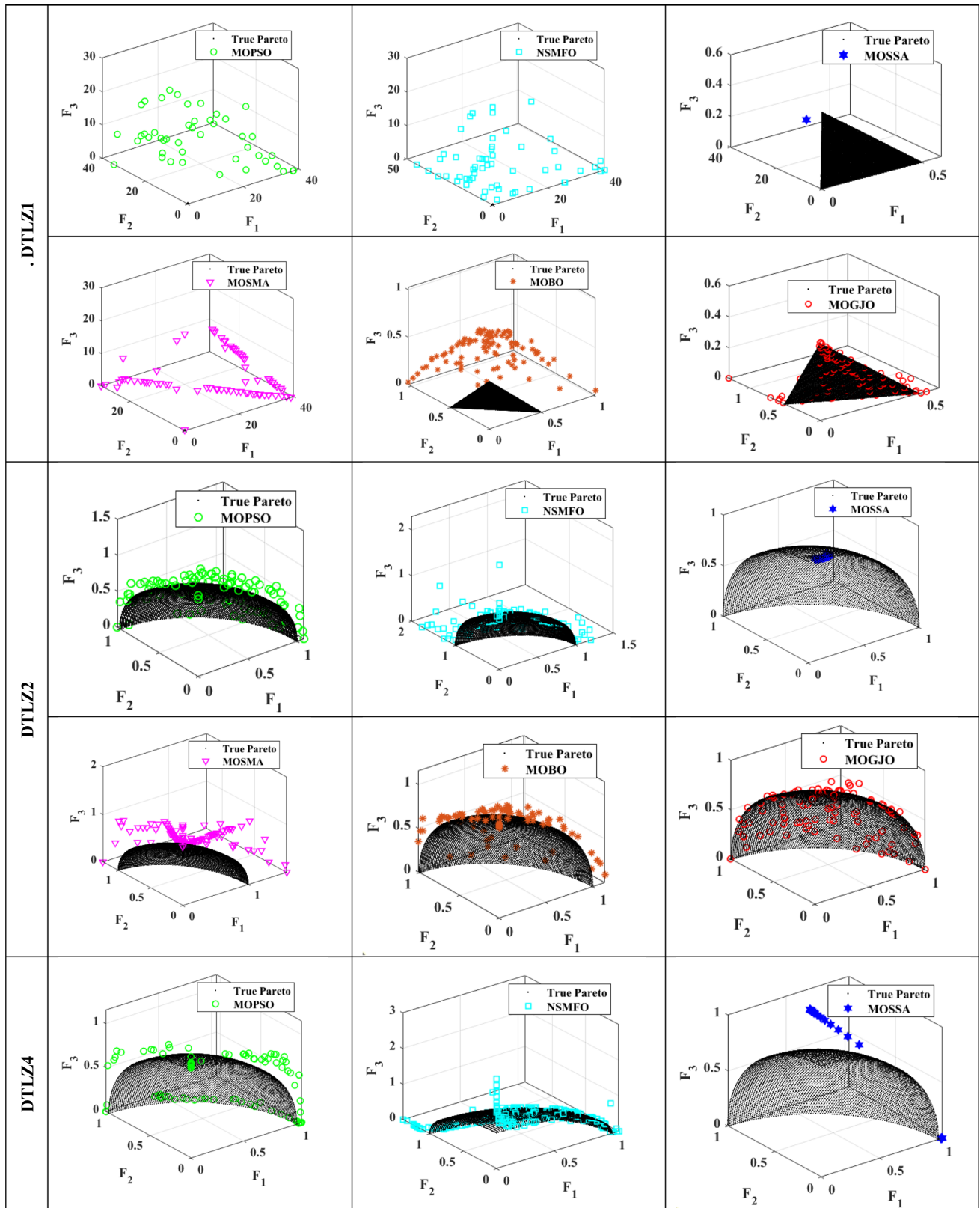


Fig. 3 continued

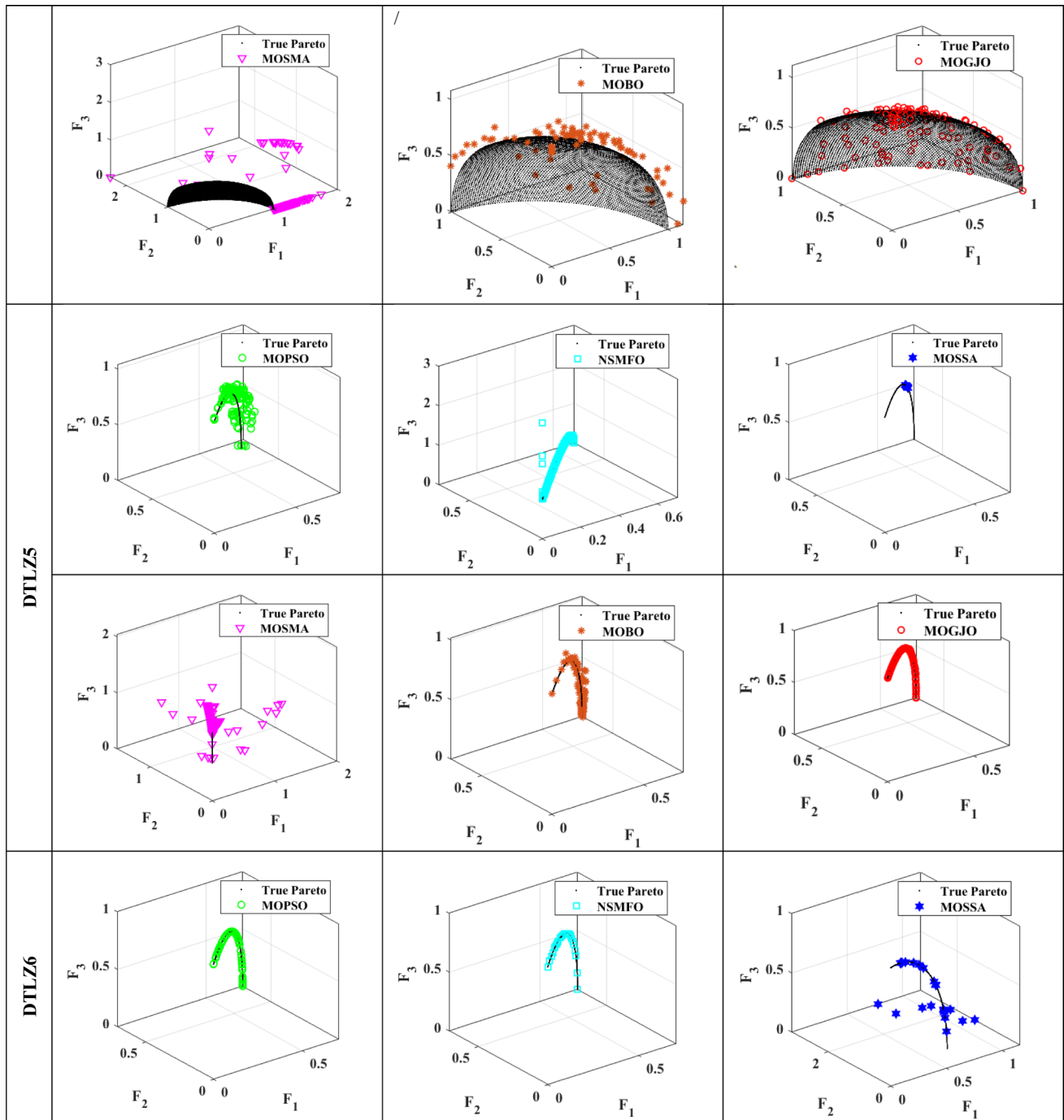


Fig. 3 continued

$$g_5(\mathbf{x}) = \left(\sqrt{\left(\frac{745x_4}{x_2x_3} \right)^2 + 16.9e6} \right) / 0.1x_6^3 - 1 \leq 0,$$

$$g_6(\mathbf{x}) = \left(\sqrt{\left(\frac{745x_5}{x_2x_3} \right)^2 + 157.5e6} \right) / 0.1x_7^3 - 1 \leq 0,$$

