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RESEARCH

Crisscross Team Game Algorithm for Economic-Emission Power Dispatch Problem with Multiple Fuel Options

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Abstract

This paper proposes a crisscross team game algorithm (CTGA) to solve single and multi-objective optimization problems. CTGA integrates dual crisscross mechanisms orthogonally with operators of the team game algorithm (TGA) to balance exploration and exploitation. The proposed amalgamation enhances the search capabilities and convergence behaviour of TGA. The economic-emission power dispatch (EEPD) problem of thermal units with multiple fuel options and the crucial operational limitations of an electric power system is successfully solved using the proposed algorithm. The objectives, operating cost, and emission of pollutants are combined by the non-interactive technique exploiting the price penalty method. On the basis of the replacement technique and proportional power sharing of the unmet load demand, feasible solutions are discovered heuristically. The applicability of the proposed algorithm is verified on unconstrained (viz. unimodal and multimodal) standard benchmark optimization problems, along with five electric power test problems having real-world constraints, including restricted operation zones and ramp-rate limits. CTGA's superior performance over TGA in experimental evaluations and graphical representations explicitly demonstrates the necessity of the proposed amalgamation. The Wilcoxon signed-rank test and Friedman test illustrate CTGA's eminence over other competing algorithms. The suggested algorithm has fewer sensitive parameters to tune.

Keywords Meta-heuristic search · Team game algorithm · Crisscross operations · Multiple fuel options · Price penalty factor · Multi-objective power load dispatch

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Nomenclature

a_{ij}, b_{ij}, c_{ij}, d_{ij}, and e_{ij}	Cost coefficients of *i*th thermal generator with *j*th fuel option having units (\$/MW^{2}h), (\$/MWh), (\$/h), (\$/h), and (rad/MW), respectively
A_f	Multiplier in the range of (0, 1)
B_{oo}, B_{io}, and B_{ij}	Loss coefficients having units (MW), unit less and (MW^{-1}), respectively
DR_i and UR_i	Down- and up-rate ramp limits of the *i*th generator, (MW/h)
$F_j(X_{ji})$ and $F_j^{new}(X_{ji}^{new})$	Old and new performances of players of ball owner team, respectively
F^{Cap}, F_A^{Cap}, and F_B^{Cap}	Performance of best player in ball owner team, team A and team B, respectively
g_1 and g_2	Iteration counters
G_1^{max} and G_2^{max}	Maximum iteration values for g_1 and g_2 countrs, respectively
h_f	Price penalty factor (PPF) having unit (\$/lb)
L_n	Pre-set count
N_b	Number of buses in power system network
N_G and N_f	Total number of generators and total number of fuel options
N_{FE}	Number of function evaluations
N_P	Population of players/members of a team
Nzi	Number of prohibited zones for *i*th generator
P_D and P_L	Load demand (MW) and power loss in transmission lines (MW)
P_{di}	Load demand at *i*th bus
X_{dk}^{opp}	Randomly selected *k*th ($k \in \left[1, N_G\right]$) attribute of *d*th ($d \in \left[1, N_P\right]$) player of opponent team
P_i and P_i^O	Present and previous real power generated by *i*th generator, respectively in (MW)
P_{Ii} and Q_{Ii}	Injected active and reactive power at *i*th bus in (MW) and (MVar), respectively
X_i^{Cap}, A_i^{Cap}, and B_i^{Cap}	*i*th Attribute of best player of ball owner team, team A and team B, respectively
P_i^{min} and P_i^{max}	Lower and upper limits for the power generation by *i*th generator in (MW)
P_{ij}^{min} and P_{ij}^{max}	Lower and upper limits for *i*th generator and *j*th fuel option in MW
$P_{i,k}^L$ and $P_{i,k}^U$	Lower and upper limit of *k*th POZ for *i*th generator, in (MW)
X_{ji}, A_{ji}, and B_{ji}	*i*th Attribute of the *j*th player of ball owner team, team A and team B, respectively
X_{ji}^{new}	Updated value of X_{ji} (MW)
r	Exterior penalty factor with a large value

R_{ij}	Real part of element of Z-bus of power system network
TR_j	Pre-set limit counter of each player
$\lvert V_i \rvert$ and δ_i	Voltage magnitude (pu) and angle (rad) at *i*th bus, respectively
y_{ji}	Uniform random number between $(-1, +1)$
z, z_i z_{ji}	Uniform random number between (0, 1)
α_{ij}, β_{ij}, γ_{ij}, η_{ij}, and δ_{ij}	Pollutant's emission coefficients of *i*th thermal generator with *j*th fuel option having units (lb/MW^{2}h), (lb/MWh), (lb/h), (lb/h), and (MW^{-1}), respectively

1 Introduction

In electric power system operation, from the generation and transmission fields, economic load dispatch (ELD) of electric power generated from thermal units is one of the most important optimization problems. The ELD problem is to schedule the committed thermal generating units with a minimum operating cost in a constrained environment [1]. As a result of increasing concern over environmental protection, in 1990, amendments to the Clean Air Act were passed, necessitating power utilities to reduce the emission of gaseous pollutants like SO_2 and NOx [2], thereby converting the ELD problem into a multi-objective power load dispatch (MoPLD) problem. A small reduction in the operating cost or pollutant emission of a thermal generator has a significant effect on the overall operating cost incurred and environment for the total power generation over a long period of time.

The classic optimization techniques such as lambda iteration [3], gradient search [4], Lagrange relaxation [5], and dynamic programming [6] have been used to solve ELD problems, but the objective function should be linear or quadratic and differentiable. While considering various aspects of power systems like the valve point loading (VPL) effect, avoiding prohibited operating zones (POZ), ramp-rate limits, and multi-fuel options (MFO), the ELD problem becomes non-convex and discontinuous, due to which these classical techniques are unable to search for the global optimal solution. Moreover, the emission of pollutants and generators' operating cost functions are of a conflicting nature, which makes the procedure cumbersome with classical techniques. To overcome the limitations of these techniques, metaheuristic methods inspired by nature, human behaviour, swarm intelligence, physics, chemistry and biological behaviour, etc. have been proven to be the best alternatives to handle non-convex and non-differentiable types of optimization problems. Some of the popular methods that have been used to solve the ELD problem are the genetic algorithm (GA) [7], the differential evolution (DE) [8], the particle swarm optimization (PSO) [9], island based harmony search algorithm (*i*HS) [10], etc. These methods have a fast response time when searching for a global solution in a large search space, but they fail to achieve solution accuracy. Hence, various improved variants of these methods by blending them with one or more methods or local search methods were used to solve ELD and MoPLD problems.

In the literature, some of the hybrid methods used to solve ELD and MoPLD problems are hybrids of GA and PSO [11], fast non-dominated time-varying acceleration coefficient-particle swarm optimization combined with an exchange market algorithm [12], hybrid differential evolution with biogeography-based optimization [13], etc. Abdi et al. [14] performed a comparison of six metaheuristics, namely GA, PSO, the teaching learning-based optimization (TLBO) algorithm [15], the invasive weed optimization (IWO) algorithm [16], the artificial bee colony (ABC) algorithm [17], and the shuffled frog-leaping algorithm (SFLA) [18], for solving the ELD in several case studies under different conditions. GA performed best in terms of solution quality and computation time, followed by PSO and TLBO. Singh et al. [19] introduced the synergic predator–prey optimization (SPPO) technique to determine the economic dispatch of thermal power with the VPL effect and MFO. The initial position of the prey particle is based on the comparison of the solution with its opposite solution, and synergy in exploration and exploitation of search is balanced by the predator's effect. Nourianfar et al. [20] combined two metaheuristic techniques to solve the MoPLD problem: adaptive inertia-weighted particle swarm optimization that improved exploitation and an exchange market algorithm that explores solutions globally. A multiple constraint ranking technique was used for constraint handling. Kaur and Narang [21] proposed the space transformational invasive weed optimization (ST-IWO) algorithm to solve multi-objective optimal power flow problem in which conflicting objectives were dealt with non-interactive approach. The proposed model is applied to the ten-unit system, and the problem is solved by the random drift particle swarm optimization method. Dehnavi et al. [22] considered emissions of pollutants as well and proposed an optimal integrated model for a dynamic economic emission dispatch problem with an emergency demand response programme. To minimize fuel costs and emissions and to determine the best incentive, an imperialist competitive algorithm was used.

Some of the recently implemented algorithms in literature to solve ELD and MoPLD problems are tabulated in Table 1, which depicts the consideration of various aspects of power systems, viz. the valve point loading (VPL) effect, prohibited operating zones (POZ), ramp-rate limits (RRL), multiple fuel options (MFO), and transmission line losses. The documented algorithms in Table 1 suffer from one or more problems like stuckness in the local minima region, premature or untimely convergence, a lack of balance between exploration and exploitation strategies, adjustment of parameters, and sluggish convergence behaviour while solving highly complex non-linear engineering optimization problems.

In spite of the remarkable research work done by researchers on the optimization techniques, metaheuristic search techniques have one or more limitations, like being sensitive to many parameters, encoding schemes, use of potential operators, switching from exploration to exploitation to maintain synergy between them, start of the algorithm with a good initial population, and stagnation tendency to local solution. Exploration and exploitation conflict while the search is being conducted. Generally speaking, excessive exploitation causes premature convergence, while excessive exploration induces random search. Preserving a good balance between exploration and exploitation is essential to the effectiveness of population-based algorithms. Numerous studies have shown that efficient control over this balance can increase the algorithm's effectiveness [41]. In the hunt for improving a particular parameter of an optimization problem, sometimes another parameter is compromised.

Table 1 Algorithms to solve ELD and MoPLD problems

Problem	Technique/algorithm	Year	Aspects of power system					Ref
			VPL	POZ	RR	MFO	P_L	
Economic load dispatch (ELD)	Memetic sine cosine algorithm (MSCA)	2022	✓	✓	✓	✓	✓	[23]
	Gradient-based optimizer (GBO)	2021	✓	✓	✓	✓	✓	[24]
	Modified krill herd algorithm (MKHA)	2021	✓	✓	✓	×	✓	[25]
	Improved directional bat algorithm (IDBA)	2020	✓	✓	✓	×	✓	[26]
	Cauchy-Gaussian quantum-behaved bat algorithm (CGQBA)	2020	✓	✓	✓	✓	✓	[27]
	Full mixed-integer linear programming (FMILP)	2020	✓	✓	✓	×	✓	[28]
	Improved Jaya algorithm (IJA)	2020	✓	✓	✓	✓	✓	[29]
	Conglomerated modified ion-motion and crisscross search optimizer (C-MIMO-CSO)	2019	✓	✓	✓	✓	✓	[30]
	Ameliorated grey wolf optimization (AGWO)	2019	✓	✓	✓	×	✓	[31]
Multi-objective power load dispatch (MoPLD)	Search and Rescue optimization algorithm (SAR)	2022	×	×	×	×	×	[32]
	Multi-objective squirrel search algorithm (MOSSA)	2021	✓	×	×	×	×	[33]
	Constrained multi-objective equilibrium optimizer algorithm (EOA)	2021	✓	×	×	×	✓	[34]
	Emended salp swarm algorithm (ESSA)	2020	✓	✓	✓	×	✓	[35]
	Modified teacher learning-based optimization (MTLBO)	2020	✓	×	×	×	✓	[36]
	Efficient fitness-based differential evolution (EFDE)	2019	✓	✓	✓	×	✓	[37]
	Chaotic improved harmony search algorithm (CIHSA)	2019	✓	×	✓	×	✓	[38]
	Modified genetic algorithm and an improved version of particle swarm optimization (MGAIPSO)	2019	✓	✓	✓	✓	✓	[39]
	Adaptive predator–prey optimization (APPO)	2018	✓	✓	✓	✓	✓	[40]

The symbol (✓) indicates considered aspects of power system

The symbol (×) indicates not considered aspects of power system

Hence, the scope of improvement is envisaged in the existing metaheuristic search techniques while implementing to solve complex non-linear and highly constrained engineering optimization problems.

Team game algorithms (TGA) [42] are a meta-heuristic optimization technique that is based on team game tactics in a group sports with a ball such as basketball, football, or volleyball. In a team game, players' coordination is an important factor, as the passing of the ball is required to proceed. The players may commit mistakes, and the other team can take advantage of their mistake. Some players may get exhausted or injured during a game, so substitution with a fresh player is required. It may boost the performance of the team. All such processes are simulated with operators in TGA to find the best global solution. In TGA, the operations performed by each player (agent) are as follows: passing of a ball, making mistakes, and substitution of a player. Passing a ball is a logical operation, and making a mistake is a heuristic operation. A substitution operator replaces a tired player on any team with another player even if the ball-owning player goes out of the field. By passing the ball, it is presumed that the game has been won by the team, and the best player is introduced, even if the player may belong to the losing team of that match. Shams et al. [43] implemented an improved team game optimization algorithm to track maximum power point tracking (MPPT) so that the photovoltaic (PV) system operates optimally. In the metaheuristic, the convergence speed is increased and only one tuning parameter is required. Maafi et al. [44] presented an improved version of the team game algorithm for benefiting the advantages of new effective operators, non-dominated Pareto solution scheme, sigma method, and dynamic elimination technique. The major issue in team game algorithms is that only one operator is in action at a time because of passing, mistakes, and substitution operators, which curbs the exploration capability.

In light of the above-mentioned limitations, a crisscross team game algorithm (CTGA) which integrates a dual crisscross mechanism to enhance the intra-team capabilities by collaborative learning and individual skill updation of each player as per the need for competition is proposed in this paper to solve the economic-emission power dispatch problem with multiple fuel options and the valve point loading effect. The *B*-coefficients are evaluated by performing load flow using the Gauss–Seidel method. The objectives of the optimization problem, namely operating cost and emission of pollutants, are unified to formulate the EEPD problem using a price penalty factor. In team games, players continuously learn from and get motivation from each other and exchange positions at every turn, which may result in improved team performance. So, to improve the exploration capability, the dual crisscross mechanism has been integrated with TGA in the proposed CTGA. An arithmetic crossover between two or more different players that affects all dimensions is referred to as collaborative learning. Collaborative learning enables team players to learn from the best player and other players on the team. The individual skills of each player are improved using a two-dimensional crossover approach. Individual improvement in skills aids certain players' stagnant dimensions in avoiding the early convergence of the dimensions. The integration of dual crisscross operators with TGA improves the solution accuracy as well as the convergence rate. The application of CTGA to solve EEPD problems yields effective results and has a mere need for parameter tuning. The proposed amalgamation elevates the algorithm to the state-of-the-art, embracing the qualities required in a perfect heuristic algorithm, such as a balance of exploitation and exploration capabilities, fast convergence behaviour, and fewer parameters to tune.

To validate the applicability of CTGA, a simulation study is performed on unconstrained and constrained standard benchmark optimization problems as well as six standard power system test problems in small, medium, and large test system categories with single and multiple objectives. The paper is categorized into seven sections. Section 2 presents the EEPD problem with MFO and VPL effects, incorporating various constraints. In Section 3, the constraint-handling techniques used for obtaining the optimized results of the problem are discussed. The proposed CTGA technique to solve the EEPD problem is explained in Section 4. To justify the results obtained, a comparative study has been performed and is discussed in Section 5. In Section 6, the proposed algorithm is analyzed statistically. Section 7 concludes the paper, followed by references.

2 Economic-Emission Power Dispatch Problem

The classical economic load dispatch problem is defined as the minimization of the total operating cost of the committed thermal units of a power system while meeting the total load demand plus transmission losses within the limits of the committed thermal generating units. Despite paying attention to real-time complexity, it should also avoid the prohibited operation zone and satisfy the ramp-rate limits while considering the valve-point loading effects on the cost characteristics. To energize the thermal generating units, there are multi-fuel options like natural gas, coal, and oil, from which the most economical option is to be selected for a given interval of operation. The selection of fuel is based on the minimum and maximum power limits of the generator. As described in Fig. 1, fuel type 1 is selected if the power P_i of i^{th} generator is between P_{i1}^{min} and P_{i1}^{max}.

The maximum power limit P_{i1}^{max} of fuel 1. This becomes the minimum power limit P_{i2}^{min} of fuel 2 and so on. The inclusion of multiple fuel options and valve point loading effects makes the problem multi-modal and discontinuous in nature. Beyond this, the minimization of pollutant emissions concludes the problem as a multi-objective optimization problem in which operating cost and pollutant

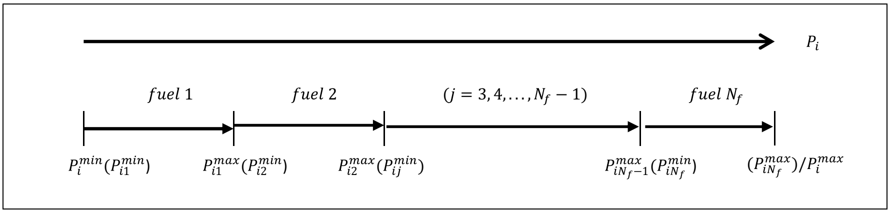


Fig. 1 Selection of fuel out of multi-fuel options

emission objectives are in conflict. The valve point loading effect is introduced by the sine term. The objectives of the multi-objective load dispatch problem are stated below.

Operating Cost The operating cost is minimized, and the operating cost is a function of active power generation considering the fuel option based on operating limits.

$$\text{Minimize } F_1(P) = \sum_{i=1}^{N_G} F_{1i}\left(P_i\right)(\$/h) \tag{1}$$

where

$$F_{1i}\left(P_i\right) = \left(c_{ij} + b_{ij}P_i + a_{ij}P_i^2 + \left|e_{ij}sin\left(f_{ij}\left(P_{ij}^{min} - P_i\right)\right)\right|\right) ;P_{ij}^{min} \le P_i \le P_{ij}^{max} \left(j = 1, 2, ..., N_f\right)$$

and $P = [P_1, P_2, ..., P_{N_g}]^T$

Pollutant's Emission The pollutant's emission is minimized, and the pollutant's emission is a function of active power generation considering the fuel option based on operating active power limits.

$$\text{Minimize } F_2(P) = \sum_{i=1}^{N_G} F_{2i}\left(P_i\right)(Kg/h) \tag{2}$$

where

$$F_{2i}\left(P_i\right) = \left(\gamma_{ij} + \beta_{ij}P_i + \alpha_{ij}P_i^2\right) + \eta_{ij}e^{\delta_{ij}P_i};P_{ij}^{min} \le P_i \le P_{ij}^{max} \quad \left(j = 1, 2, \dots, N_f - 1\right)$$

The operating cost and emission of pollutants are minimized simultaneously, which are in conflict and subject to operational and physical constraints. The equality and inequality constraints are stated below.

