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Solution of the Multi-Objective Optimal Power Flow Problem Using Oppositional-Based Algorithm

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ABSTRACT

An efficient optimal power flow (OPF) algorithm allows the finest setting of the plant by solving multi-objective optimization problem to minimise the overall operating cost. This paper proposes the quasi oppositional backtrack search algorithm (QOBSA) for optimal setting of OPF control variables. The QOBSA is stochastic algorithm which gives committed and robust results compared to the traditional methods. This technique has been implemented to test the control parameters for the IEEE 30-bus with single and multi-objective functions like the minimization of fuel cost, minimization of total voltage deviation (TVD), voltage stability enhancement, emission reduction, and multi-fuel cost minimization. The result provides better voltage profile at every bus based on L-index which in turn greatly reduces the burden on load buses. The QOBSA code has been developed in the MATLAB platform and tested with the help of IEEE 30-bus and the outcomes have been compared with ongoing literature.

KEYWORDS

Multi-Objective Optimization, Opposition-Based Learning (OBL), Optimal Power Flow (OPF), Quasi Oppositional Backtrack Search Algorithm (QOBSA)

1. INTRODUCTION

Carpentier has introduced the term optimal power flow (OPF) in 1962 (Carpentier 1962). The OPF is an important tool for an efficient power system operation and planning in modern power system (Shaheen, Ragab, and Sobhy 2016). The main purpose of the OPF is to set control variable in such a way that economic and secure operation of power system take place. Active and reactive power generations at the generating station, reactive power output from the different reactive power sources like shunt capacitor, on load tap changing transformer etc. are chosen to control their parameters for getting multi-objective solutions. The OPF problem is a non-linear and highly constrained problem. Many traditional optimization techniques have been successfully implemented to solve the OPF problems. Most common traditional techniques can be mentioned as gradient algorithms (Peschon, Bree, and

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Hajdu 1971; Burchett et al. 1982), Newton method (Crisan and Mohtadi 1992), linear programming (LP) (Lobato et al. 2001; Zehar and Sayah 2008), quadratic programming (QP) (Reid and Hasdorff 1973; Granelli and Montagna 2000) and interior point method (IPM) (Vargas, Quintana, and Vannelli 1993; Momoh and Zhu 1999). These methods have average convergence characteristics and some of them widely popular in common practice. However, these methods give local optimum solution for complex objective function problems in a power system. Many meta-heuristic techniques, single objective and multi objective structures (Houssein et al. 2022a, 2022b; Bhattacharjee et al. 2014, 2015, Sony et al. 2022; Rani 2016; Das 2014) are also used to solve OPF problems. The modelling of OPF reflects operating issues as per its objective function. Genetic algorithm (GA) (Bakirtzis, Anastasios G., et al. 2002; Attia, Turki, and Abusorrah 2012) is one of the most popular techniques. In (Bakirtzis, Anastasios G., et al. 2002), authors have used enhanced genetic algorithm (EGA) to solve the OPF problem. Various control variables such as switchable shunt devices, transformer tap-setting, generator bus voltage magnitudes, and active power outputs are considered for the optimization. Authors have proposed adaptive genetic algorithm in (Attia, Turki, and Abusorrah 2012). The main contribution, for adaptive genetic algorithm, is described as adjusting population size. Kritsana and Akihiko (2009) have presented improved evolutionary programming (EP) to solve OPF problem considering voltage stability problem. Differential evaluation (DE) based approach has been proposed by the authors (Abou, Abido, and Spea 2010). In the proposed DE method, non-smooth piecewise quadratic function has been used. Improved evolutionary programming (IEP) has been offered by authors (Ongsakul, and Tantimaporn 2006) with Gaussian and Cauchy mutation operators for solving OPF problems. Multi-objective OPF has been solved with particle swarm optimization (PSO) (Choudhury and Patra 2016). Simulated annealing optimization technique is used in (Roa-Sepulveda and Pavez-Lazo 2003). Authors Roy, Ghoshal, and Thakur (2010) have proposed a novel biogeography based optimization (BBO) method to solve OPF with valve point non-linearities of generators. Optimal reactive power flow problem has been solved using artificial bee colony algorithm in (Kürşat and Kılıç 2012). Modified shuffle frog leaping algorithm (Niknam, Narimani, Jabbari, and Malekpour 2011) has been applied to OPF considering environmental and emission issues. Modified sine-cosine algorithm (MSCA) has been applied to OPF problems considering fuel cost minimization and reactive power allocations in (Attiaa, Sehiemya, and Hasanienb 2018). An Enhanced genetic algorithm (EGA) called NSGA –III integrated with adaptive elimination stratagem (Zhangab, Wanga, Tanga, Zhoua, Zengb 2019). A modified teaching learning based optimization for multi-objective OPF problem implemented in (Haghighia, Seifia, and Niknamb 2014). Quasi- Oppositional modified Jaya algorithm for multi-objective implemented in (Warid, Hizam, Mariun, and Wahab 2018).

A new optimization technique backtracking search optimization algorithm (BSA) is proposed by Pinar Civicioglu (2013). This technique is based on the concept of selection, mutation, and crossover operators. The BSA can control the value of search direction effectively in mutation operation. The operators generate very large value which helps to find solution from its current state. This accelerates the process of finding global solution. The operators can also generate small values of the variables at that same time. This helps the algorithm to find a solution in the neighbourhood of its current state and the same suitable to get global search value. There is another advantage of the BSA is that it has memory to store population from randomly chosen past generation. This is used in generating search direction matrix for next iteration. The memory of BSA helps to gain advantage from past value and to find next generation. The crossover operator uses a complex and nonlinear structure to create new individual in each generation. These attractive and versatile qualities of BSA (Bhattacharjee K., et al. 2021, 2018, 2015) motivated authors to implement in solving multi objective OPF problem with BSA.

The key contributions of this work can be mentioned as, (a) the QOBSA has been introduced for the first time to solve the OPF problem in this paper, (b) crucial control variables for OPF e.g. the minimization of fuel cost, minimization of TVD, voltage stability enhancement, emission reduction, and multi-fuel cost minimization have been accounted to build robust OPF algorithm, (c) L-index has been used in this work to encourage improved voltage profile for the system, (d) the proposed

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approach has been verified with IEEE 30-bus standard system, and the outcome shows the superiority of the algorithm over some of the recently developed approach.

Section 2 of the manuscript provides a mathematical formulation of the OPF problem. Section 3 provides a short description on BSA algorithm. Section 4 presents the oppositional based leaning. Section 5 provides information on steps to follow to get solution of OPF problem by BSA. The various test system and results are discussed in section 6. The conclusion of the manuscript is given in section 7.

2. PROBLEM FORMULATION

The solution of OPF problem is challenging due to non-linearity, non-convexity, and highly constraint problem definition. The OPF problem is used to optimize given objective, subjected to system physical limits (Bhattacharjee, Bhattacharya, Shah, and Patel 2021). Due this complexity, OPF problem remain popular but challenging task among power system researcher. The OPF problem can be computed as follows.

The outcome of OPF problem is taken under consideration of steady state performance of power system with different set of objective functions. This can be done through optimal adaption of independent variable while fulfilling various inequality and equality constraints. The OPF problem may be illustrated in mathematical form as given below:

$$Minimize\, J_x = \left\{J_1\left(x\right), J_2\left(x\right),\ J_3\left(x\right) \ldots\ldots J_n\left(x\right)\right\} \tag{1}$$

$$Subjected\, to, G_i\left(x\right) \geq 0, i = 0,1,\ldots,m \tag{2}$$

$$H_i\left(x\right) = 0\ , i = 0,1,\ldots,p \tag{3}$$

where $J_n\left(x\right)$ represents the mth objective function. There are m number of objective functions. Here m and p are number of equality and inequality constraints.

