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Solution of Combined Economic Emission Dispatch Problem Using Improved and Chaotic Population-Based Polar Bear Optimization Algorithm

SAQIB FAYYAZ[1], MUHAMMAD KASHIF SATTAR[2], MUHAMMAD WASEEM[3,4], M. USMAN ASHRAF[5], AFTAB AHMAD[4], HAFIZ ASHIQ HUSSAIN[2], (Member, IEEE), AND KHALID ALSUBHI[6]

[1]Government College of Technology (GCT) at Rawalpindi, Rawalpindi 46000, Pakistan
[2]Department of Electrical Engineering, HITEC University at Taxila, Taxila 47070, Pakistan
[3]School of Electrical Engineering, Zhejiang University, Hangzhou 310027, China
[4]Department of Electrical Engineering, University of Engineering and Technology at Taxila, Taxila 47080, Pakistan
[5]Department of Computer Science, University of Management and Technology at Sialkot, Sialkot 53310, Pakistan
[6]Department of Computer Science, King Abdulaziz University, Jeddah 21589, Saudi Arabia

Corresponding author: M. Usman Ashraf (usmanashraf@yahoo.com)

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ABSTRACT This paper proposes a novel improved polar bear optimization (IPBO) algorithm and employs it along with polar bear optimization (PBO) and chaotic population-based variants of polar bear optimization algorithm to solve combined economic emission dispatch (CEED) problem. PBO is a meta-heuristic technique inspired by the hunting mechanisms of polar bears in harsh arctic regions based only on their sense of sight. Polar bears in nature exhibits hunting of prey not only on their sight but also on their keen sense of smell. Hence, a novel improved variant of PBO which enhances its operation by equipping it with tracking capabilities utilizing polar bears sense of smell has been proposed in this study. The validity of novel IPBO is tested through 5 benchmark functions and 140 units Korean ED problem. Furthermore, the impact of different population initialization methods is also observed on the capabilities of conventional PBO. The proposed chaotic population based PBO, improved PBO (IPBO) and PBO are employed to solve IEEE 3 unit and 6-unit CEED problem. CEED is a multi-objective power system optimization problem with conflicting objectives of cost and emission. The simulations performed undertake each objective individually as well as collectively. The results achieved by each technique are analyzed statistically through Wilcoxon rank sum test (WRST), probability density function and cumulative density function. Both the statistical and numerical analysis of results showcase the strength of each solution technique as well as their ability to improve cost and emissions in the solution of CEED problem.

INDEX TERMS Improved polar bear optimization (IPBO), economic emission dispatch (CEED), optimization, cost, emission.

I. INTRODUCTION

All global energy trends indicate monumental increase in electric energy demand in coming years. According to IEA [1], global electrical energy demand increased in 2017 by 2%. Despite the environmental awareness and focus of governments to integrate renewable into the grid, this increased demand was largely fulfilled by traditional thermal generators. The renewable sources contribution was increased by a percentage of 15.1% for wind and 21.9% for PV in the year 2017 but still the total contribution of renewable in global energy mix stands at 26.1%. The thermal sources contribute a whopping 59.4% of global electricity demand. Renewable sources are prime candidate in

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distributed generation (DG) and several renewable issues in DG are under research [2]. While thermal generators Thermal generators have proven their mantle for many decades and our current grids are designed to work around them. Despite their efficiency, resilience, and reliability they come with the added baggage of environmentally hazardous emissions. The SO_2, CO_2, and NO_X emissions from thermal units have adverse environmental impact and contribute to global warming. As the renewable energy future is still in progress, the emerging challenge nowadays is to handle thermal generation sources such that we can obtain maximum power from them at reduced cost and emissions [3]. The action of controlling thermal generators for a fixed load demand under several physical and operational constraints is a renowned problem of power system operation characterized as economic dispatch (ED) [4]. ED is a specific objective optimization problem with the intention to attain power dispatch at least probable cost with no violation of any constraints. The addition of emission objective turns ED into multi-objective problem aiming minimization of both cost and emission for a power demand without violating any constraints. This multi-objective problem is termed as combined economic emission dispatch (CEED) problem [5], [6].

Both ED and CEED are non-linear, complex, and computationally intensive power system operational problems. This mathematically complexity makes them ideal candidate for optimization algorithms to tackle and prove their mantle. Many modern populations based meta-heuristic and nature inspired techniques have been employed to solve these problems. The outcomes of these problems are beneficial to initiate different demand response actions and demand side flexibility assessment [7]–[10]. Several prominent optimizations algorithms that tried to solve these problems include: Genetic algorithm (GA) [11], simulated annealing (SA) [12], differential evolution (DE) [13], [14], moth swarm optimization algorithm (MSA) [15], spider monkey optimization (SMO) [16], particle swarm optimization (PSO) [17], [18], grey wolf optimizer (GWO) [19], gravitational search algorithm (GSA), fire fly algorithm (FFA) [20], [21], harmony search algorithm (HSA) [22], [23], spiral optimization algorithm (SOA) [24], squirrel search algorithm (SSA) [25], harris hawks optimization (HHO) [26], sine-cosine algorithm (SCA) [27], artificial bee colony (ABC) [28], bacterial forging algorithm (BFA) [29], flower pollination algorithm (FPA) [30], differential evolution (DE) [31], modified flower pollination algorithm (FPA) [32], Fluid search optimization (FSO) [33], improved ABC (IABC) [34], modified BFA (MBFA) [35], whale optimization algorithm (WOA) [36], hybrid hierarchical evolution (HHE) [37], hybrid particle swarm gravitational search algorithm (PSOGSA) [38], chaos turbo PSO (CTPSO) [39], new global PSO (NGPSO) [40], multi-objective PSO (MOPSO) [41], multi-objective DE based PSO (MODE/PSO) [42] quantum inspired glowworm swarm optimization (QGSO) [43], combination of continuous greedy randomized adaptive search procedure and self-adaptive differential evolution (C-GRASP-SaDE) [44], combination of continuous greedy randomized adaptive search procedure and modified differential evolution (C-GRASP-MDE), successful history-based adaptive DE variants with linear population size reduction (L-SHADE), improved L-SHADE (IL-SHADE) [45], and cooperative coevolving particle swarm optimization CCPSO [32].

All these algorithms are population-based strategies having fixed population and they locate the optimum solution within a search space using two distinct stages of search namely local and global search [46]. All these algorithms were successful in achieving solution of the desired problem with varying degree of accuracy and time [47], [48]. Despite the achievement of a successful solution from these techniques the research for a better solution is continuous because of availability of new solution techniques being developed and the opportunity in optimized solution outlined by no free lunch theorem (NFL) [49], [50]. Initially PBO was used by author to solve ED problem [51] and it showed remarkable results. But as stated by NFL theorem the prospect to enhance mechanism of PBO and the possibility to achieve better solution of ED and CEED problem through this proposed novel IPBO were main motivating factors behind this research. In this paper we present solution of CEED problem using polar bear optimization (PBO) [52] algorithm, chaotic population PBO and a novel Improved Polar Bear Optimization (IPBO) algorithm. PBO is a nature instigated population-based metaheuristic approach that simulates the hunting abilities of polar bears in nature. PBO has three couplet stages of search such as global search, local search, and dynamic population. Different to other population methods PBO has capacity to change its population hence decreased number of calculations per iteration causes reduction in time required for execution. The proposed novel IPBO augments the working of PBO and is initially validated by applying it to 5 benchmark functions and large scale 140-unit Korean grid ED problem. The proposed techniques are utilized to work out CEED 3 unit and 6-unit system and the results attained are compared with outcomes in literature.

In this paper, the sections are organized as follows, first section presents the outline of CEED problem, second section gives summary and mathematical formulations of PBO, novel improved PBO (IPBO) and chaotic PBO variants, third section shows the case studies comprising simulation results along with statistical analysis among PBO variants, finally fourth section conveys the conclusion.

