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Optimal reactive power dispatch with uncertainties in load demand and renewable energy sources adopting scenario-based approach

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Abstract: Optimizing reactive power flow in electrical network is an important aspect of system study as the reactive power supports network voltage which needs to be maintained within desirable limits for system reliability. A network consisting of only conventional thermal generators has been extensively studied for optimal active and reactive power dispatch. However, increasing penetration of renewable sources into the grid necessitates power flow studies incorporating these sources. This paper presents a formulation and solution procedure for stochastic optimal reactive power dispatch (ORPD) problem with uncertainties in load demand, wind and solar power. Appropriate probability density functions (PDFs) are considered to model the stochastic load demand and the power generated from the renewable energy sources. Numerous scenarios are created running Monte-Carlo simulation and scenario reduction technique is implemented to deal with reduced number of scenarios. Real power loss and steady state voltage deviation of load buses in the network are set as the objectives of optimization. Success history based adaptive differential evolution (SHADE) is adopted as the basic search algorithm. SHADE has been successfully integrated with a constraint handling technique, called epsilon constraint (EC) handling, to handle constraints in ORPD problem. The effectiveness of a proper constraint handling technique is substantiated with case studies for deterministic ORPD on base configurations of IEEE 30-bus and 57-bus systems using SHADE-EC algorithm. The single-objective and multi-objective stochastic ORPD cases are also solved using the SHADE-EC algorithm. The results are discussed, compared and critically analyzed in this study.

Keywords: Optimal reactive power dispatch · wind power · solar power · scenario-based approach · success history based adaptive differential evolution · epsilon constraint handling

1. Introduction

Optimal reactive power dispatch (ORPD) is a sub-problem of optimal power flow (OPF). Control and management of reactive power are necessary in the system so that voltages at all system buses remain within acceptable limits and network real power loss is minimum. Reactive power flow cannot be avoided in the system as most system loads are inductive and components such as transformers and transmission lines consume reactive power. Therefore, in a network, the reactive power generation should be sufficient to supply the VAR (volt-ampere reactive) consumers but should not be high enough to cause excessive heat loss and unwanted voltage drop. In ORPD, minimization of system real power loss is set as an objective with the basic concept that reactive power flow incurs real (active) power loss. In a typical network, generator bus voltages, settings of passive devices such as transformers and shunt VAR compensators are adjusted to achieve the desired objective. During optimization, constraints on load bus voltage, generator reactive power capabilities, line capacities and power balance must be satisfied. The cumulative sum of voltage deviations of load buses in the network is also set as an objective in ORPD problem. This objective ensures that voltages at consumer terminals are closed to the desired level (usually 1 p.u.) with control of reactive power flow. However, this objective does not warrant lowest real power loss of the system. The two objectives of real power loss and voltage deviation can also be considered together in optimization to obtain a compromise solution. Nevertheless, the objectives are framed based on the importance exercised on certain aspects of the network.

Numerous publications studied the ORPD problem for systems consisting of conventional thermal units. In earlier days, classical mathematical methods such as quadratic programming [1] and interior-point methods [2] were extensively used. With the advancement of computational intelligence, abundant evolutionary algorithms are being tried and tested on non-linear, non-convex power system optimization problems including ORPD. Basic form of differential evolution (DE) was applied to optimize ORPD objectives in [3]. Quasi-oppositional based learning for population initialization was incorporated in differential evolution to form quasi-oppositional differential evolution (QODE) in [4] to propose solutions for ORPD on standard bus systems with conventional generators. In quasi-oppositional teaching learning based optimization algorithm (QOTLBO) [5], the same philosophy of quasi-

