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MaOTLBO: Many-objective teaching-learning-based optimizer for control and monitoring the optimal power flow of modern power systems

Pradeep Jangir[a], Premkumar Manoharan[b*], Sundaram Pandya[c] and Ravichandran Sowmya[d]

[a]Rajasthan Rajya Vidyut Prasaran Nigam Limited, Sikar, Rajasthan 332025, India
[b]Department of Electrical and Electronics Engineering, Dayananda Sagar College of Engineering, Bengaluru, Karnataka 560078, India
[c]Department of Electrical Engineering, Shri. K. J. Polytechnic, Bharuch, Gujarat 392001, India
[d]Department of Electrical and Electronics Engineering, National Institute of Technology, Tiruchirappalli, Tamil Nadu 620015, India

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A B S T R A C T

This paper recommends a new Many-Objective Teaching-Learning-Based Optimizer (MaOTLBO) to handle the Many-Objective Optimal Power Flow (MaO-OPF) problem of modern complex power systems while meeting different operating constraints. A reference point-based mechanism is utilized in the basic version of Teacher Learning-Based Optimizer (TLBO) to formulate the MaOTLBO algorithm and directly applied to DTLZ test benchmark functions with 5, 7, 10-objectives and IEEE-30 bus power system with six different objective functions, namely the minimization of the voltage magnitude deviation, total fuel cost, voltage stability indicator, total emission, active power loss, and reactive power loss. The results obtained from the MaOTLBO optimizer are compared with the well-known standard many-objective algorithms, such as the Multi-Objective Evolutionary Algorithm based on Decomposition with Dynamical Resource Allocation (MOEA/D-DRA) and Non-Dominated Sorting Genetic Algorithm-version-III (NSGA-III) presented in the literature. The results show the ability of the proposed MaOTLBO to solve the MaO-OPF problem in terms of convergence, coverage, and well-Spread Pareto optimal solutions. The experimental outcomes indicate that the suggested MaOTLBO gives improved individual output and compromised solutions than MOEA/D-DRA and NSGA-III algorithms.

1. Introduction

The electricity system's primary function is to provide cost-effective electrical energy to meet dynamic demand. Among the most relevant operating units and extensively discussed topics in the operation of electrical power systems and the current monitoring system is the Optimal Power Flow (OPF) problem, which has attracted many researchers in the last few years. One of the highest operational requirements of the electrical power and energy management system is the OPF problem. The OPF aims to minimize the cost function of the power system by retaining the various inequality and equality constraints. The load flow equations are equality constraints, whereas inequality constraints are independent and dependent variables. Except for slack-bus control, reactive power injection, transformer tap settings, and the generator bus voltages are the control parameters of the actual power generator. Slack bus capacity, line flows, generator reactive power and load bus voltages are the dependent variables. The main goal of the OPF, however, is to reduce the amount of fuel. Nonetheless, voltage unbalances are seen as a promising challenge for energy management activity due to the continued growth in power consumption and unparalleled distribution and load production capacity. Concurrently, ineffective reactive power sources in the electricity

* Corresponding author
E-mail: mprem.me@gmail.com (P. Manoharan)
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network cause significant losses in transmission. In such cases, the voltage profile gap and loss of transmission may need to be considered as part of the objectives of the OPF problem.

Numerous optimizers for addressing OPF problems have been published in the literature. Carpentier was the first researcher to formulate a non-linear problem approach for the OPF in 1962. Since then, many methodologies, along with linear programming, interior-point methods, Lagrangian relaxation, reduced gradient technique, and Newton-Raphson, have been established based on traditional methods (Capitanescu and Wehenkel, 2013; de Carvalho et al., 2008; Monoh et al., 1999; Santos and da Costa, 1995). Nevertheless, these conventional techniques fail to manage nonlinear fitness functions. The authors of (Momoh et al., 1999) reported that non-linear programming could resolve issues involving non-linear objectives and constraints. Even so, this strategy has several disadvantages, such as algorithmic complexity, huge execution time arising in enormous simulations, excessive statistical iterations, and unsafe convergence properties. The OPF is typically a high-dimensional problem of non-smooth and nonlinear optimization. Due to consideration of valve-point loading of thermal generators, these characteristics become much more noticeable and predominant. Therefore, optimization strategies must be established to successfully overcome these disadvantages and difficulties.

The Many-Objective Optimal Power Flow (MaO-OPF) is a many-objectives optimization problem in modern complex power systems with complicated internal linkages between several optimizing cost functions. Conventional programming methods such as Newton and interior-point methods, which are very convenient for solving one objective problem (Azizipanah-Abarghooee et al., 2014; Ghasemi et al., 2014), would face challenges in solving MaO-OPF problems. The MaO-OPF challenge has Pareto optimum solutions rather than a single global optimal solution. Heuristic optimizers have progressed accurately and comprehensively in recent years thanks to their straightforward applications and flexibility. In recent years, numerous heuristic optimizers featuring specific strategies have been presented to address the MaO-OPF problem. The strategies are classified mainly into two sets. As per the preference data of policymakers or other relevant processes, one would be to turn multiple objectives throughout the MaO-OPF problem into just a single objective. The authors (Rosehart et al., 2003; Yalcinoz & Köksoy, 2007) merged multiple objectives with a weight factor into a single function, but this approach is subject to severely on weight range. The authors (X. Liu and Xu, 2010; Salgado & Rangel, 2012; Surender Reddy and Bijwe, 2019) optimized only one desired target and restricted the remaining ones to or below those thresholds, making establishing constraint limits difficult. The concepts like the ε-constraint method (Davoodi et al., 2018; Lashkar Ara et al., 2012) and fuzzy membership (He et al., 2015) were used to transform many-objective optimal power flow issues into single-objective OPF problems. This optimization tool mainly includes several runs to obtain Pareto-optimal Solutions (PSs) for the MaO-OPF problem, which is very time-intensive.

Multi-Objective Evolutionary Algorithms (MOEAs) could be grouped into indicator-based and Pareto-based techniques as per the selection processes. The former MOEAs types are standard Pareto-based methods, such as Non-dominated Sorting Genetic Algorithm-II (NSGA-II) (Deb et al., 2002), Strength Pareto Evolutionary Algorithm-Version II (SPEA-II) (Yuan et al., 2017), NSGA-III (Deb and Jain, 2014; Jain and Deb, 2014), and enhanced NSGA-III (Wang et al., 2018; Zhang et al., 2019). At the same time, indicator-based MOEAs (Zitzler and Künzli, 2004) can manage many-objective optimization issues with techniques such as S-Metric Selection Evolutionary Multiobjective Optimization Algorithm (SMS-EMOA) (Beume et al., 2007), Hypervolume Estimation (HypE) algorithm (Bader and Zitzler, 2011), and Generational Distance-based Many-Objective Evolutionary Algorithm (GD/MaOEA) (Y. Liu et al., 2019). The latter typically only gives greater attention to certain algorithm performance metrics. The Pareto front offered optimal solutions for all objectives with the best solution. Any new problems can be easily integrated into any MOEA/D-DRA (Zhang et al., 2020), such as those focused on Pareto, after converting the problem formulation. All such methods are only tested for benchmark problems and have not been proven successful in handling MaO-OPF. Therefore, the enhancement of algorithm performance is an essential avenue for improvement. Furthermore, when handling many-objective OPF problems, the traditional MOEA algorithm's efficiency depends profoundly on its parameter adjustment. To acquire outcomes closer to the real Pareto Front (PF) and to improve the variety of solutions and the convergence rate, subsequent modification effort of MOEAs is required.

TLBO is a relatively novel algorithm that proves its performance in solving challenging design optimization problems (Rao et al., 2011). It is free from algorithmic-specific controlling parameters and has shown less computational complexity concerning other algorithms. The authors of (Gonzalez-Alvarez et al., 2012) investigated the TLBO for the multi-objective (typically three objectives) Motif Discovery problem and found its dominance with several other MOEAs. However, with many conflicting objectives (typically more than four), multi-objective optimization's complexity grows rapidly, making optimization problems quickly intractable. Such problems are challenging and typically referred to as many-objective optimization problems. Thus, in this investigation, the basic version of the Teacher Learning-Based Optimizer (TLBO) is converted to Many-Objective Teacher Learning-Based Optimizer (MaOTLBO) to handle the OPF problem using a reference point mechanism. The effectiveness of the proposed MaOTLBO is confirmed through standard test functions and finally applied to the MaO-OPF problem. The following are major contributions to the paper.

- Development of a novel many-objective algorithm based on TLBO called MaOTLBO utilizing reference point mechanism.
- Validation of MaOTLBO on seven many-objective numerical problems and standard IEEE-30 bus system with six objectives.

- Comparison analysis is made in terms of performance metrics called Generational Distance (GD), Hyper-Volume (HV), and Spread (SP).

The remainder of this work is structured as follows. The problem formulation of the MaO-OPF problem is discussed in section 2 through the flowchart. The formulation procedure of the proposed MaOTLBO is discussed in Section 3, and its usage to solve the MaO-OPF problem is also discussed. Section 4 discusses the results of the suggested MaOTLBO while handling both benchmark functions and MaO-OPF problems for the IEEE 30-bus system. In Section 5, the concluding remarks are provided.