Power Balance Equation The total active power generation by the committed generators must meet the power demand and transmission power losses [1]. This is known as the equality constraint and is given below.

$$\sum_{i=1}^{N_G} P_i = P_D + P_L \tag{3}$$

Transmission line losses, P_L are represented by Kron's loss formula expression as a quadratic function and B-coefficients are calculated by performing a.c. load flow method [1]:

$$P_L = \sum_{i=1}^{N_G} \sum_{j=1}^{N_G} P_i B_{ij} P_j + \sum_{i=1}^{N_G} B_{io} P_i + B_{oo} \quad (MW) \tag{4}$$

where

$$B_{ij} = \frac{R_{ij}}{\left|V_i\right|\left|V_j\right|}\frac{\cos\left(\theta_i - \theta_j\right)}{\cos\varphi_i \cos\varphi_j}\left(i = 1,2,\dots,N_b, j = 1,2,\dots,N_b\right) \tag{5}$$

$$B_{io} = -\sum_{i=1}^{N_b}\left(B_{ij} + B_{ji}\right)P_{dj} \tag{6}$$

$$B_{oo} = \sum_{i=1}^{N_b}\sum_{j=1}^{N_b} P_{di}B_{ij}P_{dj} \tag{7}$$

$$\theta_i = \delta_i - \varphi_i \ \left(i = 1,2,\dots,N_b\right) \text{ and } \varphi_i = \tan^{-1}\frac{Q_{Ii}}{P_{Ii}}$$

$$P_{Ii} = P_i - P_{di}\left(i = 1,2,\dots,N_b\right)$$

Generation Limits The active power generation of committed thermal generators is restrained to their minimum and maximum generating limits.

$$P_i^{min} \le P_i \le P_i^{max} \quad (\mathrm{i} = 1,2,...,N_G) \tag{8}$$

Prohibited Operating Zone (POZ) In order to avoid the operation of a generator in some specific regions, which may be due to vibrations in shaft bearings, between the minimum and maximum limits of a generator, POZ is imposed as follows:

$$\begin{cases} P_i^{min} \le \ P_i \le \ P_{i,1}^L & ;(i = 1,2,\dots,N_G) \\ P_{i,k-1}^U \le P_i \le P_{i,k}^L & ;\left(k = 1,2,\dots,N_{zk}; i = 1,2,\dots,N_G\right) \\ P_{i,Nzi}^U \le P_i \le P_i^{max} & ;(i = 1,2,\dots,N_G) \end{cases} \tag{9}$$

Ramp-Rate Limit (RRL) To limit the sudden increase or decrease of the active power generation by a generator, RRLs are imposed.

$$max\left(P_i^{min}, P_i^O - DR_i\right) \le P_i \le min\left(P_i^{max}, P_i^O + UR_i\right)\left(i = 1,2,\dots,N_G\right) \tag{10}$$

Economic-Emission Dispatch Problem The stated objectives of the optimization problem in Eqs. (1) and (2) are non-commensurable. To resolve the non-commensurability of the objectives, they are unified with the price penalty factor (PPF) [45] to define a scalar-constrained multivariable optimization problem. The PPF is stated as the ratio of the fuel cost to the emissions of pollutants from the thermal generator, while objectives are evaluated at either minimum or maximum power generation limits. The unified objective function to be minimized is as follows:

$$Minimize\ F_T(P) = F_1(P) + h_f F_2(P) \tag{11}$$

Subject to the constraints discussed in Eqs. (3), (8), (9), and (10).

To get the feasible solution of the optimization problem given in Eq. (11), the variable P is searched within their limits using the proposed crisscross team game algorithm.

2.1 Computation of Price Penalty Factor

The optimization problem has two objectives. Here, both objectives are quadratic polynomials, due to which both objectives can be clubbed by a penalty called the price penalty factor. The price penalty factor, "h_f", is defined as the minimum average of the ratio of operating costs to the pollutants emitted by thermal units evaluated at their power outputs. More precisely, the price penalty factor is stated as the ratio of the fuel cost to the emissions of pollutants from the thermal generators, while objectives are evaluated at either their minimum (P_{ij}^{min}) or maximum (P_{ij}^{max}) power generation for all kinds of fuels. The price penalty factor, "h_{f1}", is defined as the ratio of the total operating cost of all committed generators operating at the minimum generation level for all types of fuel to the total pollutants emitted by all the committed generators operating at their maximum generation level for all kinds of fuel. Mathematically, it is stated below.

$$h_{fk} = \frac{\sum_{j=1}^{N_f} F_1(x_{mj})}{\sum_{j=1}^{N_f} F_2(x_{nj})} \quad (k = 1, 2, 3, 4) \tag{12}$$

where

$$\begin{aligned}
x_{1j} &= \left[P_{1j}^{min} P_{2j}^{min} \ldots P_{N_g j}^{min}\right]^T \quad (j = 1, 2, \ldots, N_f) \\
x_{2j} &= \left[P_{1j}^{max} P_{2j}^{max} \ldots P_{N_g j}^{max}\right]^T \quad (j = 1, 2, \ldots, N_f) \\
k &= \begin{cases} 1\ ; m = 1 \ and\ n = 1 \\ 2\ ; m = 1 \ and\ n = 2 \\ 3\ ; m = 2 \text{ and } n = 1 \\ 4\ ; m = 2 \text{ and } n = 2 \end{cases} \\
h_f &= \min\left(h_{f1}, h_{f2}, h_{f3}, h_{f4}\right)
\end{aligned} \tag{13}$$

3 Constraint Handling

Direct and indirect methods are used to solve constrained optimization problems. Direct methods explicitly handle the constraints, but in indirect methods, the constrained optimization problem is converted into an unconstrained optimization problem. The constraint handling techniques for various constraints using direct and indirect methods are discussed as follows:

Handling Power Balance Equation The equality constraint is handled heuristically by an iterative process in which the difference (ΔP_d) in power demand plus transmission losses and power generated by the committed generating units is computed as follows:

$$\Delta P_d = P_D + P_L - \sum_{i=1}^{N_G} P_i \tag{14}$$

If $\Delta P_d = 0$, there is no violation of the energy balance equation, and the solution is feasible. But, if $\Delta P_d \neq 0$, it means there is a violation of the energy balance equation and a solution is infeasible. The generation of electricity is insufficient, if $\Delta P_d > 0$. The power generated is a surplus, if $\Delta P_d < 0$. In the event that the power generated is insufficient, it is proportionally added to the active power generated by each generator to meet total load demand and transmission losses, avoiding the violation of maximum generation limits. In the event of a power generation surplus, it is subtracted proportionally from the active power generated by each generator to meet total load demand and losses, avoiding violations of minimum generation limits and ramp-rate limits. So, to satisfy the equality constraint, active power generation is modified with the following Eq.:

$$P_i = \begin{cases} P_i + M\text{in}\left(BP_i, \left|min\left(P_i^{max}, P_i^0 + UR_i\right) - P_i\right|\right) & ;(\Delta P_d > 0) \\ P_i - M\text{in}\left(BP_i, \left|P_i - max\left(P_i^{min}, P_i^0 - DR_i\right)\right|\right) & ;\left(\Delta P_d < 0\right) \quad (i = 1, 2, ..., N_G) \\ P_i & ;\left(\Delta P_d = 0\right) \end{cases} \tag{15}$$

where

$$BP_i = \left|\Delta P_d\right| z_i \left(\frac{P_i}{\sum_{i=1}^{N_g} P_i} \right)$$

Besides this, an exterior penalty method is also used to avoid the violation of equality constraints if they still exist. As a result, the augmented fuel cost function is as follows:

$$F_P = F_T + r(\Delta P_d)^2 \tag{16}$$

POZ Handling System constraints specified in Eq. (4) can be handled by avoiding power generation in POZ. If the POZ limits are breached, the generation can be updated by the Eq. described below.

$$P_i = \begin{cases} P_{ik}^L - \left(1 - \frac{P_{ik}^L}{P_{ik}^U}\right) z_i & ;\left(P_i - P_{ik}^L\right) \leq \left(P_{ik}^U - P_i\right) \\ P_{ik}^U + \left(1 - \frac{P_{ik}^L}{P_{ik}^U}\right) z_i & ;\text{else} \end{cases} \quad \left(k = 1,2, \ldots, N_{zk}; i = 1,2, \ldots, N_G\right) \tag{17}$$

Handling Generation Limits and Ramp-Rate Limit Inequalities constraints, that is, minimum and maximum values of generators' generation, are updated by clubbing them with restrictions on the increase and decrease of generation from particular values using the replacement method as follows:

$$P_i = \begin{cases} P_i & ;max\left(P_i^{min}, P_i^0 - DR_i\right) \le P_i \le min\left(P_i^{max}, P_i^0 + UR_i\right) \\ max\left(P_i^{min}, P_i^0 - DR_i\right) & ;P_i > max\left(P_i^{min}, P_i^0 - DR_i\right) \\ min\left(P_i^{max}, P_i^0 + UR_i\right) & ;P_i < min\left(P_i^{max}, P_i^0 + UR_i\right) \quad (i = 1, 2, \ldots, N_G) \end{cases} \tag{18}$$

4 Crisscross Team Game Algorithm

A team game is a structured physical activity in which players cooperate to achieve a common goal. In team games, players on the same team cooperate to win the match. To accomplish their goals, team members establish goals, assign points and scores, make decisions, collaborate with one another, handle conflict, and find solutions. If the game is to be played in a regulated manner, the player must be in the appropriate location at the appropriate time. Team game is a sports with many plays playing with one ball and has unique characteristics, such as reliance on team members. Learning entails taking advantage of team members' mistakes. Such acts of team games are simulated as optimization operators, and, based on them, a heuristic algorithm has been developed by Mahmoodabadi et al. [42] and named the team game algorithm (TGA). The elemental idea of the crisscross team game algorithm (CTGA) has been explained by mentioning the reason and logic for amalgamating TGA.

Confucius believed that the best course of action was always to practise moderation. The crisscross search technique uses a pair search mechanism with horizontal crossover and vertical crossover, which performs several crossover operations in counter-clockwise orientations to reproduce a population of moderation solutions at each generation [46]. In order to keep a population in the best possible historical position and speed up convergence, moderated solutions that outperform those in the parent population can persist. The vertical crossover makes it easier for some stationary population segments to avoid premature convergence. Crossover that is both horizontal and vertical enhances solution precision and convergence. The switching between exploration and exploitation for the solution in TGA is excellent, but the choice of its operators has provided significant motivation to improve the algorithm. Only one operator is in action at a time (iteration), which limits the exploration capability. In real-world team game, some players performed admirably while others made mistakes. As a result, learning from teammates is a continuous process at all times. Similarly, players keep on exchanging their positions as per the rules of the game and reflect on their performance while playing at different positions. So, the CTGA is proposed to integrate a dual crisscross mechanism orthogonally with TGA to improve the efficacy by introducing two more operators, namely the collaborative learning and individual skill updation of player during practise session. In the proposed CTGA, players represent the population, and the attributes of players are updated by specific equations. Consequently, their performance is evaluated and their objective function is appraised. Basically, two teams are there to compete against each other. Teammates' cooperation and tactics against the other team's players help achieve the goal of winning the game.

While implementing CTGA on the problem in this paper, attributes of players (variables) represent the power output of generators. Evaluating the performance of players means calculating the operating cost of generators or unified objective, i.e. the objective function of the optimization problem. The step-wise procedure for implementing CTGA on the EEPD problem is explained below.

4.1 Initialization

The initialization phase starts with randomly initializing players in the search space, which are the probable solutions. The initial players are chosen at random, as shown below.

$$P_{ji} = P_i^{min} + \left(P_i^{max} - P_i^{min}\right) z_{ji} \quad \left(i = 1, 2, ..., N_G; j = 1, 2, ..., 2 \times N_P\right) \tag{19}$$

The vector $P_j = \left[P_{j1} P_{j2} \ldots P_{jN_G}\right]^T$

After initializing the players by Eq. (15), the members of the teams are further equally divided into two teams, A and B.

$$A_{ji} = P_{ji} \quad \left(i = 1, 2, ..., N_G; j = 1, 2, ..., N_P\right) \tag{20}$$

$$B_{ji} = P_{ji} \quad \left(i = 1, 2, ..., N_G; j = N_P + 1, N_P + 2, ..., 2 \times N_P\right) \tag{21}$$

The vectors A_j and B_j are $A_j = \left[A_{j1} A_{j2} \ldots A_{jN_G}\right]^T$ and $B_j = \left[B_{j1} B_{j2} \ldots B_{jN_G}\right]^T$, respectively.

4.2 Performance Evaluation

After dividing the players into two teams: team A and team B, for a given optimization problem, their corresponding performances, $F_j^A\left(A_j\right)$ and $F_j^B\left(B_j\right)$, are evaluated using Eq. (16) by ensuring the feasibility of the solutions. The best performances of players from team A and team B are found among all players using the following expressions:

$$F_A^{Cap} = Min\left\{F_j^A\left(A_{ji}\right); j = 1, 2, \ldots, N_P\right\} \tag{22}$$

$$F_B^{Cap} = Min\left\{F_j^B\left(B_{ji}\right); j = 1, 2, \ldots, N_P\right\} \tag{23}$$

The attributes of the best player of team A corresponding to F_A^{Cap} is obtained as $A_i^{Cap}(i = 1, 2, \ldots, N_G)$ and attributes of the best player of team B corresponding to F_B^{Cap} is obtained as $B_i^{Cap}(i = 1, 2, \ldots, N_G)$. The best performance out of both the teams, F^{Gbest}, i.e. global best and corresponding player's attributes, $P_i^{Gbest}(i = 1, 2, \ldots, N_G)$ are calculated as follows:

$$F^{Gbest} = Min\left\{F_A^{Cap}, F_B^{Cap}\right\} \tag{24}$$

$$P_i^{Gbest} = \begin{cases} A_i^{Cap}\left(i = 1, 2, \ldots, N_G\right) & ;\left(F_A^{Cap} < F_B^{Cap}\right) \\ B_i^{Cap}\left(i = 1, 2, \ldots, N_G\right) & ;\left(F_B^{Cap} < F_A^{Cap}\right) \end{cases} \tag{25}$$

4.3 Team Selection

The toss is performed to hand over the ball to a team after evaluating the performance of the initialized players of both teams, as described below:

$$X_j = \begin{cases} A_j \ if \ z \ \leq \ 0.5 \ ; \text{Team A as Ball Owner} \\ B_j \ if \ z \ > 0.5 \ ; \text{Team B as Ball Owner} \end{cases} \left(j = 1,2, \ldots, N_P\right) \tag{26}$$

The vector $X_j = \left[X_{j1} X_{j2} \ldots X_{jN_G}\right]^T$.

In team selection, if team A is selected, it acts as the ball owner team, and team B will act as the opponent team, and vice versa. On the selection of team A, $F_j\left(X_j\right)$ is assigned to $F_j^A\left(A_j\right)$. The best objective function value and it's attributes are also replaced as $F^{Cap} \leftarrow F_A^{Cap}$ and $X_i^{Cap} \leftarrow A_i^{Cap}(i = 1, 2, \ldots, N_G)$. A similar action is performed on the selection of team B.

4.4 Passing and Mistake Operators

The passing operator of the algorithm simulates the passing of the ball in order to update the attribute of a player on a team. The mistake operator allows a player from the ball owner's team and a player from his opponent's team to interact with each other in order to improve the mistake and update the team's attributes. The selection of passing and mistaken operations is based on probability. The updated attribute of a player, X_{ji}^{new}, based on passing and mistaken operation, is presented below:

$$X_{ji}^{new} = \begin{cases} X_{ji} + z_{ji}\left(2X_i^{Cap} - X_{ji} - X_{jl}\right) & ; z_i \leq \ P_p \quad \text{(Passing operation)} \\ X_{ji} + y_{ji}\left(X_{dk}^{opp} - X_{di}\right)] & ; else \quad (Mistakeoperation) \end{cases} \\ \left(i = 1,2, \ldots, N_G; j = 1,2, \ldots, N_P\right) \tag{27}$$

$P_p = (1.0 - A_f \frac{g_1}{G^{max}})$ is a self-adjusting probability factor. l and d are random numbers belonging to $[1, N_G]$ and $[1, N_P]$, respectively. Multiplier, A_f was kept fixed at 0.1 by Mahmoodabadi et al. [42].

4.5 Substitution Operator

This is a limit operator that comes into action when a particular player is tired and performs improperly or is continuously unable to improve its performance in the specified iterations. A limit check is applied to the performance; if it is not improving for some pre-set count, then that player is substituted by a fresh player with the strategy performed as follows:

$$TR_j = \begin{cases} TR_j + 1 & ; F_j^{new}(X_j^{new}) \geq F_j(X_j) \\ TR_j & ; else \end{cases} \quad (j = 1, 2, \ldots, N_P) \tag{28}$$

$$X_{ji}^{new} = \begin{cases} X_{ji} + \left(X_i^{Cap} - X_{di} + X_{ei} - X_{fi}\right) z_{ji} & ; TR_j = L_n \\ X_{ji} & ;else \end{cases} \quad (i = 1,2,...,N_G; j = 1,2,\ldots,N_P) \tag{29}$$

Once substitution occurs, TR_j is set to zero. d, e, and f are random numbers belonging to $[1, N_P]$.

4.6 Out-of-the-Field Players

The position of the players in the field is checked while applying all operators. The position of out-of-the-field players [44] is updated with a new impact player using Eq. (19).