oppositional learning was infused in teaching-learning based optimization algorithm. A newly surfaced nature-inspired optimization method called moth-flame optimization (MFO) was applied in [6] to minimize single objective functions of ORPD. In attempting the same problem, the authors in [7] tried to establish efficacy and robustness of exchange market algorithm (EMA) due to presence of both exploration and exploitation at two phases, viz. balanced market and oscillation market, of the algorithm. The variants of gravitational search algorithm such as improved gravitational search algorithm (IGSA) [8], opposition-based gravitational search algorithm (OGSA) [9] etc. also have been popularly used for ORPD problem. In finding solutions for ORPD, hybridized algorithms like hybrid particle swarm optimization and imperial competitive algorithms (PSO-ICA) [10], hybrid Nelder–Mead simplex based firefly algorithm (HFA) [11], hybrid modified imperialist competitive algorithm and invasive weed optimization (MICA-IWO) [12] etc. performed better in combined manner than when applied individually with their respective constituting algorithms. Fuzzy adaptive heterogeneous comprehensive learning particle swarm optimization (FAHCLPSO) [13] algorithm and Gaussian bare-bones water cycle algorithm (NGBWCA) [14] showed competitive results for solutions of ORPD. In summary, either basic or the improved version of an algorithm was tried in the literature for real-parameter optimization problem of ORPD. Multi-objective formulation and solutions of ORPD are found in [15] using multi-objective grey wolf optimizer (MGWO), in [16] using multi-objective particle swarm optimization.

ORPD incorporating uncertain load and wind power was studied in some articles. Probabilistic multi-objective optimal power flow considering correlation in wind speed and load was presented in [17]. Load uncertainty was modeled with two-point estimate method (TPEM) [18] in multi-objective ORPD problem. An enhanced firefly algorithm was proposed in [19] for multi-objective optimal active/reactive power dispatch with load and wind power generation uncertainties. Scenario-based approach for uncertainty modeling of load and wind power generation was proposed in [20–22]. Stochastic multi-objective ORPD (SMO-ORPD) integrating wind power generation uncertainties was studied in [20] with objectives of minimizing real power loss and voltage stability. Ref. [21] considered two objectives of minimizing real power loss and O&M (operation and maintenance) cost of windfarm for ORPD problem. Real power loss, voltage deviation and voltage stability index were considered as the objectives of optimization for ORPD problem in [22]. To the best of our knowledge, no literature has attempted stochastic ORPD problem with uncertain load demand, wind and solar (i.e. photovoltaic or PV) power. Solar energy being abundant and almost ubiquitous, PV system is becoming an integral part of the smart grid. Therefore, ORPD study integrating both wind and solar power becomes essential. However, inclusion of many renewable sources escalates the complexity of optimal power dispatch problem. Besides variability in load demand, uncertainty from renewable sources needs to be considered. The stochastic ORPD can be framed either as a single or a multi-objective optimization problem incorporating uncertain load demand, wind and solar power. This paper focuses primarily on single objective optimization aspect and proposes an approach to formulate and solve single-objective ORPD problem with stochastic load demand, wind speed and solar irradiance adopting scenario-based approach. Real power loss and aggregate voltage deviation (of load buses) are optimized individually for the test system. A multi-objective case study, considering both the objectives simultaneously, is also performed for the adapted network by transforming the multi-objective optimization problem into a single objective one using weighted sum approach. Normal probability density function (PDF) is considered to model the uncertainty in demand. Stochastic nature of wind speed is modeled using Weibull PDF and that of solar irradiance is modeled using lognormal PDF as in many other publications [23–25]. One thousand scenarios are generated running Monte Carlo simulation for each of these uncertain parameters. Scenario reduction technique is applied to select a specific number of representative scenarios. The ORPD problem is solved for the selected discrete scenarios using success history based adaptive differential evolution (SHADE) [26] algorithm, an advanced variant of differential evolution (DE) algorithm. In classical DE, control parameters viz. scale factor (F), crossover rate (CR) and population size (Np) are user defined. However, in SHADE, only population size is to be defined and a reasonable size of population would be able to effectively perform the search in pursuit of the global optimum. Scale factor (F) and crossover rate (CR) are automatically adapted based on success history of previous generations. In summary, the algorithm hardly depends on the user defined parameters. Further SHADE, L-SHADE [27] i.e. linear population size reduction technique of SHADE, and their variants have been among the top performing algorithms for single objective real-parameter numerical optimization till CEC 2017 competition [28]. SHADE and L-SHADE have been successfully applied to power system problems of discrete [29] and continuous variables [30,31]. Motivated by the competitive performance of the algorithm on single objective real parameter optimization, we test it on the problem of ORPD. Further, ORPD being a constrained optimization problem, a proper constraint handling technique is necessary to satisfy the defined limits on certain system parameters. Penalty function method has been the most popular technique in handling system constraints and in this method, the objective function is penalized for violating constraints. The performance of this approach largely depends on the value of penalty coefficient which is selected by tedious trial and error method. Small penalty coefficient over-explores the infeasible region, thus delaying the process of finding feasible solutions, and may prematurely converge to an infeasible solution. On the other hand, large penalty coefficient may not explore the infeasible region properly, thereby resulting in untimely convergence [32]. Ref. [32] applied several constraint handling techniques such as superiority of feasible solutions (SF), self-adaptive penalty (SP), epsilon