$$g_7(\mathbf{x}) = x_2x_3/40 - 1 \leq 0,$$

$$g_8(\mathbf{x}) = 5x_2/x_1 - 1 \leq 0,$$

$$g_9(\mathbf{x}) = x_1/12x_2 - 1 \leq 0,$$

$$g_{10}(\mathbf{x}) = (1.5x_6 + 1.9)/x_4 - 1 \leq 0,$$

$$g_{11}(\mathbf{x}) = (1.1x_7 + 1.9)/x_5 - 1 \leq 0,$$

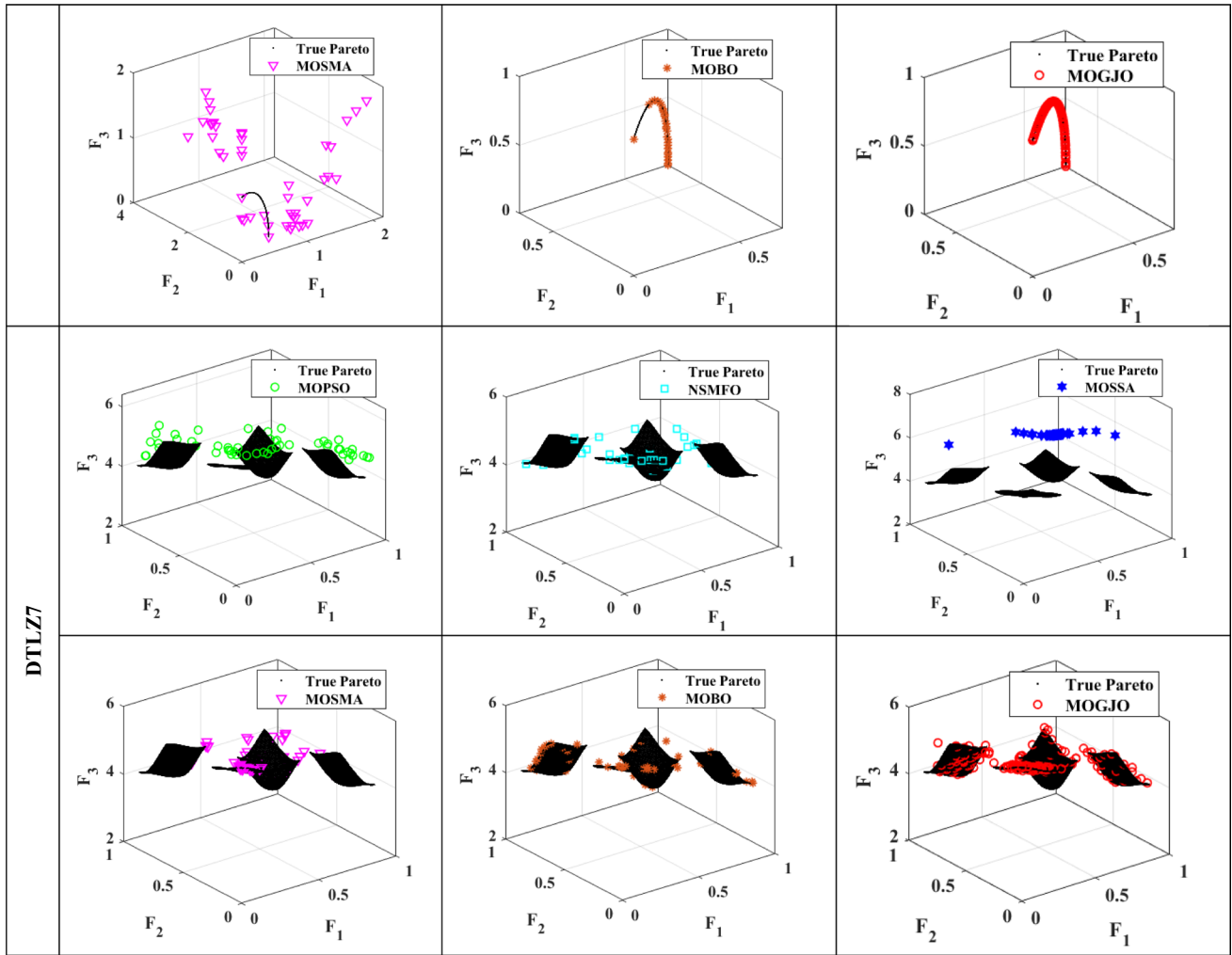


Fig. 3 continued

Fig. 4 Friedman test between MOGJO with its competing methods in terms of GD

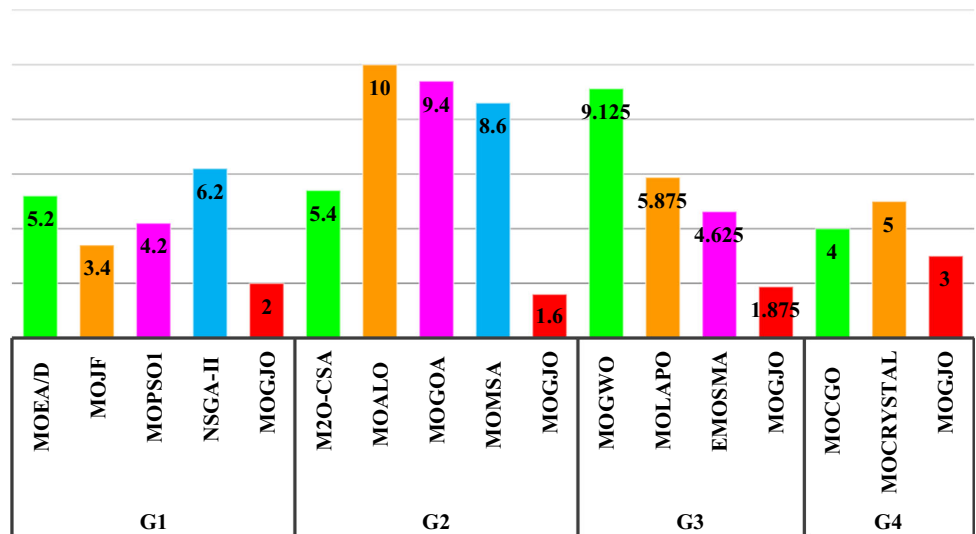


Table 4 Results of Wilcoxon test using significance level ($p \leq 0.05$) for GD and HV metrics

Metric	MOGJO versus MOPSO	MOGJO versus NSMFO	MOGJO versus MSSA	MOGJO versus MOSMA	MOGJO versus MOBO
GD	1.09E−02	7.69E−03	7.69E−03	7.69E−03	7.69E−03
HV	7.69E−03	3.00E−02	7.69E−03	1.09E−02	2.84E−02

$$2.6 \leq x_1 \leq 3.6, 0.7 \leq x_2 \leq 0.8, 17 \leq x_3 \leq 28, \\ 7.3 \leq x_4, x_5 \leq 8.3, 2.9 \leq x_6 \leq 3.9, 5 \leq x_7 \leq 5.5.$$

5.8.3 Description of DBD problem

The multi-plate disk brake is used in airplanes that aims to simultaneously minimize the overall mass of the brake as well as braking time. The design parameters are the inner and outer radii, the engaging force, and the friction surfaces (plates). Moreover, this problem is regarded as mixed-integer problems as the friction surfaces takes a discrete value. Also, this design is subjected to some constraints: the pressure sustained by the plates, distance among the radii of the friction plates, brake length, maximum limit of temperature, and the braking torque. The mathematical model is formulated as follows.

$$\text{Min} : \begin{cases} f_1(x) = 4.9e - 5(x_2^2 - x_1^2)(x_4 - 1) \\ f_2(x) = ((9.82e6)((x_2^2 - x_1^2)/x_3x_4(x_2^3 - x_1^3))) \end{cases} \quad (35)$$

Subject to:

$$g_1(x) = 20 + x_1 - x_2 \leq 0 \\ g_2(x) = 2.5(x_4 + 1) - 30 \leq 0 \\ g_3(x) = x_3/3.14(x_2^2 - x_1^2)^2 - 0.4 \leq 0 \\ g_4(x) = 2.22e - 3x_3(x_2^3 - x_1^3)/(x_2^2 - x_1^2)^2 - 1 \leq 0 \\ g_5(x) = 900 - ((2.66e - 2x_3x_4(x_2^3 - x_1^3))/(x_2^2 - x_1^2)) \leq 0 \\ 55 \leq x_1 \leq 80, 75 \leq x_2 \leq 110, \\ 1000 \leq x_3 \leq 3000, 2 \leq x_4 \leq 20$$

5.8.4 Description of FBTD problem

The simultaneously minimization of the volume and displacement of joints represents the main aim of FBTD, where the design variables of this design are considered as the areas of joints. The mathematical model is described as follows.

$$\text{Min:} \begin{cases} f_1(x) = L(2x_1 + \sqrt{2}x_2 + \sqrt{x_3} + x_4) \\ f_2(x) = F \frac{L}{E} \left(\frac{2}{x_2} + \frac{2\sqrt{2}}{x_2} - \frac{2\sqrt{2}}{x_3} + \frac{2}{x_4} \right) \end{cases} \quad (36)$$

Subject to:

$$1 \leq x_1, x_4 \leq 3, \\ \sqrt{2} \leq x_2, x_3 \leq 3, \\ F = 10, L = 200, E = 2e5.$$

The results of the proposed MOGJO and the compared algorithms obtained for the engineering design problems are assessed using the statistical measures of the SP and HV. The obtained results of these metrics are reported in Table 7. Based on observation of the SP results obtained in Table 7, the proposed MOGJO ensures the best statistical results compared to the other competitors for the engineering designs, WBD, SRD, DBD, and FBTD, where the best results are marked with bold font. Also, by observing the HV metric, it can be concluded that the MOGJO provides the best performance on all engineering designs by the comparisons with the other presented algorithms. According to the presented metrics, it can be revealed the MOGJO has a good convergence and coverage for the studied engineering optimization designs. Moreover, the searched POFs by the proposed MOGJO algorithm for all considered designs are depicted in Fig. 6.