2. Problem Formulation

The many-objective OPF problem is one of the significant real-world many-objective optimization problems in modern complex power systems. The primary statement of the problem of many-objective analysis is explained as follows.

$$\begin{aligned} &\min \quad [f_1(x) f_2(x) \cdots f_M(x)] \\ &\text{subject to} \\ &\begin{cases} h_j(x) = 0, & j = 1,2,\cdots,H \\ g_i(x) \geqslant 0, & i = 1,2,\cdots,G \end{cases} \end{aligned} \tag{1}$$

where G and H are the sums of inequality and equality limits, and M is the total number of cost functions naturally higher than three. In MaO-OPF, the concern is configured (Zhang et al., 2020) as dividing the overall Reactive Power Loss (RPL), Active Power Loss (APL), Voltage Magnitude Deviation (VMD), Voltage Stability Indicator (VSI), Total Emission (TE), and the Total Fuel Cost (TFC) of an entire grid structure, considering six objective functions often listed in the literature as an instance shown in Fig. 1. In Fig. 1, all six objective functions, along with their equality constraints, such as real and reactive power constraints, and inequality constraints, such as transformer, generator, shunt VAR, and security constraints, are clearly defined.

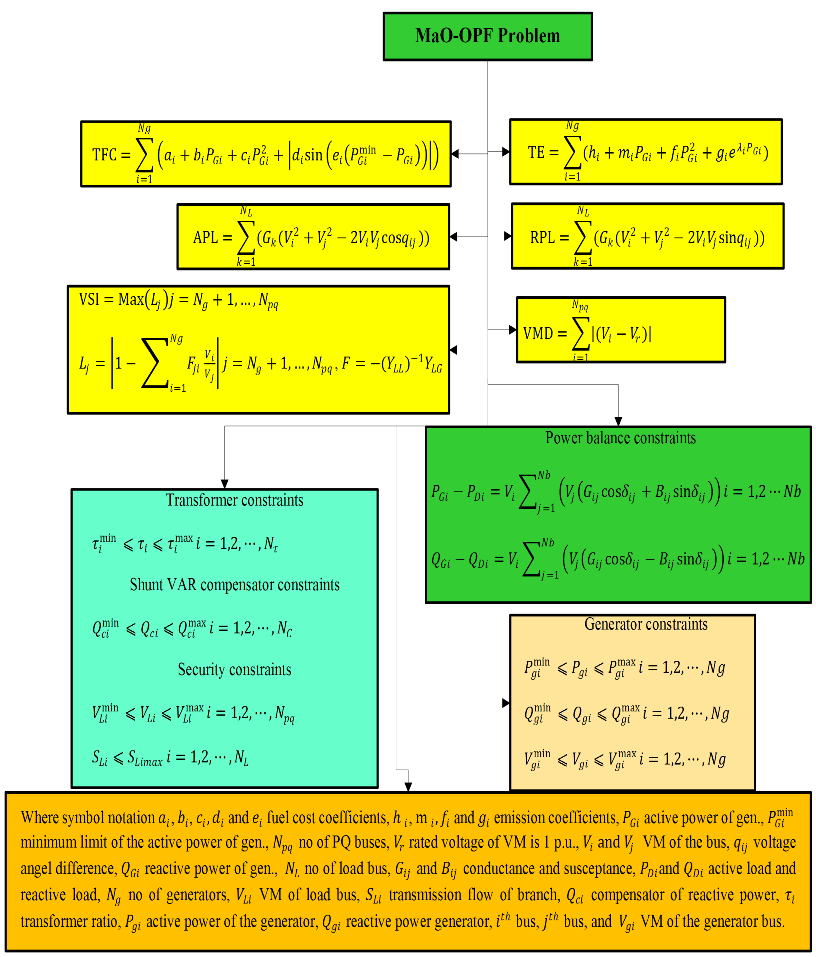


Fig. 1. Flowchart of OPF problem with objective function and constraints

3. Many-Objective Teacher Learning-Based Optimizer (MaOTLBO)

This section of the paper briefly introduces the concepts of the original TLBO algorithm and presents the comprehensive procedure for formulating the proposed MaO-TLBO algorithm

3.1. Teacher Learning-Based Optimizer (TLBO)

The TLBO is a population-based algorithm reported by (Rao et al., 2011, 2012), which works on the influence of the teacher on the outcomes of the learners in a classroom. For the reader's convenience and to avoid the repetition of the same contents, the concept of the TLBO algorithm is presented using pseudocode and the flowchart. The pseudocode and flowchart of the TLBO with its detailed process are explained in Fig. 2 and Fig. 3. It is observed from the pseudocode and flowchart that the teacher phase updates the population in each generation by the teacher phase, and the learner phase of the TLBO is considered as the primary search process. The readers are encouraged to refer to the base paper for more detailed information.

3.2. Implementation of Proposed Algorithm

In this paper, the MaOTLBO algorithm is proposed based on the reference point mechanism introduced by Das and Dennis (Das and Dennis, 1998). The flowchart of the MaOTLBO algorithm with the step-by-step process is explained in Fig. 4. It is observed from the flowchart that the population is updated by the generating reference point (H), Normalization, Association, Niching, and TLBO algorithm in each generation as the key search process (Sandeep and Narsingrao, 2021).

```
START
Define objective function F(X), population size (n), set number of design variables (m), limits on design variables
(LB, UB), and set termination criterion ('FEmax', or 'gmax'); where, F(X) is the objective function and 'X' is the
design vector. The class has 'n' number of learners (i.e. population size, i=1,2,...,n) studying 'm' number of the
subjects (i.e. design variables, j=1,2,...,m).                                          /* Initialization /*
Initialize the randomly generated population within its (LB, UB) and evaluate it.   /* Initialize population /*
FE = 0
for g = 1 to gmax do                                                   /* Initialize the optimization loop /*
        Arrange the population in ascending order of F(Xi) values
        Identify the best solution (Xteacher) of the pop. and calculate mean of each design variables (Xmean).
                for i = 1 to n do                                                    /* The teacher phase /*
                TF = 1 + round [rand(0,1)] /* TF is teaching factor /*
                Xi' =Xi+rand(0,1)*(Xteacher−TF*Xmean)               /* Generate new pop. in teacher phase /*
                FE = FE + 1                                                   /* Count Function evaluation /*
                if F(Xi' )<F(Xi) then                                                   /* Greedy selection/*
                        Xi=Xi'
                end if
                if F(Xk' )<F(Xl) then                                                  /* The learner phase /*
                        Xi' =Xi+rand(0,1)*(Xk−Xl) /*'k' and 'l' are random selected populations, k ≠ l ≠ i /*
                else                                            /* Generate new population in learner phase /*
                        Xi' =Xi+rand(0,1)*(Xl−Xk)
                end if
                FE = FE + 1                                                   /* Count Function evaluation /*
                if F(Xi' )<F(Xi) then                                                  /* Greedy selection /*
                        Xi=Xi'
                end if
                if FE ≥ FEmax then                                                 /* Termination criterion /*
                        break optimization loop
                end if
                end for                                                          /* Population loop ends /*
end for                                                                        /* Optimization loop ends /*
STOP
```

Fig. 2. Pseudocode of basic TLBO algorithm

First, the systematic method of Das and Dennis (Das and Dennis, 1998) is used to obtain reference point (*H*), TLBO algorithm parameters, and the population size (*N*) to generate a random population (P_i) in solution space (*S*). The parent population is denoted as P_t, which a set of generated reference points and Q_t represents the offspring population is generated through the TLBO algorithm shown in Fig. 1 and Fig. 2 with the size N. The grouping is signified as $R_t = P_t \cup Q_t$, consisting of $2N$ members; after that, Normalize (R_t) and Associate each (R_t, H) with one reference point. It categorizes the members in R_t to formulate various non-dominated levels (F_1, F_2, …, F_l, F_n). As per the classification, to start with F_1, it selects the best members from R_t to formulate the next population, P_{t+1}, as follows. Assume that $|F_1 \cup F_2 \cup \ldots F_l \ldots \cup F_{n-1}| < N$ and $|F_1 \cup F_2 \cup \ldots F_l \ldots \cup F_n| \geq N$.