2.1. Problem Objective

The prime objective of solving OPF problems includes environmental, economic, and technical benefits. Most common objective function found in common practice is minimizing FC. It is considered as primary or most common economical objective function. Other technical objectives can be mentioned as reduction of APL and TVD, voltage stability improvement with help of L−index, etc. Lastly, minimizing the total emission can be observed as environmental objective.

As mentioned earlier one of the most popular objectives for the OPF problem is the minimization of FC for generated active power of an interconnected system. It is mathematically formulated in quadratic function and can be represented as the *F1* is expresses as follows:

$$Min\, F_1 = \sum_{i=1}^{NG}\left(a_i + b_i P_{G_i} + c_i P_{G_i}{}^2\right)\left(\$ / h\right) \tag{4}$$

The second objective function of the OPF problem is APL minimization (F_2). It can be expressed as follows:

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$$Min\ \ F_2\left(x\right)=\sum_{i=1}^{NG}\left(G_k\left(V_i^2+V_j^2\ \ -2V_iV_j\cos\delta_{ij}\right)\right) \tag{5}$$

The third objective $\left(F_3\right)$ is to minimize the TVD at PQ buses. It can be stated as follows:

$$Min\ \ F_3\left(x\right)=\sum_{i=1}^{NB}\left|V_i-1\right| \tag{6}$$

The fourth objective function is the total emission minimization. Nowadays the superfluous emissions of greenhouse gases leave adverse effect to the environment. This is implied that the fossil-fuel based power plants have greenhouse gases as a major by-product. One of the main motives of this work is to enhance social welfare by decreasing these emissions. The non-linear form of emission function can be expressed as follows:

$$Min\ \ F_4\left(x\right)=\sum_{i=1}^{NG}10^{-2}\left(a_i+b_iP_{G_i}+c_iP_{G_i}{}^2\right)+\left|\xi_ie^{\lambda_iP_{G_i}}\right|\left(ton\ /\ hr\right) \tag{7}$$

The fifth objective function is enhancement of voltage stability. With help of popular $\left(L-index\right)$, it can be mentioned as follows:

$$L_j=\left|1-\sum\nolimits_{i=1}^{NG}F_{ij}\frac{V_i}{V_j}\angle\left(\theta_{ij}+\delta_i-\delta_j\right)\right|\quad j=1,2,3.....NL \tag{8}$$

$$F_{ji}=-\left[Y_{LL}\right]^{-1}\left[Y_{LG}\right] \tag{9}$$

Now, the maximum value of L_j is taken as a global indicator for the complete system. Lower values of L_{max} assures the improved stability of the system:

$$F_5\left(x\right)=L_{max}=\max\left(L_j\right)j=1,2,\ldots,NL \tag{10}$$

2.2. Constraints for the Proposed Objective Functions

Same as the other optimization problems the OPF problems are also dealt with equality and inequality constraints.

2.2.1 Equality Constraints

Here, r is the set of equality constraints representing the typical load flow equations:

$$P_{Gi}-P_{Di}-V_i\sum\nolimits_{\mathrm{j}=1}^{NB}V_{\mathrm{j}}\left(B_{\mathrm{ij}}\sin\theta_{\mathrm{ij}}+G_{\mathrm{ij}}\cos\theta_{\mathrm{ij}}\right)=0$$

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where:

$$i = 1,2,3,\ldots,NB \tag{11}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j \left(G_{ij} \sin\theta_{ij} + B_{ij} \cos\theta_{ij} \right) = 0$$

where:

$$i = 1,2,3,\ldots,NB \tag{12}$$

NB is total number of buses, P_G and Q_G are the active and reactive power generation, respectively. G_{ij} and B_{ij} are the transfer conductance and Susceptance between bus i and j, respectively. $Y_{ij} = G_{ij} + B_{ij}$ is the admittance matrix. The phase angle difference θ_{ij} is between voltages at buses *i* and *j*.

2.2.2 Inequality Constraints

Here, h is set of inequality constraints as follows.

2.2.2.1 Physical Limit of Generator

For all generator, including reference bus: active and reactive power outputs and voltages are limited within their permitted lower and upper bound as follows:

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max},\ i = 1\ldots NG \tag{13}$$

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max},\ i = 1\ldots NG \tag{14}$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max},\ i = 1\ldots NG \tag{15}$$

2.2.2.2 Physical Limit of Transformer

Tap setting of transformer are limited within their permitted lower and upper bound as follows:

$$T_{Ti}^{\min} \le T_{Ti} \le T_{Ti}^{\max}, i = 1,\ldots,NT \tag{16}$$

2.2.2.3 Physical Limit of Shunt VAR Compensator

Shunt VA_R compensator constraints permitted within their lower and upper bound as follows:

$$Q_{Ci}^{min} \le Q_{ci} \le Q_{Ci}^{max}, i = 1,\ldots,NC \tag{17}$$

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2.2.2.4 Security Constraints

These include the constraints of voltage at load buses and transmission line loading. Voltage of each PQ bus are restricted within their lower and upper limits. Line flow through each transmission line is restricted by their capacity limits. These constraints are expresses as follows:

$$V_{L_i}^{min} \le V_{L_i} \le V_{L_i}^{max}, i = 1, \ldots, NL \tag{18}$$

$$S_{l_i} \le S_{l_i}^{max}, i = 1, \ldots, nl \tag{19}$$

The Inequality constraints $\lambda_P, \lambda_V, \lambda_Q, \lambda_s$ of dependent variables which contains P_{G_1}, V_L, Q_G, S_l can be included into an objective function as quadratic natured penalty terms so that final output remains within operating limits. Penalty function can be expressed as follows:

$$J_{aug} = J + \lambda_p \left(P_{G_1} - P_{G_1}^{lim}\right)^2 + \lambda_V \sum_{i=1}^{NL} \left(V_{L_1} - V_{L_i}^{lim}\right)^2 + \lambda_Q \sum_{i=1}^{NG} \left(Q_{G_1} - Q_{G_i}^{lim}\right)^2 + \lambda_S \sum_{i=1}^{NG} \left(S_{l_1} - S_{l_i}^{lim}\right)^2 \tag{20}$$

Here, x^{lim} is the limit value of dependent variable. If x is higher than the upper limit value or x is lower than the lower limit value then it takes values as follows:

$$x^{lim} = \begin{cases} x^{max}, x > x^{max} \\ x^{min}, \ \ x < x^{min} \end{cases} \tag{21}$$

3. QUASI OPPOSITIONAL BACKTRACKING SEARCH ALGORITHM (QOBSA)

QOBSA algorithm has been discussed in two parts in this section. At first the conventional BSA algorithm has been mentioned then the process for hybridization has been mentioned.

3.1 Backtracking Search Algorithm (BSA)

It is a population based stochastic evolutionary algorithm. This is a bio-inspired algorithm. It replicates and mostly similar to the social group of living creature return on random interval to the hunting areas that were formerly found productive for getting food. The structure of BSA can be classified into five processes i.e. initialization, selection-I, mutation, crossover, and selection-II. For the better understanding of the basic BSA algorithm, the steps have been described in the following section.