4.7 Dual Crisscross Mechanisms

Crisscross operations help the players' collective learning from one another and individual skill improvement. An arithmetic crossover that operates on all dimensions between two or more different players is called collaborative learning. The individual skill update is a crossover operation between two dimensions that is applied to every player.

Collaborative Learning While playing the game in a regulated manner, the player must be in the appropriate location at the appropriate time. In team games, as per the directions of the coach or as per the game's rules, the positions of players are updated following collaborative learning. A moderate solution for a player is updated by collaborating with at least three players including the captain via the following equation:

$$X_{ji}^{new} = X_{ji} + \left(X_{ki} - X_{mi}\right) z_{ji} + \left(X_i^{Cap} - X_{ji}\right) z_{ji} \left(i = 1,2,...,N_G; j = 1,2,...,N_P\right) \tag{30}$$

where k and m are random numbers belonging to $[1, N_P]$.

After performing collaborative learning, the performance of players is evaluated with updated attributes.

Individual Skill Updation To accomplish their goals, team members try to contribute by upgrading their individual skill to achieve the winning score. During the match, the playing player updates his/her inherent skill attributes by looking at other teammate's skills using the following equation.

$$X_{ji}^{new} = z_{ji}X_{ji} + \left(1 - z_{ji}\right)X_{jk}\left(i = 1,2,\ldots,N_G; j = 1,2,\ldots,N_P\right) \tag{31}$$

where $k \in [1, N_G]$ is a uniform random number.

After updating the individual skill of players, the performance of players is evaluated with updated attributes.

4.8 Stopping Criterion

In this paper, the stopping criterion to terminate the algorithm is the maximum number of iterations, G^{max}. The stepwise procedure of the proposed CTGA to get a solution of the EEPD problem is given by Algorithms I and II.

Algorithm 1 Stepwise procedure of CTGA to find the solution of EEPD problem

```
    Input all the parameters (i.e., $N_P$, $N_G$, $G_1^{max}$ and $G_2^{max}$)
    Initialize the players, $P_{ji}$ $((i = 1,2,..,N_G); j = 1,2,..,2 \times N_P)$ using Eq. (19)
    Constitute teams, A and B using Eq. (20) and (21) respectively.
    Get the feasibility of players' attributes (solution) using Eq. (14), (17) and (18)
    Evaluate the performance of both the teams $F_j^A(A_j)$ and $F_j^B(B_j)$ $(j = 1,2,\ldots,N_P)$ using Eq. (16).
    Find best player of team A, $F_A^{Cap} = \min\{F_j^A(A_j); j = 1,2,\ldots,N_P\}$ and $A_i^{Cap}$ $(i = 1,2,..,N_G)$.
    Find best player of team B, $F_B^{Cap} = \min\{F_j^B(B_j); j = 1,2,\ldots,N_P\}$ and $B_i^{Cap}$ $(i = 1,2,..,N_G)$.
    Find the global best solution $F^{Gbest}$ and $P_i^{Gbest}$ $(i = 1,2,..,N_G)$ using Eq. (24) and (25).
    Set the counter, $g_1 = 1$
WHILE($g_1 \le G^{max}$) DO
        IF $(rand(\ ) < 0.5)$ THEN
            CALL Algorithm-II for Team A to find $(F_j^A(A_j)$ and $A_{ji}$ ; $i = 1,2,..,N_G); j = 1,2,..,N_P$
        ELSE
            CALL Algorithm-II for Team B to find $(F_j^B(B_j)$ and $B_{ji}$ ; $i = 1,2,..,N_G); j = 1,2,..,N_P$
        ENDIF
        Find best player of team A, $F_A^{Cap} = \min\{F_j^A(A_j); j = 1,2,\ldots,N_P\}$ and $A_i^{Cap}$ $(i = 1,2,..,N_G)$.
        Find best player of team B, $F_B^{Cap} = \min\{F_j^B(B_j); j = 1,2,\ldots,N_P\}$ and $B_i^{Cap}$ $(i = 1,2,..,N_G)$.
        Find the global best solution $F^{Nbest}$ and $P_i^{Nbest}$ $(i = 1,2,..,N_G)$ using Eq. (24) and (25).
        IF $(F^{Nbest}(P^{Nbest}) < F^{Gbest})$ THEN
         $F^{Gbest} \leftarrow F^{Nbest}(P^{Nbest})$,and $P_i^{Gbest} \leftarrow P_i^{Nbest}(i = 1,2,..,N_G)$
        Increment the counter$g_1 = g_1 + 1$
ENDDO
STOP
END
```

Algorithm 2 Stepwise procedure of team game operators

```
Enter with $N_P$, $N_G$, $G_2^{max}$, $(F_j(X_j)$ and $X_{ji}; i = 1,2,...,N_G); j = 1,2,...,N_P)$, $F^{Cap}$ and $X_i^{Cap}$ $(i = 1,2,..,N_G)$ using Eq. (26).
FOR $j = 1, N_P$
    IF $(TR_j = L_n)$ THEN
        Substitution operator: $X_{ji}^{new} = X_{ji} + (X_i^{Cap} - X_{di} + X_{ei} - X_{fi})z_{ji}$   $(i = 1,2,..,N_G)$
    ELSE IF $(z_j \le P_p)$ THEN
        Passing operator: $X_{ji}^{new} = X_{ji} + z_{ji}(2X_i^{Cap} - X_{ji} - X_{jd})$   $(i = 1,2,..,N_G)$
    ELSE IF
        Mistake operator: $X_{ji}^{new} = X_{ji} + z_{ji}(X_{dk}^{opp} - X_{di})$   $(i = 1,2,..,N_G; i \ne d)$
    ENDIF
    Get the feasible solution using Eq. (14), (17) and (18).
    Evaluate their performance, $F_j^{new}(X_{ji}^{new})$ using Eq. (16).
    IF $(F_j^{new}(X_{ji}^{new}) < F_j(X_{ji}))$ THEN
        $X_{ji} \leftarrow X_{ji}^{new}$ $(i = 1,2,..,N_G)$ and $F_j(X_{ji}) \leftarrow F_j^{new}(X_{ji}^{new})$,
    ENDIF
ENDFOR
Update the smallest function value, $F^{Cap}$ and corresponding best solution, $X_i^{Cap}(i = 1,2,..,N_G)$.
Set the counter, $g_2 = 1$
WHILE$(g_2 \le G_1^{max})$ DO
    FOR $i = 1, N_P$
        Perform collabarative learning operation using Eq. (30).
        Get the feasible solution using Eq. (14), (17) and (18).
        Compute, $F_j^{new}(X_{ji}^{new})$ using Eq. (16).
        IF $(F_j^{new}(X_{ji}^{new}) < F_j(X_{ji}))$ THEN
            $X_{ji} \leftarrow X_{ji}^{new}$ $(i = 1,2,..,N_G)$ and $F_j(X_{ji}) \leftarrow F_j^{new}(X_{ji}^{new})$
        ENDIF
        Update the smallest function value, $F^{Cap}$ and corresponding best solution, $X_i^{Cap}(i = 1,2,..,N_G)$.
        Perform individual skill updation operation using Eq. (31).
        Get the feasible solution using Eq. (14), (17) and (18).
        Compute, $F_j^{new}(X_{ji}^{new})$ using Eq. (16).
        IF $(F_j^{new}(X_{ji}^{new}) < F_j(X_{ji}))$ THEN
            $X_{ji} \leftarrow X_{ji}^{new}$ $(i = 1,2,..,N_G)$ and $F_j(X_{ji}) \leftarrow F_j^{new}(X_{ji}^{new})$
        ENDIF
        Update the smallest function value, $F^{Cap}$ and corresponding best solution, $X_i^{Cap}(i = 1,2,..,N_G)$.
    ENDFOR
    Increment the counter, $g_2 = g_2 + 1$
ENDDO
RETURN
END
```

5 Experimental Results and Analysis

To investigate the performance of the proposed CTGA comprehensively, it is implemented on the unconstrained standard benchmark optimization problems [47] and power system operation-related test problems. Unconstrained optimization problems cover unimodal, multimodal, discontinuous, separable, and non-separable functions. The potential of the proposed algorithm is analyzed in an unconstrained environment as well as considering equality and inequality constraints following the heuristics. Various practical aspects of power system operation are considered, like transmission loss, multiple fuel options (MFO), valve point loading (VPL) effect, avoiding POZ, and ramp-rate constraint. Transmission losses are computed. The *B*-coefficients are derived from load flow using the Gauss–Seidel method. Further, to achieve an optimized generation schedule for the EEPD problem, the proposed CTGA is implemented, and results are compared with other state-of-the-art algorithms available in the literature. For simulation and coding purposes, the FORTRAN language is used on a 2.20 GHz Intel Core i7 processor with 16 GB of RAM.

To examine the experimental outcomes qualitatively, four widely used evaluation metrics are used, as described below.

- The quality of the solutions is evaluated using the function evaluations' average and standard deviation. Small average and standard deviation values correspond to superior solutions for minimization problems.
- To examine the TGA and CTGA algorithms' convergence behaviour, convergence curves are made for the best trial run for iterations that do not further improve the best result already obtained.
- Whisker box plots are constructed to demonstrate the proposed CTGA's superior resilience to TGA.
- A comprehensive examination is conducted using non-parametric tests, such as the Wilcoxon signed-rank test and the Friedman test. The former is used to identify the statistically significant differences between two algorithms, and the latter is used to display an algorithm's overall performance in terms of optimization across all algorithms undertaken for comparison.

5.1 Standard Benchmark Optimization Problems

To validate its applicability in solving optimization problems, the proposed CTGA is implemented on various standard benchmark optimization problems. The control parameters, selected after performing a number of simulations, for solving these benchmark problems are as follows: dimension, D is set to 30; population size N_P to 40; multiplying factor, A_f to 0.5; pre-set limit counter, L_n to 9; maximum number of iterations, G^{max} to 2000; and maximum number of iterations for learning and exchange operators, G_1^{max} to 5. For optimizing each function, 30 independent trial runs are performed to justify a global solution. In order to fairly compare the performance of TGA and CTGA, results are analyzed for the same number of function evaluations, which is an alternative to CPU time for the comparison.

5.1.1 Unconstrained Functions

To test the efficacy of the proposed CTGA, it is implemented on various functions as listed in Table 2. The nature of functions undertaken for study is continuous, discontinuous, separable, and non-separable [47]. The obtained results for unconstrained functions are presented in Table 2 in terms of minimum, maximum, average, and standard deviation (StDev) values of objectives. Mahmoodabadi et al. [42] compared the results obtained by TGA with the results achieved by genetic algorithms with traditional crossover (GATC), genetic algorithms with multiple crossover (GAMC), and the gravitational search algorithm (GSA), and it has been observed that TGA gives better results.

Table 2 Performance analysis of TGA and CTGA on unconstrained functions

Test function		Search range	Algorithm	Function evaluation			StDev
				Minimum	Maximum	Average	
F1	Sphere function	$(-100, 100)^D$	TGA	0.0	0.0	0.0	0.0
			CTGA	0.0	0.0	0.0	0.0
F2	Schwefel's 2.22 function	$(-10, 10)^D$	TGA	7.42E−17	1.27E−15	4.17E−16	3.57E−16
			CTGA	0.0	0.0	0.0	0.0
F3	Schwefel's 1.2 function	$(-100, 100)^D$	TGA	0.174E−28	0.332E−25	0.346E−26	0.619E−26
			CTGA	0.0	0.0	0.0	0.0
F4	Schwefel's 2.21 function	$(-100, 10)^D$	TGA	0.049	1.393	0.295	0.304
			CTGA	0.0	0.0	0.0	0.0
F5	Rosenbrock function	$(-5, 10)^D$	TGA	0.396	76.990	17.703	16.989
			CTGA	0.0	0.0	0.0	0.0
F6	Step function	$(-100, 100)^D$	TGA	0.0	0.0	0.0	0.0
			CTGA	0.0	0.0	0.0	0.0
F7	Quartic function	$(-1.28, 1.28)^D$	TGA	0.005	0.026	0.012	0.004
			CTGA	0.976E−04	0.112E−03	0.100E−03	0.375E−05
F8	Schwefel's 2.26 function	$(-500, 500)^D$	TGA	712.559	3001.62	2017.36	480.70
			CTGA	−0.0176	−0.0176	−0.0176	−0.0176
F9	Rastrigin function	$(-5.12, 5.12)^D$	TGA	21.890	69.647	43.516	12.250
			CTGA	0.0	0.0	0.0	0.0
F10	Ackley function	$(-32, 32)^D$	TGA	1.065E−14	0.931	0.093	0.284
			CTGA	0.0	3.55E−15	3.31E−15	9.00E−16
F11	Griewank function	$(-600, 600)^D$	TGA	0.0	5.16E−02	7.38E−03	0.012
			CTGA	0.0	0.0	0.0	0.0
F12	Generalized penalized 1 function	$(-50, 50)^D$	TGA	0.802E−16	0.936	0.159	0.265
			CTGA	0.802E−16	0.802E−16	0.802E−16	0.431E−31

Superscript letter "D" denotes Dimension

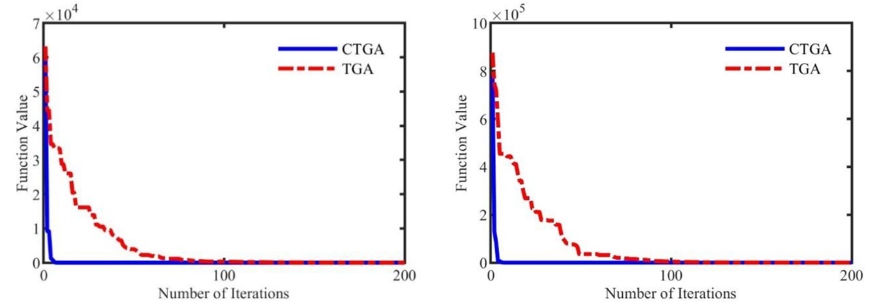
For functions F1, F6, and F11, the implemented algorithms achieve the same optimal solution. For functions F5, F8, and F9, TGA is unable to achieve the optimal solution, whereas CTGA achieves the ideal global value of the optimal solution for all the functions. It can be easily inferred from the results tabulated in Table 2 that CTGA is more proficient than TGA in achieving the optimal solution in terms of minimum value and standard deviation.

To compare the convergence behaviour of both algorithms, convergence curves are drawn for the results of undertaken functions as shown in Fig. 2. The convergence behaviour for function F2 is the same. So the curves for function F2 are left out. In the rest of all the functions, CTGA converges faster than TGA to the optimal value. As in functions F1, F6, and F11, both TGA and CTGA achieve the same optimal value, but the convergence speed of CTGA is faster than that of TGA, as shown in Fig. 2. So, in terms of convergence, CTGA performs better than TGA.

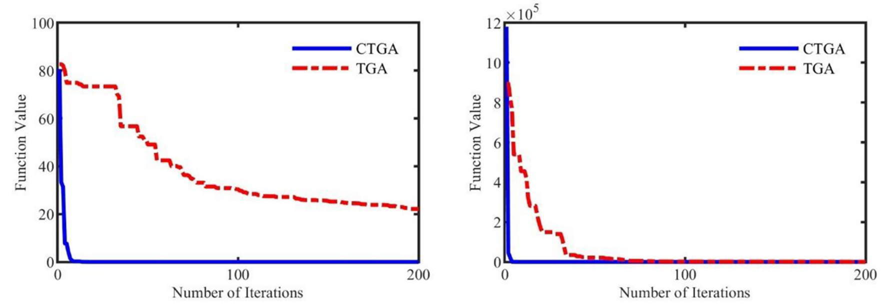
To test the robustness of the proposed algorithm, CTGA, whiskers box plots are drawn for all the F1 to F12 functions using TGA and CTGA and are shown in Fig. 3. The quartiles have less difference between each other in terms of results achieved by the CTGA. Outliers are observed in box plots drawn from the results achieved by TGA. It can be observed that CTGA provides robust results.

Table 3 shows the comparison of the results of unconstrained functions in terms of the average and standard deviation (StDev) values. CTGA results are compared with the Harris hawk optimizer (HHO), genetic algorithm (GA), particle swarm optimization (PSO), biogeography-based optimization (BBO), flower pollination algorithm (FPA), grey wolf optimizer (GWO), bat algorithm (BA), firefly algorithm (FA), Cuckoo search algorithm (CSA), Moth-flame optimization (MFO) algorithm, teacher learning based optimization (TLBO), and differential evolution (DE), and the results are presented by Kumar and Dhillon [48] and are reproduced in Table 3. The parameter settings for all the algorithms used for comparison purposes are given by Heidari et al. [49]. The CTGA gives better results in terms of average and standard deviation when compared with the other techniques reported in the literature.

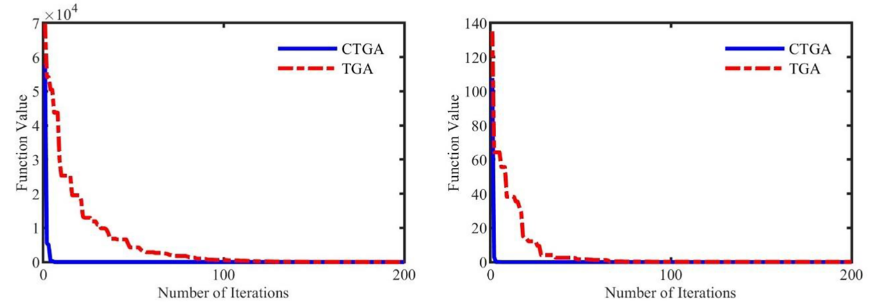
Empirical Analysis In order to compare the effectiveness of the proposed CTGA with some existing algorithms, the Wilcoxon signed-rank test is employed to determine the statistically significant difference between CTGA and its competitors from two perspectives. The first step is to test each function's difference, and the results are presented with "plus (+)", "equals to (=)", and "minus (−)" signs which signify CTGA's performance on the related function being better, similar to, or worse than that of the comparative method. Second, the difference between all functions is checked, and the findings are shown in terms of "R^+", "R^-", and "*p*-value". R^+ denotes the sum of rankings for the functions on which CTGA outperforms the comparative method, and R^- denotes the opposite. A *p*-value of more than 0.05 indicates that the difference between CTGA and the comparison method is not significant, while a *p*-value of less than 0.05 shows that the difference is significant. Table 4 represents the analysis of the Wilcoxon signed-rank test on results of unconstrained functions F1 to F12.