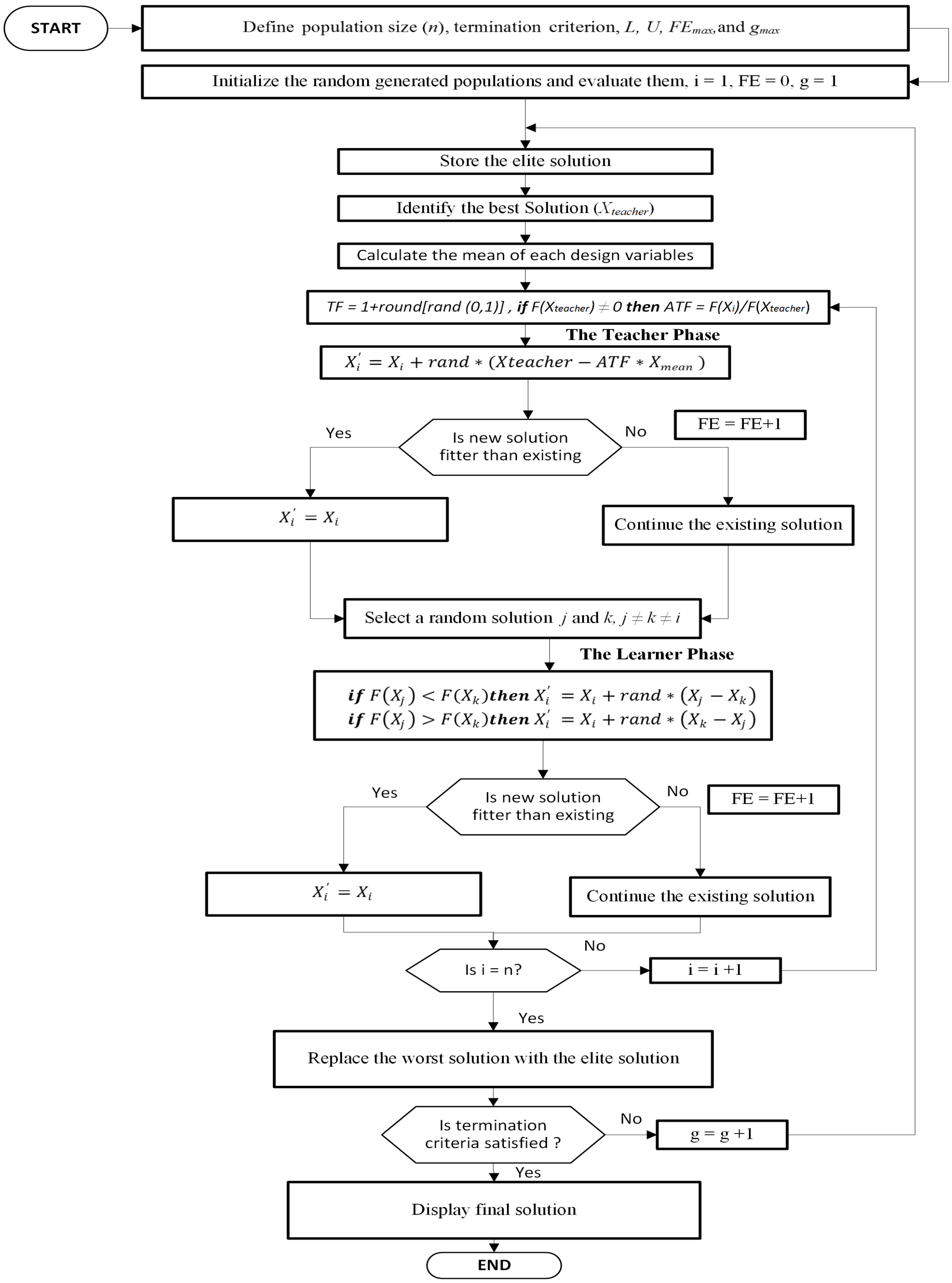


Fig. 3. Flowchart of basic TLBO algorithm

Then, all non-dominated levels in $F_1, F_2, \ldots F_l$.., and F_{n-1} and a few non-dominated levels in F_n are accepted and substituted in P_{t+1}, even other non-dominated levels in F_n, $n>r$, are excluded. If $|F_1 \cup F_2 \cup \ldots F_l \cup F_n| = N$, then $P_{t+1} = F_1 \cup F_2 \cup \ldots F_l \cup F_n$ is designed, and further operations are stopped. If $|F_1 \cup F_2 \cup \ldots \cup F_n| > N$, then $N - |F_1 \cup F_2 \cup \ldots \cup F_{n-1}|$ schedules are chosen in F_r to optimize the solution diversity of the r^{th} front, which are included in P_{t+1} such that $|P_{t+1}| = N$. The following are the stepwise progressions to form the $(t+1)^{th}$ individual from t^{th} population, as shown in Fig. 4, and the flowchart of the MaOTLBO algorithm with the step-by-step process is explained in Fig. 5.

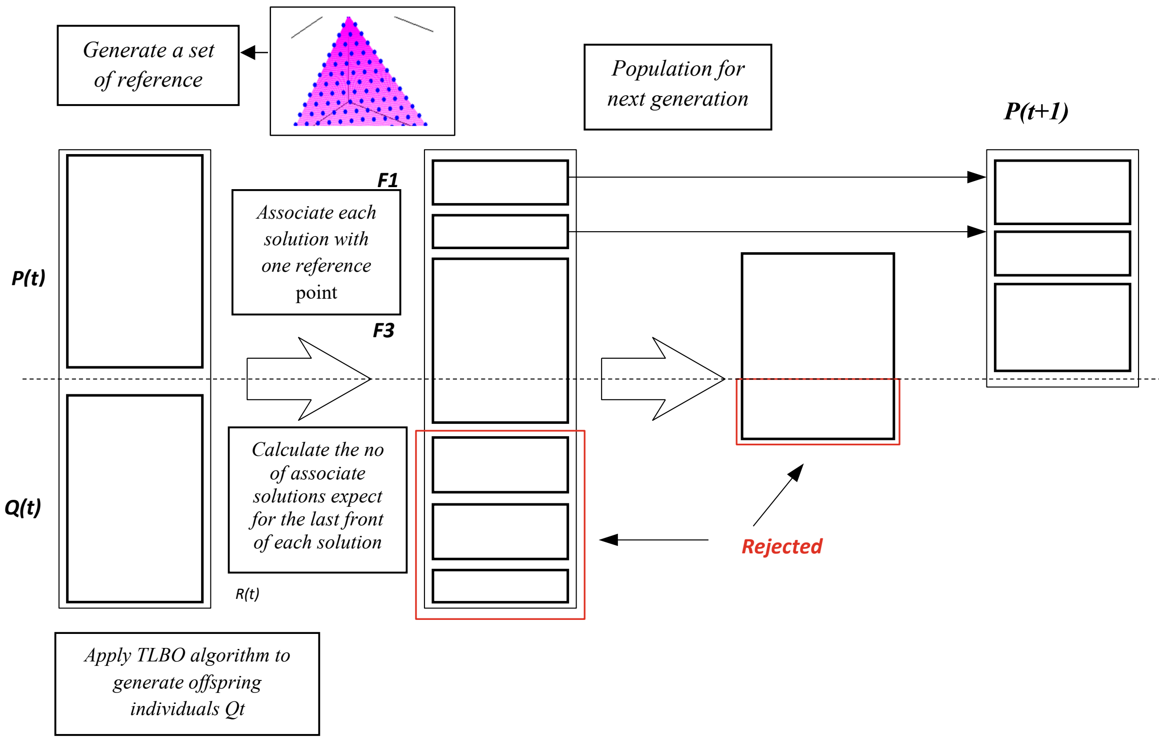


Fig. 4. Detailed process to make the $(t+1)^{th}$ population from t^{th} population.

3.3. *Procedure for Many-objective Optimal Power Flow Problem Solution*

The method for handling the MaO-OPF (Bouchekara et al., 2016; Chaib et al., 2016; Jangir and Jangir, 2018; Tian et al., 2017; Trivedi et al., 2018) stated in this study using MaOTLBO can be discussed as follows: non-dominated stages with a reference-point-based selection procedure MaOTLBO optimizer for the MaO-OPF problem and a flowchart with the step-by-step procedure is shown in Fig. 6.

3.4. *Hybrid Constraints Handling Mechanism*

In general, the many-objective OPF problem is a composite-constrained optimization problem (Zhang et al., 2020). The structure utilizes both the penalty and repair function methods to overcome complex constraints. The objective function of the MaO-OPF issue is therefore expressed as follows.

$$x = \begin{cases} x^{\min}, if\ x < x^{\min} \\ x, if\ x^{\min} \le x \le x^{\max} \\ x^{\max}, if\ x > x^{\max} \end{cases} \tag{2}$$

$$f_k^p = f_k + \left|\alpha \sum_{i=1}^{N_{pq}} fun_{vio}(V_{Li})\right| + \left|\beta \sum_{i=1}^{N_g} fun_{vio}(Q_{gi})\right| + \left|\gamma \sum_{i=1}^{N_L} fun_{vio}(S_{Li})\right| \tag{3}$$

where γ, β, and α are penalty coefficients, fun_{vio} is a constraint violation function with elements x, and f_k is a fitness function of the many-objective optimal power flow problem.

3.5. *Fuzzy Decision based Best Compromise Solution*

In order to find the optimum compromise solution over the compromise characteristics upon acquiring the Pareto-optimal solution, a fuzzy membership technique is used in this research (Zhang et al., 2020). The best outcome from the available Pareto-optimal solutions, which assign a level of fulfillment to each objective, can be found in fuzzy membership functions.

Each problem of j^{th} the solution is stated by a fuzzy membership function μ^i, assumed the inaccurate landscape of the decision-makers. Adopt that μ^{ij} is a monotonous function, and it is represented as follows.