3.1.1 Initialization

Same as the other optimization algorithms, BSA randomly generates the starting population within its specified boundary condition:

$$\begin{aligned} &for\, i = 1 : popsize \\ &for\, j = 1 : problemsize \\ &pop\left(i, j\right) = rand * \left(up\left(j\right) - low\left(j\right)\right) + low\left(j\right) \\ &end \\ &end \end{aligned} \tag{22}$$

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where $i = 1,2,3\ldots, popsize$; $j = 1,2,3,\ldots, problemsize$; $low(j)$ and $up(j)$ are the lower and upper bounds of the problem size respectively.

3.1.2 Selection-I

As discussed above, this algorithm stores the location of enriching food resources. Previous location is helpful to find feasible search dimension matrix. Historical population $(hist_pop)$ can be calculated as follows:

$$hist_pop(i,j) = rand * (up(j) - low(j)) + low(j) \tag{23}$$

Here, $hist_pop$ set is updated until a better fitness value is found. Historical population is updated as follows:

$$if\ \ arand < brand \tag{24}$$

$$hist_pop(i,j) = pop(i,j) \tag{25}$$

where, $arand$ and $brand$ are random number between 0 and 1. After this order of $hist_pop$ is randomly shuffled as follows:

$$hist_pop = hist_pop(randperm(popsize),:) \tag{26}$$

where, $randperm$ is random permutation of $popsize$ and it is used to change the position of different set within the $hist_pop$.

3.1.3 Mutation

The starting form of trial population Mutant is generated using equation (27) and this process is called as mutation:

$$Mutant = pop + F * (hist_pop - pop) \tag{27}$$

where $hist_pop - pop$ is the search direction matrix and F is the amplitude of search direction matrix. So it basically controls the search dimension matrix. Due to the experience of previous generation, BSA generates trial population. The value of F is given by $F = 4 * randn$, where $randn\, N(0,1)$. Here, N is the standard normal distribution.

3.1.4 Crossover

The initial value of trial pop for the crossover is $Mutant$. The target population individuals belong to trial individual with better fitness value. The crossover process of BSA divided into two steps. The first step uses, map, binary integer-valued matrix, is created. The size of map is $popSize \times problemSize$. The map indicates the individual trial population T to be updated with individual value of pop. If $map(i,j) = 1$, then trial pop updated with $T(i,j) = pop(i,j)$. In the second step, it uses $mixrate$ and it is used to control the individual population element which will mutate with the trial pop using

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$\left(mixrate * rand * ProblemSize\right)$. In this scenario, $mixrate$ is relatively differing from the crossover process works in other algorithms.

3.1.5 Selection-II

This is the second stage selection. Trial population $\left(T\right)$ and pop are compared with corresponding value and then the pop is updated. After this, if best independent population $\left(pop\right)$ had superior fitness value than global minimum value then global minimum value replace by best independent population $\left(pop\right)$.

3.2 Opposition-Based Learning (OBL)

The conviction of OBL is given by Tizhoosh (2005) and Warid et al. (2018). This method accelerates the rate of convergence and helps to find out global optimum solution. In this method, two populations are to be generated, i.e. current population and opposition population within the feasible space. Here, opposite number needs to be generated closer to the global solution then any randomly generated number. Opposite number and opposite point are calculated as below Mandal and Roy (2011).

3.2.1 Opposite Number

Let y be a real number between $\left[m,n\right]$. Now, its opposition number y^o is calculated as:

$$y^o = m + n - y \tag{28}$$

where m and n are two minima and maxima points in search space.

3.2.2 Opposite Point

Here, $P\left(y_1, y_2, y_3, \ldots, y_q\right)$ is a point in q-dimensional space, then the opposite point $OP\left(y_1^o, y_2^o, \ldots, y_q^o\right)$ can be calculated as below:

$$y_i^{op} = m_i + n_i - y_i \tag{29}$$

where:

$$y_i \in \left[m_i, n_i\right]; i = 1, 2, \ldots, q$$

3.2.3 Quasi-Opposite Number

It is the number formed between the centre of feasible space and its opposite number. Here, y is any real number between [m, n]. Its quasi-opposite point y_i^{op} is calculated as:

$$y_i^{qo} = rand\left(\frac{m+n}{2}, y_i^{op}\right) \tag{30}$$

Basic flow of OPF with QOBSA has been mentioned in the below steps:

Step 1: Initialize the penalty factors, $mixrate$. State the minimum and maximum limits of all the dependent variable. Set termination criteria as $MaxIter$.

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Step 2: Initialize population as pop, $qopop$ (Quasi-Opposite population) within the control limits.

Step 3: If $qopop$ has better value than pop then update pop with that value. Run the load flow using NR method. Check all the constraints; the constraints specified in equation (13) to (19). If there is any violation of constraint, then go to step 2.

Step 4: Compute the value of $fitness$, $fitness\left(pop\right)$ for individual $popsize$ and $problemsize$. This paper contains different $fitness$ functions so all the objective function taken under consideration.

Step 5: Initialize the $hist_pop$ using equation (23). Update $hist_pop$ if equation (24) is true. Next randomly shuffle the $hist_pop$ using equation (26).

Step 6: Proceed with mutation process as per equation (27).

Step 7: Proceed with the crossover process as given above.

Step 8: Run the load flow again with the help of individual trial population $\left(T\right)$. Trial population $\left(T\right)$ should fulfil the respective control limit for computed dependent variables. If this condition satisfies then solution set to be considered as feasible solution. If the values are not within control limit then solution can be previous solution. If all constraints are satisfied, then go for next objective function.

Step 9: $qopop$ can be calculated centred on $jumping_rate$ with help of equation (30). The $jumping_rate$ is determined as follows:

$$a = jumping_rate\Big|_{max} - jumping_rate\Big|_{min} \tag{31}$$

$$b = a * \left(\frac{MaxIter - Iter}{MaxIter}\right) \tag{32}$$

$$jumping_rate = a - b \tag{33}$$

where $a = jumping_rate\Big|_{max}$ and $b = jumping_rate\Big|_{min}$ considered at maximum and minimum value. $Iter$ is present iteration.

Step 10: Compare the computed results with trial population $\left(T\right)$. The *pop* needs to be updated if trial population $\left(T\right)$ has better feasible solution. Sorting of all three populations is done then whichever has a better solution than global solution, replace the current global solution with that otherwise it is the same.

Step 11: Repeat the process again from step 2 for next iteration. If stopping criteria reached (in this case, $MaxIter$) then terminate loop and print the results.

4. SIMULATION AND RESULTS

In order to illustrate the effectiveness of the proposed QOBSA technique, it has been tested on IEEE 30 bus test system.

4.1 Characteristics of the Test System

Characteristics of IEEE 30-bus system shown in Table 1. The bus data, line data, generator data and lower and upper limits of all the independent variables are presented in (Zimmerman et al.). The

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Table 1. Details of test system IEEE-30 bus system

System components	Numbers	Positions at buses/lines
Buses	30	----
Branches	41	----
Generators	6	At buses 1, 2, 5, 8, 11 and 13
Shunt capacitors	9	At buses 10, 12, 15, 17, 20, 21, 23, 24 and 29
Transformers	4	lines 6–9, 6–10, 4–12, and 28–27

proposed algorithm has been applied to solve multi-objective function OPF problem with system physical limits. The emission cost coefficient data taken from (Mahdi et al. 2019).

Voltage of each PQ bus is limited within their lower and upper bounds. Flow of line through each transmission line is limited by their capacity limits.