5.9 Dynamic economic-emission power dispatch (DEEPD)

The DEEPD problem represents MOO problem that aims to minimize the objectives of fuel cost and emission levels in the power system stations. The term dynamic implies that the operation is performed over a specific time horizon with taking into account the dynamic changes in load. To maintain the real power balance in the power system, the output of the generators must be adjusted in accordance with changes in load in the power system. Therefore, the solution the DEEPD problem not only brings economic advantages but also lowers atmospheric pollutant gas emissions [64]. Moreover, the fuel cost equation acquires some ripples in its operation curve caused by opening and closing the steam valves of the turbine. Due to the ripples' nonlinear effect on the quadratic fuel cost equation, the

Table 5 Statistical metric of GD by the proposed MOGJO and state-of-the-art algorithms

Method	MOGJO		MOJF		MOEAD		MOPSO1		NSGA-II		MOCGO		MOCryStAl	
	Average	S.D	Average	S.D	Average	S.D	Average	S.D	Average	S.D	Average	S.D	Average	S.D
ZTD1	2.02E-04	9.65E-06	5.80E-04	5.00E-05	4.94E-02	1.72E-02	7.90E-04	1.10E-04	2.60E-01	3.34E-02	5.04E-05	1.17E-05	2.59E-04	4.01E-04
ZTD2	7.51E-05	6.56E-05	2.18E-03	2.03E-03	1.34E-01	3.34E-02	7.80E-04	1.40E-04	8.93E-01	2.07E-01	3.59E-05	3.15E-06	1.70E-04	4.76E+00
ZTD3	1.29E-04	4.52E-06	1.70E-04	1.00E-05	5.55E-02	1.16E-02	5.90E-04	1.10E-04	2.56E-01	2.24E-02	1.38E-04	2.09E-05	2.00E-04	1.67E-04
ZTD4	1.65E-04	2.35E-05	2.13E-02	2.93E-02	5.80E+00	2.23E+00	2.05E+00	3.79E+00	1.08E+01	3.10E+00	1.23E+100	2.59E+00	1.86E+01	1.19E+01
ZTD6	1.31E-02	2.35E-05	3.53E-02	2.23E-02	4.58E-01	1.04E-01	3.99E-02	2.90E-02	1.52E+00	2.00E-01	7.77E-02	2.00E-02	1.01E-02	3.04E-03
DTLZ1	6.66E-02	6.01E-02	1.04E+00	1.00E+00	1.89E+00	8.70E-01	4.19E+00	3.39E-01	4.96E+00	2.00E+00	Na	Na	Na	Na
DTLZ2	2.74E-02	9.35E-03	7.52E-03	1.75E-03	9.43E-03	1.85E-03	2.66E-02	4.41E-03	1.98E-02	4.94E-03	3.05E-02	8.81E-03	2.16E-01	7.84E-03
DTLZ4	1.67E-02	1.49E-02	2.26E-02	5.84E-03	1.00E-02	4.34E-03	1.98E-02	4.04E-03	2.51E-02	2.43E-02	3.39E-02	1.61E-02	2.00E-01	2.56E-02
DTLZ5	2.78E-03	5.31E-03	3.33E-03	1.52E-03	1.38E-03	5.90E-04	5.97E-03	2.93E-03	1.57E-03	3.50E-03	Na	Na	Na	Na
DTLZ6	9.98E-06	1.48E-06	5.00E-04	1.20E-04	9.58E-02	6.47E-02	5.60E-04	1.90E-04	8.94E-01	1.40E-02	Na	Na	Na	Na
DTLZ7	3.05E-03	3.27E-04	9.33E-03	2.79E-03	2.02E-01	9.66E-02	8.79E-03	8.30E-04	8.11E-01	8.78E-02	Na	Na	Na	Na
Method	EMOSMA		MOGOA		MOALO		MOLAPO		MOGWO		M2O-CSA		MOMSA	
Metric	Average	S.D	Average	S.D	Average	S.D	Average	S.D	Average	S.D	Average	S.D	Average	S.D
ZTD1	1.05E-02	5.27E-03	4.00E-02	1.00E-02	6.00E-02	2.00E-02	2.49E-04	8.80E-06	1.58E-02	2.52E-02	3.08E-04	2.11E-04	0.028	0.014
ZTD2	1.00E-04	1.00E-04	6.00E-02	2.00E-02	9.00E-02	4.00E-02	2.80E-04	3.70E-05	2.45E-02	5.45E-03	4.72E-05	4.38E-06	0.029	0.024
ZTD3	2.00E-04	1.00E-04	9.00E-02	3.00E-02	8.00E-02	3.00E-02	1.24E-01	1.55E-02	1.42E-01	9.36E-03	3.08E-03	4.60E-04	0.017	0.005
ZTD4	Na	Na	3.40E-01	1.30E-01	3.20E-01	1.10E-01	Na	Na	Na	Na	3.72E-04	2.30E-04	0.391	0.294
ZTD6	1.54E+00	2.12E-01	1.90E-01	6.00E-02	2.10E-01	5.00E-02	Na	Na	Na	Na	8.08E-02	1.70E-01	0.063	0.024

Bold font indicate best results obtained

Na Not available

Table 6 Statistical measures for GD metric by the proposed and compared optimizers for constrained suits

Test function	Statistical metric	MOPSO	NSMFO	MSSA	MOSMA	MOBO	MOGJO
SRN	Best	4.8371E−02	1.1491E−01	9.4999E−04	3.1638E−01	1.3732E−01	1.8990E−02
	Mean	7.4294E−02	1.8969E−01	5.9990E−03	5.1648E−01	1.7690E−01	2.1887E−02
	Median	7.4450E−02	1.5928E−01	5.5556E−03	5.0107E−01	1.7607E−01	2.0808E−02
	Worst	9.0994E−02	3.0816E−01	1.4117E−02	8.3128E−01	2.1054E−01	2.7240E−02
	St. Dev	1.6321E−02	7.4425E−02	5.0812E−03	2.0403E−01	2.6373E−02	2.9750E−03
BHN	Best	6.1659E−02	6.8026E−02	2.8214E−03	6.7603E−02	6.2490E−02	2.2486E−02
	Mean	7.8622E−01	1.0753E−01	2.1760E−02	7.0837E−02	1.0556E−01	2.3762E−02
	Median	2.2043E−01	8.7162E−02	1.2971E−02	6.9523E−02	8.9104E−02	2.3887E−02
	Worst	2.2248E +00	1.6355E−01	4.6683E−02	7.6272E−02	1.7057E−01	2.4833E−02
	St. Dev	9.7030E−01	4.5321E−02	2.0937E−02	3.4070E−03	4.5494E−02	8.2212E−04
KIT	Best	2.6340E +00	3.0036E +00	1.6520E +00	2.5677E +00	3.1672E +00	4.6025E−04
	Mean	2.8005E +00	3.0100E +00	1.6550E +00	2.5937E +00	3.2745E +00	3.1838E−03
	Median	2.7874E +00	3.0109E +00	1.6550E +00	2.5900E +00	3.2995E +00	1.5423E−03
	Worst	2.9641E +00	3.0148E +00	1.6571E +00	2.6251E +00	3.4340E +00	1.4401E−02
	St. Dev	1.1800E−01	4.1659E−03	2.1525E−03	2.3022E−02	1.1037E−01	4.2824E−03
TNK	Best	1.0607E−03	1.9577E−03	2.9092E−04	1.4475E−02	1.5783E−03	2.6114E−04
	Mean	6.4610E−03	2.5221E−03	6.8262E−04	1.7697E−02	2.1911E−03	3.5615E−04
	Median	6.7285E−03	2.1908E−03	6.7617E−04	1.8960E−02	1.8139E−03	3.6479E−04
	Worst	1.5764E−02	3.5838E−03	1.1470E−03	1.9836E−02	3.8323E−03	4.2497E−04
	St. Dev	5.9585E−03	6.5212E−04	3.0579E−04	2.4138E−03	9.3199E−04	5.1993E−05

realistic model of DEEPD formulation must take this into account, leading to many local optima. Additionally, considering the dynamic term as well as power balance constraints lead to non-monotonic, non-linear, non-convex, and non-smooth characteristics into DEEPD formulation and thus finding a compromise solution under aforementioned characteristics is a true challenge to the power system operations. The mathematical formulation is expressed as follows [64].

$$\text{Cost: } f_1(PG) = \sum_{h=1}^H \sum_{i=1}^{NG} (c_i + b_i PG_{i,h} + a_i PG_{i,h}^2) + |d_i(\sin(e_i(PG_i^{\min} - PG_{i,h})))| \tag{37}$$

$$\text{Emission: } f_2(PG) = \sum_{h=1}^H \sum_{i=1}^{NG} (m_i + l_i PG_{i,h} + k_i PG_{i,h}^2) + n_i(\exp^{q_i PG_{i,h}}) \tag{38}$$

Subject to:

$$\sum_{i=1}^{NG} PG_{i,h} = PD_h + PL_h \tag{39}$$

$$PL_h = \sum_{i=1}^{NG} \sum_{j=1}^{NG} PG_{i,h} B_{ij} PG_{j,h} + \sum_{i=1}^{NG} B_{0i} PG_{i,h} + B_{00} \tag{40}$$

$$PG_i^{\min} \leq PG_{i,h} \leq PG_i^{\max}, i = 1, 2, \dots, NG \ \& \ h = 1, 2, \dots, 24 \tag{41}$$

where H defines the dispatch period that usually taken as 24 h. $PG_{i,h}$ denotes the produced power by the generator i at time h , a_i, b_i, c_i represent the coefficients of fuel cost, d_i, e_i represent the coefficients acquired by valve effect of the i th generator. l_i, m_i, n_i, k_i, q_i denote the coefficients of emission function of the i th unit. PG_i^{\min} defines the lower bound for generation unit PG_i .