constraint (EC) and stochastic ranking (SR) on the problem of ORPD with DE being the basic search algorithm. Our research presented in this paper evaluates the performance of EC with SHADE as the basic search algorithm. The integration technique of EC with SHADE is suggested in this work. SHADE-EC algorithm is employed to perform optimization in all case studies. Simulations results are analyzed in detail for cases with and without stochastic load demand and renewable power. The contribution of the article can be summarized as below:

- Formulation of ORPD problem incorporating uncertain load demand, wind and solar power in IEEE 30-bus test system.
- Generation of numerous scenarios for uncertain demand and renewable energy applying Monte-Carlo method and selection of representative scenarios using backward reduction algorithm of scenario reduction.
- Integrating SHADE algorithm with epsilon constraint (EC) handling technique to perform optimization tasks of the constrained ORPD problem.
- A comparative study of the deterministic ORPD for base configurations of IEEE 30 and 57-bus test systems.
- Detailed analyses of the status of all constraints in deterministic and stochastic ORPD problem.
- Stochastic single and multi-objective optimizations and solutions of ORPD for the adapted IEEE 30-bus system.

In organizing rest of the paper, section 2 includes details of mathematical modeling for ORPD problem with the constraints involved. Section 3 explains the uncertainty modeling of load demand, wind and solar power followed by scenario generation and scenario reduction techniques. The constraint handling method EC and integration of EC with SHADE are elaborated in section 4. Detailed analyses of results and comparison of deterministic and stochastic ORPD are provided in section 5. The paper ends with conclusion in section 6.

2. Mathematical formulation and numerical data

The ORPD problem is non-convex and non-linear. The optimization is subject to many equality and inequality constraints. Mathematically, the general form of ORPD is:

$$\begin{aligned} &\text{Minimize: } f(x, u) \\ &\text{subject to: } g(x, u) \leq 0 \\ &\quad h(x, u) = 0 \end{aligned} \quad (1)$$

where x is the vector of control or independent variables, u is the vector of state or dependent variables. $f(x, u)$: objective function of ORPD, $g(x, u)$: set of inequality constraints, $h(x, u)$: set of equality constraints.

2.1. Objective functions

A sub-problem of optimal power flow (OPF) is ORPD where values of active power generation from all generators except swing (or slack) generator are fixed and known [33]. In power flow study, total generation must be equal to the sum of demands and losses in the network. Swing generator balances the active power as well as the reactive power flow in the network. In ORPD, control variables which manage reactive power are the generator terminal voltages, settings of shunt VAR compensators and transformer taps. The two commonly used optimization objectives for ORPD are minimization of real power loss and minimization of voltage deviation of the network from desired value of 1 p.u.

2.1.1. Real power loss

The objective function of real power loss (P_{loss}) in the network is calculated as [4]:

$$\text{Minimize } P_{loss} = \sum_{k=1}^{nl} G_{k(ij)} [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_{ij})] \quad (2)$$

where P_{loss} is usually expressed in MW, V_i and δ_i are the voltage magnitude and voltage angle, respectively at i -th bus; $\delta_{ij} = \delta_i - \delta_j$, is the difference in voltage angles of bus i and bus j , $G_{k(ij)}$ is the transfer conductance of branch k connecting buses i and j and nl is the number of branches (i.e. transmission lines) in the network.

2.1.2. Aggregate voltage deviation

The index of voltage deviation is a measure of voltage quality in the network. The index is also important from the aspect of system security. It is formulated as the summation of voltage deviations at all load buses (PQ buses) in the network from ideal value of 1 p.u. Mathematically, the minimization of the objective is expressed as [4]:

$$\text{Minimize } VD = \left(\sum_{p=1}^{NL} |V_{L_p} - 1| \right) \quad (3)$$

where V_{L_p} is the bus voltage of p -th load bus (PQ bus) and NL is the number of load buses.