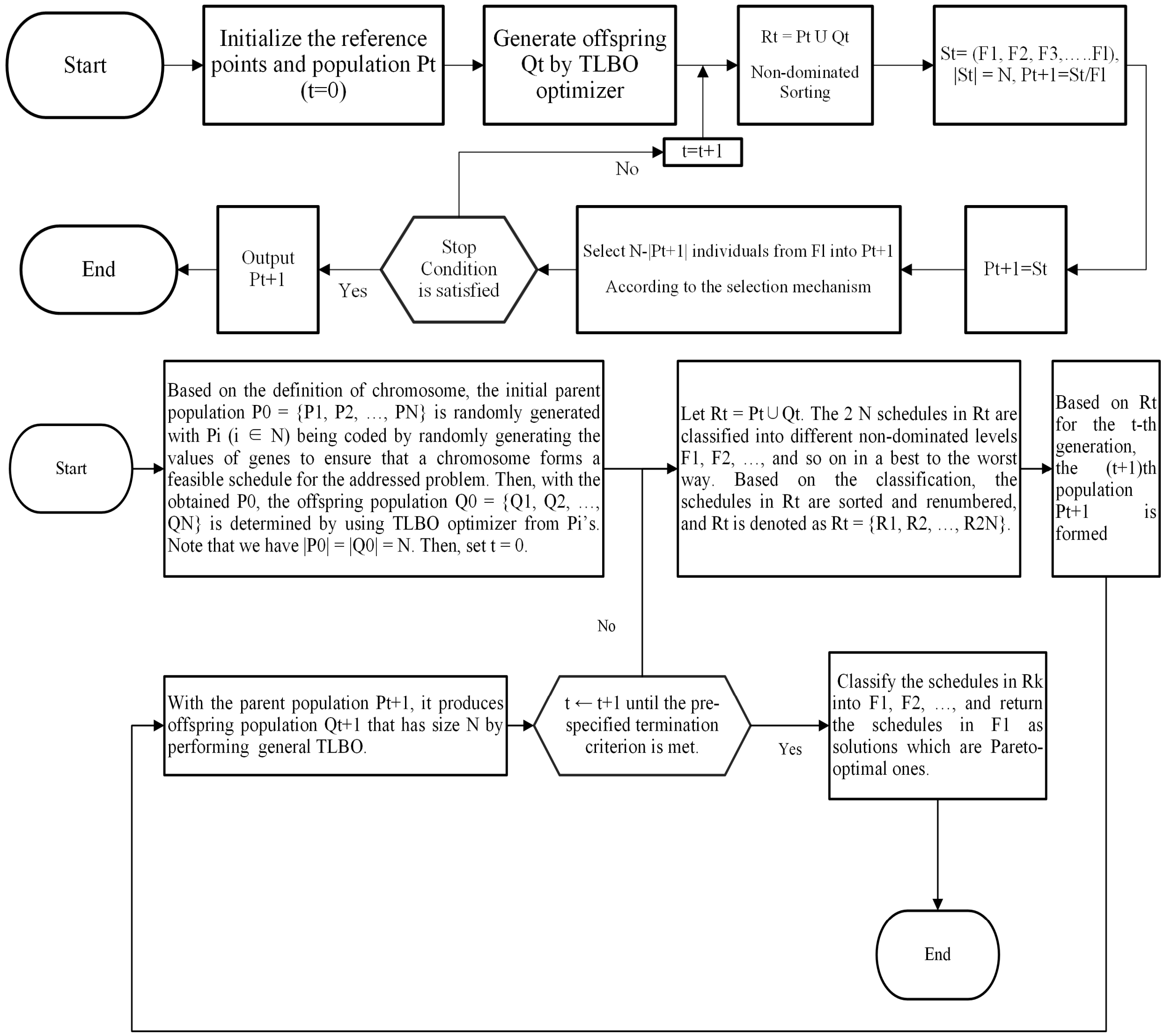


Fig. 5. Flowchart of MaOTLBO algorithm

$$\mu^{ij} = \begin{cases} 1, f^j \leqslant f^j_{\min} \\ \dfrac{f^j_{\max} - f^j}{f^j_{\max} - f^j_{\min}}, f^j_{\min} \leqslant f^j \leqslant f^j_{\max} \\ 0, f^j \geqslant f^j_{\max} \end{cases} \tag{4}$$

At each non-dominated solution, the normalized membership function can be formulated as follows:

$$\mu^i = \frac{\sum_{j=1}^{N_{obj}} \mu^{ij}}{\sum_{i=1}^{M} \sum_{j=1}^{N_{obj}} \mu^{ij}} \tag{5}$$

where *M* denotes non-dominated solution counts, N_{obj} denotes the number of the fitness function, and $f^j_{\max}$ and $f^j_{\min}$ are the maximum and minimum objective function values. The best-compromised solution is the one with a maximum value of μ^i.

4. Simulation Results and Discussions

Unlike NSGA-III (Zhang et al., 2019) and MOEA/D-DRA (Zhang et al., 2020) optimizers, the proposed MaOTLBO optimizer discovers the equally spaced PF and better convergence and coverage and recognizes that each non-inferior Pareto optimal solution meets all the constraints. Firstly, the effectiveness of the MaOTLBO optimizer is confirmed on the DTLZ test suite, and later, it is applied to the OPF problem on the IEEE-30 bus system. The validation is carried out through the MATLAB 2016b software on all test data, and it is performed on a PC with an Intel(R) Core (TM) i3 @ 2.40 GHz with 6 GB RAM.

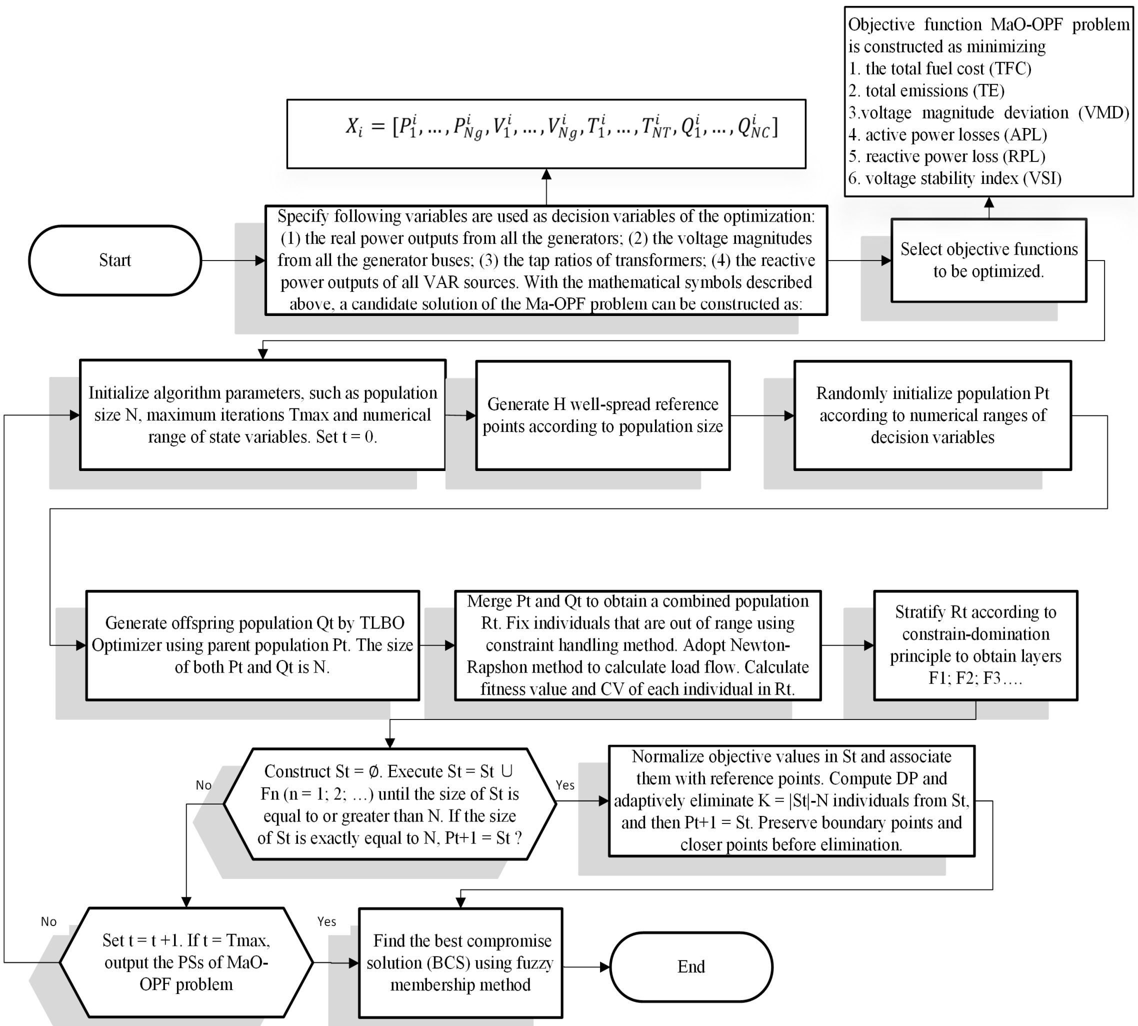


Fig. 6. Flow chart for solving MaO-OPF problem using MaOTLBO algorithm

4.1. Algorithm Parameters and Evaluation Metrics

Across all design examples, including the DTLZ test suite and OPF problem with a defined population size of 100 and 50,000 functional evaluations for all optimizers and the simulation of each optimizer is performed 30 times individually. The probability of crossover rate $Pc = 1$, the distribution index of simulated binary crossover $disC = 20$, mutation rate $proM = 1$, and the distribution index of polynomial mutation $disM = 20$. Diverse performance metrics are utilized to contrast the MaOTLBO algorithm with other techniques, and it is given as follows (Kumar et al., 2022; Mirjalili et al., 2017; Premkumar et al., 2021; Robert et al., 2020).

$$\text{Spacing (SP)} \triangleq \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(\overline{d} - d_i\right)^2} \tag{6}$$