II. PROBLEM FORMULATION

CEED is a multi-objective constrained optimization problem with the objective of arranging electrical power outputs from varied generation units such that the entire operational cost and emission is minimalized with no violation of the respective constraints like generation limits, power balance and valve point effect. CEED problem may also involve the calculation of transmission loses acquired by every single generating unit at its corresponding power output. Arithmetically, the main purpose of CEED problem is reduction of operational cost and emission of generation entities that can be presented in equation (1) as

$$Objective\ Function = W * \sum_{i=1}^{Nx} F_{P_i} + (1-W) * \sum_{i=1}^{Nx} E_{P_i} \tag{1}$$

where, N_x is the total number of generation units, i represents the i^{th} generator under consideration and W is the weightage factor which determines contribution of fuel cost or emission in total objective value, its value is in range (0,1). F_{P_i} and E_{P_i} indicate total fuel cost ($/h) and emissions (ton/h) for i^{th} unit respectively and are explained in mathematical form below.

$$\sum_{i=1}^{Nx} F_{P_i} = \sum_{i=1}^{Nx} aP_i^2 + bP_i + c \tag{2}$$

$$\sum_{i=1}^{Nx} F_{P_i} = \sum_{i=1}^{Nx} aP_i^2 + bP_i + c + (e * abs(\sin(f * (P_{il} - P_i)))) \tag{3}$$

Here equation (2) signifies the quadratic estimate of thermal units fuel cost curves without valve point effect while equation (3) characterizes the detailed cost equation comprising the valve point impact. In above equations *a, b, c, e* and *f* are cost coefficients, N_x is the maximum number of generation units available for scheduling, P_i is the i^{th} generating unit and P_{il} is the least power limit of i^{th} generating unit.

Similarly, from [34] and [53] the emission from each thermal generation can be defined as summed quadratic and exponential functions as:

$$\sum_{i=1}^{Nx} E_{P_i} = \sum_{i=1}^{Nx} \eta P_i^2 + \beta P_i + \alpha + \xi * e^{(\lambda * P_i)} \tag{4}$$

where α, β, η, ξ and λ are emission coefficients. The CEED must comply with the following equality and inequality constraints.

A. EQUALITY CONSTRAINTS

Equality constraints include power generation balance that the load demand is met by considering the transmission line losses shown in equation (5).

$$P_{generated} = P_{required} + P_{loss} \tag{5}$$

where $P_{generated}$ is the total power scheduled, $P_{required}$ is the power demand and P_{loss} is the transmission loss incurred at respective level of power scheduled and can be computed from loss coefficient matrix B formed by Kron's transmission loss formula shown in Eq. (6).

$$P_{loss} = \sum_{i=1}^{Nx} \sum_{k=1}^{Nx} (P_i B_{ik} P_k) + \sum_{i=1}^{Nx} (B_{i0} P_i) + B_{00} \tag{6}$$

where; B_{ik}, B_{i0} and B_{00} are transmission loss coefficients.

B. INEQUALITY CONSTRAINTS

In CEED, Inequality constraint is mainly named as generation limits on each generator shown in equation (7).

$$P_{il} < P_i < P_{ih} \tag{7}$$

where; P_{il} and P_{ih} are the lower and upper limits of i^{th} generation unit and P_i is the power scheduled on the i^{th} generation unit.

C. PENALTY FUNCTION

The overall fitness function including equality constraints and objective can be obtained by penalty function formed as equation (8).

$$Fitness = penalty * abs\left(\sum_{i=1}^{Nx} Pi - P_{required} - P_{Loss}\right) + Objective\ Function \tag{8}$$

III. OVERVIEW OF PROPOSED METHODOLOGY

A general overview and mathematical description of each technique under consideration is presented below.

A. POLAR BEAR OPTIMIZATION ALGORITHM (PBO)

Polar bear optimization [51] is a population based meta-heuristic optimization algorithm that simulates the hunting abilities of polar bear in severe arctic territories. PBO algorithm has three distinctive phases of search in search space namely local search by encircling and catching prey, global search by gliding ice floats and dynamic population. Each of these stages represents some vital characteristic of Polar Bear's hunting method in arctic zones and is described below.

PBO algorithm begins its search by arbitrarily adjusting each polar bear having n coordinates as characterized by $\bar{x} = (x_0, x_1, \ldots\ldots, x_{n-1})$ and then propels itself to find optimum solution in search space using global and local search strategies.

Global search process imitates Polar Bears nature to glide on arctic ice bergs in exploration of food, this behavior is modeled using following equation.

$$(\bar{x}_j^{\,t})^i = (\bar{x}_j^{\,t-1})^i + sign\,(\omega)\,\alpha + \gamma \tag{9}$$

where; $(\bar{x}_j^{\,t})^i$ is movement of i^{th} polar bear having j coordinates in t^{th} iteration towards the optimum, α is random number in range (0, 1), ω is distance between the present bear and optimum bear and γ is random number in the range (0, ω). The distance is dealt in Euclidian metrics and is given as

$$d((\bar{x})^{(i)}, \left(\bar{x})^{(j)}\right) = \sqrt{\sum_{k=0}^{n-1} ((x_k)^{(i)} - (x_k)^{(j)})^2} \tag{10}$$

During local search, the bears surround the prey and shot it with their teeth. This performance is efficiently modeled employing trifolium equations. To transmute polar bears behavior into these equations two parameters are characterized known as distance of vision 'a' chosen at random in range (0, 0.3) and angle of tumbling Φ_o chosen at random in range (0, $\frac{\pi}{2}$). From these limits, radius of vision is computed as

$$r = 4\,\text{acos}\,(\Phi_o)\,sin(\Phi_o) \tag{11}$$

This radius is utilized to calculate movement in local search space for each spatial coordinate correspondingly as

$$\begin{cases} x_0^{new} = x_0^{actual} \pm rcos(\Phi_1) \\ x_1^{new} = x_1^{actual} \pm [rsin\,(\Phi_1) + rcos\,(\Phi_2)] \\ x_2^{new} = x_2^{actual} \pm [rsin\,(\Phi_1) + rsin\,(\Phi_2) + rcos\,(\Phi_3)] \\ \quad \ldots \\ x_{n-2}^{new} = x_{n-2}^{actual} \pm [\sum_{k=1}^{n-2} rsin\,(\Phi_k) + rcos\,(\Phi_{n-1})] \\ x_{n-1}^{new} = x_{n-1}^{actual} \pm [\sum_{k=1}^{n-2} rsin\,(\Phi_k) + rsin\,(\Phi_{n-1})] \end{cases} \tag{12}$$

where Φ_1, Φ_2 and Φ_3 are chosen randomly in the range $(0, \pi)$.

Ultimately, to model the impact of severe arctic climatic conditions and bring in uncertainty to the optimization strategy, PBO algorithm initializes with 75% of population while the left over 25% depends on population growth controlled by reproduction of best or malnourishment of worst. To execute this approach a new constant k is introduced having value in range (0, 1). Dependent on k, creation or destruction of individuals will be performed according to following ruling.

$$\begin{cases} Death & if\ k < 0.25 \\ Reproduction & if\ k > 0.75 \end{cases} \tag{13}$$

The individuals are destroyed reliant on k until population in more than 50% while the reproduced individual is provided as

$$(\bar{x}_j^t)^{reproduced} = \frac{\bar{x}_j^{t(best)} + \bar{x}_j^{t(i)}}{2} \tag{14}$$

where; $\bar{x}_j^{t(best)}$ the best solution is up to current iteration and $\bar{x}_j^{t(i)}$ is selected arbitrarily from among top 10% of best individuals up to current iteration.

B. CHAOTIC POPULATION PBO

In chaotic population-based version of PBO we simply initialize the population of polar bears based on chaotic tent map. Chaotic tent map [54] is mathematically defined as

$$\begin{cases} x\,(i+1) = 2 * x\,(i) * value & if\ x > 0.5 \\ x\,(i+1) = 2 * (1 - x\,(i)) * value & if\ k \leq 0.5 \end{cases} \tag{15}$$

where *x (0)* is randomly selected from range (0, 1) such that *x (0)* is not equal to 1/2, 1/4, 2/3 and 3/4. Value represents the scaling factor to which the generated chaotic population will be scaled to. In our case we have used to scaling values.

$$Value = Upper_{scale} = P_{ih} \tag{16}$$

$$Value = Mid\_scale = ((P_{ih} - P_{il}) + P_{il})/2 \tag{17}$$

C. IMPROVED PBO

PBO algorithm was designed to mimic the hunting capabilities of polar bears based on their sense of sight completely ignoring polar bears scavenging capabilities. Polar bears have very sharp sense of smell and they make use of it during extreme conditions to find food. To incorporate this feature into already existing PBO algorithm we devised a unique two-tier global search stage in which 1 bear among 30% of least fit bears is selected to undergo global search based on their sense of smell mimicking its scavenging capabilities in extreme food shortage. This behavior is modeled using Levi flight equation (18) taken from [55] as shown below.