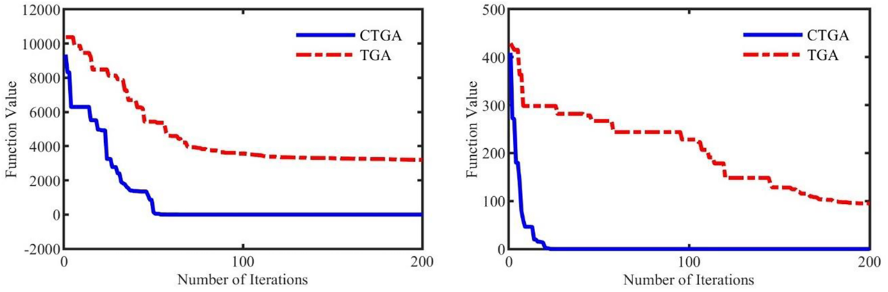
(i) Function, F1 (ii) Function, F3



(iii) Function, F4 (iv) Function, F5

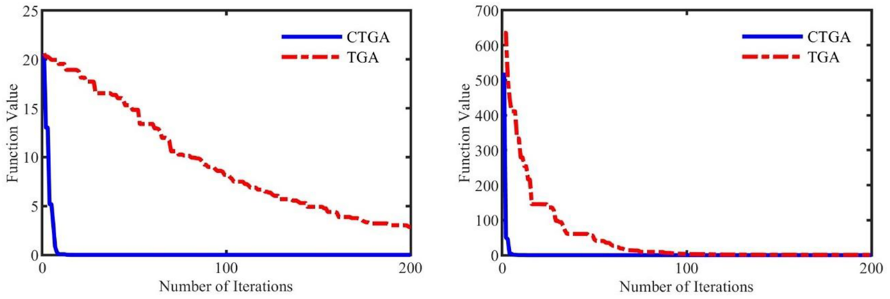


(v) Function, F6 (vi) Function, F7



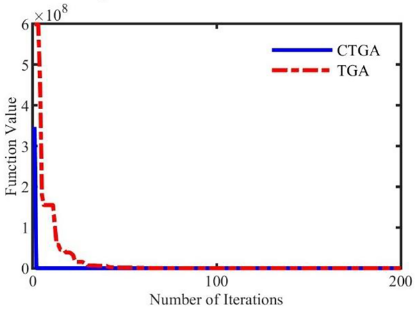
(vii) Function, F8 (viii) Function, F9

Fig. 2 Convergence curves of unconstrained functions



(ix) Function, F10

(x) Function, F11



(xi) Function, F12

Fig. 2 (continued)

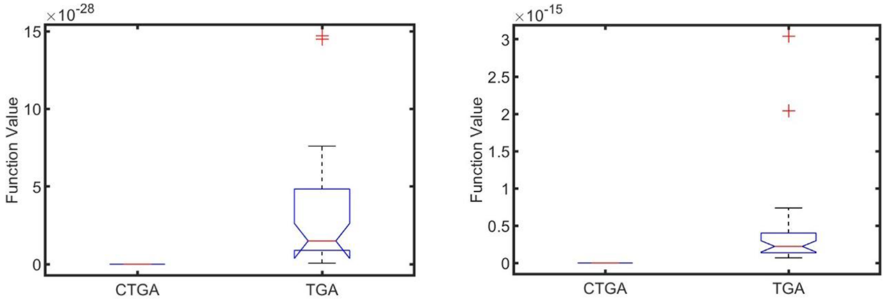
CTGA performs better than HHO, GA, PSO, BBO, FPA, GWO, BA, FA, CS, MFO, TLBO, DE, and TGA on more than 8 to 11 functions, out of 12 functions. Further evidence supporting CTGA's better performance over competing algorithms comes from the fact that it achieves higher R^+ values than competing algorithms. *p*-values of HHO, BBO, and TLBO are greater than 0.05 which shows that there is no statistically significant difference between CTGA and the HHO, BBO, and TLBO algorithms. The *p*-value for GA, PSO, FPA, GWO, BA, FA, CS, MFO, DE, and TGA are less than 0.05 which shows that the difference is significant.

The results of the Friedman test are used to further analyze overall performance, and they are presented as "average ranking" results, which represent the average rank outcomes across all functions. A lower ranking value denotes better optimization performance all around.

The CTGA's average ranking scores on unconstrained functions (F1–F12) across all competing methods are shown in Fig. 4. CTGA attains a 1.33 average rank value that is minimum than HHO, GA, PSO, BBO, GWO, BA, FA, CS, MFO, TLBO, DE, and TGA.

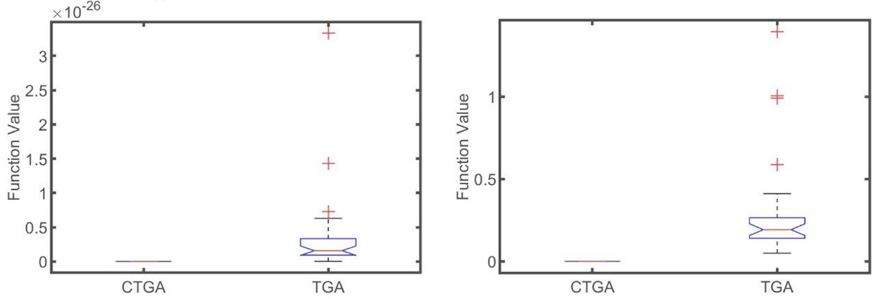
5.2 Power System Test Problems

In order to verify the applicability of the proposed method to solve the power system operation problems, CTGA is implemented on five electric power system test



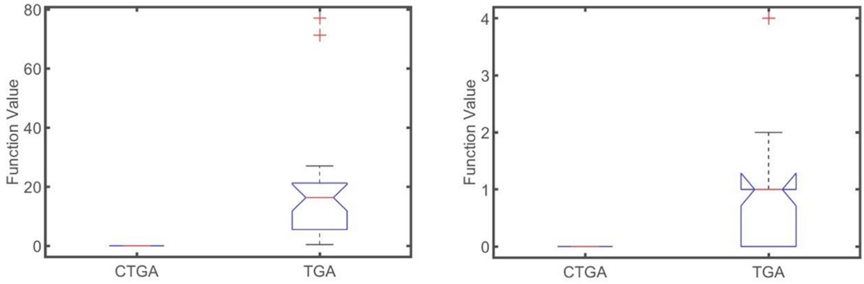
(i) Function, F1

(ii) Function, F2



(iii) Function, F3

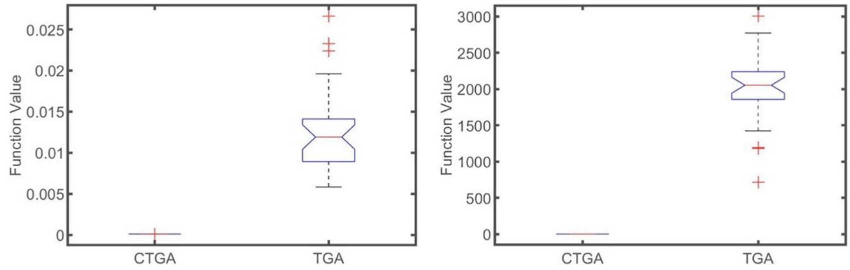
(iv) Function, F4



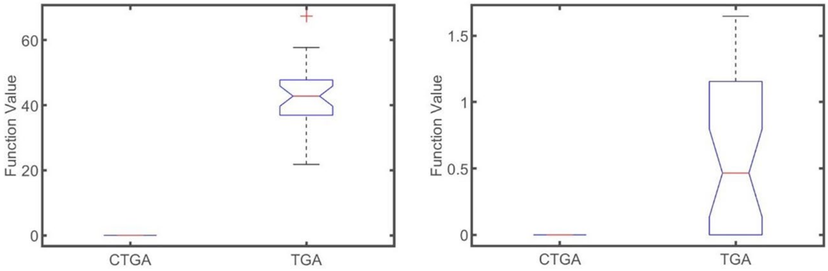
(v) Function, F5

(vi) Function, F6

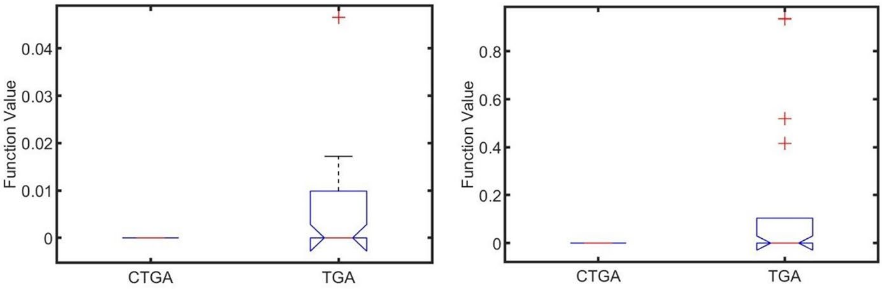
Fig. 3 Whiskers box plots of unconstrained functions



(vii) Function, F7 (viii) Function, F8



(ix) Function, F9 (x) Function, F10



(xi) Function, F11 (xii) Function, F12

Fig. 3 (continued)

problems considering different aspects of the power system, as tabulated in Table 5. The parameters of any global search technique must be tuned because they affect the quality of the solutions. In CTGA and TGA, parameters to be tuned are A_f and L_n and are set to 0.5 and 9, respectively, for all the undertaken power system test problems in this paper.

The maximum number of iterations G^{max} and G_1^{max} are set to 550 and 5, respectively. The penalty factor, r is taken as 10^5. Table 6 provides information on team size, labeled as N_P, and different power demands marked as P_D, along with their associated transmission losses, P_L, and unmet demand, $\left|\Delta P_D\right|$, for the test problems under study. Additionally, it displays the number of function evaluations, denoted as N_{FE}, needed to achieve the optimal solution across various load demands for the analyzed test systems. Both algorithms are run for 30 independent trials, and the

Table 3 Comparison of results by CTGA on unconstrained functions [48]

Method	F1		F2		F3		F4	
	Average	StDev	Average	StDev	Average	StDev	Average	StDev
HHO	3.95E−97	1.72E−96	1.56E−51	6.98E−51	1.92E−63	1.05E−62	1.02E−47	5.01E−47
GA	1.03E+03	5.79E+02	2.47E+01	5.68E+00	2.65E+04	3.44E+03	5.17E+01	1.05E+01
PSO	1.83E+04	3.01E+03	3.58E+02	1.35E+03	4.05E+04	8.21E+03	4.39E+01	3.64E+00
BBO	7.59E+01	2.75E+01	1.36E−03	7.45E−03	1.21E+04	2.69E+03	3.02E+01	4.39E+00
FPA	2.01E+03	5.60E+02	3.22E+01	5.55E+00	1.41E+03	5.59E+02	2.38E+01	2.77E+00
GWO	1.18E−27	1.47E−27	9.71E−17	5.60E−17	5.12E−05	2.03E−04	1.24E−06	1.94E−06
BA	6.59E+04	7.51E+03	2.71E+08	1.30E+09	1.38E+05	4.72E+04	8.51E+01	2.95E+00
FA	7.11E−03	3.21E−03	4.34E−01	1.84E−01	1.66E+03	6.72E+02	1.11E−01	4.75E−02
CS	9.06E−04	4.55E−04	1.49E−01	2.79E−02	2.10E−01	5.69E−02	9.65E−02	1.94E−02
MFO	1.01E+03	3.05E+03	3.19E+01	2.06E+01	2.43E+04	1.41E+04	7.00E+01	7.06E+00
TLBO	2.17E−89	3.14E−89	2.77E−45	3.11E−45	3.91E−18	8.04E−18	1.68E−36	1.47E−36
DE	1.33E−03	5.92E−04	6.83E−03	2.06E−03	3.97E+04	5.37E+03	1.15E+01	2.37E+00
TGA	0.00E+00	0.00E+00	4.17E−16	3.57E−16	3.46E−27	6.19E−27	2.95E−01	3.04E−01
CTGA	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
Method	F5		F6		F7		F8	
	Average	StDev	Average	StDev	Average	StDev	Average	StDev
HHO	1.32E−02	1.87E−02	1.15E−04	1.56E−04	1.40E−04	1.07E−04	−1.25E+04	1.47E+02
GA	1.95E+04	1.31E+04	9.01E+02	2.84E+02	1.91E−01	1.50E−01	−1.26E+04	4.51E+00
PSO	1.96E+07	6.25E+06	1.87E+04	2.92E+03	1.07E+01	3.05E+00	−3.86E+03	2.49E+02
BBO	1.82E+03	9.40E+02	6.71E+01	2.20E+01	2.91E−03	1.83E−03	−1.24E+04	3.50E+01
FPA	3.17E+05	1.75E+05	1.70E+03	3.13E+02	3.41E−01	1.10E−01	−6.45E+03	3.03E+02
GWO	2.70E+01	7.78E−01	8.44E−01	3.18E−01	1.70E−03	1.06E−03	−5.97E+03	7.10E+02
BA	2.10E+08	4.17E+07	6.69E+04	5.87E+03	4.57E+01	7.82E+00	−2.33E+03	2.96E+02
FA	7.97E+01	7.39E+01	6.94E−03	3.61E−03	6.62E−02	4.23E−02	−5.85E+03	1.16E+03
CS	2.76E+01	4.51E−01	3.13E−03	1.30E−03	7.29E−02	2.21E−02	−5.19E+19	1.76E+20
MFO	7.35E+03	2.26E+04	2.68E+03	5.84E+03	4.50E+00	9.21E+00	−8.48E+03	7.98E+02
TLBO	**2.54E+01**	4.26E−01	3.29E−05	8.65E−05	1.16E−03	3.63E−04	−7.76E+03	1.04E+03
DE	1.06E+02	1.01E+02	1.44E−03	5.38E−04	5.24E−02	1.37E−02	−6.82E+03	3.94E+02
TGA	1.77E+01	1.70E+01	0.00E+00	0.00E+00	1.20E−02	4.00E−03	2.02E+03	4.81E+02
CTGA	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**1.00E−04**	**3.75E−06**	**−1.76E−02**	**−1.76E−02**
Method	F9		F10		F11		F12	
	Average	StDev	Average	StDev	Average	StDev	Average	StDev
HHO	0.00E+00	0.00E+00	8.88E−16	4.01E−31	0.00E+00	0.00E+00	2.08E−06	1.19E−05
GA	9.04E+00	4.58E+00	1.36E+01	1.51E+00	1.01E+01	2.43E+00	4.77E+00	1.56E+00
PSO	2.87E+02	1.95E+01	1.75E+01	3.67E−01	1.70E+02	3.17E+01	1.51E+07	9.88E+06
BBO	0.00E+00	0.00E+00	2.13E+00	3.53E−01	1.46E+00	1.69E−01	6.68E−01	2.62E−01
FPA	1.82E+02	1.24E+01	7.14E+00	1.08E+00	1.73E+01	3.63E+00	3.05E+02	1.04E+03
GWO	2.19E+00	3.69E+00	1.03E−13	1.70E−14	4.76E−03	8.57E−03	4.83E−02	2.12E−02
BA	1.92E+02	3.56E+01	1.92E+01	2.43E−01	6.01E+02	5.50E+01	4.71E+08	1.54E+08
FA	3.82E+01	1.12E+01	4.58E−02	1.20E−02	4.23E−03	1.29E−03	3.13E−04	1.76E−04
CS	1.51E+01	1.25E+00	3.29E−02	7.93E−03	4.29E−05	2.00E−05	5.57E−05	4.96E−05
MFO	1.59E+02	3.21E+01	1.74E+01	4.95E+00	3.10E+01	5.94E+01	2.46E+02	1.21E+03

Table 3 (continued)

Method	F1		F2		F3		F4	
	Average	StDev	Average	StDev	Average	StDev	Average	StDev
TLBO	1.40E+01	5.45E+00	6.45E−15	1.79E−15	0.00E+00	0.00E+00	7.35E−06	7.45E−06
DE	1.58E+02	1.17E+01	1.21E−02	3.30E−03	3.52E−02	7.20E−02	2.25E−03	1.70E−03
TGA	4.35E+01	1.23E+01	9.30E−02	2.84E−01	7.38E−03	1.20E−02	1.59E−01	2.65E−01
CTGA	**0.00E+00**	**0.00E+00**	**3.31E−15**	**9.00E−16**	**0.00E+00**	**0.00E+00**	**8.02E−17**	**4.31E−32**

Data in bold emphasis indicate results achieved by proposed algorithm

results of the best trial are used for analysis and comparison purposes. Analytical methods, specifically the λ-method and the simplex search (SS) method, are also used to solve some of the test problems in order to compare with the results obtained from heuristic search optimization methods.

Test Problem T1 In the power test problem T1, a small 30-bus, 41-line system with six generators is under study. The power system meets 283.4 MW of active power demand and 123.95 MVar of reactive power. Input data for cost coefficients and line data for power are referred to in [51]. To evaluate the B-coefficient for the calculation of transmission loss, the Gauss–Seidel method is applied to perform load flow after every better result is obtained. The proposed algorithm is implemented on the system, and the results are tabulated in Table 7 for comparison between real-coded genetic algorithm (RCGA) [51], TGA, and CTGA. Table 8 tabulates the corresponding generation schedule of the best trial. The results are compared with those of RCGA obtained by Abido [51], and the operating cost is lower. CTGA produces better results than TGA because the standard deviation is lower. Table 6 gives the transmission losses, unmet demand, and number of function evaluations. The power balance equation is satisfied and converges to 0.0001, taking 130,042 function evaluations.