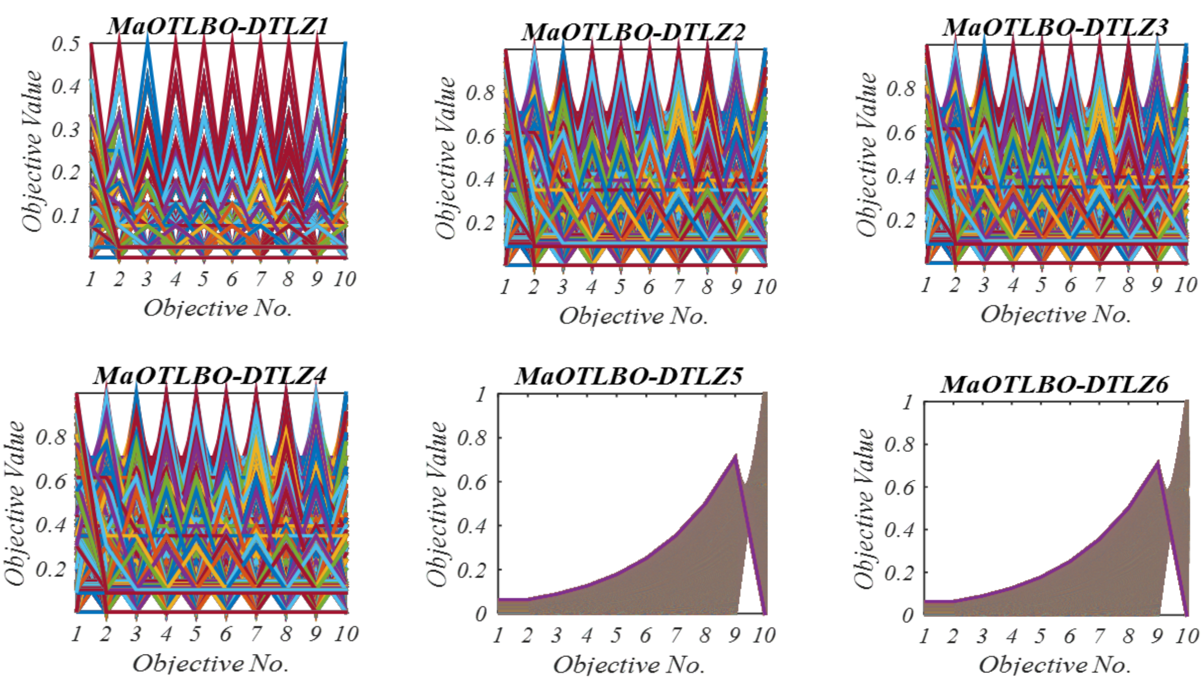
$$\text{Generational Distance (GD)} = \frac{\sqrt{\sum_{i=1}^{no} d_i^2}}{n} \tag{7}$$

$$\text{Hyper Volume(HV)} = \Lambda\left(\bigcup_{s \in PF} \{ s' \mid s \prec s' \prec s^{nadir} \}\right) \tag{8}$$

where n is the number of obtained PS, no is the number of True PS, d_i is the Euclidean distance, $\overline{d}$ is the mean of all d_i, n is the number of obtained PS, and $d_i = \min_j\left(|f_1^i(\vec{x}) - f_1^j(\vec{x})| + |f_2^i(\vec{x}) - f_2^j(\vec{x})\right)$ for all $i,j=1,2,\ldots,n$. To check the effectiveness of algorithms in terms of quicker convergence (Metric GD), uniformity coverage (Metric SP), and combined convergence-coverage called diversity maintenance (Metric HV) have been utilized.

4.2. Results Obtained for DTLZ Test Suite

First, it is important to observe the performance of the proposed MaOTLBO algorithm using the standardized test many-objective optimization problems called DTLZ test suite with 5, 7, and 10 objective benchmark functions (Tian et al., 2017), to validate the efficiency of MaOTLBO in solving the many-objective optimization problems. The proposed MaOTLBO algorithm is compared with the well-known many-objective optimization algorithms called NSGA-III and the MOEA/D-DRA algorithms. All algorithms are used to solve the test functions during all 30 individual runs. The average and the standard deviations (STD) of GD, SP, and HV outcomes for all 9 benchmark functions are listed in Table 1. A bold letter in Table 1 would be the cell that holds the best GD, SP, and HV values for the respective benchmark problems. The optimal Pareto front using the MaOTLBO algorithm on all DTLZ test suites is illustrated in Figure 7. These results also indicate that MaOTLBO can obtain a good distribution of solutions to most problems, and the distribution of MaOTLBO is well uniform in Figure 7, which poses a challenge to maintaining population diversity. It is noted from Table 1 that the proposed MaOTLBO delivers the better mean HV (Diversity Performance) >80%, GD (Convergence Performance) >75%, and SP (Coverage Performance) >68% for the DTLZ problems. Overall, it can be assumed that MaOTLBO is a good optimizer for convergence, coverage, and diversity maintenance for many-objective general-purpose optimization. Fortunately, as defined in the theory of no free lunch, it cannot be assured that an algorithm with a great result would be successful for the other one when addressing a specific issue. Thus, the analysis of applied meta-heuristics is often a problematic issue. The GD metric results are illustrated in Table 1, MaOTLBO found a least 48.15 value in the Friedman rank test value, followed by MOEA/D-DRA and NSGA-III. Therefore, MaOTLBO has an improved convergence quality as per Friedman's Rank Test (FRT) values at a 95% significance level. For the SP measure, according to Table 1, the Friedman rank test value specifies the top rank of 40.75 by MaOTLBO and, thus, at a 95% significance level, displays its improved coverage quality. Moreover, The HV metric results are illustrated in Table 1, from which Friedman assigned the rank of 55.25, 22.22, and 25.92 to the MaOTLBO, NSGA-III, and MOEA/D-DRA techniques, respectively. Hence at FRT 95% significance level, MaOTLBO performs better than others by indicating its optimal solution density in the closeness of the true PF.



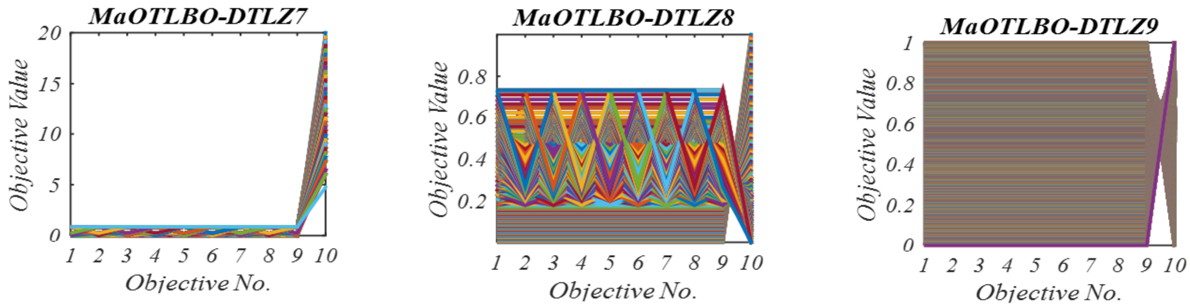


Fig. 7. Obtained Pareto front on DTLZ1-DTLZ9 10-objective problems using MaOTLBO algorithm

As seen in Fig. 7, the Pareto front is obtained by the MaOTLBO algorithm for 10 objective cases. As seen in Fig. 7, the proposed MaOTLBO converges to a large number of optimal solutions with good diversity maintenance for all selected DTLZ test functions.

Table 1
GD, SP, and HV indicators comparison based on DTLZ1-DTLZ9 5, 7, 10-objectives test benchmarks