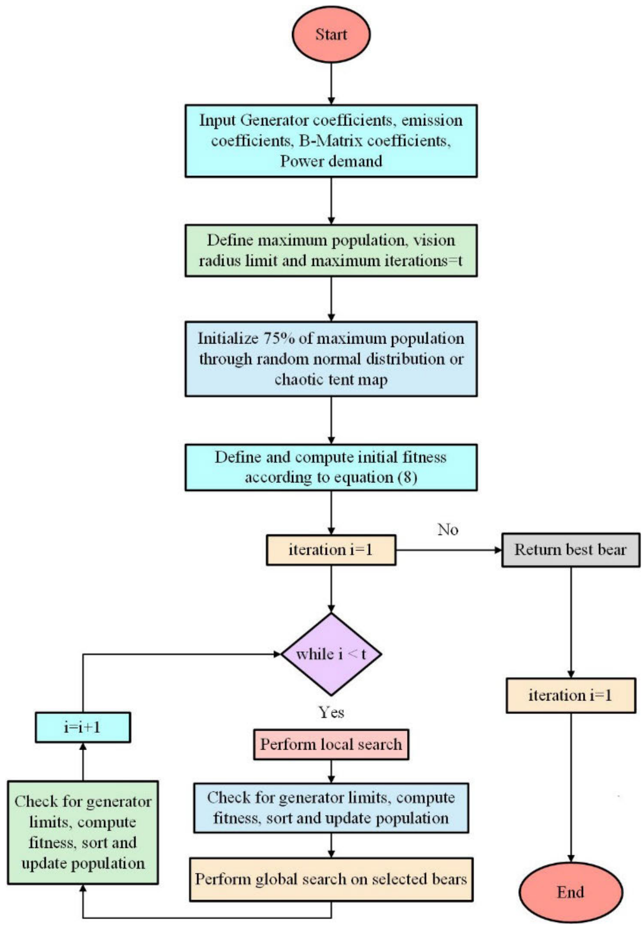


FIGURE 1. Flow diagram to solve CEED by proposed methodology.

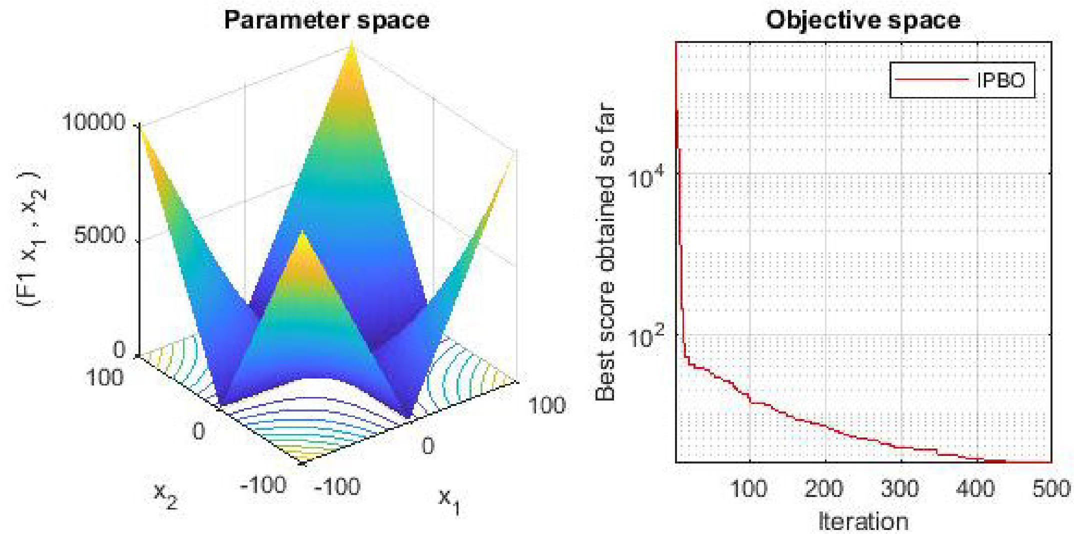
$$\bar{x}_j^{t(actual)} = \bar{x}_j^{t(actual)} + L_j * (\bar{x}_j^{t(best)} - \bar{x}_j^{t(actual)}) \tag{18}$$

where L is the levy factor that maps the random flight behavior of birds. Here it is used here to map wind movement which carries the smell. So, at a global search stage two bears take two different trajectories, most fit bear undergoes ice float global search whereas least fit bears resort to scavenging.

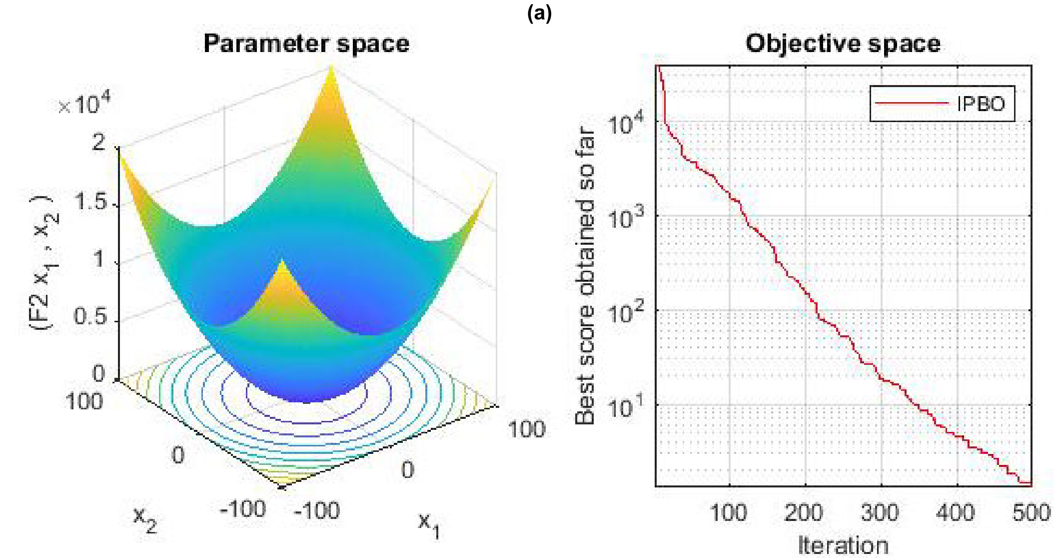
In this paper the proposed techniques will be used to solve CEED problem. The overall solution strategy for solution of CEED problem followed by each technique is outlined in flowchart shown in Fig. 1.

IV. SIMULATION RESULTS

Before tackling the CEED system the validity of proposed novel IPBO was tested by applying it to unimodal and multi-modal benchmark functions and compared with the state of art approaches. IPBO was also implemented to take on large scale 140-unit Korean grid ED problem at a demand



(a)



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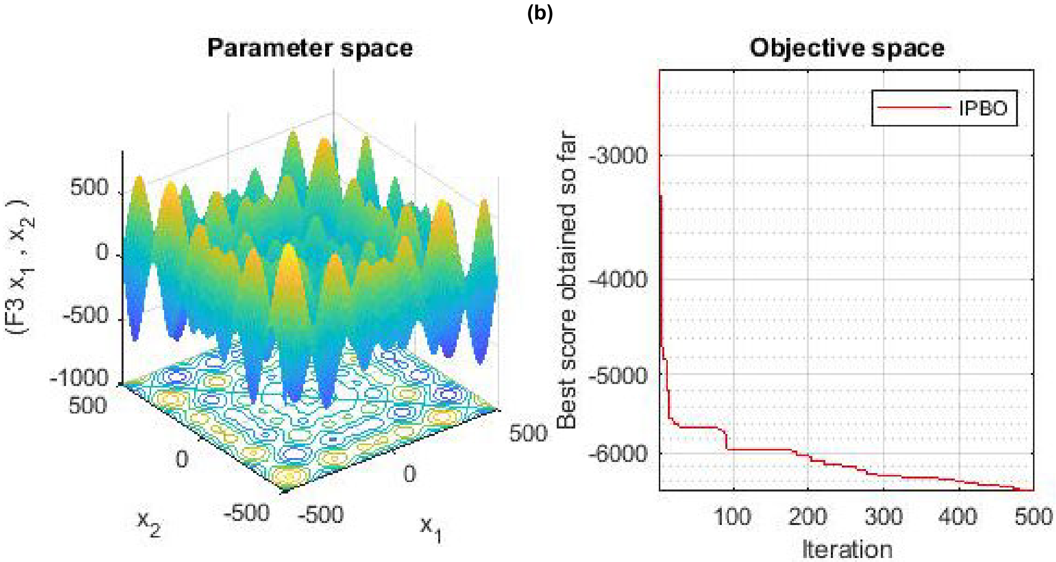


(c)

FIGURE 2. Convergence characteristics by IPBO for different test functions (a) F1 (b) F2 (c) F3 (d) F4 (e) F5.