Equation (39) expresses the power balance constraint for the generated power at time h , where PD_h defines the power demand at time h and PL_h denotes the transmission loss at time h that is expressed in Eq. (40). Where B_{ij}, B_{0i} , and B_{00} denote the ij th member of the B-loss matrix, the i th member of the loss coefficient vector, and a constant, respectively. Equation (41) defines the boundaries of the search region, where PG_i^{\min} and PG_i^{\max} denote the lower and upper bounds, respectively. In this context, the proposed method is applied on the IEEE 30-bus system, where the single-line diagram is depicted in Fig. 7 [51]. The load profile for DEEPD was taken from data available in [65].

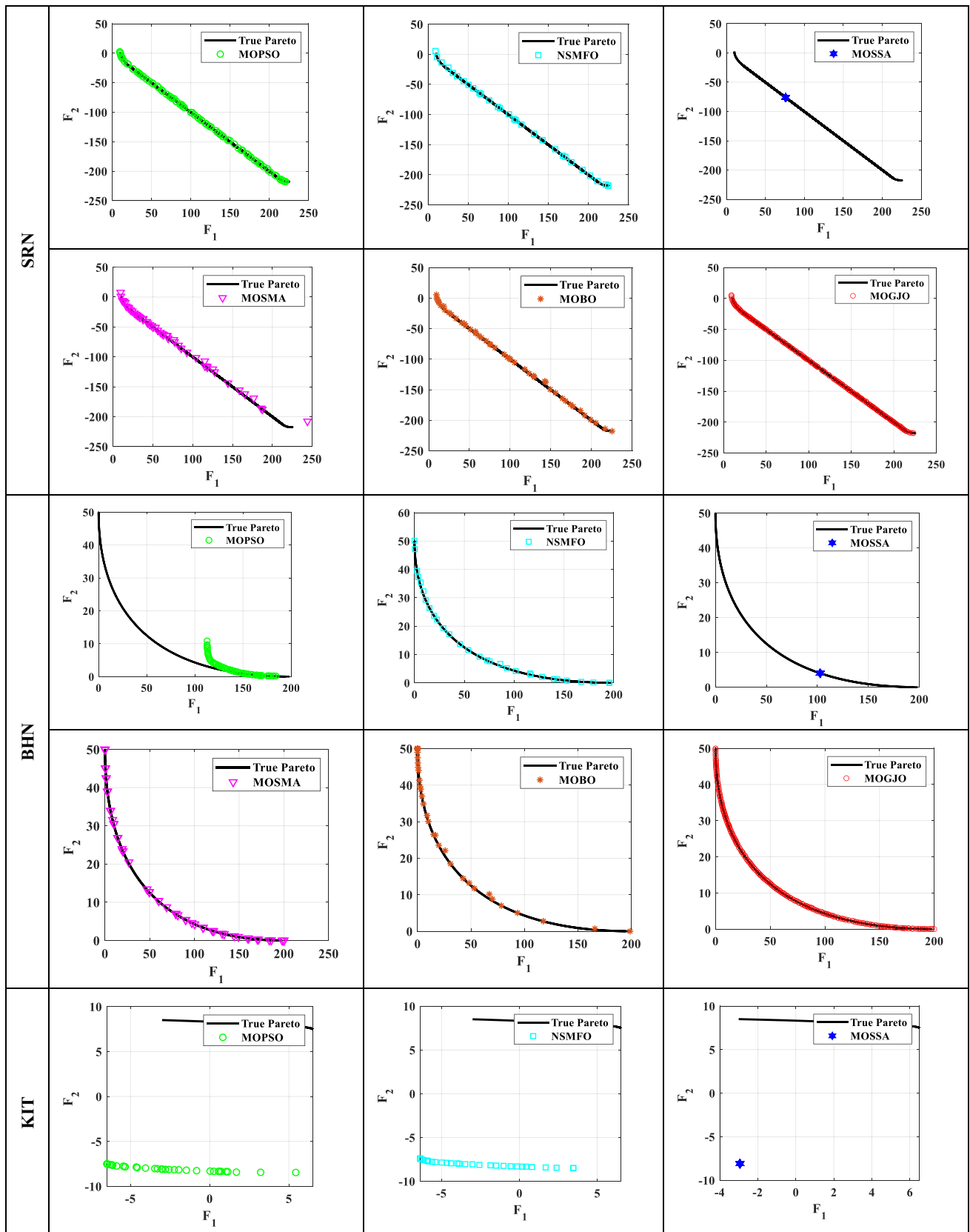


Fig. 5 The obtained POF for constrained suits using the proposed MOGJO and compared ones

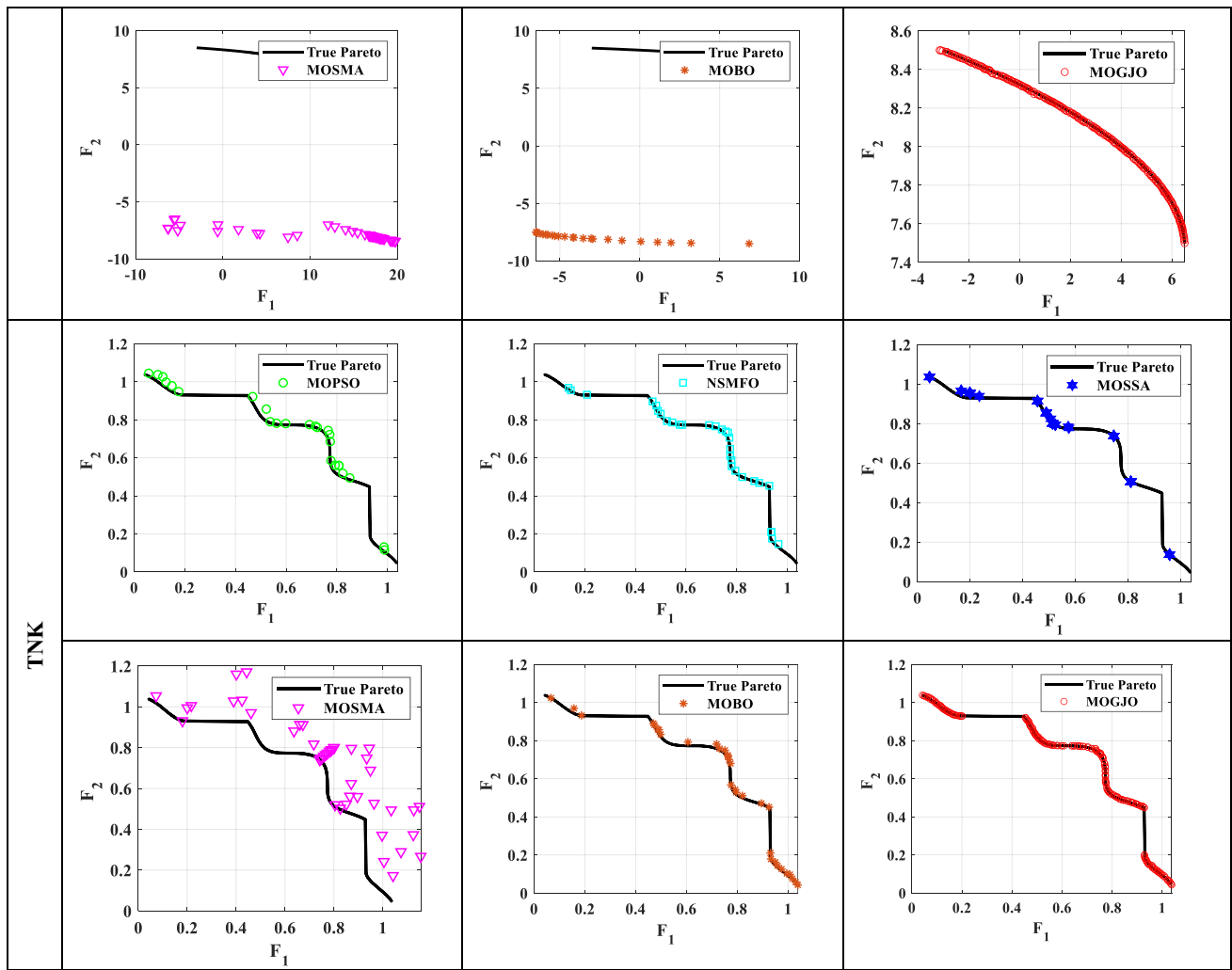


Fig. 5 continued

To evaluate the applicability of the proposed MOGJO, it is investigated on the DEEPD problem for every hour, where the POF obtained for each hour along with the compromise solution is depicted as in Fig. 8. The bar plot of the obtained real generated power of the compromise solution is depicted in Fig. 9. Moreover, the reached compromise solution by the proposed MOGJO is compared with existing algorithms in terms of dominance relation and savings regarding the fuel cost and emission levels, where the fuel cost and emission obtained by the GSOMP [65] are 25924.4\$ and 6.0041 ton, and the obtained the fuel cost and emission by MOMVO [64] are 25831.48\$ and 5.9666 ton. Based on the recorded results, the proposed algorithm achieves daily savings in fuel costs and emission levels over the other competitors by 489.5001\$ and 0.0882 ton for MOMVO, and by 582.4201\$ and 0.1257 ton for GSOMP. The compromise solution of the fuel cost and emission reached by the proposed MOGJO at each hour as

well as the generated power per hour is recorded in Table 8.