Table 4 Wilcoxon signed-rank test results of unconstrained functions (F1–F12)

CTGA vs	+	=	−	R^+	R^-	p-value
HHO	8	2	2	56	19	**0.232**
GA	11	0	1	68	10	0.021
PSO	11	0	1	71	7	0.009
BBO	10	1	1	65	12	**0.053**
FPA	11	0	1	67	11	0.026
GWO	11	0	1	66	12	0.034
BA	11	0	1	72	6	0.006
FA	11	0	1	66	12	0.034
CS	11	0	1	66	12	0.034
MFO	11	0	1	67	11	0.026
TLBO	10	1	1	65	12	**0.053**
DE	11	0	1	67	11	0.026
TGA	10	2	0	75	0	0.002

p-values above the significance level (>0.05) are shown in bold

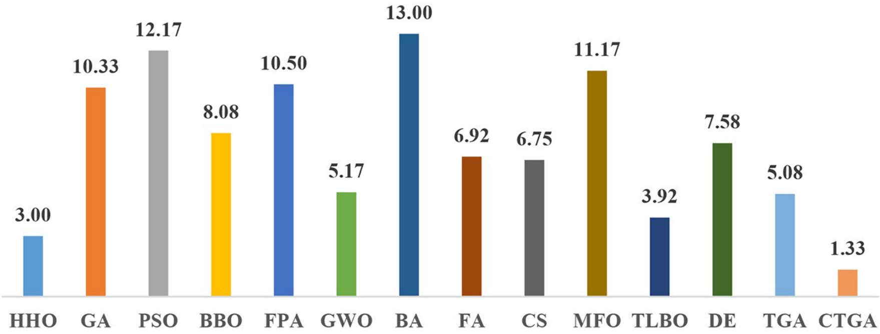


Fig. 4 Average ranking values of unconstrained functions (F1–F12)

Test Problem T2 The cost coefficient input data for power system test problem T2 have been obtained from [52]. It is a small, 10-generator, multi-fuel option system. Transmission loss coefficients (*B*-coefficients) are taken from [19]. Team size and the number of function evaluations, to achieve the optimal solution, are mentioned in Table 6. Table 9 presents a comparison of the operating cost obtained by the proposed algorithm with the operating cost obtained by other algorithms implemented on the same problem available in the literature for different power demands.

The minimum operating cost obtained for 2700 MW load demand by CTGA is 700.6916 $/h, which is comparatively less than the operating cost obtained by the simplex-search method (SS), TGA, and synergic predator–prey optimization (SPPO) [19]. Table 9 also presents results compared with the λ-method, SS method, and TGA for load demands of 1620 MW, 2160 MW, and 3240 MW. The minimum operating cost achieved by implementing CTGA is the least among the compared methods for all the load levels. StDev is also less than 1, which is a near-to-ideal condition for testing the robustness of an algorithm. The generation

Table 5 Details of the power system test problems undertaken for the study

Test problem		Thermal unit	Case	Valve-point loading	Ramp-rate limits	Prohibited operating zones	Multi-fuel options	Transmission losses	Reference
Single objective	T1	6	30-bus	×	×	×	×	✓	[51]
	T2	10	-	✓	×	✓	✓	✓	[19, 52]
	T3	40	1	×	✓	✓	×	✓	[53]
			2	✓	×	×	×	×	[54]
			3	✓	×	×	×	✓	[54, 55]
			4	✓	×	×	✓	×	[52]
	T4	140	-	✓	✓	✓	×	×	[56]
Multi-objective	T5	10	1	✓	×	×	✓	✓	[19, 52, 57]
			2		×	✓	✓	✓	

Table 6 Team size and results related to transmission power losses, unmet demand, and function evaluation on test problems

Test system	Thermal units	Case	Team size, N_P	Power demand, P_D (MW)	Transmission losses, P_L (MW)	Unmet demand, $\left\|\Delta P_D\right\|$ (MW)	Function evaluations, N_{FE}
T1	6	30-bus	20	283.4	2.927	0.0001	130042
T2	10		15	1620	49.5081	0	19335
				2160	87.1452	0.0001	16215
				2700	141.5813	0.0001	16410
				3240	207.4302	0.0001	18945
T3	40	1	20	5000	57.5521	0.0001	35740
				7000	81.3236	0.0001	41620
				8000	104.9407	0.0001	38260
		2	25	5250	-	0	262550
				8400	-	0	262550
				10500	-	0.001	241550
		3	20	5250	225.1540	0.0001	650040
				8400	566.8046	0.0001	650040
				10500	971.714	0.0	507040
		4	25	6480	-	0	127550
				8640	-	0.0001	121175
				10800	-	0.0001	154750
				12960	-	0	184500
T4	140	-	30	37006	-	0.0001	226860
				49432	-	0.0001	252060
				54276	-	0.0001	221190
T5	10	1	30	1620	49.5172	0.0002	209620
				2160	87.2945	0.0002	208360
				2700	141.434	0.1472	251430
				3240	207.0973	0	202480
		2	30	1620	49.2973	0	200380
				2160	87.2846	0	205000
				2700	140.9383	0.6429	201660
				3240	207.0319	0	199540

schedule for demands of 1620 MW, 2160 MW, 2700 MW, and 3240 MW obtained by CTGA is presented in Table 10.

It is evident from Table 6 that the power balance equation is completely met for a load demand of 1620 MW, achieved with 19,335 function evaluations. The power balance equation converges to 0.0001 with 16,215, 16,410, and 18,945 function evaluations for load demands of 2160 MW, 2700 MW, and 3240 MW, respectively.

Test Problem T3—Case 1 Case 1 of the power system test problem T3 is a 40-generator system with power demands of 5000 MW, 7000 MW, and 8000 MW in the medium-sized test system category. Data for input, that is, cost coefficients, ramp-rate limits,

Table 7 Comparison of operating cost (test problem T1)

S. No	Algorithm	Operating cost ($/h)			StDev	Transmission losses (MW)
		Minimum	Maximum	Average		
1	RCGA [51]	607.807	NA0	NA	NA	3.38
2	TGA	606.63	673.94	610.78	11.922	2.914
3	**CTGA**	**606.66**	**611.84**	**608.29**	**1.025**	**2.927**

Data in bold emphasis indicate results achieved by proposed algorithm

prohibited operating zones (POZ), and *B*-coefficients, are taken from [53]. All the practical constraints, like the valve-point loading effect, ramp-rate limits, POZ, and transmission losses, are considered to analyze the performance of the proposed algorithm.

Table 11 tabulates the comparison of the operating cost of the system yielded by CTGA with other contending algorithms for power demands of 5000 MW, 7000 MW, and 8000 MW. For 7000-MW power demand, the results obtained from λ-method, two-phase neural networks (NN) [53], adaptive personal best base oriented particle swarm optimization (APSO) [19], ameliorated grey wolf optimization (AGWO) [31], improved directional bat algorithm (IDBA) [26], and SS method are compared with those of CTGA. The operating cost yielded by λ-method is the lowest among the techniques undertaken for comparison and unmet demand at 0.16×10^{-02} (MW). The proposed method, CTGA, has a higher operating cost of 0.07 ($/h), but it has a lower unmet demand, $|\Delta P_D|$ is 0.15×10^{-03} (MW) than the by λ-method. Furthermore, transmission losses with the proposed algorithm are 0.0228 MW lower than with the λ-method. The proposed algorithm yields a better average value of operating costs in comparison to AGWO [31] and IDBA [26]. So the overall performance of CTGA is competitively good as compared to competing methods. Similarly, for power demands of 5000 MW and 8000 MW, CTGA performs competitively better as compared to the λ-method, SS method, and TGA. λ -method gives competing results because operating cost is represented by differential quadratic function without VPL.

Table 8 Generation schedule obtained by proposed method (test problem T1)

Unit *i*	P_i^{min}(MW)	CTGA Power, P_i (MW)	RCGA [51] Power, P_i (MW)	P_i^{max}(MW)
1	05	10.634	10.86	150
2	05	31.415	30.56	150
3	05	54.169	58.18	150
4	05	100.429	98.46	150
5	05	52.903	52.88	150
6	05	36.774	35.84	150
Total generation, $\sum P_i$(MW) =		286.326	286.78	
Operating cost ($/h)		606.66	607.807	

Table 9 Comparison of operating cost (test problem T2)

S. No	P_D(MW)	Algorithm	Operating cost ($/h)			StDev	Transmission losses (MW)
			Minimum	Maximum	Average		
1	1620	λ-method [1]	261.7302	NA	NA	NA	48.9322
		SS	260.4105	NA	NA	NA	49.3671
		TGA	259.5137	262.9294	259.7507	0.6621	49.5175
		CTGA	**259.4220**	**259.4951**	**259.4429**	**0.0153**	**49.5081**
2	2160	λ-method [1]	425.1728	NA	NA	NA	87.6685
		SS	430.8924	NA	NA	NA	87.7820
		TGA	421.1408	421.6534	421.3202	0.1085	87.2172
		CTGA	**420.9215**	**421.0843**	**421.0281**	**0.0292**	**87.1452**
3	2700	SPPO [19]	700.776	NA	NA	NA	141.642
		λ-method [1]	701.1019	NA	NA	NA	141.6387
		SS	752.6111	NA	NA	NA	143.1675
		TGA	700.8479	705.6429	701.8112	1.3118	141.610
		CTGA	**700.6863**	**700.8544**	**700.7541**	**0.0319**	**141.5813**
4	3240	λ-method [1]	1053.8530	NA	NA	NA	212.1329
		SS	1062.0280	NA	NA	NA	211.2516
		TGA	1052.9088	1053.9243	1053.3324	0.3204	207.3339
		CTGA	**1052.6980**	**1053.5350**	**1053.0122**	**0.2670**	**207.4302**

NA not available

Data in bold emphasis indicate results achieved by proposed algorithm

The respective generation schedules are detailed in Table 12. From Table 6, it is observed that the power balance equation is satisfied and converges to 0.0001 for all the power demands by taking 35740, 41620, and 38260 function evaluations, respectively.

Test Problem T3—Case 2 Case number two of the power system test problem T3 is a Taiwanese power system with 40 generators. In this problem, valve point loading effects are considered, thus making the problem non-convex in nature. Cost coefficients are taken from [54]. Transmission losses are neglected in this case. Table 6 shows the team size required to achieve the best solution. Results obtained by the proposed algorithm and TGA are compared with other contending algorithms in Table 13 for 5250-MW, 8400-MW, and 10,500-MW power demands. For 10,500-MW power demand, the contending algorithms are λ-method, improved particle swam optimization (IPSO) [56], self-tuning improved random drift particle swarm optimization (ST-IRDPSO) [58], MSOS [59], chaotic bat algorithm (CBA) [60], AGWO [31], cross-entropy and sequential quadratic programming (CE-SQP) [61], backtracking search algorithm (BSA) [62], emended salp swarm algorithm (ESSA) [35], hybrid artificial algae algorithm (HAAA) [63], conglomerated modified ion motion optimization and crisscross search optimizer (C-MIMO-CSO) [30], modified crow search algorithm (MCSA) [64], and SS method. It can be seen that the proposed algorithm competes well with the other algorithms used to solve the same problem. The performance of TGA is not satisfactory for the considered case. Modified symbiotic organisms search (MSOS) [59] performs better than all

Table 10 Generation schedule obtained by proposed method (test problem T2)

Unit i	P_i^{min}(MW)	P_D= 1620 MW		P_D= 2160 MW		P_D= 2700 MW		P_D= 3240 MW		P_i^{max}(MW)
		Fuel type,j	Power, P_i (MW)	Fuel type,j	Power, P_i (MW)	Fuel type,j	Power, P_i (MW)	Fuel type,j	Power, P_i (MW)	
1	100	1	140.3073	1	173.5112	2	222.9885	2	242.3312	250
2	50	3	129.3113	1	194.3410	1	217.8529	1	223.3061	230
3	200	1	200.0026	1	236.1499	1	294.7958	2	499.9161	500
4	99	1	120.6421	3	228.3967	3	243.4448	3	249.3696	265
5	190	1	190.0037	1	220.0150	1	335.2759	3	489.9769	490
6	85	2	119.6253	3	227.0262	3	243.2974	3	248.7946	265
7	200	1	200.0011	1	226.1244	1	306.0332	3	491.2632	500
8	99	1	118.3778	3	230.0089	3	242.9089	3	247.3481	265
9	130	1	251.2349	1	298.7931	3	439.8554	3	440.0000	440
10	200	1	200.0019	1	212.7789	1	295.1284	1	315.1245	490
$\sum P_i$(MW)		1669.5081		2247.1453		2841.5812		3447.4303		
P_L(MW)		49.5081		87.1452		141.5813		207.4302		

Table 11 Comparison of operating cost (test problem T3—case 1)

S. No	P_D(MW)	Algorithm	Operating cost ($/h)			StDev	Transmission losses (MW)
			Minimum	Maximum	Average		
1	5000	λ-method [1]	81259.2	NA	NA	NA	57.5648
		SS	81796.52	NA	NA	NA	58.9185
		TGA	81259.4519	81304.7147	81275.9311	12.2697	57.3351
		CTGA	**81259.2**	**81364.3201**	**81274.8765**	**21.4425**	**57.5521**
2	7000	λ-method [1]	100499.9	NA	NA	NA	81.8464
		Two phase NN [53]	105236.0	NA	NA	NA	142.0
		APSO[19]	101295.8	102057.2	103851.1	987.34	NA
		AGWO[31]	100499.9	100500.0	100500.0	0.020	81.8061
		IDBA[26]	100499.9	100500.0	100500.0	0.020	81.8061
		SS	103732.2	NA	NA	NA	88.6788
		TGA	100532.17	100729.08	100594.63	45.0560	83.844
		CTGA	**100499.97**	**100500.04**	**100499.99**	**0.020**	**81.8236**
3	8000	λ-method [1]	113572.8	NA	NA	NA	104.9377
		SS	115626.7	NA	NA	NA	103.6016
		TGA	113592.6078	114693.0617	114024.4694	447.4282	105.3501
		CTGA	**113572.81**	**114275.8544**	**113648.0702**	**209.5136**	**104.9407**

Data in bold emphasis indicate results achieved by proposed algorithm

NA not available

algorithms in terms of maximum and average values along with minimum StDev, but CTGA attains a slightly improved minimum value of operating cost as compared to it. Table 13 additionally compares the results obtained by the proposed method, CTGA with those from the λ-method, SS method, and TGA for demands of 5250 MW and 8400 MW. The proposed method performs better for all load levels. The respective generation schedules for the best trial out of 30 independent trials are tabulated in Table 15. In Table 6, it is observed that the power balance equation fully satisfies for load demands of 5250 MW and 8400 MW, requiring 262550 function evaluations each, while for 10500 MW, it converges to 0.001 with 241550 function evaluations.

Test Problem T3—Case 3 Under case 3 of power system test problem T3, transmission losses are considered in addition to case 2 of test problem T3 for 5250-MW, 8400-MW, and 10500-MW power demands. Cost coefficients are collected from [54], and *B*-coefficients are available in [55]. Table 6 shows the team size, N_P required to achieve the best solution. Table 14 presents a comparison of the operating cost obtained by the proposed algorithm for a 10,500-MW power demand with the best solutions achieved by the λ-method, MCSA [64], GWO [50], HAAA [63], AGWO [31], C-MIMO-CSO [30], MSOS [59], and SS method.

CTGA achieves a minimum value of operating cost that is extremely near the best value of operating cost, which is 136,431.2 ($/h), achieved by C-MIMO-CSO [30]. At the same time, the proposed algorithm has a lower average operating

Table 12 Generation schedule obtained by proposed method (test problem T3—case 1)

Unit *i*	P_i^{min}(MW) *i* j	Power demand, P_D (MW)			P_i^{max}(MW)	Unit *i*	P_i^{min}(MW)	Power demand, P_D (MW)			P_i^{max}(MW)
		5000	7000	8000				5000	7000	8000	
		P_i(MW)	P_i(MW)	P_i(MW)				P_i(MW)	P_i(MW)	P_i(MW)	
1	40	40	40.0014	80	80	22	254	306	460	460	550
2	60	60	94.552	100	120	23	254	320	460	460	550
3	80	80	135.9231	190	190	24	254	305.7635	459.9988	460	550
4	24	24	24.0073	42	42	25	254	288.0704	460	460	550
5	26	26	26.0001	42	42	26	254	280	460	460	550
6	68	68	88.5904	115	140	27	254	280.0709	459.9995	460	550
7	110	110	164.9999	165	300	28	10	10	10	13.0522	150
8	135	135	217	217	300	29	10	10	10.0001	13.4675	150
9	135	172.6472	264.9977	265	300	30	10	10	10	13.7386	150
10	130	130	130.0002	165	300	31	20	20	20.0001	20	70
11	94	205	205	320.7426	375	32	20	20	20	20	70
12	94	205	205	300.9396	375	33	20	20	20	20	70
13	125	125	125.0001	125.0001	500	34	20	20	20	20	70
14	125	125	125.001	280	500	35	18	18	18	18	60
15	125	125	125.001	270	500	36	18	18	18	18	60
16	125	125	125.0027	270	500	37	20	20	20	20	60
17	125	125	125	270	500	38	25	25	25	25	60
18	220	290	469.9828	470	500	39	25	25	25	25	60
19	220	290	467.0075	470	500	40	25	25	25	25	60
20	242	288	457.1636	468	550	$\sum P_i$(MW)		5057.5520	7081.8235	8104.9406	
21	242	288	465.5943	468	550	P_L(MW)		57.5521	81.8236	104.9407	

Table 13 Comparison of operating cost (test problem T3—case 2)

S. No	P_D(MW)	Algorithm	Operating cost ($/h)			StDev
			Minimum	Maximum	Average	
1	5250	λ-method [1]	68883.07	NA	NA	NA
		SS	71338.48	NA	NA	NA
		TGA	68303.8956	69194.1566	68656.0542	221.0552
		CTGA	**68243.3796**	**68864.9278**	**68442.2834**	**161.8990**
2	8400	λ-method [1]	101858.6	NA	NA	NA
		SS	103318.4	NA	NA	NA
		TGA	97209.9209	99980.9581	98461.6485	686.5087
		CTGA	**96793.7439**	**97888.1587**	**97329.0741**	**282.9078**
3	10500	λ-method [1]	124156.20	NA	NA	NA
		IPSO [56]	121403.5362 (121412.5362)[a]	121525.4934	121445.3269	32.4898
		ST-IRDPSO [58]	121412.535	NA	121443.792	33.44
		MSOS [59]	121412.5355	121412.5355	121412.5355	2.47×10^{-11}
		CBA [60]	121412.55	121436.15	121418.98	1.611
		AGWO [31]	121404.30 (121413.30)[a]	121446.70	121412.30	7.5040
		CE-SQP [61]	121412.88	121423.65	NA	NA
		BSA [62]	121415.6139	121474.8823	121524.9577	NA
		ESSA [35]	121412.5	121517	121450.6	31.0236
		HAAA [63]	121412.7	121438	121434.8	4.574287
		C-MIMO-CSO [30]	121412.5	121517.8	121454.2	28.8122
		MCSA [64]	121412.14	121414.324	121413.4419	0.8761
		SS	129477.60	NA	NA	NA
		TGA	121585.735	121979.768	121777.523	132.801
		CTGA	**121412.529**	**121528.845**	**121451.603**	**46.3223**

Data in bold emphasis indicate results achieved by proposed algorithm

NA not available

[a] Actual calculated cost from the given generation schedule

cost than C-MIMO-CSO (6.673 $/h). It can be concluded that the proposed algorithm is superior to C-MIMO-CSO in terms of improved average value, maximum value, and StDev. CTGA calculates transmission losses that are higher than TGA and C-MIMO-CSO [30]. As far as the overall performance of CTGA is concerned, it can be concluded that the proposed algorithm performs better and competes well in terms of robustness. Table 14 also provides a comparison of the operating costs for demands of 5250 MW and 8400 MW where CTGA performs competitively better than the λ-method, SS method, and TGA. The generation schedules obtained by implementing the proposed algorithm are tabulated in Table 15. In Table 6, the power balance equation is met for a 10500-MW demand with 507040 function evaluations, while converging to 0.0001 for demands of 5250 MW and 8400 MW with 650,040 function evaluations.