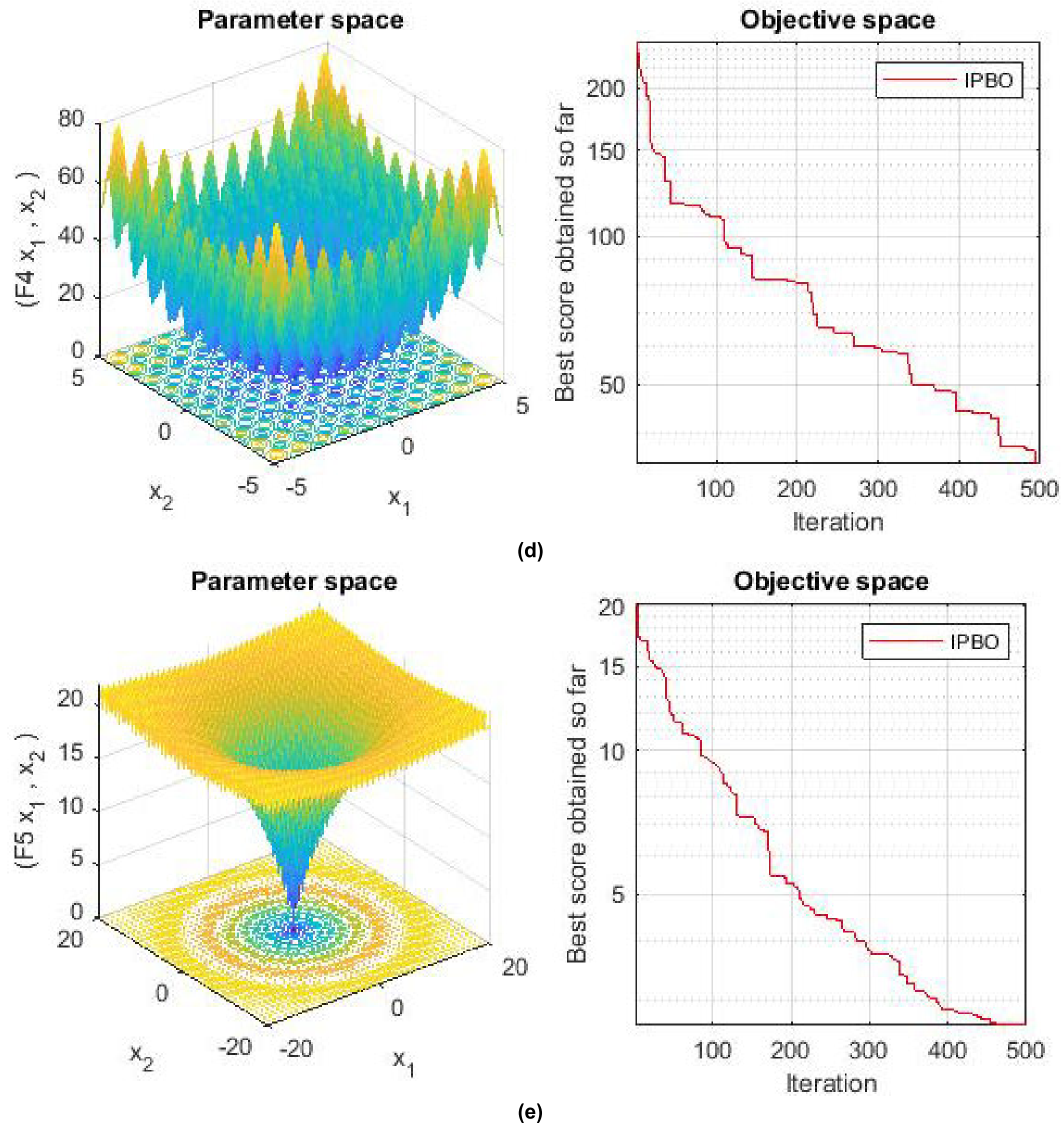


FIGURE 2. *(Continued.)* **Convergence characteristics by IPBO for different test functions (a) F1 (b) F2 (c) F3 (d) F4 (e) F5.**

of 49342 MW under two distinct cases. Finally, IPBO along with chaotic population based PBO variants were applied to solve.

- IEEE 3-unit CEED test system at a load demand of 850 MW
- IEEE 6-unit CEED test system at a load demand of 283.4 MW.

Simulations were performed on MATLAB 2016 software on Intel Core M-5Y10c@0.8GHz (4 CPU), 4GB RAM system. 20 runs were performed for each case of CEED problem having 100 bears and 100 iterations. For 140-unit ED problem iterations were kept at 1000.

A. VALIDATION FOR BENCHMARK FUNCTIONS

In this subsection, the validity of proposed IPBO is tested by applying it to five standard test functions presented by equation (19) to (23). The equation (19) and (20) represent unimodal functions whereas equations (21) to (23) represent multi-modal functions.

$$F_1(x) = \sum_{i=1}^{n} |x_i| + \prod_{i=1}^{n} |x_i| \tag{19}$$

$$F_2(x) = \sum_{i=1}^{n} (|x_i + 0.5|)^2 \tag{20}$$

$$F_3(x) = \sum\nolimits_{i=1}^{n} -x_i \sin\sqrt{|x_i|} \tag{21}$$

$$F_4(x) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10] \tag{22}$$

$$F_5(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum\nolimits_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e \tag{23}$$

TABLE 1. Performance comparison of different techniques for test functions with IPBO.

F	IPBO		SSA [25]		PSO [17]		GSA [38]		BFA [29]		FPA [32]		MSA [15]		FFA [21]	
	avg	std	avg	std	avg	std	avg	std	avg	std	avg	std	avg	std	avg	std
F1	0.1714	0.1926	0.2272	1.0000	0.2858	0.0867	0.0000	0.0084	1.0000	0.4826	0.5394	0.3095	0.5152	0.1338	0.3064	0
F2	0.062	0.1782	0	0.0000	0.7212	0.5303	0.3944	0.2328	1.0000	1.0000	0.0153	0.0561	0.754	0.3097	0.041	0.0223
F3	0.5816	0.2225	1	0.0071	1	0.0094	1	0.0026	0	1	1	0.0021	1	0	1	0.0009
F4	0.2808	0.2142	0.4254	0.9502	0.3548	0.6283	0	0.329	0.6155	1	0.5894	0.6006	0.9074	0.5564	0.8299	0.1451
F5	0.1194	0.1754	0.0598	0.5279	0.5917	0.9783	0	0	0.9443	0.4541	0.7708	1	1	0.2696	0.6937	0.4449

TABLE 2. Simulation results for best cost of IEEE 140-unit test system (case 1).

Technique	Minimum cost ($/h)	Average cost ($/h)	Maximum cost ($/h)	Time (sec)
QGSO[43]	1,655,679.43	1,655,679.43	1,655,679.43	18.61
CCPSO[32]	1,655,685	1,655,685	1,655,685	42.9
HHE[37]	1,655,679.41	NA	NA	8.233
FPA[32]	1,655,685.80	1,655,709.06	1,655,732.32	10.24
MFPA[32]	1,655,679.39	1,655,679.42	1,655,679.43	5.57
CTPSO[39]	1,655,685.00	1,655,685.00	1,655,685.00	76.9
IPBO	1557055.117	1559009.743	1560568.583	43.4637516

TABLE 3. Simulation results for best cost of IEEE 140-unit test system (case 2).

Technique	Minimum cost ($/h)	Average cost ($/h)	Maximum cost ($/h)	Time (sec)
QGSO[43]	1,657,962.73	1,657,962.74	1657.776	31.67
CCPSO[32]	1,657,962.73	1,657,962.73	1,657,962.73	150
HHE[37]	1657962.713	NA	NA	8.798
FPA[32]	1,657,962.72	1,658,001.70	1,659,518.67	NA
MFPA[32]	1,657,962.77	1,658,051.90	1,658,570.77	12.67
CTPSO[39]	1,657,962.69	1,657,962.75	1,657,962.82	5.71
PSO [17]	1657962.73	1657962.73	NA -	NA
C-GRASP–SaDE[44]	1657962.727	1658006.271	1658583.527	NA
C-GRASP–MDE[45]	16661666.74	1685973.32	1897207.15	NA
L-SHADE[45]	1.65800279	1.65911846	1.66316679	16.97
IL-SHADE[45]	1.657962.7303	1657965.3	1658090.54	9.45
IPBO	1561978.58	1565065.933	1568208.99	45.32663351

The simulations were performed for 30 independent runs keeping dimension of each function at 20 and the iterations were kept at 500. IPBO was able to achieve solution of each test function as represented by Fig.2.