5.10 Further discussion

In this work, the performance of the MOGJO was applied on some benchmark suits including the ZDT suit with optimizing bi-objective functions, DTLZ suits with optimizing three-objective functions, constrained test suits and real engineering applications such as the welded beam design, speed reduced design, four-bar truss, disk brake design, and real DEEPD problem. The assessment of the proposed MOGJO was carried out by the comparisons with other optimization algorithms, and some performance metrics such as HV, SP, and GD. The statistical outcomes of assessment metrics affirmed that the MOGJO algorithm performs well regarding the converge and coverage features toward POF without suffering, while the compared counterparts may suffer from converge and coverage

Table 7 Statistical measures for GD and HV metrics by the proposed MOGJO and compared optimizers for engineering designs

Design	Statistics	HV									
		SP					HV				
		MOPSO	NSMFO	MOSMA	MOBO	MOGJO	MOPSO	NSMFO	MOSMA	MOBO	MOGJO
WBD	Best	2.56E-01	5.27E-01	4.75E-01	9.08E-01	8.89E-02	6.97E-01	6.85E-01	6.68E-01	6.79E-01	7.00E-01
	Mean	8.95E+00	6.59E-01	6.52E+00	1.76E+00	9.49E-02	5.65E-01	6.51E-01	6.50E-01	6.05E-01	6.87E-01
	Median	4.22E-01	6.98E-01	6.62E-01	1.39E+00	9.29E-02	6.81E-01	6.66E-01	6.49E-01	6.47E-01	6.90E-01
	Worst	4.11E+01	7.74E-01	2.89E+01	3.82E+00	1.07E-01	7.59E-02	5.95E-01	3.09E-01	4.40E-01	6.73E-01
	St. Dev	1.80E+01	1.08E-01	1.25E+01	1.20E+00	5.73E-03	2.74E-01	3.54E-02	1.80E-01	9.61E-02	1.11E-02
SRD	Best	2.62E+01	1.06E+02	4.15E+01	5.81E+02	1.42E+01	2.42E-01	3.01E-01	2.10E-01	3.05E-01	3.08E-01
	Mean	8.05E+01	1.11E+02	5.72E+01	5.94E+02	1.53E+01	1.22E-01	2.99E-01	2.09E-01	3.01E-01	3.07E-01
	Median	8.29E+01	1.15E+02	5.12E+01	5.97E+02	1.51E+01	9.01E-02	2.96E-01	2.09E-01	3.01E-01	3.07E-01
	Worst	1.22E+02	1.15E+02	8.66E+01	5.99E+02	1.72E+01	2.16E-03	2.94E-01	2.08E-01	2.88E-01	3.07E-01
	St. Dev	3.96E+01	5.07E+00	1.79E+01	7.06E+00	9.44E-01	9.44E-02	6.63E-03	8.28E-04	8.11E-03	2.38E-04
DBD	Best	7.61E-02	2.79E-01	1.93E-01	1.45E-01	3.54E-02	5.99E-01	5.96E-01	5.78E-01	5.98E-01	6.07E-01
	Mean	1.07E-01	3.26E-01	3.30E-01	1.78E-01	4.01E-02	5.87E-01	5.94E-01	5.01E-01	5.95E-01	6.07E-01
	Median	1.04E-01	3.36E-01	3.22E-01	1.89E-01	3.81E-02	5.97E-01	5.95E-01	5.58E-01	5.96E-01	6.07E-01
	Worst	1.30E-01	3.64E-01	4.14E-01	1.98E-01	5.52E-02	5.49E-01	5.90E-01	3.97E-01	5.92E-01	6.06E-01
	St. Dev	2.31E-02	3.57E-02	8.90E-02	2.42E-02	6.04E-03	2.14E-02	2.30E-03	9.18E-02	2.41E-03	1.22E-04
FBTD	Best	2.76E+00	1.02E+01	6.59E+00	5.32E+00	1.18E+00	1.73E-01	1.70E-01	1.67E-01	1.70E-01	1.74E-01
	Mean	3.04E+00	1.41E+01	1.12E+01	1.63E+01	1.32E+00	1.69E-01	1.07E-01	1.65E-01	1.69E-01	1.74E-01
	Median	3.01E+00	1.28E+01	1.08E+01	1.61E+01	1.33E+00	1.72E-01	1.07E-01	1.64E-01	1.69E-01	1.74E-01
	Worst	3.58E+00	2.09E+01	1.68E+01	2.67E+01	1.43E+00	1.57E-01	1.06E-01	1.63E-01	1.68E-01	1.74E-01
	St. Dev	3.29E-01	4.12E+00	3.66E+00	7.77E+00	8.41E-02	6.85E-03	4.45E-04	1.83E-03	5.94E-04	1.81E-05

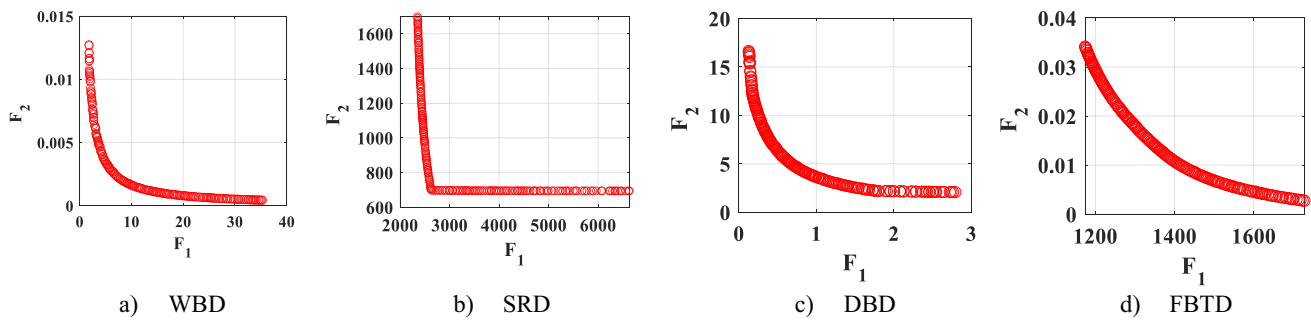


Fig. 6 The obtained POF for the engineering designs by the proposed MOGJO

features toward POF. At the same time, the POF obtained by the proposed MOGJO, and its competitors are depicted, where the visualization perspective realized that the proposed MOGJO algorithm can reach more concise shape with the true POF for most of the test functions. Moreover, the proposed MOGJO is further verified by the comparisons with some implemented algorithms including MOPSO, NSMFO, MSSA, MOSMA, MOBO, and some state-of-the-art methods including MOJF, MOEA/D, MOPSO1, NSGA-II, MOCGO, MOCryStAl, EMOSMA, MOGOA, MOALO, MOLAPO, MOGWO, M2O-CSA, and MOMSA. The obtained results using the statistical metrics along with the nonparametric tests have affirmed the progressive and competitive performance of the proposed algorithm compared to its competitors. In this regard, the Wilcoxon rank sum test affirmed that the MOGJO

algorithm is significantly better than the compared methods, with a 95% significance level. On the other hand, the Friedman test was detected the significance of average ranking among the compared algorithm, and it was confirmed that the proposed MOGJO outperforms the best and worst algorithms, MOJF and MOALO, among the state-of-the-art algorithms by an average rank greater than 41% and 84% on for ZDT and DTLZ1, respectively. Finally, the results of engineering designs and real dynamic economic-emission power dispatch (DEEPD) problems demonstrated that the MOGJO algorithm has good applicability to deal with challenging tasks with complicated search space constraints. Furthermore, the proposed algorithm saved the overall energy cost and total emission of the DEEPD problem by 1.89%, and 1.48%, respectively, compared with the best existing results. Therefore, it can be concluded that the presented methodology provides progressive and competitive performance with existing multi-objective optimization methods in terms of ductility and coverage. The main reasons behind the superior performance of the MOGJO can be interpreted as follows: Firstly, the incorporation of chaotic logistic and opposition searching can provide a good exploration aspect, where this can explore new positions in opposite directions of current ones which improves the diversity of solutions. Secondly, the integrating of elite strategy that operates in surviving the best solutions can improve the intensifying of solutions and improve the convergence aspect. Finally, the embedding of the relevant tools related to multi-objective strategy into GJO algorithm can make adaption to deal with the MOO issues such as the external archive population to maintain the best non-dominated solutions during the iterative process, conception of crowding distance to avoid the archive size explosion, and the selection of pair golden jackals from the archive population can guide the whole population to attain the Pareto front with good balance among the exploration and the exploitation searching. Furthermore, we anticipate that the provided methodology will inspire practitioners and engineers to use it in dealing with practical applications such as climate changes and