2.2. Control or independent variables

The control variables are represented in vector form as:

$$x = [V_{G_1} \dots V_{G_{NG}}, Q_{C_1} \dots Q_{C_{NC}}, T_1 \dots T_{NT}] \quad (4)$$

where V_{G_i} is the voltage magnitude at i -th PV bus (generator bus), Q_{C_k} is the shunt compensation at k -th bus and T_j is the j -th branch transformer tap. NG, NC and NT are the number of generators, VAR compensators and transformers, respectively. Majority of the study cases in our work consider transformer tap settings and shunt VAR compensator ratings as discrete variables. Only selected few cases, as mentioned in result section, consider these as continuous variables. Remaining all other variables are continuous.

2.3. State or dependent variables

The state variables in vector form can be represented as:

$$u = [V_{L_1} \dots V_{L_{NL}}, Q_{G_1} \dots Q_{G_{NG}}, S_{l_1} \dots S_{l_{nl}}] \quad (5)$$

where Q_{G_i} is the reactive power of the generator connected to bus i , V_{L_p} is the bus voltage of p -th load bus (PQ bus) and S_{l_q} is the line loading of q -th line. NL is the number of load buses, while nl is the number of transmission lines in the network.

2.4. Constraints

The equality and inequality constraints pertaining to ORPD problem are segregated and provided herein.

2.4.1. Equality constraints

The equality constraints are the power balance equations given by:

$$P_{G_i} - P_{D_i} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\delta_{ij}) + B_{ij} \sin(\delta_{ij})] = 0 \quad \forall i \in NB \quad (6)$$

$$Q_{G_i} - Q_{D_i} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\delta_{ij}) - B_{ij} \cos(\delta_{ij})] = 0 \quad \forall i \in NB \quad (7)$$

where $\delta_{ij} = \delta_i - \delta_j$, is the difference in voltage angles of bus i and bus j , NB is the number of buses, P_D and Q_D are active and reactive load demands, respectively. G_{ij} is the transfer conductance and B_{ij} is the susceptance between buses i and j , respectively.

2.4.2. Inequality constraints

The inequality constraints are for the operational limits of the equipment and the security constraints associated with the network.

$$\text{a) Generator constraints:} \quad V_{G_i}^{\min} \leq V_{G_i} \leq V_{G_i}^{\max} \quad \forall i \in NG \quad (8)$$

$$Q_{G_i}^{\min} \leq Q_{G_i} \leq Q_{G_i}^{\max} \quad \forall i \in NG \quad (9)$$

$$\text{b) Transformer constraints:} \quad T_j^{\min} \leq T_j \leq T_j^{\max} \quad \forall j \in NT \quad (10)$$

$$\text{c) Shunt compensator constraints:} \quad Q_{C_k}^{\min} \leq Q_{C_k} \leq Q_{C_k}^{\max} \quad \forall k \in NC \quad (11)$$

$$\text{d) Security constraints:} \quad V_{L_p}^{\min} \leq V_{L_p} \leq V_{L_p}^{\max} \quad \forall p \in NL \quad (12)$$

$$S_{l_q} \leq S_{l_q}^{\max} \quad \forall q \in nl \quad (13)$$

It is worthwhile to note that the control variables among the inequality constraints are self-limiting. During optimization, the algorithm picks a feasible value for each control variable. The effective handling of state or dependent variables with a CH technique is described in section 4.

This paper considers base configurations of IEEE 30 and IEEE 57-bus systems to perform selected cases of deterministic ORPD and compare the results of those cases with previously reported results. The base configurations have all thermal generators. To execute stochastic ORPD including a wind generator and a PV unit, the IEEE 30-bus system is modified. The thermal generator at bus 5 is replaced with a wind power generating source. A photovoltaic (PV) power unit substitutes the thermal generator at bus 8. Table 1 summarizes parameters for the systems under study. The diagram of the modified system is presented in Fig. 1.