From Table 1, it can be seen IPBO is able to achieve better average results in almost all cases. Its solution. strength is also highlighted in solution of multi-modal functions where it outclasses most of its competitors.

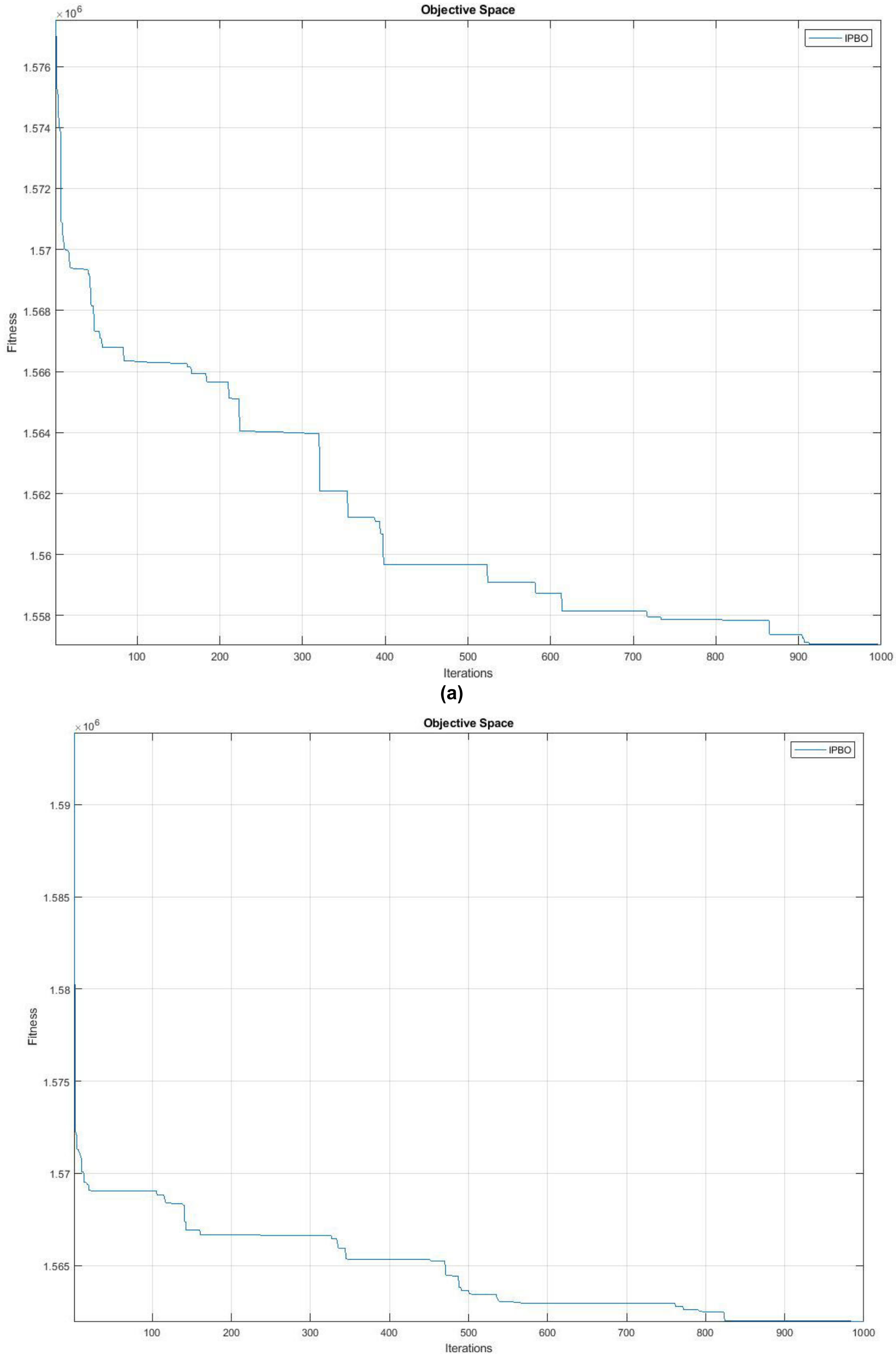
B. IEEE-140 UNIT TEST SYSTEM

Previously, PBO has been applied by the author to tackle small scale economic dispatch problem [52]. The knowledge gained from that research helped fine tune IPBO to take large scale ED problem. IPBO was employed to solve 140-unit Korean grid ED problem for two cases. The data was taken from [39]. In first case, IPBO is solved for only convex cost solution at a load demand of 49342 MW. Whereas in case 2, 12 units are subjected to valve point effect and 4 units have POZ constraints. The result achieved are presented in Table 2 and Table 3 along with other similar solutions available in literature. Furthermore, the convergence characteristics for both case 1 and case 2 by IPBO is presented in Fig. 3 as follows.

From Table 2 and Table 3, IPBO was able to achieve better solution as compared to QGSO, CCPSO, HHE, FPA, MFPA, CTPSO for case 1 and QGSO, CCPSO, HHE, FPA, MFPA, CTPSO, PSO C-GRASP-SaDE, C-GRASP-MDE, L-SHADE, IL-SHADE for case 2 respectively. The improvement in cost was observed to be as high as 6% both for case 1 and case 2.

C. IEEE 3-UNIT TEST SYSTEM

The data for IEEE 3-unit test system including cost coefficients, NO_x coefficients and SO_2 coefficients was taken



(b)

FIGURE 3. Convergence characteristics of IPBO for of IEEE 140-unit system for (a) Case 1 (b) Case 2.

from [56]. The scaling factor for NO_x and SO_2 were taken from [57] having value147582.78814 ($/ton) and 970.031569 ($/ton) respectively. Table 4 shows results for 3-unit system. From the Table 4 all techniques were successful in achieving solution of CEED problem for minimization of fuel cost, NO_x emission and SO_2 emission, respectively. When

TABLE 4. Simulation results for IEEE 3-unit test system.

Generation	W=1 Fuel cost minimization			
	PBO	PBO CM	PBO CU	IPBO
P1 (MW)	388.854	383.216	385.3133	394.5319
P2 (MW)	335.9092	324.4301	337.6036	333.4933
P3 (MW)	125.2369	142.3483	127.0632	121.9748
Total Cost ($/h)	8194.433	8196.611	8194.402	8194.362
NO_x Emission (ton/h)	0.100103	0.101626	0.100461	0.09956
SO_2 Emission (ton/h)	8.896021	8.90368	8.899334	8.890564
Generation	W=0 NOx minimization			
	PBO	PBO CM	PBO CU	IPBO
P1 (MW)	490.6739	493.0545	490.8404	497.2576
P2 (MW)	255.6122	259.1261	250.2253	248.1651
P3 (MW)	103.7144	97.81908	108.9345	104.5773
Total Cost ($/h)	8222.967	8223.861	8223.924	8227.276
NO_x Emission (ton/h)	0.095173	0.095284	0.095182	0.095139
SO_2 Emission (ton/h)	8.830027	8.828756	8.830897	8.828417
Generation	W=0 SO_2 minimization			
	PBO	PBO CM	PBO CU	IPBO
P1 (MW)	542.8469	535.0348	536.3222	546.3512
P2 (MW)	229.8309	230.322	232.4914	223.1638
P3 (MW)	77.32217	84.64301	81.17854	80.48505
Total Cost ($/h)	8260.365	8253.697	8254.643	8261.622
NO_x Emission (ton/h)	0.096985	0.09621	0.096498	0.096772
SO_2 Emission (ton/h)	8.820902	8.821078	8.8209	8.820861

TABLE 5. Simulation results for best cost of IEEE 6-unit test system (case 1 and 2).

Generation	W=1 Fuel cost minimization							
	Case 1				Case 2			
	PBO	PBO CM	PBO CU	IPBO	PBO	PBO CM	PBO CU	IPBO
P1 (MW)	9.1147	11.06058	12.12171	11.01249	14.24608	12.03478	10.66651	13.25247
P2 (MW)	32.57429	30.15488	28.96399	31.38762	31.09548	29.11269	27.38862	29.17842
P3 (MW)	52.36375	55.18432	52.73379	52.61793	54.51063	58.05382	58.70539	56.49826
P4 (MW)	101.949	99.74634	101.472	100.4571	99.177	99.88262	98.09819	98.03903
P5 (MW)	53.26717	50.20563	55.21137	51.75962	54.87626	47.36503	56.0242	54.0513
P6 (MW)	34.13105	37.04756	32.89559	36.14503	32.12505	39.48343	35.04295	34.85668
Ploss (MW)	NA	NA	NA	NA	2.6305	2.53237	2.525869	2.47617
Total Cost ($/h)	600.2641051	600.1931	600.2595	600.1009	606.2969	606.1227	606.091	605.8329
NOx Emission (ton/h)	0.222929	0.220761	0.222388	0.221079	0.219838	0.220536	0.220913	0.219401

TABLE 6. Simulation results for best emission of IEEE 6-unit test system (case 1 and 2).