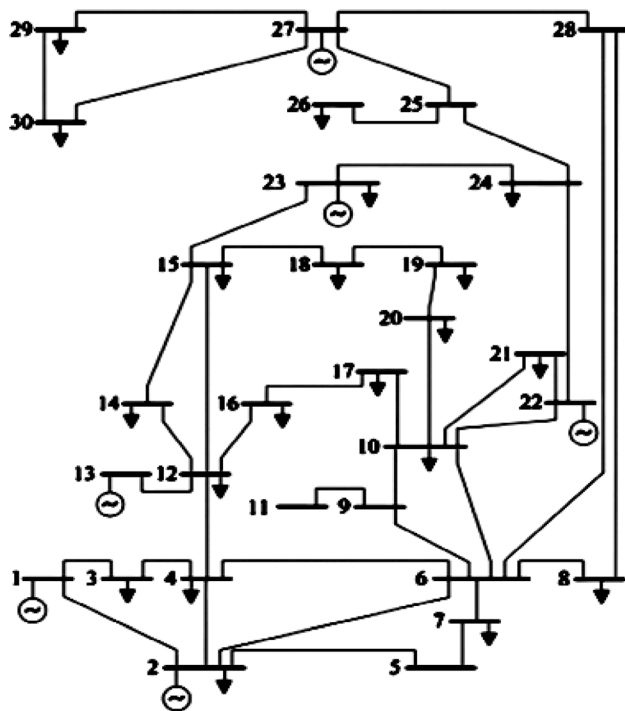


Fig. 7 The structure of IEEE 30-bus system using the single-line diagram [51]

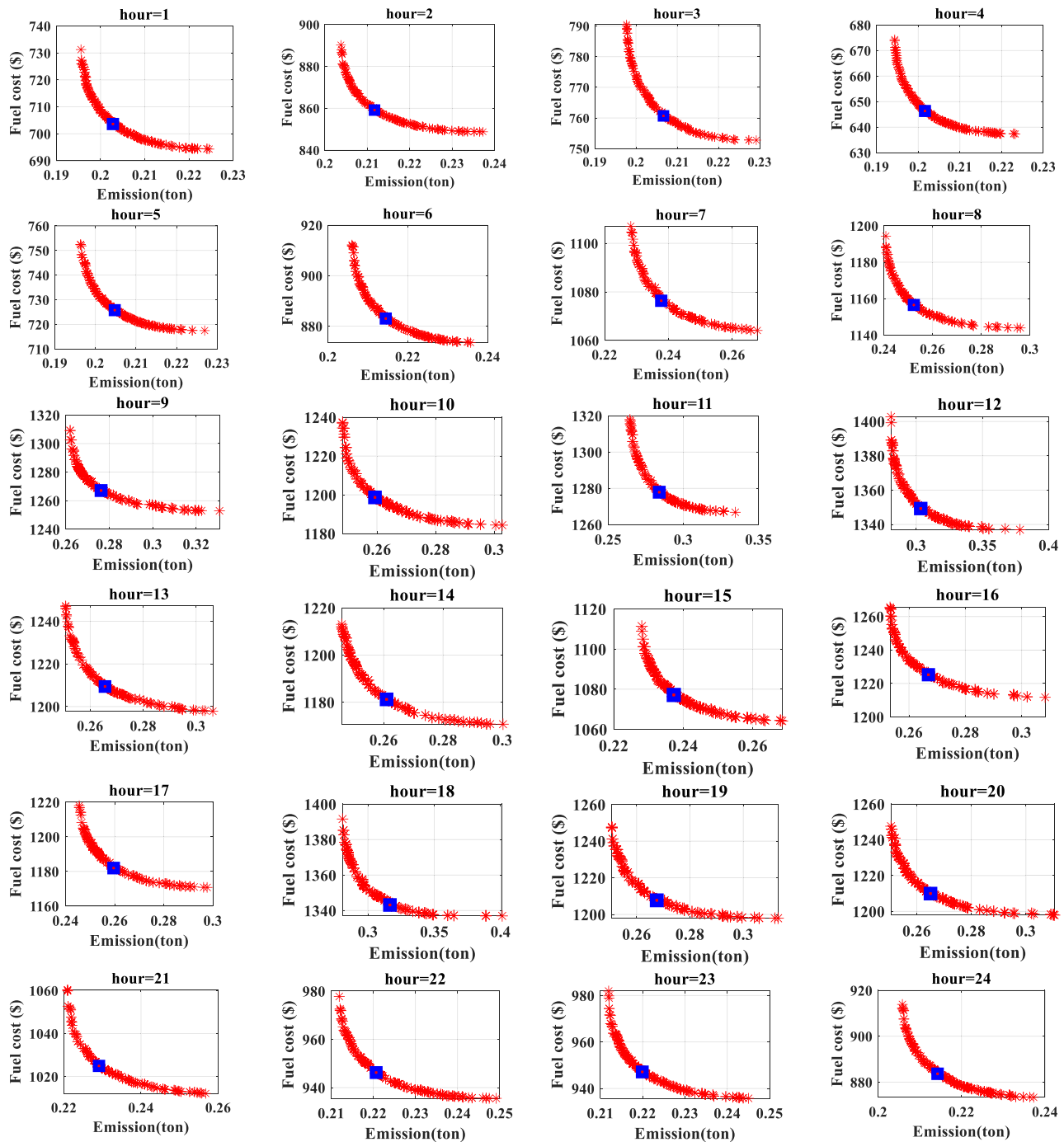


Fig. 8 POFs for each hour of the dispatch period (red star) and compromise solution (blue square)

renewable energy sources that aims to simultaneously optimize large-scale multi- and many-objective optimization problems.

5.11 Benefits and limitations of the proposed algorithm

5.11.1 Benefits of the algorithm

- Enhanced exploration: The algorithm integrates the chaotic logistic and opposition-based learning concepts with the MOGJO algorithm to explore more promising

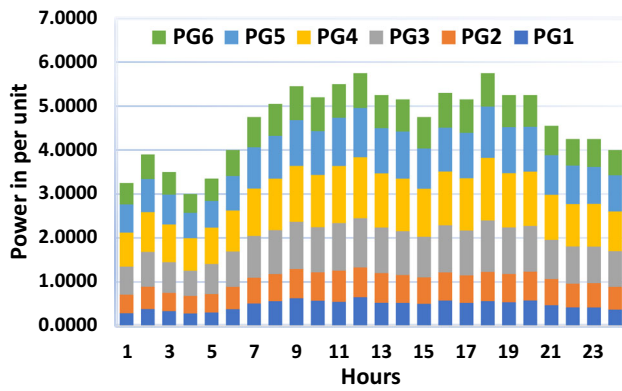


Fig. 9 Bar plot of the generated power corresponding to compromise solution of the DEEPD problem

areas during the search process, leading to improve the spread performance along the entire Pareto front.

- **Guided exploitation:** The use of the elite-based strategy in the MOGJO helps to introduce guidance pattern into the updating process, leading to emphasize the exploitation feature with promoting the convergence performance toward the POF.

- **Robustness:** The algorithm can strike a good balance among the exploitative and explorative features, demonstrating the robustness performance over the compared ones for most of the studied problems.
- **Assistance-based tool:** Fuzzy technique is adopted to assist the DM mission to select the best compromise solution (CS) from the overall POF.

5.11.2 Limitations of the algorithm

- **Limited scalability:** The algorithm is highly susceptible to worsening while dealing with many-objective problems. More specifically, since MOGJO optimizes the objectives of a MOO problem simultaneously, there is a chance that the algorithm loses performance when the MOO problem has more than two objectives. So, the proposed algorithm can be further integrated with other searching strategies to create a more effective and robust algorithm for optimizing many-objective problems.
- **Limited applicability:** The algorithm’s effectiveness may depend on the specific features of the problem

Table 8 The best compromise solution reached by the proposed algorithm for the DEEPD problem

<i>h</i>	<i>PD_h</i>	<i>PG₁</i>	<i>PG₂</i>	<i>PG₃</i>	<i>PG₄</i>	<i>PG₅</i>	<i>PG₆</i>	Emission (ton)	Fuel cost (\$)
1	3.2500	0.2880	0.4228	0.6388	0.7741	0.6399	0.4863	0.2028	703.6166
2	3.9000	0.3855	0.5062	0.7928	0.9037	0.7525	0.5593	0.2117	859.1323
3	3.5000	0.3372	0.4146	0.6980	0.8584	0.6797	0.5122	0.2067	760.6734
4	3.0000	0.2839	0.3985	0.5718	0.7420	0.5762	0.4276	0.2016	646.3300
5	3.3500	0.3044	0.4225	0.6810	0.8270	0.6094	0.5057	0.2048	725.7823
6	4.0000	0.3807	0.5092	0.8026	0.9321	0.7863	0.5892	0.2145	883.0348
7	4.7500	0.5088	0.5894	0.9479	1.0783	0.9379	0.6877	0.2377	1076.3574
8	5.0500	0.5620	0.6181	0.9976	1.1724	0.9728	0.7270	0.2523	1156.5174
9	5.4500	0.6301	0.6636	1.0748	1.2717	1.0411	0.7688	0.2762	1267.1308
10	5.2000	0.5737	0.6461	1.0251	1.1887	0.9973	0.7691	0.2593	1198.6784
11	5.5000	0.5473	0.7120	1.0790	1.2994	1.0975	0.7642	0.2840	1277.8676
12	5.7500	0.6542	0.6759	1.1200	1.3881	1.1206	0.7913	0.3033	1349.2569
13	5.2500	0.5273	0.6728	1.0385	1.2313	1.0271	0.7531	0.2656	1209.4003
14	5.1500	0.5243	0.6345	0.9963	1.1948	1.0705	0.7296	0.2610	1181.2043
15	4.7500	0.5031	0.6013	0.9246	1.0908	0.9179	0.7122	0.2373	1077.1114
16	5.3000	0.5758	0.6418	1.0712	1.2240	0.9964	0.7907	0.2669	1225.2375
17	5.1500	0.5236	0.6282	1.0189	1.1900	1.0314	0.7578	0.2596	1181.9437
18	5.7500	0.5654	0.6638	1.1706	1.4242	1.1667	0.7593	0.3166	1343.1344
19	5.2500	0.5373	0.6457	1.0570	1.2361	1.0448	0.7291	0.2675	1207.7034
20	5.2500	0.5800	0.6557	1.0379	1.2371	1.0184	0.7208	0.2650	1209.9368
21	4.5500	0.4710	0.5957	0.8900	1.0258	0.9017	0.6658	0.2291	1024.9511
22	4.2500	0.4234	0.5369	0.8494	0.9607	0.8780	0.6014	0.2207	946.2351
23	4.2500	0.4212	0.5513	0.8319	0.9711	0.8401	0.6345	0.2199	947.1190
24	4.0000	0.3701	0.5186	0.8125	0.9033	0.8221	0.5733	0.2143	883.6251
Total								5.8784	25341.9799