4.1.1 Definition of Different Case Studies for OPF Problem

This work contains 11 case studies and their definition tabulated in Table 2. The case studies reflect different objective functions. The main motive to simulate the case studies separately and all together is to understand the effect of each of the parameters separately for the OPF.

4.2. Results of Single Objective Case Studies

Optimal settings of the independent variables, obtained in proposed QOBSA, are given in Tables 3 and 4. There are three events for the single objective case study. Here, event 1 considers the minimization of FC. The convergence characteristic for FC is shown in Figure 1. The total FC is decreased to 799.079 $/h compared to initial case FC of 901.88 $/h which gives reductions almost

Table 2. Different case studies involving single/multiple objective

Test System	Case	Fuel cost (F_1)	V.D (F_2)	APL (F_3)	L-max (F_4)	Emission (F_5)
IEEE-30 bus	1	ü	-	-	-	-
	2	-	-	ü	-	-
	3	ü	ü	-	-	-
	4	ü	-	-	ü	-
	5	ü	-	ü	-	-
	6	ü	-	-	-	ü
	7	ü	ü	-	ü	-
	8	ü	-	ü	-	ü
	9	ü	ü	-	-	ü
	10	ü	ü	ü	-	-
	11	ü	ü	ü	ü	-
	12	ü	ü	ü	-	ü
	13	ü	ü	ü	ü	ü

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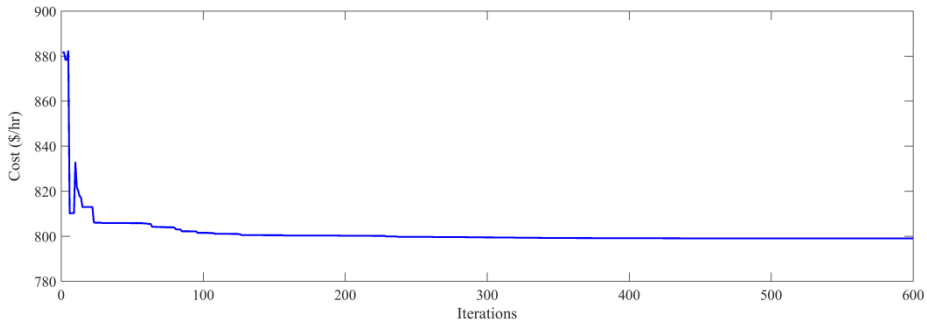
Figure 1. Convergence characteristics for case 1



equal to 11.3985%. This elaborates the efficacy of the proposed algorithm for solving OPF problem. Case 2 is about the minimization of APL. The convergence characteristics of APL minimization has been shown in Figure 2. The comparison of the above case studies is described in Table 5.

4.3 Results of Bi-Objective Case Studies

In the single objective analysis, there may be violation of some quantities, like during case 1 there is a violation of TVD. So this bi-objective study helps to improve the responses of those quantities. Here, case study 3 advocates FC and TVD minimization. Case study 4 states FC and L-index minimization. On the other side, case study 5 includes FC and APL minimization, and case study 6 includes FC and emission minimization. Comparative studies of above test cases are given in Table 6. Figure 3, Figure 4, Figure 5, and Figure 6 show the results of case studies from 3 to 6. The utilization of suggested QOBSA can leads to more aggressive solution results for various case studies compared with method described in literature.

4.4 Triple Objective Cases

In this part of study, three objectives have been considered together. Here, case study 7 includes FC, TVD, and L-max minimization. Case study 8 combines FC, APL, and emission minimization. Comparative studies for the above test cases are given in Table 7. Figure 7 shows the results of case study 7. In case studies 7 and 8, results of FC are better than the described in the literature. Moreover, in the case study 8, result of emission is better compared to describe in the literature. Similar explanations can be given for case 9 and 10. The convergence characteristics for case 9 and 10 have been plotted in Figures 9 and 10. These results show a notable difference and effectiveness of suggested QOBSA algorithm.

Figure 2. Convergence characteristics for case 2

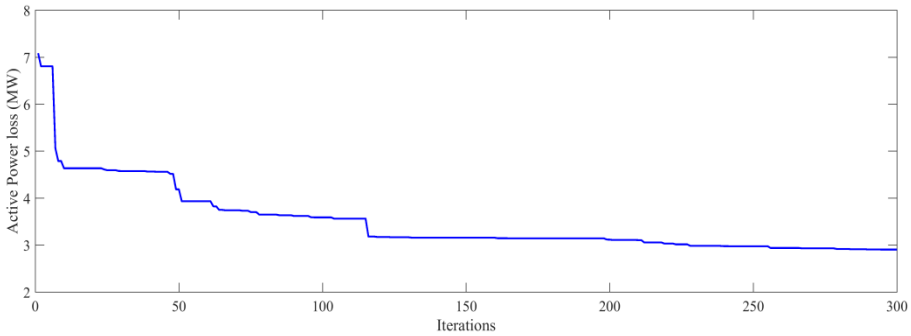


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Table 3. Simulation results for OPF problem of cases 1-6 for IEEE 30-bus power system

	Min	Max	Initial Case	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
P_1	50	200	99.21	**176.973**	51.7938	174.7498	174.7781	173.0902	112.8198
P_2	20	80	80	**48.606**	79.6016	48.7258	47.5106	48.6233	56.4426
P_5	15	50	50	**21.445**	50.0000	21.4475	21.0692	21.7382	29.6647
P_8	10	35	20	**21.095**	35.0000	22.4164	21.7741	23.6578	35.0000
P_{11}	10	30	20	**11.90**	30.0000	12.4906	13.5389	12.6303	28.6011
P_{13}	12	40	20	**12.00**	40.0000	13.1155	13.7053	12.0000	26.3652
V_1	0.95	1.10	1.05	**1.10**	1.0686	1.0435	1.0734	1.0998	1.0694
V_2	0.95	1.10	1.04	**1.087**	1.0645	1.0271	1.0561	1.0849	1.0563
V_5	0.95	1.10	1.01	**1.062**	1.0484	1.0103	1.0301	1.0544	1.0071
V_8	0.95	1.10	1.01	**1.067**	1.0521	1.0017	1.0566	1.0634	1.0410
V_{11}	0.95	1.10	1.05	**1.10**	1.1000	1.0315	1.09	1.0994	1.0684
V_{13}	0.95	1.10	1.05	**1.099**	1.0993	1.0086	1.0963	1.1000	1.1000
$T_{11}\ (6-9)$	0.90	1.10	1.078	**1.018**	1.0321	0.9973	0.9666	1.0092	0.9829
$T_{12}\ (6-10)$	0.90	1.10	1.069	**0.934**	0.9000	0.9442	0.9395	0.9111	0.9937
$T_{15}\ (4-12)$	0.90	1.10	1.032	**0.991**	0.9595	0.9751	0.9558	0.9776	1.0359
$T_{36}\ (28-27)$	0.90	1.10	1.068	**0.991**	0.9624	0.9646	0.9411	0.9609	0.9671
$Q_{C_{10}}$	0	5	0.0	**0.966**	5.0000	2.4365	5.0000	4.7407	1.7407