Generation	W=0 Emission minimization							
	Case 1				Case 2			
	PBO	PBO CM	PBO CU	IPBO	PBO	PBO CM	PBO CU	IPBO
P1 (MW)	41.85036	40.20513	39.9026	40.1104	41.87887	40.90031	42.95367	41.53996
P2 (MW)	45.10133	44.59711	46.38345	45.55353	44.07921	47.53835	45.66145	47.34597
P3 (MW)	56.33878	54.06859	53.58488	53.64885	52.69595	55.46995	53.89627	53.67572
P4 (MW)	37.81901	38.55061	38.02265	40.27268	41.65293	35.14021	38.67073	39.25895
P5 (MW)	53.96752	53.0706	54.44519	52.6541	55.50044	57.32235	56.97402	53.41579
P6 (MW)	48.32216	52.93427	51.06161	51.15823	51.15325	50.54375	48.86215	51.75921
Ploss (MW)	NA	NA	NA	NA	3.56064	3.51493	3.618291	3.595593
Total Cost ($/h)	638.4086	638.0367	638.2785	636.402	643.872	649.344	646.8508	646.8918
NOx Emission (ton/h)	0.194292	0.194241	0.19421	0.194229	0.194269	0.194304	0.19428	0.194195

TABLE 7. Simulations results for best compromise solution of IEEE 6-unit test system (case 1 & 2).

Generation	W=0.5 Best Compromise							
	Case 1				Case 2			
	PBO	PBO CM	PBO CU	IPBO	PBO	PBO CM	PBO CU	IPBO
P1 (MW)	21.06766	19.11547	13.18519	17.33686	15.37845	17.81509	14.98842	17.91746
P2 (MW)	40.15215	33.39876	33.51866	29.45883	36.9351	36.81358	36.39815	35.2072
P3 (MW)	62.42745	60.6415	59.55283	62.101	54.90675	59.64902	55.02458	55.31129
P4 (MW)	73.90186	70.04046	75.60161	76.84799	101.2353	84.71652	86.28568	89.68432
P5 (MW)	55.09309	62.10737	62.14228	59.25601	38.40416	51.20247	51.97427	48.70396
P6 (MW)	30.75736	38.09729	39.39905	38.44054	39.35631	35.70108	41.37769	39.18839
Ploss (MW)	NA	NA	NA	NA	2.816041	2.497755	2.648788	2.612608
Total Cost ($/h)	607.682	607.5901	605.0695	604.9146	608.0635	608.6138	608.3772	607.7676
NOx Emission (ton/h)	0.205346	0.204356	0.207804	0.20773	0.219706	0.209615	0.210323	0.211556

compared among each other IPBO outclassed all its companions achieving an improvement as high as 0.027452% in cost, 0.1525% in NO_x emissions and 0.002464% in SO_2 emission, respectively.

D. IEEE 6-UNIT TEST SYSTEM

The data for 6-unit system including cost coefficients, NOx coefficients and B matrix was taken from [34]. The scaling factor of NOx values was 1000 ($/ton). The results for 6-unit system for case 1 without considering loses and case 2 including loses are tabulated in Table 5 for best cost solution. From Table 5 IPBO was able to achieve an improvement as high as 0.0272% and 0.0766% in cost for case 1 and case 2, respectively.

Similarly, Table 6 and 7 represent best emission and best compromise solutions. From Table 6 IPBO was able to achieve an improvement as high as 0.0325% and 0.056% in emission for case 1 and 2, respectively. Whereas data from Table 7 indicates that IPBO achieves best compromise solution at minimum cost at a comparable level of emission.

Table 8 and 9 show comparison of case 1 and case 2 respectively with other techniques available in literature. From Table 8 it can be seen that IPBO was able to achieve best cost and best compromise solution as compared to MSA [15], FFA [21], PSOGSA [38], MBFA [35], SOA [24], PSO [17], MOPSO [41], DE [31], and MODE/PSO [42], respectively. Other PBO variants PBO, PBO-CM and PBO-CU were also successful in achieving comparable cost and compromise solutions. The improvement in cost was in the range 0.88$ to 0.0105$ when compared to literature and in the range 0.0163$ to 0.092$ when compared to other PBO variants for best cost solution. For best compromise solution IPBO was able to achieve a cost improvement in the range 19.69$ to 1.88$ when compared to literature at a comparable emission level. For IPBO achieved comparable emission levels at an improved cost as compared to literature whereas PBO, PBO-CM

TABLE 8. Comparison of best results for case 1 with promising techniques in literature.

Technique	Case 1					
	Best Cost Solution (w=1)		Best Emission Solution (w=0)		Best Compromise Solution (w=0.5)	
	Fuel Cost ($/h)	Emission (ton/h)	Fuel Cost ($/h)	Emission (ton/h)	Fuel Cost ($/h)	Emission (ton/h)
MSA [15]	600.1114	0.22215	638.27583	0.194203	606.80105	0.20329
FFA [21]	600.1114	0.22214	638.27398	0.194203	606.79835	0.20329
PSOGSA [38]	600.1114	0.22215	638.27452	0.194203	606.79841	0.20329
MBFA [35]	600.17	0.22	636.73	0.1942	610.906	0.2
SOA [24]	600.986	0.20889	640.749	0.18729	624.604	0.18708
PSO [17]	600.13	0.2199	636.62	0.1943	NA	NA
MOPSO [41]	600.12	0.2216	637.42	0.1942	608.65	0.2017
DE [31]	600.1114	0.2221	638.2907	0.1942	NA	NA
MODE/PSO [42]	600.115	0.22201	638.27	0.194203	NA	NA
PBO	600.2641051	0.222929	638.4086	0.194292	607.682	0.205346
PBO-CM	600.1931	0.220761	638.0367	0.194241	607.5901	0.204356
PBO-CU	600.2595	0.222388	638.2785	0.19421	605.0695	0.207804
IPBO	600.1009	0.221079	636.402	0.194229	604.9146	0.20773

TABLE 9. Comparison of best results for case 2 with promising techniques in literature.

Technique	Case 2					
	Best Cost Solution (w=1)		Best Emission Solution (w=0)		Best Compromise Solution (w=0.5)	
	Fuel Cost $/h	Emission ton/h	Fuel Cost $/h	Emission ton/h	Fuel Cost $/h	Emission ton/h
MSA [15]	605.99837	0.220728	646.20486	0.194179	612.2519	0.203571
FFA [21]	605.99837	0.220728	646.20731	0.194179	612.25302	0.20357
PSOGSA[38]	605.99837	0.220728	646.20838	0.194179	612.25222	0.203571
MBFA[35]	607.67	0.2198	644.43	0.1942	616.496	0.2002
PSO [17]	607.84	0.2192	642.9	0.1942	NA	NA
MOPSO[41]	607.79	0.2193	644.74	0.1942	615	0.2021
DE[31]	608.0658	0.2193	645.085	0.1942	NA	NA
MODE/PSO[42]	606.0073	0.2209	646.0243	0.1942	NA	NA
IABC[34]	605.4258	0.2209	646.0455	0.1942	NA	NA
FSO[33]	605.89	0.2211	646.69	0.194178	NA	NA
NGPSO[40]	605.99837	NA	NA	0.19417851	623.863672	0.19697487
PBO	606.2969	0.219838	643.872	0.194269	608.0635	0.219706
PBO-CM	606.1227	0.220536	649.344	0.194304	608.6138	0.209615
PBO-CU	606.091	0.220913	646.8508	0.19428	608.3772	0.210323
IPBO	605.8329	0.219401	646.8918	0.194195	607.7676	0.211556

and PBO-CU showed comparable cost and emissions reviewer.