being addressed such as multi-modal, non-separable or deceptive natures, and it maybe could not grantee the best performance for all optimization tasks.

6 Conclusion and future work

This paper proposes a guided multi-objective golden jackal optimization (MOGJO) based on opposition mechanism and elite-based-based learning scheme to deal with MOO issues. While preserving the searching capability of the GJO, a dynamic opposition strategy and guidance strategy based on the elite non-dominated solutions are equipped into GJO algorithm to reach the promising regions of POF, and thus, diversity and coverage toward the POF is preserved to the greatest extent attainable through the integration of two mechanisms. Moreover, the crowding distance conception is also incorporated to emphasize the survivability of solutions and avoid the premature convergence. The suggested MOGJO algorithm can find the optimal Pareto frontier in a variety of testing functions and engineering challenges. The proposed algorithm was tested on 21 cases, including 11 unconstrained MOO issues with two objective or three objective, 5 constrained MOO issues, 4 high-constraint engineering design application, and one real power system problem. Quantitative results were performed by using three performance indicators (GD, HV, and SP) along with comparisons with some well-known implemented algorithms and other algorithms from the literature. In this sense, the performance of proposed MOGJO is verified with MOPSO, NSMFO, MSSA, MOSMA, MOBO, MOJF, MOEA/D, MOPSO1, NSGA-II, MOCGO, MOCryStAl, EMOSMA, MOGOA, MOALO, MOLAPO, MOGWO, M2O-CSA, and MOMSA. The obtained results show that the proposed MOGJO algorithm can provide progressive and competitive performance with the compared algorithms for most of the ZDT, DTLZ problems. Also, for constrained problems, the results on the studied problems demonstrated that the MOGJO can explore the promising regions under the constraints challenging with providing superior results than the compared algorithms. At the same time, MOGJO algorithm can attain the Pareto optimal front of the real shape for most of the studied problems. Finally, the results of engineering designs and real dynamic economic-emission power dispatch (DEEPP) problems affirmed that the MOGJO algorithm has good applicability to deal with challenging tasks with complicated search space constraints. Finally, Wilcoxon rank sum test was performed on GD, and HV indicators, and the results demonstrated that the MOGJO algorithm is significantly better than the compared methods, with a 95% significance level. Furthermore, the results

of the nonparametric Friedman test were performed to detect the significant of average ranking among the compared algorithm, where the results confirmed that the proposed MOGJO outperforms the best algorithm, MOJF, among thirteen state-of-the-art algorithms by an average rank of Friedman test greater than 41% for ZDT and DTLZ1 suits while outperforming the worst one, MOALO, by 84%. Furthermore, the proposed algorithm saved the overall energy cost and total emission of the DEEPP problem by 1.89%, and 1.48%, respectively, compared to the best existing results. Therefore, it can be claimed that the suggested methodology performs outstanding ductility and coverage among existing multi-objective optimization methods.

With respect to future work, some considerations can be explored. Though MOGJO has outstanding performance in most of the studied cases, it is susceptible to performance loss for large-scale and multi-modal problems. More studies can also be conducted on improving the global searching ability of the proposed algorithm in terms of convergence and coverage trends using other improvement strategies to be competitive enough with top performing methods in the literature. Additionally, future studies could examine the performance of the proposed algorithm for large-scale many-objective tasks that have four or more objectives. Also, adapting the performance of the proposed algorithm to deal with real-life MOO issues, such as CEC2020 Real-World Constrained Optimization competition, wind farm layout optimization problem, DEEPP problem based on renewable technologies, and deep learning technique-based prediction of the load dispatch period for the DEEPP problem, is part of our future direction. Please note that the MOGJO cannot be viewed as the optimum methodology for all situations because there is no such methodology, as it is evident from “no free lunch” (NFL) theorem. Furthermore, since MOGJO uses stochastic population-based optimization, it can still encounter a stagnation challenge, especially while dealing with some more challenging datasets including huge dimensions and/or complicated constraints.

Acknowledgements This work has been supported by an internal grant project of VSB-Technical University of Ostrava (SGS project, Grant Number SP2023/076).

Funding There is no funding for this study by any company.

Declarations

Conflict of interest No potential conflict of interest has been stated by the authors.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