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Table 3. Continued

	Min	Max	Initial Case	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
$Q_{C_{12}}$	0	5	0.0	**4.958**	3.3809	1.6916	4.3382	4.5377	3.3780
$Q_{C_{15}}$	0	5	0.0	**4.969**	4.5134	4.5364	5.0000	4.5925	4.6873
$Q_{C_{17}}$	0	5	0.0	**4.827**	5.0000	0.1054	5.0000	4.7640	5.0000
$Q_{C_{20}}$	0	5	0.0	**4.997**	5.0000	4.8597	4.8830	4.8416	3.4804
$Q_{C_{21}}$	0	5	0.0	**4.671**	4.9596	4.0605	5.0000	4.8596	2.3131
$Q_{C_{23}}$	0	5	0.0	**4.801**	3.8958	4.7985	5.0000	4.5215	4.3055
$Q_{C_{24}}$	0	5	0.0	**3.935**	5.0000	4.9995	4.9779	4.6873	1.4567
$Q_{C_{29}}$	0	5	0.0	**5.000**	3.0889	2.4542	4.5452	3.0259	5.0000
Fuel cost ($/h)			901.88	799.079	966.1272	803.1427	800.2926	799.2276	835.055
Active power loss			7.53	**8.619**	2.9084	9.7545	8.9224	8.3269	5.5915
Total Voltage deviation			1.1554	**1.8**	1.8566	0.1061	1.8242	1.8417	1.0869
$L_{\max}$			0.1681	**0.117**	0.1173	0.1369	0.1146	0.1167	0.1240
Emission(ton/hr)				**0.3639**	0.2054	0.3602	0.3550	0.3525	0.2417

4.5 Results of Quad and Quanta-Objective Case Studies

Quad-objective case study contains four different objective functions namely, FC, APL, TVD, and emission (case study 11 and 12). Comparative results of the present case study have been shown in Table 8. Results of present study have lowest TVD and increased voltage stability of the system. The present case study gives best solution when compared with individual case studies without violating restricted limit of voltages. Results for the present case studies i.e. 11 and 12 have been shown in Fig. 11 and 12. Quanta-objective case studies contain five different objectives i.e. FC, APL, TVD, emission, and L-max. It has been seen that, this case study gives better results of FC and L-index. Moreover, voltage limits of this case study are restricted within its permissible limits. Comparative results of the present case study are given in Table 8. Outcome for the quanta-objective case study has been shown in two parts as 13(a) and 13(b) in Fig. 13 and 14.

5. TUNING OF PARAMETERS FOR THE QOBSA

To get the optimized solution, it requires to acquire proper value of amplitude of feasible space search direction for mutation and crossover it is optimal value of $mixrate$. Here, for the F, $mixrate$ have been varied to get all possible solution for this problem. Result of case study 1 for tuning of parameter shown in Table 9.

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Table 4. Simulation results for OPF problem of cases 7-13 for IEEE 30-bus power system

	Min	Max	Case:7	Case:8	Case:9	Case:10	Case:11	Case:12	Case:13
P_1	50	200	176.5522	110.43	113.2057	172.5607	170.9573	112.0377	112.8047
P_2	20	80	48.7746	61.2151	59.2868	48.9721	48.3480	59.2073	58.7435
P_5	15	50	21.3157	28.8477	27.9651	22.0924	21.2704	28.3815	28.3120
P_8	10	35	21.5416	34.9443	34.8926	24.0757	24.2342	35.0000	34.9101
P_{11}	10	30	12.5724	30.0000	27.7718	12.9106	15.8382	28.3798	27.8161
P_{13}	12	40	12.5204	22.9066	26.2268	12.1204	12.1308	26.1613	26.8852
V_1	0.95	1.10	1.0585	1.1000	1.0289	1.0451	1.0596	1.0254	1.0492
V_2	0.95	1.10	1.0409	1.0922	1.0214	1.0287	1.0398	1.0189	1.0410
V_5	0.95	1.10	1.0029	1.0686	1.0112	1.0107	1.0056	1.0007	1.0073
V_8	0.95	1.10	1.0288	1.0813	0.9998	1.0060	1.0290	1.0023	1.0320
V_{11}	0.95	1.10	1.0336	1.1000	1.0389	1.0025	1.0579	1.0192	1.0364
V_{13}	0.95	1.10	1.0097	1.1000	0.9980	1.0078	1.0125	1.0121	1.0030
$T_{11}\left(6-9\right)$	0.90	1.10	1.0646	1.0468	1.0148	1.0166	1.0662	1.0274	1.0480
$T_{12}\left(6-10\right)$	0.90	1.10	0.9881	0.9022	0.9449	0.9054	1.0215	0.9154	1.0232
$T_{15}\left(4-12\right)$	0.90	1.10	1.0336	1.0058	0.9552	0.9756	1.0170	0.9838	1.0201
$T_{36}\left(28-27\right)$	0.90	1.10	0.9004	0.9913	0.9555	0.9665	0.9000	0.9612	0.9000
$Q_{C_{10}}$	0	5	4.9948	3.0108	4.8201	3.9088	5.0000	5.0000	4.9597

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Table 4. Continued

	Min	Max	Case:7	Case:8	Case:9	Case:10	Case:11	Case:12	Case:13
$Q_{C_{12}}$	0	5	5.0000	4.2441	0.2188	0.6984	4.9717	1.6021	4.9948
$Q_{C_{15}}$	0	5	4.9858	5.0000	4.3296	5.0000	4.8825	4.2852	4.9481
$Q_{C_{17}}$	0	5	4.9960	5.0000	0.6818	0.0875	5.0000	1.1491	4.9451
$Q_{C_{20}}$	0	5	5.0000	4.5504	4.9401	5.0000	4.7092	4.9851	4.9906
$Q_{C_{21}}$	0	5	5.0000	1.8473	4.5061	4.9526	5.0000	4.4393	5.0000
$Q_{C_{23}}$	0	5	4.9808	3.6853	5.0000	4.9859	5.0000	5.0000	4.9956
$Q_{C_{24}}$	0	5	4.9951	3.6209	4.8703	4.9245	4.9913	4.9448	5.0000
$Q_{C_{29}}$	0	5	4.9575	4.8635	1.6252	2.2823	5.0000	2.5414	5.0000
Fuel cost ($/h)			803.8310	836.8511	838.7109	803.0669	803.7119	839.9799	840.2082
Active power loss			9.9185	5.1567	5.8877	9.4298	9.5905	5.8659	6.1385
Total Voltage deviation			0.4832	1.7081	0.1108	0.1102	0.4995	0.1026	0.4947
$L_{\max}$			0.1199	0.1184	0.1368	0.1372	0.1199	0.1369	0.1197
Emission (ton/hr)			0.3617	0.2383	0.2396	0.3509	0.3460	0.2380	0.2389

Table 5. Comparison of results of single objective case studies

Cases	NISSO (Nguyen 2019)	MODA (Herbadji 2017)	SCA (Attiaa 2018)	MSCA (Attiaa 2018)	FAHSPSO-DE (Naderi 2021)	QOBSA
Case:1	799.76242	802.32	799.7627	799.31	799.8066	799.079
Case:2	2.9454	-	2.9425	2.9334	4.9989	2.9084

5.1 Sensitivity Analysis

The best, median, maximum, and standard deviation has been shown for the proposed approach. It can be seen from the below table that proposed approach is giving significant improvement in performance over the existing.