Table 14 Comparison of operating cost (test problem T3—case 3)

S. No	P_D(MW)	Algorithm	Operating cost ($/h)			StDev	Transmission losses (MW)
			Minimum	Maximum	Average		
1	5250	λ-method [1]	70842.24	NA	NA	NA	235.8208
		SS	74370.91	NA	NA	NA	230.1815
		TGA	70514.7671	72077.2577	71138.1832	368.7746	228.9924
		CTGA	**70088.3049**	**71121.1636**	**70557.7196**	**280.7610**	**225.1539**
2	8400	λ-method [1]	109308.7	NA	NA	NA	598.7468
		SS	111094.5	NA	NA	NA	666.7378
		TGA	103972.4217	107293.5954	105129.3268	861.9339	562.6399
		CTGA	**103237.6508**	**104556.7887**	**103775.4027**	**358.5872**	**566.8046**
3	10500	λ-method [1]	138767.7	NA	NA	NA	962.8763
		MCSA [64]	136448.6295	136448.9490	136448.7158	1.1005	957.4059
		GWO [50]	136446.85	136492.07	136463.96	0.098	973.2875
		HAAA [63]	136433.5	136443.4	136436.6	3.341896	971.7169
		AGWO [31]	136426.90 (136435.90)[a]	136459.00	136621.00	42.773	971.698
		C-MIMO-CSO [30]	136431.2	136576.5	136474	64.329	957.363
		MSOS [59]	136442.4827	136449.3511	136445.0400	1.99	972.3456
		SS	138286.2	NA	NA	NA	987.8301
		TGA	136446.991	137430.085	136823.599	290.232	958.172
		CTGA	**136431.969**	**136573.776**	**136467.327**	**51.805**	**971.714**

Data in bold emphasis indicate results achieved by proposed algorithm

NA not available

[a] Actual calculated cost from the given generation schedule

Table 15 Generation schedule obtained by proposed method (test problem T3—cases 2 and 3)

Unit i	P_i^{min} (MW)	P_D= 5250 MW		P_D= 8400 MW		P_D= 10,500 MW		P_i^{max} (MW)
		Case 2	Case 3	Case 2	Case 3	Case 2	Case 3	
		P_i(MW)	P_i(MW)	P_i(MW)	P_i(MW)	P_i(MW)	P_i(MW)	
1	36	73.3999	108.5783	110.7998	110.7998	110.7998	114	114
2	36	73.3999	110.7998	110.7998	110.7998	110.7998	114	114
3	60	60	60	77.8653	97.3999	97.3999	120	120
4	80	80	80	80	179.7331	179.7331	179.7331	190
5	47	47	47	87.7999	87.7999	87.7999	87.7999	97
6	68	68	68	68	68	140	140	140
7	110	110	110	259.5996	259.5996	259.5997	300	300
8	135	135	135	284.5996	284.5996	284.5997	289.4324	300
9	135	135	135	209.7998	284.5996	284.5997	300	300
10	130	130	130	130	130	130	279.5996	300
11	94	94	94	94	94	94	243.5996	375
12	94	94	94	94	94	94	94	375
13	125	125	125	125	125	214.7598	484.0391	500
14	125	125	125	125	214.7597	394.2794	484.0391	500
15	125	125	125	125	125	394.2794	484.0391	500
16	125	125	125	125	214.7597	394.2794	484.0391	500
17	220	220	220	399.5195	220	489.2794	489.2793	500
18	220	220	220	399.5195	220	489.2794	489.2793	500
19	242	242	242	421.5195	511.2793	511.2794	511.2793	550
20	242	242	242	331.7597	511.2793	511.2794	511.2793	550
21	254	254	254	523.2793	523.2793	523.2794	523.2793	550
22	254	254	433.5195	523.2793	523.2793	523.2794	523.2793	550
23	254	254	254	523.2793	523.2793	523.2794	523.2793	550
24	254	254	254	523.2793	523.2793	523.2794	523.2793	550
25	254	254	254	523.2793	523.2793	523.2794	523.2793	550
26	254	254	254	433.5195	523.2793	523.2794	523.2793	550
27	10	10	10	10	10	10	10	150
28	10	10	10	10	10	10	10	150
29	10	10	10	10	10	10	10	150
30	47	47	47	87.7999	87.7999	87.7999	87.7999	97
31	60	159.7331	159.7331	159.7331	188.9834	190	190	190
32	60	159.7331	159.7331	159.7331	189.2890	190	190	190
33	60	60	159.7331	159.7331	189.4246	190	190	190
34	90	90	90	164.7998	164.7998	164.7998	200	200
35	90	90	90	164.7998	164.7998	200	200	200
36	90	90	90	164.7998	90	194.3977	164.7998	200
37	25	87.5626	57.0570	89.1141	89.1141	110	110	110
38	25	57.0570	25	89.1141	89.1141	110	110	110
39	25	89.1141	25	89.1141	89.1141	110	110	110
40	242	242	242	331.7597	511.2793	511.2794	550	550

Table 15 (continued)

Unit i	P_i^{min} (MW)	P_D= 5250 MW		P_D= 8400 MW		P_D= 10,500 MW		P_i^{max} (MW)
		Case 2	Case 3	Case 2	Case 3	Case 2	Case 3	
		P_i(MW)	P_i(MW)	P_i(MW)	P_i(MW)	P_i(MW)	P_i(MW)	
$\sum P_i$(MW)		5250	5475.1541	8400	8966.8045	10499.999	11471.714	
P_L(MW)		0	225.1540	0	566.8046	0	971.714	

Test Problem T3—Case 4 Case 4 of the power system test problem T3 is a 40-generator system with demands of 6480 MW, 8640 MW, 10,800 MW, and 12,960 MW. In the undertaken case, multi-fuel options are considered, and cost coefficients for multiple fuels are referenced in [52]. The team size, N_P needed to achieve the optimal solution is shown in Table 6. In Table 16, the operating cost obtained by the proposed algorithm for demand of 10,800 MW is compared with other well-performing algorithms like the one-rank cuckoo search algorithm (ORCSA) [65], the improved genetic algorithm with multiplier updating

Table 16 Comparison of operating cost (test problem T3—case 4)

S. No	P_D(MW)	Algorithm	Operating cost ($/h)			StDev
			Minimum	Maximum	Average	
1	6480	λ-method [1]	996.9459	NA	NA	NA
		SS	1005.356	NA	NA	NA
		TGA	996.9039	1005.787	999.6952	2.2532
		CTGA	**996.5658**	**1002.84**	**998.5727**	**1.4920**
2	8640	λ-method [1]	1562.717	NA	NA	NA
		SS	1706.288	NA	NA	NA
		TGA	1562.6154	1571.4992	1566.1524	2.3460
		CTGA	**1560.8528**	**1563.1224**	**1561.2425**	**0.3733**
3	10,800	λ-method [1]	2510.0930	NA	NA	NA
		ORCSA [65]	2495.957	2498.15	2496.628	0.4966
		IGA-MU [52]	2499.824	NA	NA	NA
		CGA-MU [52]	2500.922	NA	NA	NA
		C-MIMO-CSO [30]	2495.683	2499.325	2496.885	0.7888
		BSA [62]	2496.817	NA	NA	NA
		SS	2797.203	NA	NA	NA
		TGA	2497.628	2499.946	2498.321	0.6940
		CTGA	**2496.575**	**2498.073**	**2497.007**	**0.5482**
4	12,960	λ-method [1]	3711.554	NA	NA	NA
		SS	3754.937	NA	NA	NA
		TGA	3702.1449	3725.4176	3707.6294	5.3082
		CTGA	**3700.7381**	**3703.2216**	**3701.4544**	**0.8890**

Data in bold emphasis indicate results achieved by proposed algorithm

NA not available

(IGA-MU) [52], the conventional genetic algorithm with multiplier updating (CGA-MU) [52], the C-MIMO-CSO [30], BSA [62], and SS method.

The simplex search (SS) method yields the worst value of operating cost as multi-fuel options are considered in this case, which increases the complexity of the problem. CTGA is the algorithm with the lowest maximum value of operating costs. CTGA's minimum operating cost is not lower than that of C-MIMO-CSO [30] and ORCSA [65]. However, in terms of robustness, CTGA outperforms C-MIMO-CSO [30], as the former has a lower standard deviation than the latter. CTGA's performance is also superior to that of TGA.

Table 16 also provides a comparison of the results obtained by CTGA with those from the λ-method, SS method, and TGA for demands of 6480 MW, 8640 MW, and 12,960 MW. The results obtained through the implementation of CTGA surpass those achieved by the λ-method, SS method, and TGA. Table 17 presents the generation schedules of the best trial by the proposed algorithm. In Table 6, for 8640-MW and 10,800-MW demands, the power balance equation converges to 0.0001 with 121,175 and 154,750 function evaluations, while fully satisfied for 6480 MW and 12,960 MW with 127,550 and 184,500 function evaluations, respectively.

Test Problem T4 The power system of test problem T4 is in the category of very large systems. A 140-generator Korean power system with valve point loading effect is considered with load demands of 3700 6 MW, 49342 MW and 54276 MW. The team size, N_P needed to achieve the optimal solution is shown in Table 6. POZs and ramp-rate limits are the constraints, along with equality and inequality constraints. Data for cost coefficients, ramp-rate limits, and POZs is taken from [56]. The proposed algorithm is implemented on the system, and the results are tabulated in Table 18 for comparison. The results for the demand 49342 MW are compared with the results obtained from Continuous quick group search optimizer (CQGSO) [66], Group search optimizer (GSO) [66], PSO with proposed constraint treatment strategy (CTPSO) [56], SPPO [19], AGWO [31] and SS method. For demands of 37006 MW and 54276 MW the obtained results by CTGA are compared with SS method and TGA.

From the comparison shown in Table 18, the minimum operating cost for power demand of 49342 MW, obtained by CTGA is 1655652.81 ($/h) which is less than the best solution available in the literature, which is 1655685 ($/h) [56]. The proposed algorithm performs amazingly for this system and submits the lowest minimum value of operating cost in the literature of power system test problems. Table 19 tabulates the corresponding generation schedule of the best trial for 49342-MW power demand. In Table 6, it is observed that the power balance equation is satisfied and converges to 0.0001 for 37006-MW, 49342-MW, and 12960-MW power demand when taking 226860 252060 and 221190 function evaluations, respectively.

Table 17 Generation schedule obtained by proposed method (test problem T3—case 4)

Unit i	P_i^{min}(MW)	P_D= 6480 MW		P_D= 8640 MW		P_D= 10,800 MW		P_D= 12,960 MW		P_i^{max}(MW)
		Fuel type,j	Power,P_i(MW)	Fuel type,j	Power,P_i(MW)	Fuel type,j	Power,P_i(MW)	Fuel type,j	Power,P_i(MW)	
1	100	1	135.5534	1	168.2823	2	222.9589	2	241.6245	250
2	50	3	123.0262	1	192.0863	1	211.1775	1	223.3192	230
3	200	1	200	1	220.9881	1	286.0587	2	499.9637	500
4	99	1	109.4964	3	223.6956	3	241.039	3	249.2311	265
5	190	1	190	1	199.5915	1	277.1374	1	319.6209	490
6	85	2	111.4862	3	225.6774	3	238.4659	3	246.107	265
7	200	1	200	1	209.0285	1	286.7154	2	355.3204	500
8	99	1	109.4472	3	223.5628	3	239.8282	3	246.9316	265
9	130	1	244.5935	1	293.8504	3	427.0272	3	439.963	440
10	200	1	200	1	202.6091	1	272.0018	1	315.1816	490
11	100	1	137.9208	1	166.3971	2	218.5298	2	244.6484	250
12	50	3	121.5064	1	192.1433	1	211.6281	1	222.8005	230
13	200	1	200	1	219.0247	1	282.5818	2	499.9584	500
14	99	1	108.6871	3	223.9697	3	238.1976	3	247.4653	265
15	190	1	190	1	200.5683	1	278.5842	1	317.3087	490
16	85	2	109.7549	3	225.9611	3	240.8716	3	249.8749	265
17	200	1	200	1	211.5561	1	286.7937	2	496.5659	500
18	99	1	109.4586	3	221.1377	3	240.7725	3	247.477	265
19	130	1	245.693	1	294.0559	3	431.8185	3	439.9276	440
20	200	1	200	1	200.0227	1	273.7173	1	318.444	490
21	100	1	136.3744	1	171.2702	2	220.7327	2	242.6626	250
22	50	3	105.5906	1	189.1258	1	214.6103	1	225.3229	230

Table 17 (continued)

Unit$i$	P_i^{min}(MW)	P_D= 6480 MW		P_D= 8640 MW		P_D= 10,800 MW		P_D= 12,960 MW		P_i^{max}(MW)
		Fuel type,j	Power,P_i(MW)	Fuel type,j	Power,P_i(MW)	Fuel type,j	Power,P_i(MW)	Fuel type,j	Power,P_i(MW)	
23	200	1	200	1	222.5031	1	280.8354	2	499.7331	500
24	99	1	109.1428	3	223.8351	3	238.6155	3	249.628	265
25	190	1	190	1	195.5819	1	278.8862	1	316.3301	490
26	85	2	110.9631	3	226.4883	3	240.87	3	246.3786	265
27	200	1	200	1	205.1345	1	290.2688	2	486.3004	500
28	99	1	110.9645	3	227.6073	3	239.8225	3	248.8122	265
29	130	1	246.2521	1	292.992	3	421.3494	3	439.8739	440
30	200	1	200	1	203.6466	1	275.1907	1	310.8442	490
31	100	1	136.3397	1	168.7101	2	217.9243	2	242.4006	250
32	50	3	122.938	1	192.3749	1	212.9755	1	229.0766	230
33	200	1	200	1	223.3972	1	279.3961	2	499.8999	500
34	99	1	110.9865	3	224.4998	3	236.8643	3	248.0201	265
35	190	1	190	1	199.5812	1	275.7222	1	323.1855	490
36	85	2	109.1858	3	225.2851	3	240.7535	3	248.5277	265
37	200	1	200	1	215.7469	1	287.534	2	480.0393	500
38	99	1	109.4926	3	225.722	3	238.8815	3	248.5455	265
39	130	1	245.1462	1	292.2766	3	426.9403	3	439.9606	440
40	200	1	200	1	200.0132	1	275.9218	1	312.7246	490
$\sum P_i$(MW)		6480		8640		10800		12960		

Table 18 Comparison of operating cost (test problem T4)

S. No	P_D(MW)	Algorithm	Operating cost ($/h)			StDev
			Minimum	Maximum	Average	
1	37006	SS	1319410.7277	NA	NA	NA
		TGA	1230447.794	1241469.247	1238178.595	5995.4190
		CTGA	**1223338.264**	**1241046.533**	**1234007.062**	**2822.8694**
2	49342	CQGSO [66]	1657962.727	1657962.741	1657962.776	NA
		GSO [66]	1728151.168	1745514.9975	1753229.5636	NA
		CTPSO [56]	1655685	1655685	1655685	7.3150
		SPPO [19]	1657962.0	NA	NA	NA
		AGWO [31]	1657962.0	1657964.0	1657963.0	0.54820
		SS	1839631.3412	NA	NA	NA
		TGA	1660129.604	1675533.494	1667438.897	4388.3463
		CTGA	**1655652.812**	**1659546.072**	**1657975.670**	**917.5395**
3	54276	SS	2089032.3256	NA	NA	NA
		TGA	2033223.913	2052423.854	2043097.79	6349.9796
		CTGA	**2033077.729**	**2051513.639**	**2041650.141**	**5093.5157**

Data in bold emphasis indicate results achieved by proposed algorithm

NA not available

[a] Actual calculated cost from the given generation schedule

Test Problem T5—Case 1 A multi-objective optimization problem is undertaken in the power system test problem T5 with 1620-MW, 2160-MW, 2700-MW, and 3240-MW power demands. Input data for cost coefficients for multiple fuels and POZs is referred to in [52]. *B*-coefficients are taken from [19], and data on CO_2 emissions is taken from [57]. In case 1 of the problem, transmission losses and valve-point loading effects are considered, along with multi-fuel options. The team size, N_P, needed to achieve the optimal solution is shown in Table 6. For load demand of 2700 MW, results obtained by TGA and the proposed algorithm are compared with the results obtained by λ-method, SS method, and APPO [40]. TGA obtains a lesser emission than that obtained by APPO [40] and CTGA. But in terms of fuel cost and combined objective function, the proposed algorithm performs best among all the three algorithms available for comparison. Table 20 also presents a comparison of the results obtained by CTGA with λ-method, SS method, and TGA for demands of 1620 MW, 2160 MW, and 3240 MW.