References

- Rizk-Allah RM, El-Sehiemy RA, Deb S, Wang GG (2017) A novel fruit fly framework for multi-objective shape design of tubular linear synchronous motor. *J Supercomput* 73(3):1235–1256
- Rizk-Allah RM, El-Sehiemy RA, Wang GG (2018) A novel parallel hurricane optimization algorithm for secure emission/economic load dispatch solution. *Appl Soft Comput* 63:206–222
- Miettinen K (2012) *Nonlinear multiobjective optimization*. Springer
- Deb K (2011) *Multi-objective optimisation using evolutionary algorithms: an introduction*. Multi-objective evolutionary optimisation for product design and manufacturing. Springer, London, pp 3–34
- Steuer RE (1986) *Multiple criteria optimization: theory, computation and application*. Wiley, New York
- Perić T, Babić Z, Matejaš J (2018) Comparative analysis of application efficiency of two iterative multi objective linear programming methods (MP method and STEM method). *CEJOR* 26(3):565–583
- Kumar S, Jangir P, Tejani GG, Premkumar M (2022) MOTEO: a novel physics-based multiobjective thermal exchange optimization algorithm to design truss structures. *Knowl-Based Syst* 242:108422
- Srinivas N, Deb K (1994) Multiobjective optimization using nondominated sorting in genetic algorithms. *Evol Comput* 2(3):221–248. <https://doi.org/10.1162/evco.1994.2.3.221>
- Coello CA, Pulido GT, Lechuga MS (2004) Handling multiple objectives with particle swarm optimization. *IEEE Trans Evol Comput* 8(3):256–279. <https://doi.org/10.1109/TEVC.2004.826067>
- Mirjalili S, Jangir P, Saremi S (2017) Multi-objective ant lion optimizer: a multi-objective optimization algorithm for solving engineering problems. *Appl Intell*. <https://doi.org/10.1007/s10489-016-0825-8>
- Mirjalili S, Saremi S, Mirjalili SM, dos Coelho LS (2016) Multi-objective grey wolf optimizer: a novel algorithm for multi-criterion optimization. *Expert Syst Appl* 47:106–119. <https://doi.org/10.1016/j.eswa.2015.10.039>
- Hancer E, Xue B, Zhang M, Karaboga D, Akay B (2015) A multi-objective artificial bee colony approach to feature selection using fuzzy mutual information. *IEEE Congr Evol Comput* 2015:2420–2427. <https://doi.org/10.1109/CEC.2015.7257185>
- Sadollah A, Eskandar H, Kim JH (2015) Water cycle algorithm for solving constrained multi-objective optimization problems. *Appl Soft Comput* 27:279–298. <https://doi.org/10.1016/j.asoc.2014.10.042>
- Premkumar M, Jangir P, Sowmya R, Alhelou HH, Heidari AA, Chen H (2020) MOSMA: Multi-objective slime mould algorithm based on elitist non-dominated sorting. *IEEE Access* 9:3229–3248
- Jangir P, Trivedi IN (2018) Non-dominated sorting moth flame optimizer: a novel multi-objective optimization algorithm for solving engineering design problems. *Eng Technol Open Access J* 2(1):17–31
- Rizk-Allah RM, Hassanien AE (2022) A hybrid equilibrium algorithm and pattern search technique for wind farm layout optimization problem. *ISA Trans* 132:402
- Rizk-Allah RM, Hassanien AE, Slowik A (2020) Multi-objective orthogonal opposition-based crow search algorithm for large-scale multi-objective optimization. *Neural Comput Appl* 32(17):13715–13746
- El-Sehiemy RA, Rizk-Allah RM, Attia AF (2019) Assessment of hurricane versus sine-cosine optimization algorithms for economic/ecological emissions load dispatch problem. *Int Trans Electr Energy Syst* 29(2):e2716
- Mousa AA, Abd El-Wahed WF, Rizk-Allah RM (2011) A hybrid ant colony optimization approach based local search scheme for multiobjective design optimizations. *Electr Power Syst Res* 81(4):1014–1023
- Laumanns M, Thiele L, Deb K, Zitzler E (2002) Combining convergence and diversity in evolutionary multiobjective optimization. *Evol Comput* 10(3):263–282
- Got A, Moussaoui A, Zouache D (2020) A guided population archive whale optimization algorithm for solving multiobjective optimization problems. *Expert Syst Appl* 141:112972
- Liu J, Wang Y, Wang X, Sui X, Guo S, Liu L (2017) An alpha-dominance expansion based algorithm for many-objective optimization. In: 2017 13th international conference on computational intelligence and security (cis) (pp. 6–10). IEEE
- Yang S, Li M, Liu X, Zheng J (2013) A grid-based evolutionary algorithm for many-objective optimization. *IEEE Trans Evol Comput* 17(5):721–736
- Batista LS, Campelo F, Guimarães FG, Ramírez JA (2011) Pareto cone ϵ -dominance: improving convergence and diversity in multiobjective evolutionary algorithms. In: International conference on evolutionary multi-criterion optimization (pp. 76–90). Springer
- He Z, Yen GG, Zhang J (2013) Fuzzy-based Pareto optimality for manyobjective evolutionary algorithms. *IEEE Trans Evol Comput* 18(2):269–285
- Yuan Y, Xu H, Wang B, Yao X (2015) A new dominance relation-based evolutionary algorithm for many-objective optimization. *IEEE Trans Evol Comput* 20(1):16–37
- Beume N, Naujoks B, Emmerich M (2007) Sms-emoa: multi-objective selection based on dominated hypervolume. *Eur J Oper Res* 181(3):1653–1669
- Brockhoff D, Wagner T, Trautmann H (2015) 2 indicator-based multiobjective search. *Evol Comput* 23(3):369–395
- Sun Y, Yen GG, Yi Z (2018) Igd indicator-based evolutionary algorithm for many-objective optimization problems. *IEEE Trans Evol Comput* 23(2):173–187
- Zhang Q, Li H (2007) Moea/D: a multiobjective evolutionary algorithm based on decomposition. *IEEE Trans Evol Comput* 11(6):712–731
- Deb K, Jain H (2013) An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: solving problems with box constraints. *IEEE Trans Evol Comput* 18(4):577–601
- Li K, Deb K, Zhang Q, Kwong S (2014) An evolutionary many-objective optimization algorithm based on dominance and decomposition. *IEEE Trans Evol Comput* 19(5):694–716
- Li H, Zhang Q (2008) Multiobjective optimization problems with complicated pareto sets, moea/d and nsga-ii. *IEEE Trans Evol Comput* 13(2):284–302
- Yang NC, Mehmood D (2022) Multi-objective bee swarm optimization algorithm with minimum Manhattan distance for passive power filter optimization problems. *Mathematics* 10(1):133
- Bakhshinezhad S, Mohebbi M (2020) Multi-objective optimal design of semi-active fluid viscous dampers for nonlinear structures using NSGA-II. *Structures* 24:678–689
- Liu M, Li Y, Zhao S et al (2022) Multi-objective optimization and test of a tractor drive motor. *World Electr Veh J* 13(2):43
- Marghny MH, Zanaty EA, Dukhan WH et al (2022) A hybrid multi-objective optimization algorithm for software requirement problem. *Alex Eng J* 61(9):6991–7005
- Singh N, Bharti PS (2022) Multi-objective parametric optimization during micro-EDM drilling of Ti-6Al-4V using teaching learning based optimization algorithm. *Mater Today Proc* 62(1):262–269

39. Lian L (2022) Reactive power optimization based on adaptive multi-objective optimization artificial immune algorithm. *Ain Shams Eng J* 13(5):101677
40. Martinez-Rico J, Zulueta E, de Argandona IR et al (2020) Multi-objective optimization of production scheduling using particle swarm optimization algorithm for hybrid renewable power plants with battery energy storage system. *J Mod Power Syst Clean Energy* 9(2):285–294
41. Fox AD, Come DW, Mayorga Adame CG et al (2019) An efficient multi-objective optimization method for use in the design of marine protected area networks. *Front Mar Sci* 6:17
42. Li H, Liu Z, Zhu P (2021) An improved multi-objective optimization algorithm with mixed variables for automobile engine hood lightweight design. *J Mech Sci Technol* 35(5):2073–2082
43. Tian C, Niu T, Wei W (2023) Volatility index prediction based on a hybrid deep learning system with multi-objective optimization and mode decomposition. *Expert Syst Appl* 213:119184
44. Nakashima RN, Junior SO (2023) Multi-objective optimization of biogas systems producing hydrogen and electricity with solid oxide fuel cells. *Int J Hydrog Energy* 48(31):11806–11822
45. Cao C, Liu F, Tan H, Song D, Shu W, Li W, Xie Z (2018) Deep learning and its applications in biomedicine. *Genom Proteom Bioinform* 16(1):17–32
46. Chen D, Li X, Li S (2021) A novel convolutional neural network model based on beetle antennae search optimization algorithm for computerized tomography diagnosis. *IEEE Trans Neural Netw Learn Syst* 34:1418
47. Yang Z, Qiu H, Gao L, Chen L, Liu J (2023) Surrogate-assisted MOEA/D for expensive constrained multi-objective optimization. *Inf Sci* 639:119016
48. Tariq I, AlSattar HA, Zaidan AA, Zaidan BB, Abu Bakar MR, Mohammed RT, Albahri AS (2020) MOGSABAT: a meta-heuristic hybrid algorithm for solving multi-objective optimisation problems. *Neural Comput Appl* 32:3101–3115
49. Wolpert DH (2023) The implications of the no-free-lunch theorems for meta-induction. *J General Philos Sci*. <https://doi.org/10.1007/s10838-022-09609-2>
50. Chopra N, Ansari MM (2022) Golden jackal optimization: a novel nature-inspired optimizer for engineering applications. *Expert Syst Appl* 198:116924
51. Rizk-Allah RM, Hassanien AE, Bhattacharyya S (2018) Chaotic crow search algorithm for fractional optimization problems. *Appl Soft Comput* 71:1161–1175
52. Rizk-Allah RM, Hassanien AE, Song D (2022) Chaos-opposition-enhanced slime mould algorithm for minimizing the cost of energy for the wind turbines on high-altitude sites. *ISA Trans* 121:191–205
53. Chou JS, Truong DN (2020) Multiobjective optimization inspired by behavior of jellyfish for solving structural design problems. *Chaos Solitons Fractals* 135:109738
54. Mirjalili S, Gandomi AH, Mirjalili SZ, Saremi S, Faris H, Mirjalili SM (2017) Salp Swarm algorithm: a bio-inspired optimizer for engineering design problems. *Adv Eng Softw*. <https://doi.org/10.1016/j.advengsoft.2017.07.002>
55. Das AK, Nikum AK, Krishnan SV et al (2020) Multi-objective Bonobo Optimizer (MOBO): an intelligent heuristic for multi-criteria optimization. *Knowl Inf Syst* 62:4407–4444. <https://doi.org/10.1007/s10115-020-01503-x>
56. Wilcoxon F (1992) Individual comparisons by ranking methods. *Breakthroughs in statistics*. Springer, pp 196–202
57. Khodadadi N, Abualigah L, Al-Tashi Q, Mirjalili S (2023) Multi-objective chaos game optimization. *Neural Comput Appl* 35:14973
58. Khodadadi N, Azizi M, Talatahari S, Sareh P (2021) Multi-objective crystal structure algorithm (MOCryStAl): introduction and performance evaluation. *IEEE Access* 9:117795–117812
59. Houssein EH, Mahdy MA, Shebl D, Manzoor A, Sarkar R, Mohamed WM (2022) An efficient slime mould algorithm for solving multi-objective optimization problems. *Expert Syst Appl* 187:115870
60. Tharwat A, Houssein EH, Ahmed MM, Hassanien AE, Gabel T (2018) MOGOA algorithm for constrained and unconstrained multi-objective optimization problems. *Appl Intell* 48(8):2268–2283
61. Nematollahi AF, Rahiminejad A, Vahidi B (2019) A novel multi-objective optimization algorithm based on lightning attachment procedure optimization algorithm. *Appl Soft Comput* 75:404–427
62. Sharifi MR, Akbarifard S, Qaderi K, Madadi MR (2021) A new optimization algorithm to solve multi-objective problems. *Sci Rep* 11(1):20326
63. Derrac J, García S, Molina D, Herrera F (2011) A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms. *Swarm Evol Comput* 1(1):3–18
64. Sundaram A (2022) Multiobjective multi verse optimization algorithm to solve dynamic economic emission dispatch problem with transmission loss prediction by an artificial neural network. *Appl Soft Comput* 124:109021
65. Guo CX, Zhan JP, Wu QH (2012) Dynamic economic emission dispatch based on group search optimizer with multiple producers. *Electr Power Syst Res* 86:8–16. <https://doi.org/10.1016/j.epsr.2011.11.015>

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.