5.2 Annual Saving

Annual saving is another important parameter to analyse the cost-effectiveness of the solutions obtained from any OPF approach. In this work, the annual saving analysis has been done and it has

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Table 6. Comparison of results of bi-objective case studies

Cases	Objective	Methods					
		MODA (Herbadji 2017)	MOICA (Ghasemi et al. 2014)	MOBSA (Daqaq 2017)	MOMICA (Ghasemi et al. 2014)	QOMJaya (Warid et al. 2018)	MOQOBSA
Case:3	Fuel cost($/h)	807.2807	805.0345	800.1085	804.96	-	803.1427
	V.D	0.023	0.1004	0.3657	0.095	-	0.1061
Case:4	Fuel Cost		-	799.8808	-	800.8923	800.2926
	L-index		-	0.1336	-	0.12485	0.1146
Case:5	Fuel Cost		850.9001	-	848.0544	826.9651	799.2276
	Active Power		4.5625	-	4.5603	5.7596	8.3269
Case:6	Fuel cost	838.604	865.3134	-	865.066	-	835.055
	Emission	0.254	0.2246	-	0.2221	-	0.2417

Figure 3. Convergence characteristics for case 3

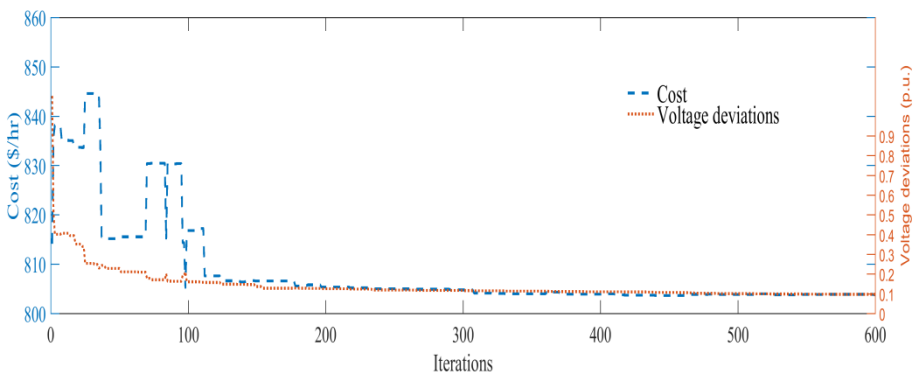

Figure 4. Convergence characteristics for case 4

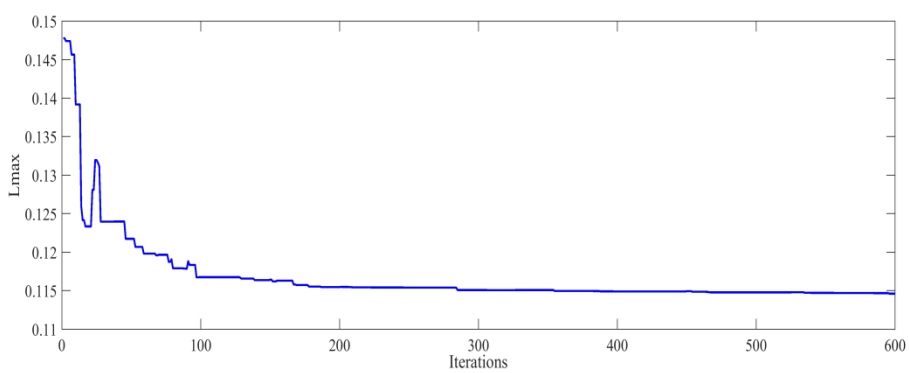

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Figure 5. Convergence characteristics for case 5

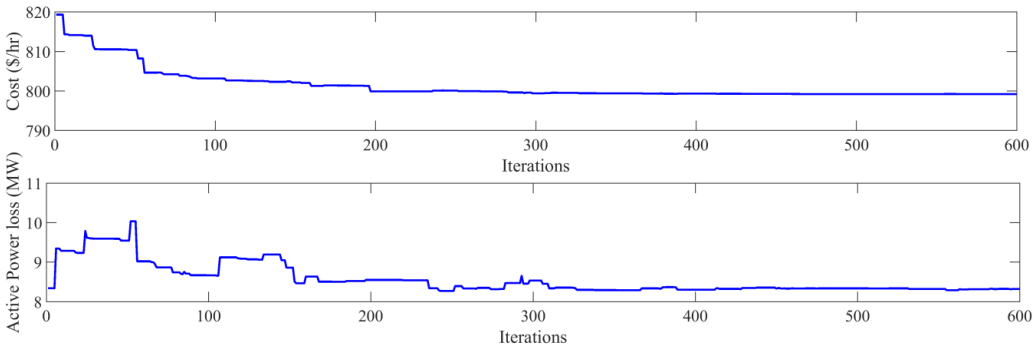

Figure 6. Convergence characteristics for case 6

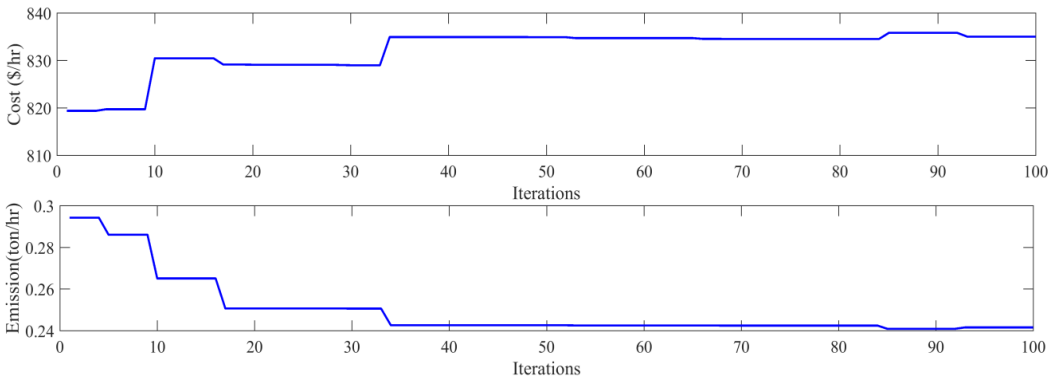

Table 7. comparison of results of tri-objective case studies

Cases	Objective	Method		
		MODA (Herbadji 2017)	**MOBSA** (Daqaq 2018)	**MOQOBSA**
Case:7	Fuel cost	-	804.3982	803.8310
	V.D	-	0.3167	0.4832
	L-index	-	0.1274	0.1199
Case:8 (Iter=300)				
	Fuel cost	867.9070	-	836.8511
	APL	4.5342	-	5.1567
	Emission	0.2640	-	0.2373
Case:9	Fuel cost	-	-	838.7109
	V.D	-	-	0.1108
	Emission	-	-	0.2396
Case:10	Fuel cost	-	-	803.0669
	V.D	-	-	0.1102
	APL	-	-	9.4298

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Figure 7. Convergence characteristics for case 7