Problem	M	D	GD			SP			HV		
			MaOTLBO	NSGA-III	MOEA/D-DRA	MaOTLBO	NSGA-III	MOEA/D-DRA	MaOTLBO	NSGA-III	MOEA/D-DRA
DTLZ1	5	9	1.5111e-1 (1.31e-1)	**1.3388e-1 (3.32e-2)**	4.7443e+0 (1.64e+0)	4.0008e-1 (3.39e-1)	**3.5385e-1 (1.20e-1)**	1.2741e+1 (6.32e+0)	**3.0051e-1 (5.21e-1)**	5.7835e-3 (1.00e-2)	1.1391e-1 (1.97e-1)
	7	11	**6.8088e-2 (1.45e-2)**	4.1172e-1 (2.32e-1)	3.6338e+0 (2.59e-1)	**2.4925e-1 (3.87e-2)**	2.5758e+0 (2.23e+0)	1.1082e+1 (2.05e+0)	**1.9612e-1 (1.42e-1)**	0.0000e+0 (0.00e+0)	1.2746e-1 (2.21e-1)
	10	14	4.2904e-1 (6.40e-1)	**1.6354e-1 (1.12e-1)**	3.3145e+0 (1.32e+0)	4.7087e+0 (7.68e+0)	**6.8481e-1 (4.89e-1)**	9.0437e+0 (2.21e+0)	**4.8566e-1 (4.55e-1)**	1.1687e-1 (1.78e-1)	3.5774e-1 (3.50e-1)
DTLZ2	5	14	**5.3118e-3 (2.44e-4)**	5.4006e-3 (1.82e-4)	5.8612e-2 (1.79e-3)	1.5727e-1 (3.11e-3)	**1.5545e-1 (1.63e-3)**	3.3890e-1 (6.79e-2)	**7.6299e-1 (2.34e-3)**	7.5758e-1 (4.47e-3)	3.1394e-1 (5.13e-3)
	7	16	**1.0326e-2 (3.32e-4)**	1.0906e-2 (7.17e-5)	5.8811e-2 (1.19e-2)	**2.0828e-1 (4.35e-3)**	2.3673e-1 (1.77e-2)	4.3960e-1 (1.48e-1)	**8.6369e-1 (1.17e-3)**	8.2585e-1 (6.23e-3)	2.7774e-1 (5.02e-2)
	10	19	**5.9071e-3 (6.60e-4)**	1.4429e-2 (2.96e-3)	5.4717e-2 (1.43e-2)	**1.4863e-1 (1.30e-2)**	3.0585e-1 (8.10e-2)	4.3462e-1 (8.83e-2)	**9.3180e-1 (1.63e-3)**	8.7087e-1 (5.10e-2)	2.5546e-1 (6.14e-2)
DTLZ3	5	14	**3.1821e+0 (1.19e+0)**	6.0672e+0 (1.92e+0)	3.0323e+1 (5.49e+0)	**1.0759e+1 (1.15e+1)**	2.9590e+1 (8.55e+0)	7.4138e+1 (3.19e+1)	**0.0000e+0 (0.00e+0)**	0.0000e+0 (0.00e+0)	0.0000e+0 (0.00e+0)
	7	16	**3.9764e+0 (9.41e-1)**	1.0796e+1 (3.52e+0)	2.4946e+1 (2.03e+0)	**1.7650e+1 (1.24e+1)**	5.0785e+1 (6.95e+0)	5.4759e+1 (1.38e+1)	**0.0000e+0 (0.00e+0)**	0.0000e+0 (0.00e+0)	0.0000e+0 (0.00e+0)
	10	19	**1.0585e+0 (1.50e-1)**	1.9933e+1 (1.63e+0)	2.6011e+1 (4.20e+0)	**2.3129e+0 (3.77e-1)**	8.9048e+1 (1.98e+1)	5.9987e+1 (1.02e+1)	**0.0000e+0 (0.00e+0)**	0.0000e+0 (0.00e+0)	0.0000e+0 (0.00e+0)
DTLZ4	5	14	5.0975e-3 (9.37e-5)	**4.5490e-3 (2.56e-4)**	1.7279e-2 (1.29e-2)	1.8827e-1 (6.02e-2)	1.3545e-1 (1.07e-2)	**9.9694e-2 (1.12e-1)**	**7.4191e-1 (4.46e-2)**	6.2664e-1 (3.46e-2)	3.6363e-1 (2.29e-1)
	7	16	**8.5609e-3 (4.94e-4)**	9.9715e-3 (4.33e-4)	1.4112e-2 (8.89e-3)	2.4235e-1 (3.03e-2)	2.5044e-1 (1.57e-2)	**1.7093e-1 (1.27e-1)**	**8.4798e-1 (1.67e-2)**	8.0933e-1 (6.48e-2)	3.8943e-1 (1.63e-1)
	10	19	1.0506e-2 (2.13e-3)	1.0743e-2 (2.20e-3)	**5.7306e-3 (1.88e-3)**	3.9286e-1 (1.54e-1)	3.2276e-1 (9.32e-2)	**2.1246e-1 (1.01e-1)**	8.8146e-1 (5.52e-2)	**8.8990e-1 (3.92e-2)**	4.8927e-1 (9.05e-2)
DTLZ5	5	14	1.7010e-1 (1.42e-2)	**8.8598e-2 (1.17e-2)**	1.7100e-1 (1.32e-2)	3.4981e-1 (8.44e-2)	1.9153e-1 (3.76e-2)	**1.7758e-1 (6.93e-2)**	9.5994e-2 (5.22e-3)	8.3354e-2 (1.42e-2)	**1.1786e-1 (1.50e-3)**
	7	16	2.5486e-1 (1.37e-1)	**8.4231e-2 (2.54e-3)**	2.7301e-1 (5.47e-2)	6.2404e-1 (3.50e-1)	**2.2926e-1 (2.01e-2)**	2.3771e-1 (5.27e-2)	8.2163e-2 (8.43e-3)	6.1815e-2 (1.10e-2)	**1.0193e-1 (9.42e-4)**
	10	19	**9.0633e-2 (1.56e-1)**	1.1639e-1 (1.58e-2)	2.4292e-1 (6.70e-2)	**2.6057e-1 (3.33e-1)**	3.3703e-1 (1.85e-2)	6.5166e-1 (1.70e-1)	9.2330e-2 (1.41e-3)	5.0154e-2 (1.62e-2)	**9.5555e-2 (4.12e-4)**
DTLZ6	5	14	**3.3917e-1 (4.67e-2)**	4.1005e-1 (1.06e-1)	4.9260e-1 (1.53e-2)	7.0418e-1 (2.53e-1)	7.4076e-1 (3.01e-1)	**2.4292e-1 (1.47e-1)**	6.9392e-2 (5.90e-2)	0.0000e+0 (0.00e+0)	**1.2198e-1 (6.08e-4)**
	7	16	**4.1434e-1 (7.65e-2)**	5.9443e-1 (6.67e-2)	4.9377e-1 (1.56e-2)	**8.4721e-1 (2.10e-1)**	1.3190e+0 (2.47e-1)	1.1396e+0 (9.04e-2)	3.1705e-2 (5.00e-2)	0.0000e+0 (0.00e+0)	**1.0439e-1 (2.34e-4)**
	10	19	5.3701e-1 (1.80e-1)	7.2785e-1 (1.63e-1)	**4.2000e-1 (5.05e-2)**	1.6662e+0 (4.05e-1)	2.1224e+0 (6.79e-1)	**1.0946e+0 (4.81e-1)**	6.0742e-2 (5.26e-2)	0.0000e+0 (0.00e+0)	**9.6820e-2 (1.65e-3)**
DTLZ7	5	24	5.1141e-2 (1.10e-2)	**3.6010e-2 (1.61e-2)**	1.2248e+0 (1.92e-1)	3.9023e-1 (4.14e-2)	**3.3618e-1 (2.20e-2)**	8.3257e-1 (1.28e-1)	1.5666e-1 (1.25e-2)	**1.6723e-1 (2.35e-2)**	2.0843e-4 (8.16e-5)
	7	26	2.3548e-1 (3.86e-2)	**1.9048e-1 (3.42e-2)**	2.0133e+0 (5.68e-1)	**5.1189e-1 (7.02e-2)**	5.3388e-1 (3.94e-2)	1.1729e+0 (1.28e-1)	**6.9526e-2 (2.95e-2)**	3.9663e-2 (2.04e-2)	2.7290e-5 (1.97e-5)
	10	29	**3.1149e-1 (2.66e-1)**	5.1313e-1 (2.53e-1)	2.0238e+0 (4.53e-1)	**6.2972e-1 (1.38e-1)**	6.6240e-1 (8.15e-2)	1.7811e+0 (5.19e-1)	2.7263e-2 (2.53e-2)	**5.6387e-2 (5.05e-2)**	3.4134e-6 (5.91e-6)
DTLZ8	5	50	2.1147e-2 (2.03e-3)	**1.7405e-2 (1.65e-3)**	1.1439e-1 (5.26e-2)	**4.3304e-2 (7.83e-3)**	5.3639e-2 (6.69e-3)	1.3635e-1 (1.35e-2)	3.0711e-1 (1.83e-2)	**3.6172e-1 (2.42e-2)**	2.1567e-1 (3.32e-2)
	7	70	**1.7237e-2 (9.34e-4)**	1.8095e-2 (1.76e-3)	1.0964e-1 (7.66e-3)	**2.5425e-2 (4.78e-3)**	5.8551e-2 (3.24e-3)	3.0704e-1 (1.02e-2)	1.8918e-1 (9.16e-3)	**2.1878e-1 (2.13e-2)**	4.1128e-2 (5.62e-3)
	10	100	**1.8500e-2 (2.11e-3)**	3.0374e-2 (1.98e-3)	1.2185e-1 (6.10e-3)	**2.6361e-2 (6.00e-3)**	1.0392e-1 (1.08e-2)	2.8158e-1 (4.76e-2)	8.0686e-2 (6.04e-3)	**8.8540e-2 (1.56e-2)**	2.1441e-3 (1.27e-3)
DTLZ9	5	50	1.3270e+0 (1.89e-1)	1.0462e+0 (2.60e-2)	**1.0383e+0 (1.20e-2)**	**3.3969e-1 (6.80e-3)**	6.0328e-1 (9.04e-2)	1.5512e+0 (2.46e-1)	**0.0000e+0 (0.00e+0)**	0.0000e+0 (0.00e+0)	0.0000e+0 (0.00e+0)
	7	70	1.4699e+0 (1.80e-1)	1.3161e+0 (2.21e-2)	**1.3053e+0 (6.78e-2)**	**3.5312e-1 (5.52e-2)**	8.2920e-1 (1.34e-1)	2.4392e+0 (1.59e-1)	**0.0000e+0 (0.00e+0)**	0.0000e+0 (0.00e+0)	0.0000e+0 (0.00e+0)
	10	100	2.4971e+0 (1.00e-1)	2.1831e+0 (4.36e-2)	**1.8884e+0 (4.26e-2)**	**3.2983e-1 (1.22e-1)**	1.0605e+0 (5.55e-2)	3.7997e+0 (3.95e-1)	**0.0000e+0 (0.00e+0)**	0.0000e+0 (0.00e+0)	0.0000e+0 (0.00e+0)
Average Friedman Rank test value			**48.15**	70.38	81.50	**40.75**	82.04	77.8	**55.25**	22.22	25.92

4.2.1. Algorithmic Complexity

This section addresses the computational complexity of three optimizers in terms of the average running time of 30 independent trials. Table 2 summarizes the average CPU time to implement the trial. It clearly shows that due to the reference point strategy in the MaOTLBO algorithm, the CPU time of the MOEA/D-DRA and NSGA-III algorithms are higher than the suggested MaOTLBO algorithm, which means that the proposed MaOTLBO algorithm is less complicated than the MOEA/D-DRA and NSGA-III algorithms.