Fig. 1. The adapted IEEE 30-bus system including a wind generator and a PV unit for stochastic ORPD study

Table 1. Summary of the systems under study

Items	IEEE 30-bus system				IEEE 57-bus system (base configuration)	
	Base configuration		Adapted configuration			
	Quantity	Details	Quantity	Details	Quantity	Details
Buses	30	Table S.1 (Supp. doc.)	30	Variable load	57	[35]
Branches	41	[34]	41	[34]	80	[35]
Thermal generators	6	Buses: 1 (swing), 2, 5, 8, 11 and 13	4	Buses: 1 (swing), 2, 11 and 13	7	Buses: 1 (swing), 2, 3, 6, 8, 9 and 12
Wind generator	-		1	Bus 5	-	
PV unit	-		1	Bus 8	-	
Shunt VAR compensation	9	Buses: 10, 12, 15, 17, 20, 21, 23, 24 and 29	9	Buses: 10, 12, 15, 17, 20, 21, 23, 24 and 29	3	Buses: 18, 25 and 53
Transformer with tap changer	4	Branches: 11, 12, 15 and 36	4	Branches: 11, 12, 15 and 36	17	Branches: 19, 20, 31, 35, 36, 37, 41, 46, 54, 58, 59, 65, 66, 71, 73, 76 and 80
Control variables	19	-	19	-	27	-
Connected load	-	283.4 MW, 126.2 MVar	-	Variable	-	1250.8 MW, 336.4 MVar
Load bus voltage range allowed	24	[0.95 – 1.05] p.u.	24	[0.95 – 1.05] p.u.	50	[0.94 – 1.06] p.u.

3. Scenario generation and reduction of uncertain load demand, wind and solar power

This section applies to the modified IEEE 30-bus system incorporating the renewable sources. While base case considers 100% loading (fixed) of the network, uncertainty in load demand is considered for the adapted network. This section discusses the uncertainty modeling of load demand and renewable power sources, followed by the techniques of scenario generation and scenario reduction.

3.1. Scenario generation of uncertain load demand, wind and solar power sources

Load uncertainty is modeled using normal probability density function (PDF) as in [20] with known mean (μ_d) and standard deviation (σ_d). The probability density of normal distribution of load (P_d) is given by:

$$\Delta_d(P_d) = \frac{1}{\sigma_d \sqrt{2\pi}} \exp \left[-\frac{(P_d - \mu_d)^2}{2\sigma_d^2} \right] \quad (14)$$

Fig. 2 shows 1000 Monte Carlo scenarios of load demand generated using normal PDF with $\mu_d = 70$ and $\sigma_d = 10$. The horizontal axis denotes the percentage loading of the network.

Fig. 2. Load demand scenarios (sample size 1000) using normal PDF ($\mu_d = 70$, $\sigma_d = 10$)

Fig. 3. Wind speed scenarios (sample size 1000) for the wind generator (bus 5) using Weibull PDF ($\alpha = 9$, $\beta = 2$)

Wind speed distribution is popularly represented with Weibull PDF [23]. The probability density of wind speed (v_w) following Weibull PDF is expressed as:

$$\Delta_v(v_w) = \left(\frac{\beta}{\alpha}\right) \left(\frac{v_w}{\alpha}\right)^{(\beta-1)} \exp \left[-\left(\frac{v_w}{\alpha}\right)^\beta \right] \quad \text{for } 0 < v_w < \infty \quad (15)$$

where α is the scale parameter and β is the shape parameter for Weibull PDF. The 1000 Monte Carlo scenarios of wind speed distribution following Weibull PDF with $\alpha = 9$, $\beta = 2$ are exhibited in Fig. 3. All PDF parameters considered in the study are realistic and mostly in line with the previous studies [23,25].

Solar irradiance (G_s) is well-known to trail lognormal distribution [23-25]. The lognormal probability density with mean (μ_s) and standard deviation (σ_s) of solar irradiance (G_s) is represented as:

$$\Delta_G(G_s) = \frac{1}{G_s \sigma_s \sqrt{2\pi}} \exp \left[\frac{-(\ln G_s - \mu_s)^2}{2\sigma_s^2} \right] \quad \text{for } G_s > 0 \quad (16)$$

It is worthwhile to note that lognormal distribution for solar irradiance considers the duration when sunlight is available (daytime). In general, as the sun is not available almost half of the time (in a whole day of 24 hours), the solar irradiance (and hence PV output) for that duration would be zero. The scenarios created for solar irradiance using Monte-Carlo method are presented in Fig. 4. Zero irradiance is initialized with 50% probability and the remaining 50% probability covers the scenarios of solar irradiance generated using lognormal distribution mean $\mu_s = 5.5$ and standard deviation $\sigma_s = 0.5$. For clarity, the solar irradiance distribution is reproduced in Fig. 5 after removing the zero irradiance.