The generation schedules corresponding to the tabulated optimal solutions of the proposed algorithm for 1620-MW, 2160-MW, 2700-MW, and 3240-MW power demands are presented in Table 21. The price penalty factor method applied in this paper to incorporate economic emission dispatch by converting a multi-objective problem into a scalar optimization problem proves to be an efficient method to solve the EEPD problem. Different values of PPF calculated for test problem T5 are shown in Table 22. In Table 6, it is observed that the power balance equation is satisfied and converges to 0.1472 when taking 251,430 function evaluations for

Table 19 Generation schedule obtained by proposed method (test problem T4)

Unit i	Power (MW)			Unit i	Power (MW)			Unit i	Power (MW)		
	P_i^{min}	P_i	P_i^{max}		P_i^{min}	P_i	P_i^{max}		P_i^{min}	P_i	P_i^{max}
1	71	119	119	48	160	250	250	95	795	837.5	978
2	120	189	189	49	160	250	250	96	578	682	682
3	125	190	190	50	160	250	250	97	615	720	720
4	125	190	190	51	165	165.04291	504	98	612	718	718
5	90	168.41867	190	52	165	165.0669	504	99	612	720	720
6	90	190	190	53	165	169.87511	504	100	758	964	964
7	280	490	490	54	165	165.49411	504	101	755	958	958
8	280	490	490	55	180	180.12429	471	102	750	965.9	1007
9	260	496	496	56	180	180.54946	561	103	750	952	1006
10	260	496	496	57	103	103.0253	341	104	713	935	1013
11	260	496	496	58	198	198.75697	617	105	718	876.5	1020
12	260	496	496	59	100	312	312	106	791	880.9	954
13	260	506	506	60	153	312.06461	471	107	786	873.7	952
14	260	509	509	61	163	164.02269	500	108	795	877.4	1006
15	260	506	506	62	95	95.54177	302	109	795	871.7	1013
16	260	505	505	63	160	511	511	110	795	864.8	1021
17	260	506	506	64	160	511	511	111	795	882	1015
18	260	506	506	65	196	490	490	112	94	94.02435	203
19	260	505	505	66	196	196.30141	490	113	94	94.182718	203
20	260	505	505	67	196	490	490	114	94	94.290366	203
21	260	505	505	68	196	490	490	115	244	244.80112	379
22	260	505	505	69	130	133.13361	432	116	244	244.48207	379
23	260	505	505	70	130	339.65306	432	117	244	246.19085	379
24	260	505	505	71	137	153.37611	455	118	95	95.18253	190
25	280	537	537	72	137	455	455	119	95	95.211572	189
26	280	537	537	73	195	195.0527	541	120	116	116.07374	194
27	280	549	549	74	175	229.93675	536	121	175	175.09067	321
28	280	549	549	75	175	212.35184	540	122	2	2.026028	19
29	300.1	501	501	76	175	268.88947	538	123	4	4.03044	59
30	260	499	499	77	175	235.51898	540	124	15	15.135148	83
31	260	506	506	78	330	330.25249	574	125	9	9.243028	53
32	260	506	506	79	160	531	531	126	12	12.661556	37
33	260	506	506	80	160	531	531	127	10	10.0047	34
34	260	506	506	81	200	542	542	128	112	112.0268	373
35	260	500	500	82	56	56.072838	132	129	4	4.00212	20
36	260	500	500	83	115	115.03304	245	130	5	5.145779	38
37	120	241	241	84	115	115.04225	245	131	5	5.034475	19
38	120	241	241	85	115	115.15404	245	132	50	50.109072	98
39	423	774	774	86	207	209.34182	307	133	5	5.001375	10
40	423	769	769	87	207	207.05642	307	134	42	42.048772	74
41	3	3.001181	19	88	175	175.19467	345	135	42	42.07046	74

Table 19 (continued)

Unit i	Power (MW)			Unit i	Power (MW)			Unit i	Power (MW)		
	P_i^{min}	P_i	P_i^{max}		P_i^{min}	P_i	P_i^{max}		P_i^{min}	P_i	P_i^{max}
42	3	3.217113	28	89	175	176.34826	345	136	41	41.042265	105
43	160	250	250	90	175	175.93188	345	137	17	17.025588	51
44	160	250	250	91	175	177.85215	345	138	7	7.831392	19
45	160	250	250	92	360	575.4	580	139	7	7.086081	19
46	160	250	250	93	415	547.5	645	140	26	26.149996	40
47	160	250	250	94	795	836.8	984	Total generation, $\sum P_i$ (MW) = 49341.9999			

2700 MW. The proposed algorithm calculates each value of PPF for case 1 of the problem in a single trial run to analyze the effects of different values of PPF, fuel cost, emission, and the combined objective function. It is clear from Table 22 that the minimum value of the combined objective function is obtained with the minimum value of PPF given by h_{f1} in this problem.

Test Problem T5—Case 2 In case 2 of problem T5, prohibited operating zones are considered in addition to the aspects considered in case 1 of the same problem. This is implemented for the first time as clarified in the literature, in which the valve point loading effect is considered while meeting equality and inequality constraints, along with prohibited operating zones and ramp limits. The team size, N_P, needed to achieve the optimal solution is shown in Table 6. The proposed algorithm produces impressive results, as fuel costs 703.6986 \$/h and gaseous pollutant emissions for 2700-MW power demand are reduced to 680.8178 lb. The optimal solution obtained by the proposed algorithm for load demands of 1620 MW, 2160 MW, 2700 MW, and 3240 MW is given in Table 20 and their generation schedules are given in Table 21. Table 20 also compares the results with λ-method, SS, and TGA for all demands. In Table 6, it is observed that the power balance equation nearly satisfies, converging to 0.0002 for power demands of 1620 MW and 2160 MW and to 0.1472 for the 2700-MW demand with 201,660 function evaluations. Additionally, it is fully met for the demand of 3240 MW with 199540 function evaluations.

6 Statistical Analysis

To verify the superiority of results statistically obtained by CTGA, various test problems are undertaken for study as per the complexity level of the problem. Thirty independent trials have been conducted on all test problems by implementing the proposed algorithm and TGA. Performance is analyzed as follows:

Table 20 Comparison of optimal solution (test problem T5)

P_D(MW)	Case	Algorithm	Fuel cost, $F_1(P)$ (\$/h)	Emission, (F_2P) (lb/h)	Combined objective function, $F_T(P)$ (\$/h)
1620	Case 1	λ-method [1]	261.5677	204.4828	262.1693
		SS	260.4422	210.8628	261.0626
		TGA	259.5267	203.9609	260.1268
		CTGA	**259.4414**	**204.2712**	**260.0424**
	Case 2	λ-method [1]	261.5861	204.3246	262.1872
		SS	260.0528	207.9889	260.6647
		TGA	259.5156	204.3676	260.1168
		CTGA	**259.4378**	**203.2547**	**260.0358**
2160	Case 1	λ-method [1]	426.7945	1512.9590	431.2453
		SS	426.0679	767.4165	428.3255
		TGA	421.4629	537.02637	423.0428
		CTGA	**421.3309**	**530.9456**	**422.8928**
	Case 2	λ-method [1]	427.9174	1088.8450	431.1206
		SS	473.2022	464.4877	474.5686
		TGA	421.6831	496.5152	423.1438
		CTGA	**421.4895**	**492.5902**	**422.9387**
2700	Case 1	APPO [40]	705.3203	777.5358	NA
		λ-method [1]	708.5110	28138.8500	791.2906
		SS	708.5046	1259.5360	712.21
		TGA	705.5369	709.0304	707.9410
		CTGA	**701.7467**	**798.2536**	**704.1114**
	Case 2	λ-method [1]	711.1426	46728.7	848.6103
		SS	705.5560	955.3428	708.3664
		TGA	703.8918	658.0352	706.0899
		CTGA	**703.6986**	**680.8178**	**705.7230**
3240	Case 1	λ-method [1]	1074.11	13028.97	1112.4390
		SS	1053.4240	3752.3320	1064.4630
		TGA	1053.1672	2540.6941	1060.6415
		CTGA	**1053.0877**	**2525.3658**	**1060.5169**
	Case 2	λ-method [1]	1067.0490	3455.5370	1077.2140
		SS	1054.7670	3418.6440	1064.8240
		TGA	1053.389	2473.005	1060.6641
		CTGA	**1053.1941**	**2491.8349**	**1060.5247**

Data in bold emphasis indicate results achieved by proposed algorithm

6.1 Convergence Behaviour

For the investigation into the convergence behaviour of CTGA, the following test problems are considered: T1 with exact *B*-coefficients, T3 case 2 featuring a power demand of 10,500 MW (includes complications of valve point loading effects), T4 with a power demand of 49,342 MW (maximum search variables), and T5 case 1 with a power demand of 2700 MW (involves the highest

Table 21 Generation schedule obtained by proposed method (test problem T5—case 1)

Unit i	P_i^{min}(MW)	P_D= 1620 MW		P_D= 2160 MW		P_D= 2700 MW		P_D= 3240 MW		P_i^{max}(MW)
		Fuel type,j	Power, P_i (MW)	Fuel type,j	Power, P_i (MW)	Fuel type,j	Power, P_i (MW)	Fuel type,j	Power, P_i (MW)	
Test problem T5—case 1										
1	100	1	141.8875	1	175.9932	2	222.9885	2	229.2968	250
2	50	3	126.1642	1	195.3203	1	217.8529	1	221.5622	230
3	200	1	200.0102	1	217.4577	1	294.7958	2	499.6875	500
4	99	1	119.5882	3	230.146	3	243.4448	3	251.511	265
5	190	1	190.0057	1	218.6228	1	335.2759	3	489.8746	490
6	85	2	121.305	3	229.9883	3	243.2974	3	253.0981	265
7	200	1	200.0493	1	230.3521	1	306.0332	3	499.887	500
8	99	1	119.8249	3	229.7436	3	242.9089	3	250.5704	265
9	130	1	250.6814	1	304.3902	3	439.8554	3	439.914	440
10	200	1	200.001	1	215.2805	1	295.1284	1	311.6957	490
$\sum P_i$ (MW)		1669.5174		2247.2947		2841.5812		3447.0973		
P_L (MW)		49.5172		87.2945		141.434		207.0973		
Test problem T5—case 2										
1	100	1	136.3727	1	177.197	2	222.9885	2	227.6223	250
2	50	3	122.995	1	195.8155	1	217.8529	1	222.7998	230
3	200	1	200.0144	1	214.9123	1	294.7958	2	499.6914	500
4	99	1	109.9073	3	229.4742	3	243.4448	3	252.3172	265
5	190	1	190.0392	1	223.2051	1	335.2759	3	489.9842	490
6	85	1	151.8075	3	229.9876	3	243.2974	3	253.7699	265
7	200	1	200.0487	1	228.7139	1	306.0332	3	499.9469	500
8	99	1	111.8388	3	229.4742	3	242.9089	3	249.7642	265
9	130	1	246.2537	1	304.3804	3	439.8554	3	439.9599	440

Table 21 (continued)

Unit i	P_i^{min}(MW)	P_D= 1620 MW		P_D= 2160 MW		P_D= 2700 MW		P_D= 3240 MW		P_i^{max}(MW)
		Fuel type,j	Power, P_i (MW)	Fuel type,j	Power, P_i (MW)	Fuel type,j	Power, P_i (MW)	Fuel type,j	Power, P_i (MW)	
10	200	1	200.0199	1	214.1246	1	295.1284	1	311.1761	490
$\sum P_i$ (MW)		1669.2973		2247.2846		2841.5812		3447.0319		
P_L (MW)		49.2973		87.2846		140.9383		207.0319		

Table 22 Different values of PPF (test problem T5) for case 1

PPF, h_{fi}(\$/lb)	$i = 1$ 2.94E−03	$i = 2$ 1.07E−01	$i = 3$ 5.28E−03	$i = 4$ 1.93E−01	h_f(\$/lb) 2.94E−03
$F_1(P)$ (\$/h)	701.5335	715.9342	701.9835	727.1855	701.5335
$F_2(P)$ (lb/h)	846.5655	241.7786	758.9625	171.8989	846.5655
$F_T(P)$ (\$/h)	704.0239	741.8830	705.9938	760.3223	704.0239

i=4 considers the PPF value $h_f = min\{h_{fi}; i \in [1,4]\}$

intricacies of computations). Convergence curves are drawn for each system with the results of the best trial of TGA and CTGA for 200 iterations; after that, no improvement in the global best solution is observed. Figure 5 shows the almost same convergence behaviour of the proposed algorithm, CTGA, and TGA for test problem T1. Figures 6 and 7 depict the convergence behaviour of CTGA and TGA, respectively, for test problem T3 case 2 and test problem T4. The comparison between the two curves derived from the results of CTGA and TGA clearly indicates that the proposed algorithm converges more precisely and faster to the global best solution as compared to TGA.

Figure 8 depicts the convergence behaviour of the proposed algorithm, CTGA, and TGA for test problem T5 case 1. It is clear from the figures that the proposed algorithm achieves a value near the optimal solution quickly and then reduces it gently, whereas TGA is unable to achieve the optimal solution