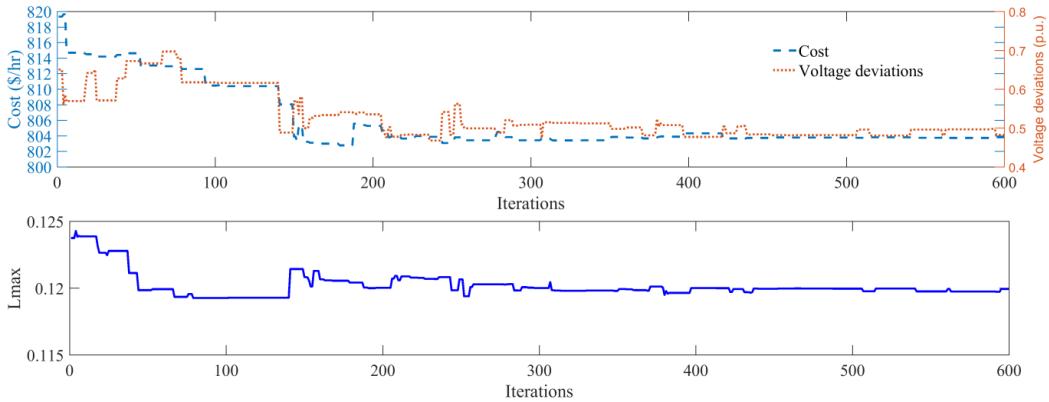

Figure 8. Convergence characteristics for case 8

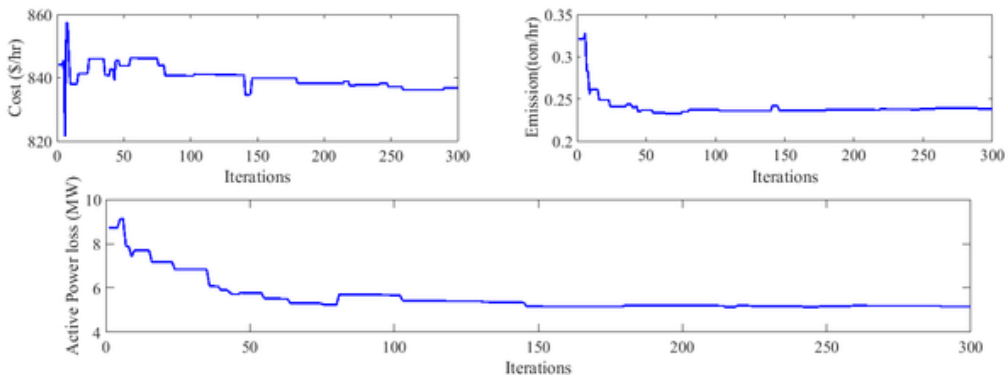

Figure 9. Convergence characteristics for case 9

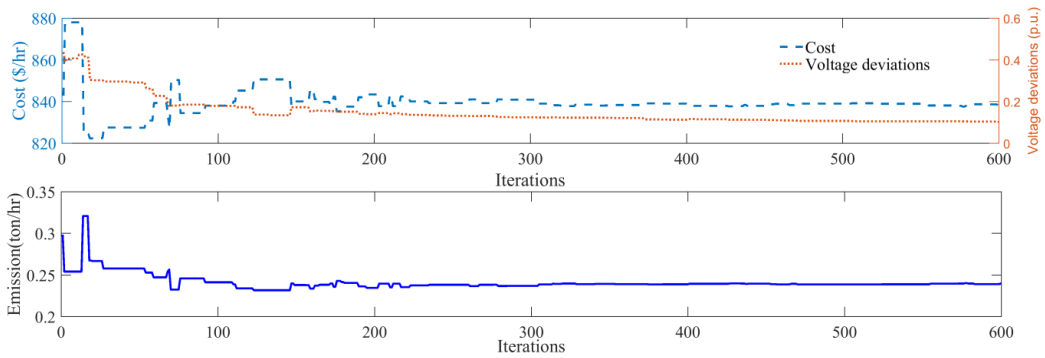

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Figure 10. Convergence characteristics for case 10

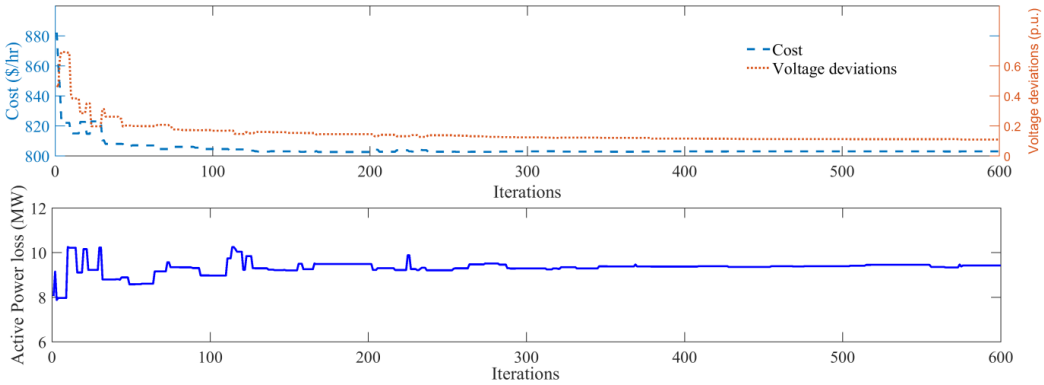

Table 8. Comparison of results of Quad and Quinta objective case studies

Cases	Objective	Method		
Case:11		**MOQOBSA**		
	Fuel cost	803.7119		
	APL	9.5905		
	VD	0.4995		
	Lmax	0.1369		
Case:12		**MODA**(Herbadji 2017)	**MOMICA** (Ghasemi 2014)	**MOQOBSA**
	Fuel cost	828.49	830.188	839.9799
	Active power	5.912	5.585	5.8659
	VD	0.585	0.298	0.1026
	Emission	0.265	0.252	0.2380
Case:13			**I-NSGA-III**	**MOQOBSA**
	Fuel cost	-	843.8571	840.2082
	Active power	-	5.7405	6.1385
	VD	-	0.2388	0.4947
	Emission	-	0.1485	0.2389
	L-max	-	0.1253	0.1197

been noticed that proposed MOQOBSA can save huge revenue when compared to some of the recent algorithms. Table 11 shows the comparative analysis. Table 12 show the reduction in emissions. For both the cases the outcomes are promising.

6. CONCLUSION

The computation of Optimum Power Flow (OPF) in the power system can be helpful in real-time control with help of various objectives, operations, and planning of new or existing thermal plants. In this paper, a new optimization algorithm, which is a combination of quasi-oppositional based

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Figure 11. Convergence characteristics for case 11