Fig. 4. Solar irradiance scenarios (sample size 1000) for the PV (bus 8) using lognormal PDF ($\mu_s = 5.5$, $\sigma_s = 0.5$)

Fig. 5. Solar irradiance scenarios (without zero irradiance) for the photovoltaic (PV)

Refs. [20-22] adopted a simplistic approach of scenario creation. Five values of load demand and equal number of wind power values were arbitrarily chosen and a total of 25 scenarios were created with all possible combinations of these scenarios. If similar method is followed, addition of a solar power source will raise the number of scenarios

to 125 (i.e. $5 \times 5 \times 5$). As it is impractical to handle so many scenarios, an appropriate scenario reduction method is necessary.

In this work, a more logical approach to scenario creation and scenario reduction is taken. The 1000 Monte-Carlo scenarios of each of load demand, wind speed and solar irradiance are combined to form a set of 1000 scenarios with each scenario representing a vector of 3 elements (demand, wind speed and solar irradiance). The i -th scenario is written as:

$$Y_i = [P_{d,i}, v_{w,i}, G_{s,i}] \quad (17)$$

The 1000 scenarios are reduced to a representative set of 25 scenarios by applying backward reduction technique [36] of stochastic programming. Increasing number of selected scenarios might improve the accuracy of results marginally, however, optimization based on 25 scenarios is good for all practical purposes.

3.2. Scenario reduction method

The method of scenario reduction using backward reduction algorithm (BRA) [36] is lucidly explained in Table 2. One scenario is removed at a time with one loop of operation of the algorithm. The operation starts with N_0 scenarios. Initially, all scenarios have equal probability (say, $\Delta_0 = 1/N_0$) of occurrence.

Table 2. Backward reduction algorithm

Steps in scenario reduction	
INITIALIZATION	<ul style="list-style-type: none"> Create N_0 scenarios with vectors Y_i in eq. (17) for $i = 1, 2, \dots, N_0$. In this problem, we consider $N_0 = 1000$. Initially, all scenarios have equal probability: $\Delta_0 = 1/N_0$. Compute distance between each pair of scenarios by calculating the norm. Distance between scenarios Y_i and Y_j is $d_{ij} = \ Y_i - Y_j\$. Formulate the distance matrix D including elements of self-distance (which is 0). Construct distance matrix D in such a way that all diagonal elements of the matrix are 0 and $d_{ij} = d_{ji}$. Initially, D matrix will be a square matrix of dimension $N_0 \times N_0$. Now, set $N_{dyn} = N_0$ and a stopping criterion N_{sc}, the number of final selected scenarios.
LOOP OPERATION:	
STEP 1	<ul style="list-style-type: none"> Find minimum distance value (excluding the elements of self-distance d_{ii}) from the distance matrix D. Two rows will contain same minimum value (as $d_{ij} = d_{ji}$). Suppose, the two rows are scenario m (row m) and scenario n (row n) with probabilities Δ_m and Δ_n, respectively.
STEP 2	<ul style="list-style-type: none"> If $\Delta_m \geq \Delta_n$, remove scenario n. Update probability $\Delta_m = \Delta_m + \Delta_n$. Else, remove scenario m. Update probability $\Delta_n = \Delta_n + \Delta_m$.
STEP 3	<ul style="list-style-type: none"> $N_{dyn} = N_{dyn} - 1$. Recalculate the distance between each pair of scenarios for the remaining scenarios and update distance matrix D.
STEP 4	<ul style="list-style-type: none"> Is $N_{dyn} > N_{sc}$? If yes, go to STEP 1 of loop operation. Else, STOP.

3.3. Selected scenarios, their probabilities and calculated power

The selected representative scenarios and their probabilities are listed in Table 3. The row corresponding to a scenario also provides data on percentage load demand, wind speed and solar irradiance for that scenario. It is worth mentioning that load data provided in Table S.1 (in the supplementary document) are for 100% loading of the network. While considering a particular scenario, the demands (loading) in all buses are multiplied by the % loading of that scenario. The methods for calculation of wind power and solar power are discussed herein from wind speed and solar irradiance, respectively.