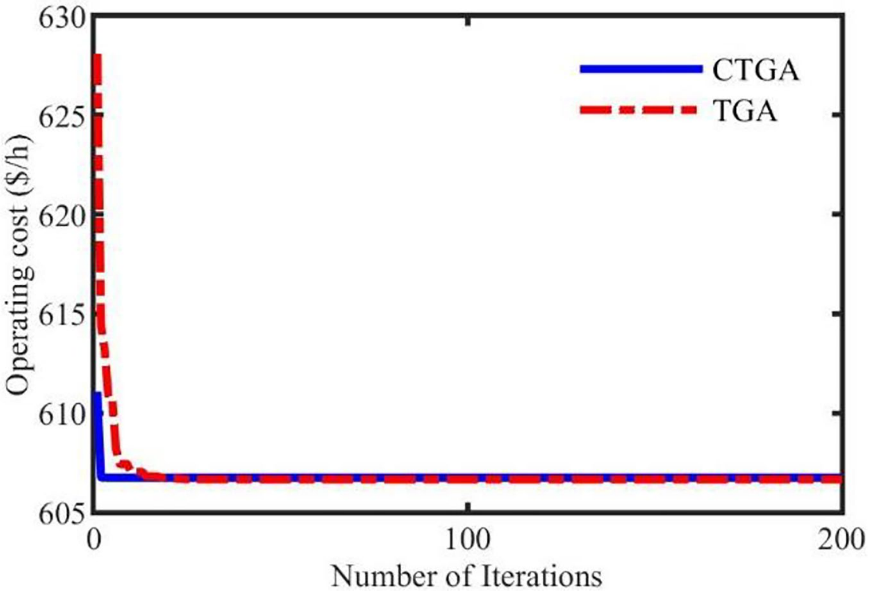


Fig. 5 Convergence curves of test problem T1

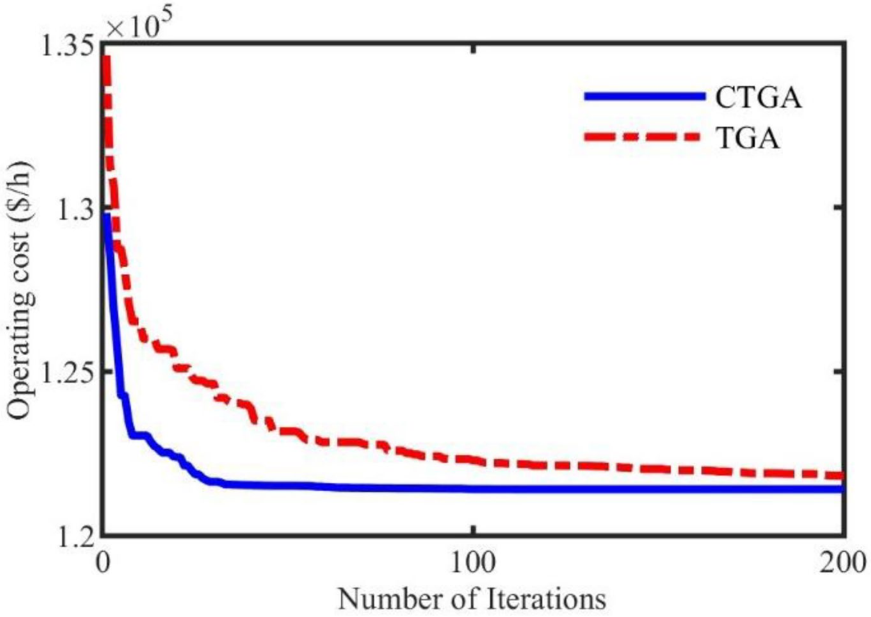


Fig. 6 Convergence curves of test problem T3—case 2

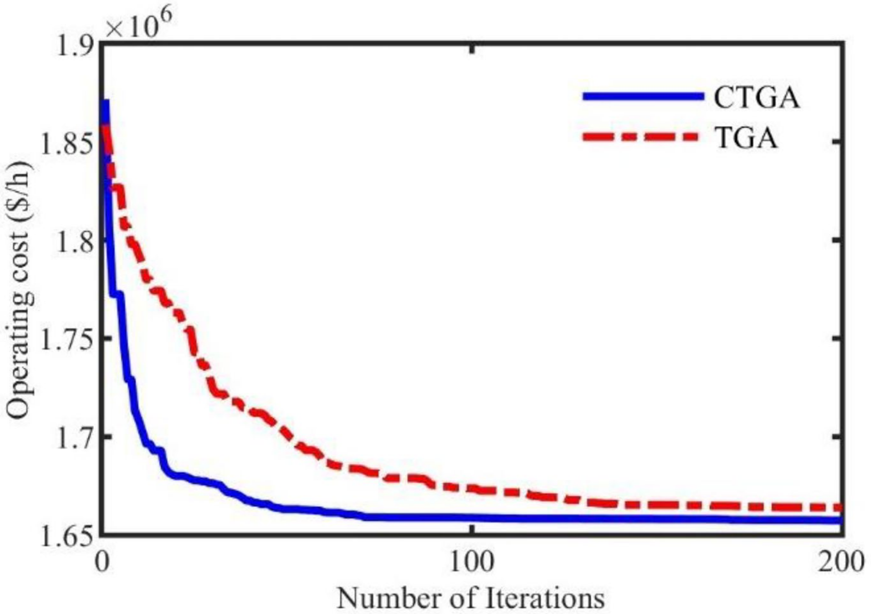


Fig. 7 Convergence curves of test problem T4

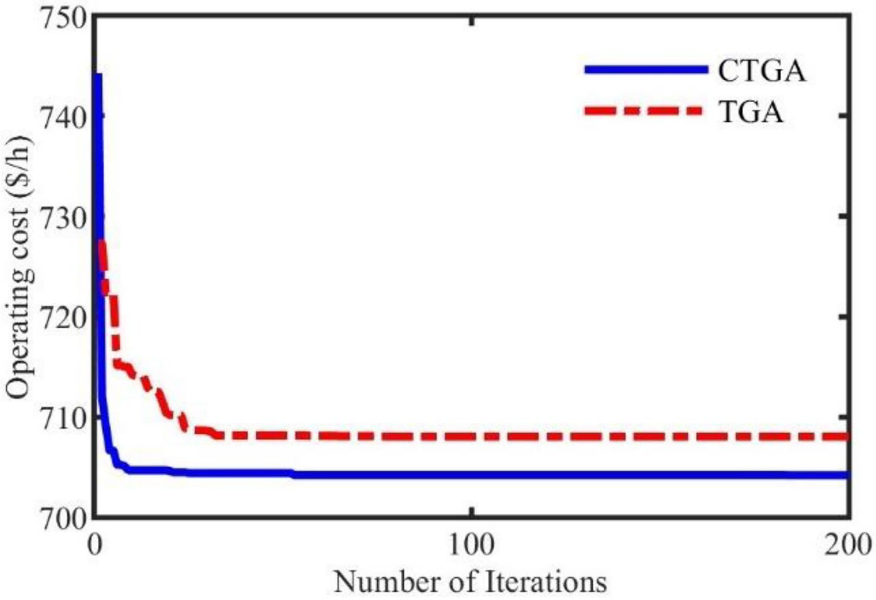


Fig. 8 Convergence curves of test problem T5—case 1

and stabilizes at a value greater than the desired one (near the global solution). Hence, it can be concluded that CTGA is a better performer than TGA in terms of convergence behaviour and proves to be an efficient algorithm to target the global best solution without getting stuck at a local solution.

6.2 Robustness

To assess the robustness and effectiveness of the proposed algorithm in consistently achieving optimal solutions, we consider test problems T1 and T2 for a 2700-MW power demand and T3 case 1 for a 7000-MW power demand. Box plots are drawn for each problem, and the performance of the proposed algorithm and TGA is compared. In Fig. 9, the whiskers box plot to test problem T1 is plotted. Figure 10 depicts that the solutions obtained by CTGA after 30 independent trial runs of test problem T2 are in a narrow band. Upper and lower quartiles nearly coincide with the mean value (second quartile). Most of the solutions lie in the upper quartile, whereas some of the solutions obtained by TGA are outliers, and the minimum value is higher than that of CTGA.

Further, as illustrated in Fig. 11 for test problem T3 case 1, the solutions obtained by the proposed algorithm have coinciding minimum, maximum, and mean values. On the other hand, the solutions yielded by TGA lie mostly in the upper quartile, and their maximum and minimum values are worse than CTGA, as shown in the whiskers box plot.

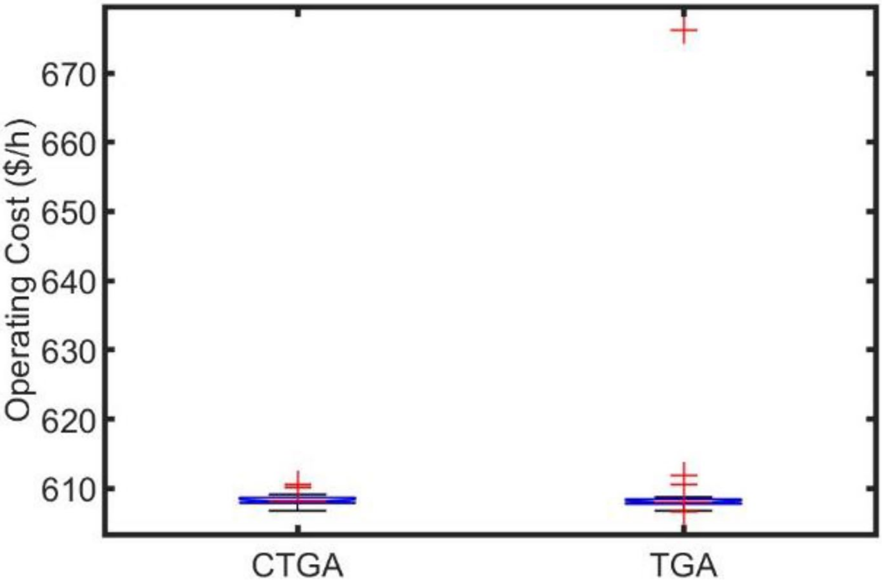


Fig. 9 Box plot of test problem T1

A similar pattern has been observed in all of the other problems tackled. TGA has outliers. CTGA gives better results than the results of TGA. CTGA performs very well as all the solutions are concentrated in the second quartile, with the

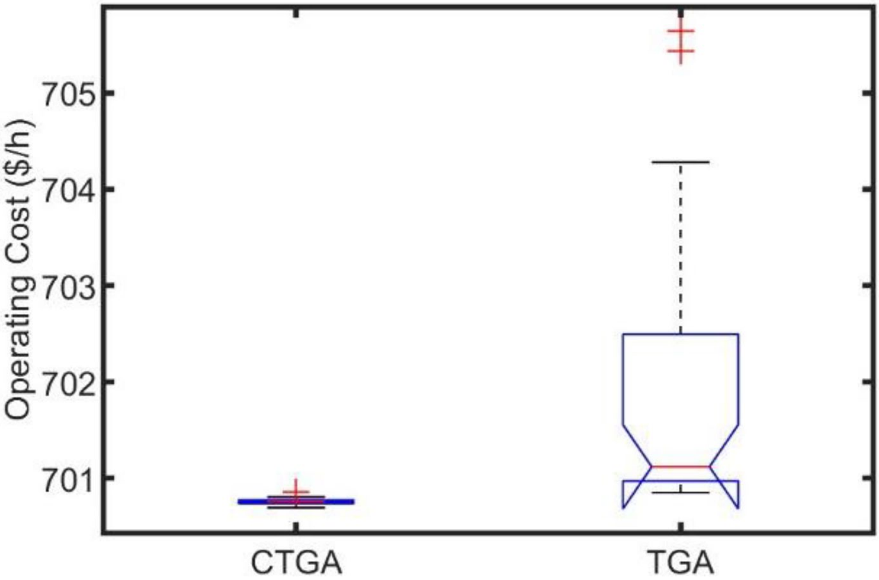


Fig. 10 Box plot of test problem T2

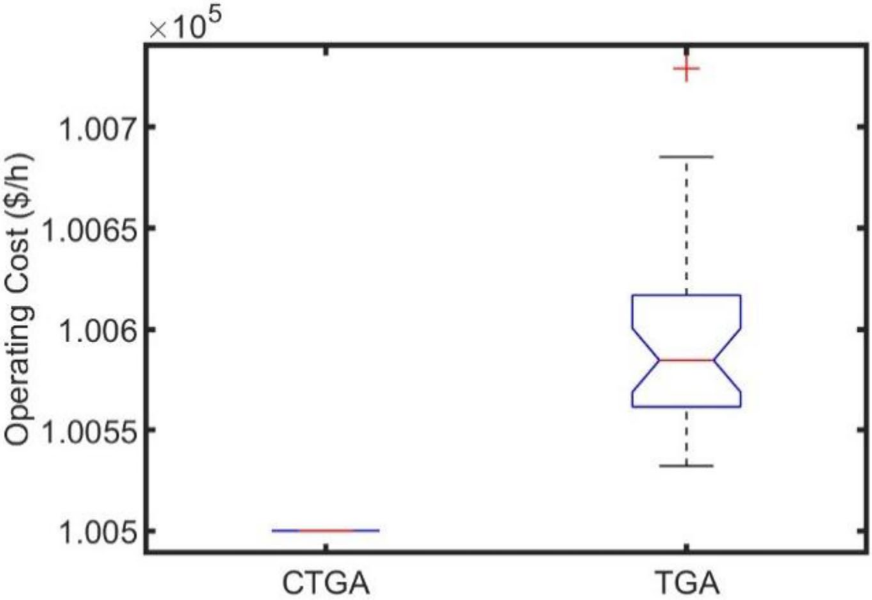


Fig. 11 Box plot of test problem T3—case 1

lower and upper quartiles lying very close to the mean value. CTGA is thriving in the robustness test, whereas TGA lags.

6.3 Parameter Tuning and Sensitivity Analysis

The parameters that need to be tuned in the proposed algorithm are the multiplier, A_f; pre-set count,L_n; and total players of both teams, N_P. After conducting simulations, these parameters are selected for the test problems. Four different test problems are analyzed to observe parameter tuning trends across power systems of varying sizes: specifically, test problem T2 for a 2700-MW power demand, case 1 of test problem T3 for a 7000-MW power demand, and test problem T4 for a 49,342-MW power demand. For the experiment, one parameter is changed at a time while the others remain constant. The parameters are varied in small steps, and the corresponding results of operating cost are tabulated in Table 23 for multiplier, A_f; pre-set count, L_n; and team players, N_P, respectively. Clearly, the population size of players varies depending on the problem at hand. Parameters A_f and L_n have the same value of 0.5 and 09, respectively, for all the test systems.

Table 23 Parameter tuning analysis

Parameters	Value	Operating cost of test problems		
		T2	T3 case 1	T4
A_f	0.2	700.78	100500.07	1657460.0
	0.3	700.78	100500.00	1657882.7
	0.4	700.73	100500.01	1660285.1
	0.5	**700.69**	**100499.97**	**1655652.8**
	0.6	700.76	100500.06	1658596.6
	0.7	700.77	100500.04	1658171
	0.8	700.74	100500.06	1659423.7
L_n	6	700.77	100500.01	1657435.8
	7	700.78	100500.01	1657454.4
	8	700.8	100500.02	1657441.7
	9	**700.69**	**100499.97**	**1655652.8**
	10	700.79	100499.98	1658427.9
	11	700.75	100500.04	1657839.6
	12	700.72	100500.04	1658196.9
N_P	10	700.77	100500.80	1662648.4
	15	**700.69**	100500.09	1658306.7
	20	700.73	**100499.97**	1663948.1
	25	700.71	100499.98	1663007.6
	30	700.75	100499.97	**1655652.8**
	35	700.78	100499.98	1656675.1
	40	700.72	100499.99	1658206.6

Data in bold emphasis indicate the minimum values of operating cost

To examine the sensitivity of parameters, the standard deviation and relative deviation from the minimum operating cost are calculated and tabulated in Table 24. It is evident from the results obtained that the solution fluctuates in a small range around the average value, and the relative deviation from the minimum operating cost is less than 1%. Similar trends have been detected in all other undertakings. So, it can be concluded that the proposed algorithm is not sensitive to the variation in parameters.

6.4 Time Analysis

To analyze the time consumption of the proposed algorithm on various types of problems for a particular demand, it is applied for 1000 function evaluations, (N_{FE}), while keeping all of the parameters the same, as tuned, for each test problem. For comparison purposes, TGA is applied similarly for the same N_{FE} and the results are tabulated in Table 25. It is clear from Table 25 that in all the test problems, the time taken by CTGA is greater than the time taken by TGA, except in test problem T4, which is a system with the highest number of search variables. The difference in time consumption of both algorithms is due to the higher

Table 24 Parameter sensitivity analysis

Test problems	Parameter	Variation domain	Step size	Operating cost				
				Minimum	Maximum	Average	StDev	Percentage relative variation
T2	A_f	0.2 – 0.8	0.1	700.69	700.78	700.75	0.032	0.009%
	L_n	6 – 12	1	700.69	700.80	700.75	0.039	0.010%
	N_P	10 – 40	5	700.69	700.78	700.73	0.032	0.007%
T3 case 1	A_f	0.2 – 0.8	0.1	100499.97	100500.07	100500.03	0.037	6.89E – 05%
	L_n	6 – 12	1	100499.97	100500.04	100500.01	0.027	4.70E – 05%
	N_P	10 – 40	5	100499.97	100500.80	100500.11	0.306	3.16E – 04%
T4	A_f	0.2 – 0.8	0.1	1655652.80	1660285.1	1658210.27	1479.807	0.175%
	L_n	6 – 12	1	1655652.80	1658427.9	1657492.73	902.161	0.122%
	N_P	10 – 40	5	1655652.80	1663948.1	1659777.90	3350.087	0.311%

Table 25 Time comparison of CTGA and TGA for various test problems. $N_{FE} = 1000$

Test problem (power demand)		T2 (2700 MW)	T3				T4 (49342 MW)	T5	
			Case 1 (7000 MW)	Case 2 (10500 MW)	Case 3 (10500 MW)	Case 4 (10800 MW)		Case 1 (2700 MW)	Case 2 (2700 MW)
Time taken (Sec:Sec/100)	CTGA	00:08	00:36	00:08	00:34	00:17	02:42	00:04	00:07
	TGA	00:05	00:30	00:06	00:25	00:16	02:54	00:03	00:06

Table 26 Results of Wilcoxon signed-rank test

CTGA vs TGA								
Test problem (power demand)	T2 (2700 MW)	T3				T4 (49342 MW)	T5	
		Case 1 (7000 MW)	Case 2 (10500 MW)	Case 3 (10500 MW)	Case 4 (10800 MW)		Case 1 (2700 MW)	Case 2 (2700 MW)
p-value ($\times 10^{-5}$)	0.17344	0.17344	1.12650	0.21266	20.51510	0.28786	0.21266	2.37040

Table 27 Wilcoxon signed-rank test on five power system test problems (nine cases)

CTGA vs	+	=	−	R⁺	R⁻	*p*-value
TGA	9	0	0	45	0	0.003

number of updating equations (learning and exchange operations) involved in CTGA than TGA, thus making CTGA an efficient algorithm.

But in problem T4, a contrasting value of time consumption is achieved. It may be due to the fact that, for the same number of function evaluations, CTGA requires a lesser number of iterations as compared to TGA, and hence, the time consumption of repeating the iterative process is reduced. The number of function evaluations by TGA and CTGA can be calculated using the expressions $(2N_P + N_P G^{max})$ and $(2N_P + \left(N_P + \left(4N_P G_1^{max}\right)\right) G^{max})$, respectively. So it can be concluded from the results tabulated in Table 25 and the experimental outcomes of all the test problems that CTGA performs better than TGA at the cost of computational time. CTGA performs outstandingly well from both perspectives (obtaining an optimal solution and time consumption) for very large systems. The computational order of CTGA is $O(n^3)$ whereas TGA has $O(n^2)$ computational order.

6.5 Wilcoxon Signed-Rank Test

Wilcoxon signed-rank test is used to validate the superiority of results of the proposed CTGA over TGA, for 30 independent trial runs of the four test problems. At a 5% significance level, the test is applied. The results of the test are tabulated in Table 26.

Wilcoxon signed-rank test is also applied to compare the results of the proposed CTGA over TGA, for five test systems (with a total of nine cases), and results are given in Table 27.

It is very clear from the result statistics that for all the test problems, the *p*-value is less than 0.05, which signifies that there is a significant difference between the solutions of both algorithms. It signifies that the null hypothesis can be rejected with a 5% significance level. Hence, it can be concluded that the proposed algorithm is capable of attaining much better-quality solutions than TGA.

7 Conclusions

A new algorithm named crisscross team game algorithm (CTGA) has been proposed in this paper to solve the economic-emission power dispatch (EEPD) optimization problem. The addition of dual crisscross mechanisms orthogonally through collaborative learning and the strengthening of individual players' skill concepts boost the exploration and exploitation capabilities of the team game algorithm with a good balance. Non-interactive technique, namely the price penalty method is used to solve multi-objective optimization problem by effectively unifying two objectives. To meet the equality constraint, the proportional power-sharing technique of unmet power demand has been successfully implemented. To investigate the superiority of CTGA over TGA, both algorithms have been implemented on standard benchmark functions and five power system-related test problems with various load demands. Obtained results for all the load levels reveal that the proposed algorithm has fast convergence behaviour, improved solution accuracy, and a near-global solution as compared to other contending algorithms. The standard deviation in the operating cost of the majority of problems under consideration is less than or close to one, demonstrating the robustness of the proposed algorithm. Cost efficiency is improved in all problems undertaken. The 140-generator test problem achieves the greatest savings, with the minimum operating cost reduced by 0.14% for load demand of 49,342 MW. Analytical methods perform well for problems with differentiable objective functions. Unlike other algorithms, for small, medium, or large test systems, CTGA has no parameter to tune except population size, which increases with the increasing dimensions of the problem. Wilcoxon signed-rank test and Friedman test justify the superiority of the proposed CTGA over contending algorithms undertaken in the study. In the future, more complex real-world problems of the power system, including dynamic power demand, CHP units, and renewable energy sources considering demand response with non-linear responsive load models, may be solved with the proposed algorithm by improving its computational time.

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Data Availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing Interests The authors declare no competing interests.

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