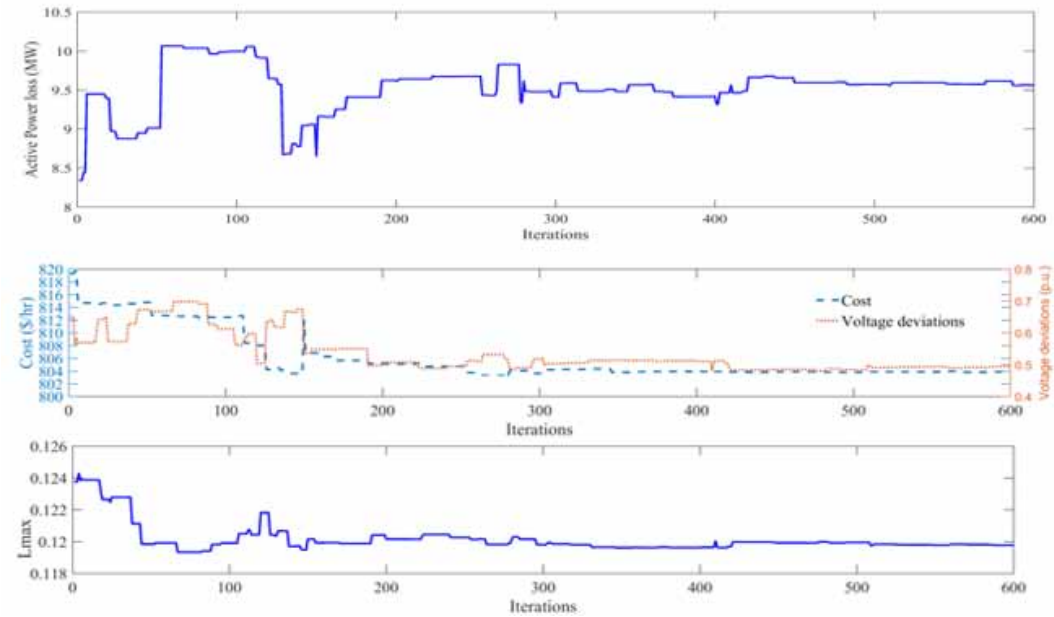
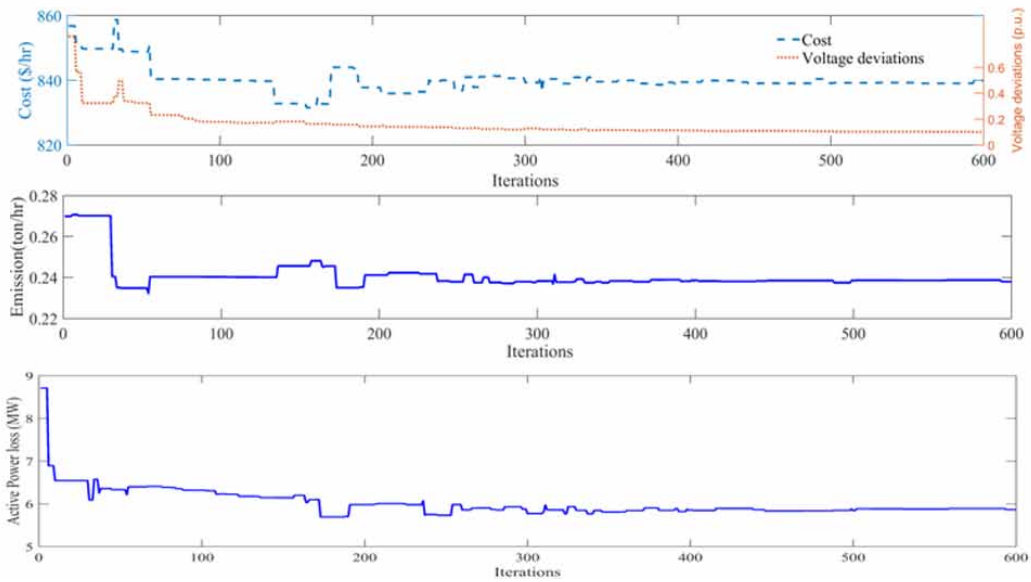


Figure 12. Convergence characteristics for case 12



learning and backtrack search algorithm, has been suggested. Thirteen distinct case studies have been considered to verify the efficacy of the proposed approach. The suggested algorithm has been successfully implemented for IEEE-30 bus with multi-objective functions. The result of proposed algorithm outperforms the other algorithm in the literature at allowable levels of economic, environmental, and technical objectives. This suggested technique leads to lowest level of fuel cost

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Figure 13. Convergence characteristics for Case: 13(a)

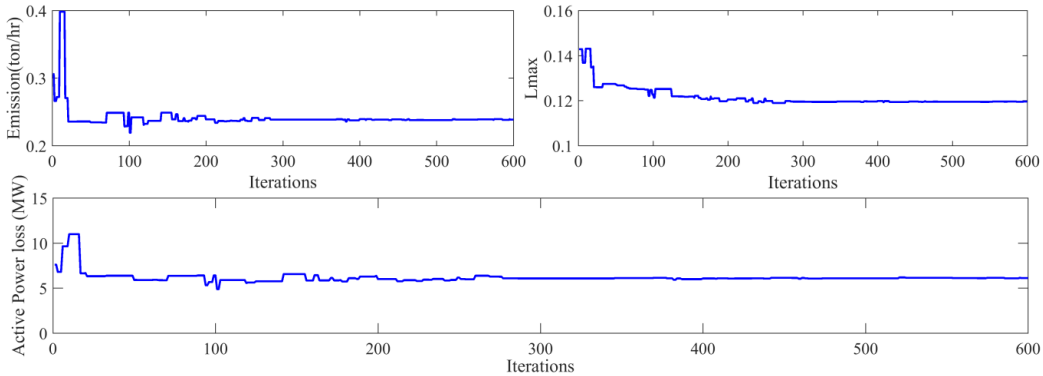

Figure 14. Convergence characteristics for Case: 13(b)

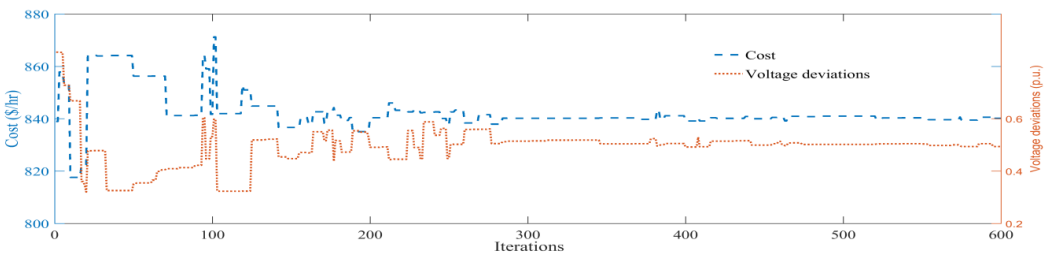

Table 9. Effect of various parameters on the performance of QOBSA

F	Mix_rate					
	1	0.9	0.7	0.5	0.3	0.1
$3 * randn$	799.094	799.109	799.128	799.183	799.134	799.208
$4 * randn$	**799.079**	**799.081**	**799.127**	**799.152**	**799.159**	**799.159**
$lognrnd\left(rand, 5 * rand\right)$	799.094	799.119	799.104	799.202	799.182	799.245
$1 / normrnd\left(0, 5\right)$	799.147	799.173	799.158	799.109	799.104	799.118

and emission. Moreover, this algorithm is robust and proves effectiveness compared with some of the other algorithms. Recently, due to the massive penetration of renewable energy resources, including electric vehicles, power system engineers are facing new operational challenges. The proposed approach can be used as a robust tool for solving the generation-demand problems in most economical way including various operational constraints.

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Table 10. Best, median, maximum, and standard deviation values for objectives

	Objective	Best	Median	Max	S.D
MOQOBSA	Fuel cost	799.0736	799.8928	806.7935	1.294855
	APL	2.995624	3.322479	4.503163	0.303047
FAHSPSO-DE (Naderi 2021)	Fuel cost	799.8066	800.7713	801.9021	1.2635
	APL	4.9989	5.4412	5.8838	0.4423

Table 11. Annual saving for case studies under consideration

Case	Methods		Saving ($/h)	Annual saving ($)
Case: 1	**MOQOBSA**	**MSCA** (Naderi 2021)		
	799.0736	799.31	0.2364	2070.864
Case: 5	**MOQOBSA**	**QOMJaya** (Daqaq 2017)		
	799.2276	826.9651	27.7375	2,42,980.5
Case: 14	**MOQOBSA**	**I-NSGA-III** (Zhangab 2019)		
	840.2082	843.8571	3.6489	31,964.364

Table 12. Annual saving in emission

Case	Methods		Saving (ton/h)	Annual saving (ton)
Case: 8	**MOQOBSA**	**MODA** (Herbadji 2017)		
	0.2373	0.2640	0.0267	233.892
Case: 12	**MOQOBSA**	**MOMICA** (Ghasemi 2014)		
	0.2380	0.252	0.014	122.64

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

DATA AVAILABILITY STATEMENT (DAS)

Authors can share the available data upon reasonable request.

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