Table 2
CPU/RUN time comparison based on DTLZ1-DTLZ9 5, 7, 10-objectives test benchmarks

Problem	M	D	RT (Minutes)		
			MaOTLBO	**NSGA-III**	**MOEA/D-DRA**
DTLZ1	5	9	**4.7296e-1 (1.50e-2)**	8.7804e-1 (3.13e-1)	2.4932e+0 (1.50e-1)
	7	11	**4.9314e-1 (1.32e-2)**	7.4806e-1 (3.28e-2)	2.4491e+0 (4.40e-2)
	10	14	**5.2553e-1 (2.68e-2)**	1.0907e+0 (2.93e-2)	2.4192e+0 (9.12e-3)
DTLZ2	5	14	**5.1360e-1 (1.04e-2)**	6.9933e-1 (3.52e-2)	2.3663e+0 (6.54e-3)
	7	16	**5.2749e-1 (3.21e-3)**	7.2468e-1 (1.84e-2)	2.4014e+0 (1.96e-2)
	10	19	**5.7693e-1 (1.18e-2)**	9.5408e-1 (1.43e-1)	2.3908e+0 (1.08e-2)
DTLZ3	5	14	**5.0084e-1 (9.87e-3)**	7.0065e-1 (7.82e-3)	2.4338e+0 (1.55e-2)
	7	16	**5.3065e-1 (1.69e-2)**	7.6244e-1 (4.43e-2)	2.4777e+0 (1.14e-2)
	10	19	**5.9451e-1 (4.96e-2)**	1.1463e+0 (1.03e-1)	2.4507e+0 (9.28e-3)
DTLZ4	5	14	**5.1780e-1 (9.19e-3)**	1.0433e+0 (7.85e-2)	2.4292e+0 (4.65e-3)
	7	16	**5.2968e-1 (2.61e-3)**	8.2475e-1 (1.71e-1)	2.4578e+0 (1.50e-2)
	10	19	**5.9166e-1 (2.16e-2)**	1.0718e+0 (2.41e-1)	2.4544e+0 (2.16e-2)
DTLZ5	5	14	**3.9972e-1 (4.88e-3)**	9.8758e-1 (1.95e-2)	2.4719e+0 (1.34e-2)
	7	16	**4.2943e-1 (3.07e-2)**	1.0549e+0 (1.09e-2)	2.5010e+0 (2.00e-2)
	10	19	**4.6936e-1 (2.16e-2)**	1.2188e+0 (2.22e-3)	2.4843e+0 (2.15e-3)
DTLZ6	5	14	**4.7261e-1 (1.35e-2)**	7.1473e-1 (1.05e-2)	2.5047e+0 (1.25e-2)
	7	16	**5.0919e-1 (1.17e-3)**	8.1703e-1 (1.14e-1)	2.5398e+0 (1.05e-2)
	10	19	**5.2672e-1 (1.58e-2)**	1.1744e+0 (4.73e-2)	2.5291e+0 (7.13e-3)
DTLZ7	5	24	**4.6978e-1 (5.43e-2)**	1.0163e+0 (1.70e-2)	2.4048e+0 (3.51e-2)
	7	26	**4.3798e-1 (1.49e-3)**	1.0092e+0 (1.15e-2)	2.4226e+0 (2.95e-3)
	10	29	**5.0459e-1 (2.64e-3)**	1.1973e+0 (2.95e-2)	2.4020e+0 (4.99e-3)
DTLZ8	5	50	**5.4945e-1 (3.01e-2)**	9.4922e-1 (8.15e-3)	3.0080e+0 (1.75e-2)
	7	70	**5.9160e-1 (5.77e-3)**	1.0822e+0 (2.29e-2)	3.2497e+0 (1.03e-2)
	10	100	**7.3873e-1 (1.67e-2)**	1.3636e+0 (1.68e-2)	3.5579e+0 (1.34e-2)
DTLZ9	5	50	**5.6509e-1 (8.67e-3)**	9.6312e-1 (4.28e-2)	2.7862e+0 (1.59e-2)
	7	70	**6.1995e-1 (4.36e-3)**	1.1960e+0 (1.29e-2)	2.9677e+0 (1.20e-2)
	10	100	**7.8097e-1 (1.10e-2)**	1.5602e+0 (1.56e-2)	3.1476e+0 (9.43e-3)

4.3. MaO-OPF Problem on IEEE-30 Bus System

On the IEEE 30-bus network, six objective cases are executed. Reference (Davoodi et al., 2018) offers the framework and information, including the operational range of dependent variables. The techniques, such as MaOTLBO, MOEA/D-DRA, and NSGA-III, optimizes all six objective functions, including TFC, TE, APL, RPL, VMD, and VSI in the IEEE-30 bus system. The normalized PFs obtained by all algorithms are shown in Fig. 8. Table 3 lists the Compromise Solutions (CS) control solutions. Table 3 lists the best values of all objective functions concerning individual objectives. It is not hard to find the CS solution, results of the proposed MaOTLBO optimizer with 914.74 $/h, 0.209 $/h, 3.96 MW, 2.09 MW, 0.250 P.U., and 0.140 P.U. dominates the CS solutions attained by the NSGA-III and MOEA/D-DRA approach. In 30 independent runs, the number of optimal solutions does not violate any device constraints, and it can be visualized in Fig. 8. Fig. 8 also shows the functionality that the optimizers, such as MOEA/D-DRA and NSGA-III, ensure that all solutions achieve the system constraints, whereas the MaOTLBO PF optimizer achieves a higher standard. In addition, in other case results, Table 3 offers comparative findings. This suggests that the MOEA/D-DRA and NSGA-III optimizers are dominated by the CS solution of the proposed MaOTLBO optimizer. Moreover, the MOEA/D-DRA algorithm is not superior to other optimizers seen in Table 3. Subsequently, the proposed MaOTLBO algorithm has 66.6 % great promise on CS and 83.33 % on other solutions. The GD metric results are illustrated in Table 4, MaOTLBO found a least 158.0 value in the Friedman rank test value, followed by MOEA/D-DRA and NSGA-III. Therefore, MaOTLBO has an improved convergence quality as per FRT at a 95% significance level. For the SP measure, according to Table 4, the Friedman rank test value specifies the top rank of 148.0 by MaOTLBO and, therefore, at a 95% significance level, displays its improved coverage quality. Moreover, The HV metric results are illustrated in Table 4, from which Friedman assigned the rank of 345.0, 284.0, and 172.0 to the MaOTLBO, NSGA-III, and MOEA/D-DRA techniques, respectively. Henceforth at FRT 95% significance level, MaOTLBO outperforms others by signifying its best solution density in the closeness of the true PF. Figure 9 provides a thorough illustration of the suggested

MaOTLBO technique's quantitative superiority over competitors in the shape of all examined performance metric convergence graphs.

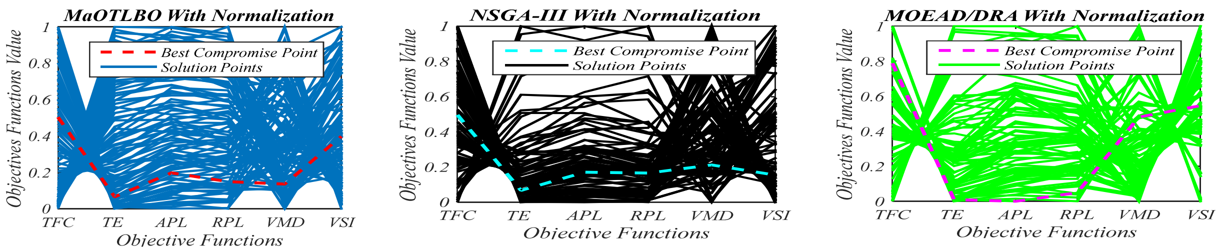


Fig. 8. Obtained Pareto front with normalization on MaO-OPF 6-objective problem using MaOTLBO, NSGA-III, and MOEA/D-DRA algorithms

Table 3
The control variables and objective functions of CS solutions for the IEEE-30 bus test system

Variables	**MaOTLBO**	**NSGA-III**	**MOEAD/DRA**	**Algo.**	**MaOTLBO**	**NSGA-III**	**MOEAD/DRA**	**MaOTLBO**	**NSGA-III**	**MOEAD/DRA**
PG2 (MW)	60.43601	56.65992	60.4193366	**Functions**	**Total Fuel Cost (TFC)**			**Voltage Magnitude Dev. (VMD)**		
PG5 (MW)	47.58379	40.80347	47.2180073	**TFC**	**800.6738**	820.89	817.2053721	841.8438	841.5732	849.6248878
PG8 (MW)	34.97247	35	34.9612129	**TE**	0.359806	0.304158	0.325013495	0.279707	0.284201	0.238684013
PG11 (MW)	29.91455	24.24042	29.7861883	**APL**	8.893769	6.914709	7.757423551	6.884539	6.40032	5.264474635
PG13 (MW)	35.81712	40	35.8171555	**RPL**	18.45555	11.27402	13.58934173	17.38888	9.765217	6.863769447
VG1 (p.u.)	1.041916	1.038859	1.04205224	**VMD**	0.838965	0.567971	0.319408549	**0.17195**	0.178242	0.205976875
VG2 (p.u.)	1.031611	1.030801	1.03132543	**VSI**	0.13906	0.13908	0.140072937	0.150194	0.144502	0.143835511
VG5 (p.u.)	1.007442	1.034171	1.00584232	**Functions**	**Total Emission (TE)**			**Voltage Stability Index (VSI)**		
VG8 (p.u.)	1.013441	1.002086	1.01313574	**TFC**	941.8844	937.6949	945.329345	822.3537	856.7966	856.7965768
VG11 (p.u.)	1.020745	1.054201	1.02058281	**TE**	**0.205166**	0.206933	0.205568737	0.271481	0.228175	0.228175461
VG13 (p.u.)	1.026657	1.027241	1.02597004	**APL**	3.924866	3.707104	3.418388194	6.418627	4.92595	4.92594989
QC10 (p.u.)	4.809894	2.484137	4.80963167	**RPL**	7.17109	0.404287	-0.491170429	12.95678	4.425922	4.425921581
QC12 (p.u.)	3.150379	3.294389	3.47840278	**VMD**	0.387014	0.274065	0.597594437	0.737127	0.803028	0.803027573
QC15 (p.u.)	0.805178	2.712811	1.17569263	**VSI**	0.155239	0.150991	0.139092296	0.138131	**0.13699**	**0.136989903**
QC17 (p.u.)	3.901862	1.090576	3.90725093	**Functions**	**Active Power Loss (APL)**					
QC20 (p.u.)	4.996929	3.183535	4.9558703	**TFC**	964.823	932.9007	946.208433			
QC21 (p.u.)	4.486818	5	4.83495557	**TE**	0.20768	0.208417	0.205906752			
QC23 (p.u.)	2.185575	3.075992	2.1810672	**APL**	**3.178643**	3.477864	3.403469891			
QC24 (p.u.)	4.200848	0.175253	4.20036123	**RPL**	-2.3356	-0.63849	-0.777808832			
QC29 (p.u.)	0.825134	4.718168	0.82502687	**VMD**	0.836485	0.636616	0.548665147			
T11 (p.u.)	1.007435	0.968016	1.00754796	**VSI**	0.140888	0.144887	0.144280934			
T12 (p.u.)	0.98493	0.941558	0.98509194	**Functions**	**Reactive Power Loss (RPL)**					
T15 (p.u.)	0.998801	1.004147	0.99910298	**TFC**	964.823	932.9007	930.1614881			
T36 (p.u.)	0.916084	0.963897	0.91607704	**TE**	0.20768	0.208417	0.206759783			
TFC ($/h)	914.7458	**886.3372**	912.951913	**APL**	3.178643	3.477864	3.515600257			
TE ($/h)	**0.209845**	0.218696	0.21018585	**RPL**	**-2.3356**	-0.63849	-0.97875683			
APL (MW)	**3.962355**	4.940211	3.98946254	**VMD**	0.836485	0.636616	0.711549733			
RPL (MW)	**2.091679**	5.001994	2.17628383	**VSI**	0.140888	0.144887	0.145993613			
VMD (P.U.)	0.250385	**0.246042**	0.24872065							
VSI (P.U.)	**0.140282**	0.145996	0.1403291							