From Table 9, it can be seen than IPBO was able to achieve best cost and best compromise solution as compared to MSA [15], FFA [21], PSOGSA [38], MBFA [35], PSO [17], MOPSO [41], DE [31], MODE/PSO [42], IABC, FSO [33], and NGPSO [40], respectively. In case of IABC [34], IPBO achieved better emission level at comparable cost for best cost solution. The overall improvement in cost was in the range 2.23$ to 0.057$ whereas for best compromise

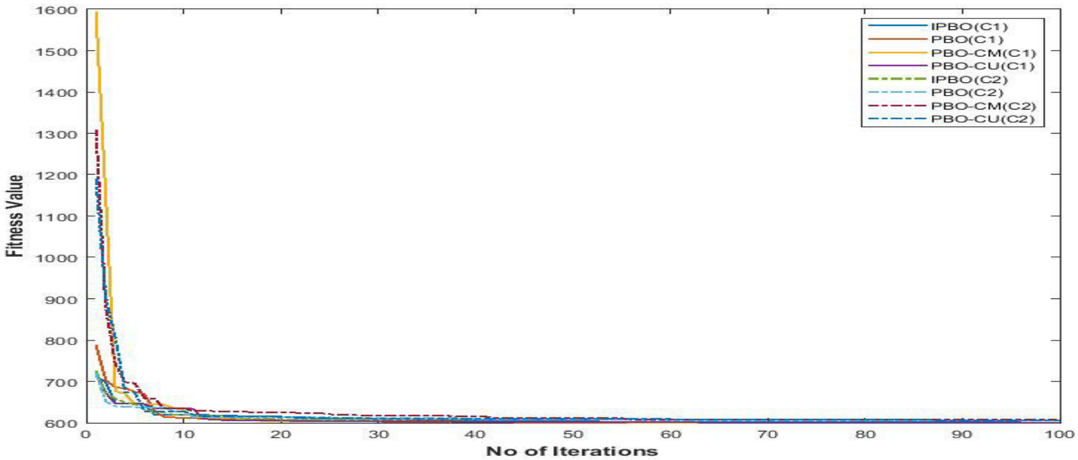


FIGURE 4. Convergence characteristics of Best Cost Solution (Case 1 and 2) for all PBO variants.

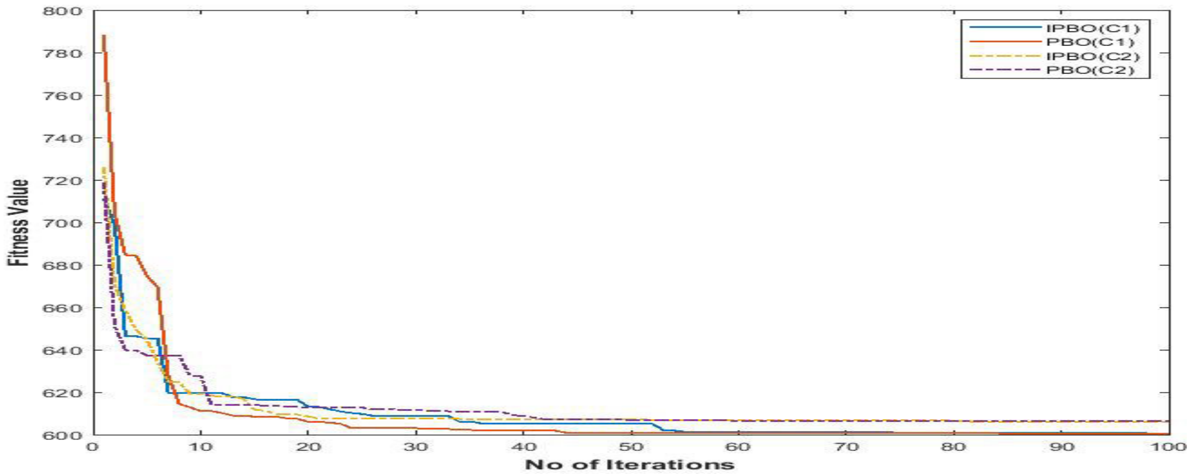


FIGURE 5. Convergence characteristics of Best Cost Solution (PBO vs IPBO) for Case 1 and Case 2.

TABLE 10. Statistical analysis performed to prove superiority of one technique in both Cases.

Cases	Case 1				Case 2			
Technique	PBO	PBO CM	PBO CU	IPBO	PBO	PBO CM	PBO CU	IPBO
Best	600.2641051	600.1931199	600.2594922	600.1008867	606.2968965	606.122654	606.0909782	605.8328669
Worst	606.5192662	605.7816929	610.7166237	602.712622	611.4471363	610.1535781	613.7864512	609.3472987
Mean	601.8345603	601.6831165	602.3342652	601.3167938	607.9523883	607.3068484	607.4731437	607.2072716
Variance	2.866013554	1.745498376	5.472850802	0.627863459	2.91549212	1.172369072	3.290308748	0.789793477
Std.	1.692930463	1.321173106	2.339412491	0.792378356	1.707481221	1.082759933	1.813920822	0.888703256
Rank	*3*	*2*	*4*	*1*	*3*	*2*	*4*	*1*

TABLE 11. Results of Wilcoxon rank sum test (WRST) for both cases.

Cases	Case 1		Case 2	
Comparison of Techniques	Results			
	Probability Value	Hypothesis	Probability Value	Hypothesis
IPBO Vs PBO	0.300200924	1	0.066596974	1
IPBO Vs PBO CM	0.242454068	1	0.662413193	1
IPBO Vs PBO CU	0.032096267	1	0.675078278	1

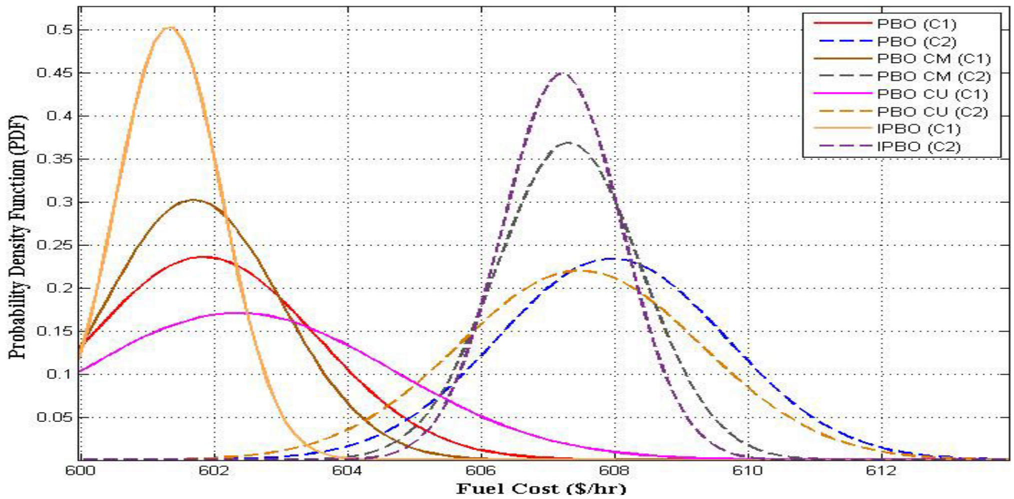


FIGURE 6. Probability Density Function (PDF) of both Cases.

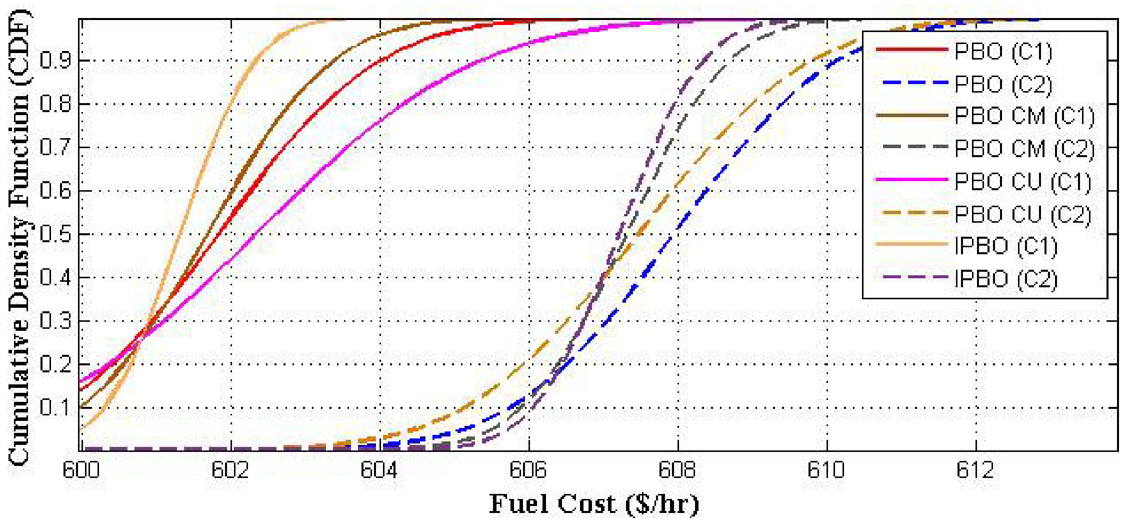


FIGURE 7. Cumulative Density Function (CDF) of both Cases.