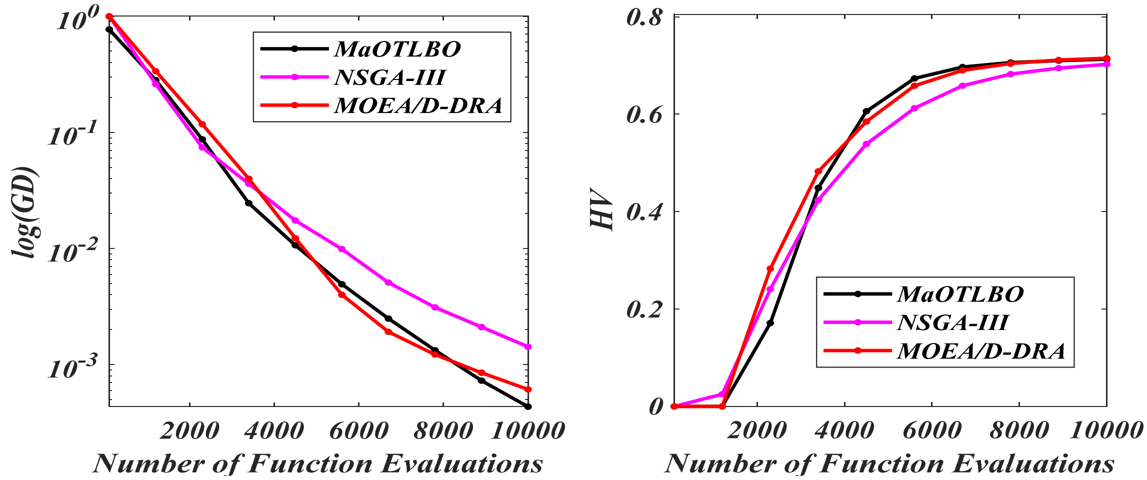


Fig. 9. GD and HV versus the number of function evaluations curve using MaOTLBO, NSGA-III, and MOEA/D-DRA optimizers

Table 4
The GD, SP, Friedman rank test, and HV comparison based on the MaO-OPF problem using MaOTLBO, NSGA-III, and MOEA/D-DRA optimizers

Problem		*D*	NSGA-III	MOEA/D-DRA	MaOTLBO
GD (Convergence) Metric					
MaO-OPF	2	25	6.1147e-4 (5.19e-4)	1.4260e-3 (1.65e-4)	**4.3464e-4 (2.53e-5)**
Friedman Rank test value			158.0	184.0	112.0
SP (Coverage) Metric					
MaO-OPF	2	25	1.1227e-2 (1.99e-3)	6.5756e-3 (4.97e-4)	**6.2299e-3 (6.39e-4)**
Friedman Rank test value			225.3	174.0	148.0
HV (Diversity) Metric					
MaO-OPF	2	25	7.1273e-1 (5.17e-3)	7.0280e-1 (1.69e-3)	**7.1527e-1 (2.87e-4)**
Friedman Rank test value			284.0	172.0	345.0

When used in conjunction with a compatible algorithm, a proper constraint handling method can push the search procedure towards a feasible global solution by using the data in the infeasible solutions. The most popular constraint-handling technique is hybrid, which adds a penalty to the objective function value of an unrealistic solution for breaching the constraints. Despite its straightforwardness and ease of application, the effectiveness of the sum of constraint violations using NSGA-III, MOEA/D-DRA, and MaOTLBO for application cases is shown in Figure 10. According to Figure 10, MaOTLBO obtained the best results in a few function evaluations compared to NSGA-III and MOEA/D-DRA algorithms because MaOTLBO includes historical data from previous iterations in the generation of offspring and parameterless optimizer.

5. Conclusion

This paper has developed a new MaOTLBO algorithm based on the reference point strategy to deal with the DTLZ benchmark with 5, 7, and 10 objectives and MaO-OPF problems with many objectives and strict constraints. All six objective functions are carried out on electric power systems to optimize the TFC, TE, APL, RPL, VMD, and VSI. Various findings from the simulation indicate that the MaOTLBO algorithm is more favorable to finding superior PFs with uniform spread and compromise solutions with zero constraint violation than MOEA/D-DRA and NSGA-III algorithms. In high-dimensional optimization problems, the benefits of the proposed MaOTLBO algorithm are evaluated by considering the DTLZ test suite with 5, 7, and 10 objectives and IEEE-30 test systems. The performance metrics, such as GD (Convergence Metric), SP (Coverage Metric), HV (Diversity Maintenance), and statistical significance Friedman Rank test for 30 independent runs also confirm that for large-scale electrical systems and DTLZ benchmark with 5, 7, 10 objectives, the MaOTLBO optimizer is capable of obtaining optimal PFs with promising diversity, and superior convergence and coverage. Thus, it is noticed that the proposed MaOTLBO algorithm can solve a highly constrained many-objective OPF problem. In the future, the proposed MaOTLBO algorithm can also be directly applied to larger power systems, such as the IEEE-57 bus and IEEE-118 bus systems.

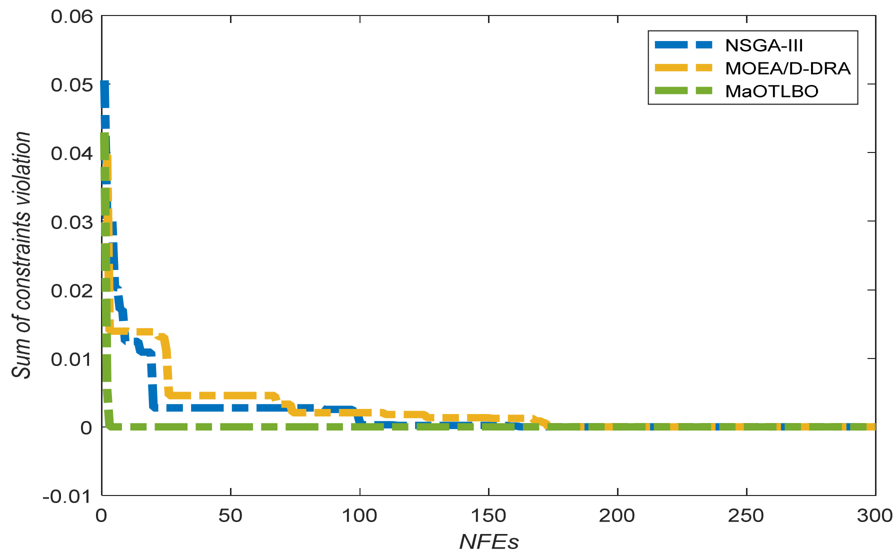


Fig. 10. Sum of constraints violations versus the number of function evaluations curve using MaOTLBO, NSGA-III, and MOEA/D-DRA optimizers

What makes the MaOTLBO optimizer the most effective? Here's a quick rundown of the factors at play. The MaOTLBO includes historical data from previous iterations in the generation of offspring and a parameterless optimizer. Because the individuals chosen in this model are chosen at random or in a predetermined manner rather than the optimal individuals in the population, the individuals chosen may be bad or good. The fast convergence speed reduces the algorithm's convergence speed and prevents it from falling into a local optimum. Furthermore, the algorithm's diversity is increased by selecting the population randomly, resulting in a Higher HV value. The higher the HV value, the better the diversity and convergence are. The algorithms MaOTLBO proposed in this paper are significantly better than the original NSGA-III and MOEA/D-DRA regarding diversity and convergence. Moreover, as the suggested methodology is the first of its kind, its further application in real-world problems is interesting.

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