solution the improvement in cost was in the range 16.09$ to 0.29$ at a comparable emission level. Other PBO variants PBO, PBO-CM and PBO-CU were also successful in solving CEED problem at comparable cost and emissions. In case of best compromise solution all PBO variant achieved better cost at comparable emission level. For best emission solution all PBO variants achieved comparable emission levels at comparable cost as compared to literature. Fig. 4 and 3 show convergence characteristics for best cost solution of both cases. In Fig. 4 all PBO variants are plotted, chaotic PBO variants start search from higher fitness values because of compulsion on initial population according to chaotic level employed. Fig. 5 shows same convergence curve excluding the higher value chaotic variants to better understand convergence behavior of IPBO as compared to PBO. From both Figures it is evident that IPBO converges to a lower value more swiftly as compared to other PBO variants. For case 1 IPBO converged to first decimal digit in 74 iterations whereas PBO, PBO-CM and PBO-CU took 84, 86, 79 iterations, respectively. Similarly, for case 2 IPBO converged to a first decimal digit in 84 iterations whereas PBO, PBO-CM and PBO-CU took 85, 90, 89 iterations, respectively.

V. STATISTICAL ANALYSIS

To demonstrate the supremacy of one method a statistical analysis is executed demonstrating best, worst, mean, standard deviation and rank of each state is performed [58]–[60]. This statistical analysis is achieved by taking the data of 20 runs individually for all methods as examined earlier and results are exhibited in Table 10.

Wilcoxon rank sum test was introduced by Wilcoxon [61], [62].This is non-parametric test that can reflect the relationship between two different data sets in both cases. The Wilcoxon rank sum test is based on the hypothesis. We made a hypothesis that most of the results of IPBO as shown in both cases are less than other techniques. The probability-value of Wilcoxon rank-sum test shows the probability that how many times the results of PBO, PBO-CM and PBO-CU are less than IPBO results. The probability-value in Table 10 shows that there is very low probability that the other cases have cost values less than IPBO for case 1. In case 2 IPBO outclasses PBO significantly whereas PBO-CM or PBO-CU show significant probability for better results but at a higher standard deviation and variance. Table 11 proves our hypothesis is true.

The results of all four techniques are taken by independent trial runs for both cases. To show the distribution of data for each case Probability Density Function (PDF) and Cumulative Density Function (CDF) are plotted as shown in Fig.6 and Fig. 7.

It can be seen from Fig. 6 that highest peak is obtained for IPBO in both cases and widest data distribution is in PBO-CU. So, statistically IPBO is best, and PBO-CU is worst. It can also be seen that slope is highest for IPBO in both the cases and it reaches to 1 first than other techniques.

VI. CONCLUSION

In this paper novel improved PBO (IPBO), PBO and chaotic population PBO were employed to solve CEED problem for the first time in literature. Also, IPBO was validated by applying it to solve 140-unit Korean grid ED problem and 5 standard benchmark functions. All the proposed algorithms were successful in achieving solution of 3 unit and 6-unit CEED problem. Statistical analysis performed established that IPBO is superior to other PBO variants when it comes to solution of CEED problem showing an improvement as high as 0.027452% in cost, 0.1525% in NO_x emissions and 0.002464% in SO_2 emission respectively for 3-unit system and an improvement as high as 0.0272% and 0.0766% in cost, and 0.0325% & 0.056% in emission for 6-unit system case 1 and case 2, respectively. From convergence behavior we can see that IPBO converges to optimum value in a smaller number of iterations as compared to other PBO variants with the difference in the range of 6 to 1 iteration. When compared to literature IPBO showed best cost and best compromise solutions for both cases. IPBO achieved an improvement in cost as high as 0.1475% and 3.255% for best cost and best compromise solutions of 6-unit system case 1, whereas an improvement in cost as high as 0.3686% and 2.65% for best cost and best compromise solutions of 6-unit system case 2 was observed. For best emission solution IPBO achieved better cost at a comparable emission level. The success of all PBO variants in achieving better solution of CEED problem is a motivating factor for further research applying IPBO and other PBO variants to engineering problems. Different demand response programs with integrated distributed energy resources will be explored for energy management in different energy consumption sectors.

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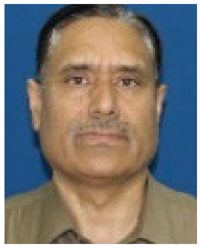
SAQIB FAYYAZ received the B.E. degree in electrical engineering from the NUST School of Electrical Engineering and Computer Sciences (SEECS), Islamabad, and the M.Sc. degree in electrical power engineering from the University of Engineering and Technology at Taxila. He is currently working as an Electrical Instructor with the Department of Electrical Technology, Government College of Technology at Rawalpindi, Pakistan. His research interests include power system optimization, meta-heuristic techniques, power system operation, and power quality. He is a registered Engineer with Pakistan Engineering Council.

MUHAMMAD KASHIF SATTAR received the B.Sc. degree in electrical power engineering from COMSATS Abbottabad, Pakistan, in 2017, with Dual Gold Medal (Campus and Institute Gold Medal) and the M.Sc. degree in electrical power engineering from the University of Engineering and Technology (UET) at Taxila, Pakistan, in 2019. He is currently working as a Lecturer with the Department Electrical Engineering, HITEC University at Taxila. He has contributed in many national/international journals and conference proceedings. He is a registered Engineer with Pakistan Engineering Council.

MUHAMMAD WASEEM received the B.Sc. and M.Sc. degrees in electrical engineering from the University of Engineering and Technology at Taxila, Pakistan, in 2012 and 2017, respectively. He is currently pursuing the Ph.D. degree with the College of Electrical Engineering, Zhejiang University, Hangzhou, China. He is also with the Department of Electrical Engineering, University of Engineering and Technology at Taxila. His research interests include power system analysis, demand side management, and smart grids.

M. USMAN ASHRAF received the Ph.D. degree in computer science from King Abdulaziz University, Saudi Arabia, in 2018. He has served as a HPC Scientist with the HPC Centre, King Abdulaziz University. He is currently an Assistant Professor and the Head of the Software Engineering Department, KUST, University of Management and Technology, Sialkot, Pakistan. His research interests include exascale computing systems, high performance computing (HPC) systems, parallel computing, HPC for deep learning and location based services system has appeared in IEEE Access, *IET Software*, *International Journal of Advanced Research in Computer Science*, *International Journal of Advanced Computer Science and Applications*, *International Journal of Information Technology and Computer Science*, and *International Journal of Computer Science and Security* and several International IEEE/ACM/Springer conferences.



AFTAB AHMAD received the B.Sc. and M.Sc. degrees in electrical engineering from the University of Engineering and Technology at Lahore, in 1985 and 1994, respectively, and the Ph.D. degree from the University of Engineering and Technology (UET) at Taxila, in 2010. He is currently working as a Professor of Electrical Engineering with the Department of Electrical Engineering, UET Taxila, and acting as the Chairman of the Electrical Engineering Department. He has supervised more than 50 Masters, one Ph.D. student, and contributed in many national/international journals and conference proceedings. His research interests include power system optimization, unit commitment, power system operation and control, and energy management systems. He is a Life Member of the Pakistan Engineering Council (PEC).

HAFIZ ASHIQ HUSSAIN (Member, IEEE) received the Ph.D. degree in telecom engineering from BUPT, China. He is currently working as an Associate Professor of Electrical Engineering with the Department of Electrical Engineering, HITEC University at Taxila, and acting as the Chairman of the Electrical Engineering Department. He has supervised more than 50 Masters, two Ph.D. students and contributed in many national and international journals and conference proceedings. His research interests include power systems, optical fiber communication, and silicon photonics. He is a Life Member of the Pakistan Engineering Council (PEC).

KHALID ALSUBHI received the B.Sc. degree in computer science from King Abdulaziz University (KAU), Jeddah, Saudi Arabia, in 2003, and the M.Math. and Ph.D. degrees in computer science from the University of Waterloo, Waterloo, ON, Canada, in 2009 and 2016, respectively. He is currently an Assistant Professor of Computer Science with KAU. His research interests include network security and management, cloud computing, and security and privacy of healthcare applications.