The output of a windfarm consisting of 25 turbines of 3 MW each is connected to bus 5. A wind turbine generates power output according to the wind speed it encounters. The relationship between output power and wind speed (v_w) is expressed as [23]:

$$p_w(v_w) = \begin{cases} 0 & \text{for } v_w < v_{w,in} \text{ and } v_w > v_{w,out} \\ p_{wr} \left(\frac{v_w - v_{w,in}}{v_{w,r} - v_{w,in}} \right) & \text{for } v_{w,in} \leq v_w \leq v_{w,r} \\ p_{wr} & \text{for } v_{w,r} < v_w \leq v_{w,out} \end{cases} \quad (18)$$

where p_{wr} is the rated output power of a single wind turbine. Cut-in, rated and cut-out wind speeds of the turbine are $v_{w,in}$, $v_{w,r}$ and $v_{w,out}$, respectively. The numerical values of the speed considered are: $v_{w,in} = 3$ m/s, $v_{w,r} = 16$ m/s and $v_{w,out} = 25$ m/s, same as the data of 3-MW turbine model Enercon E82-E4. The calculated values of wind power for different wind speeds are provided in Table 3.

The solar irradiance (G_s) to energy conversion is given by following relationship with maximum output power limited to the PV unit rated power, P_{sr} . The rated power (P_{sr}) of the PV unit is assumed to be 50 MW.

$$P_s(G_s) = \begin{cases} P_{sr} \left(\frac{G_s^2}{G_{std} R_c} \right) & \text{for } 0 < G_s < R_c \\ P_{sr} \left(\frac{G_s}{G_{std}} \right) & \text{for } G_s \geq R_c \end{cases} \quad (19)$$

where G_{std} is the solar irradiance in standard environment, set as 1000 W/m². R_c is a certain irradiance point, set as 120 W/m². The calculated values of solar power at different levels of solar irradiance are provided in Table 3.

Table 3. Selected scenarios and relevant parameters for the scenarios

Scenario number	% Loading P_d	Wind speed v_w (m/s)	Irradiance, G_s (W/m ²)	Wind power (MW)	PV power (MW)	Scenario probability, Δ_{sc}
1	105.784	1.702	1115.95	0	50	0.001
2	55.714	7.605	726.973	26.566	36.349	0.001
3	73.165	10.414	476.090	42.772	23.805	0.007
4	77.665	2.377	803.282	0	40.164	0.001
5	99.491	9.182	935.904	35.666	46.795	0.001
6	60.573	3.158	607.269	0.912	30.363	0.004
7	97.292	5.712	365.655	15.645	18.283	0.001
8	58.378	9.221	326.471	35.892	16.324	0.038
9	98.092	8.166	0	29.805	0	0.006
10	77.942	5.470	751.597	14.248	37.580	0.002
11	41.386	4.661	181.466	9.580	9.073	0.004
12	65.615	5.871	869.125	16.561	43.456	0.001
13	90.475	8.806	441.341	33.496	22.067	0.003
14	66.773	10.001	1103.501	40.393	50	0.001
15	61.498	8.628	551.278	32.470	27.564	0.009
16	68.935	6.229	0	18.629	0	0.478
17	67.603	9.084	138.834	35.103	6.942	0.093
18	71.770	9.678	379.832	38.528	18.992	0.044
19	79.921	5.271	672.788	13.102	33.639	0.004
20	72.351	7.880	411.201	28.152	20.560	0.037
21	78.322	4.813	201.152	10.458	10.058	0.048
22	66.073	11.743	95.657	50.441	3.813	0.027
23	74.465	2.538	229.271	0	11.464	0.071
24	63.754	3.245	518.084	1.416	25.904	0.012
25	67.487	14.439	275.124	65.994	13.756	0.106

A further review of Table 3 reveals that the probabilities of various scenarios are realistic. PV plant produces almost zero output power with about 50% probability (scenario 16). The probability of power output from both sources being simultaneously high is very small (e.g. scenario 14 in the order of 0.1%). The maximum and minimum possible outputs from both the sources are included in the set of selected scenarios. As the mean of normal PDF (for network loading) is considered as 70%, probability of network being overloaded is very low (scenario 1). A representative scenario (scenario 9) of high network loading and low output from renewable sources is also selected by the adopted scenario reduction technique. In summary, the set of selected 25 scenarios with the assigned probabilities represents a good approximation of the original 1000 scenarios. It may also be noted that the scenario generation and reduction techniques can be implemented for an electrical network with a larger number of stochastic variables. The user shall judiciously select the number of scenarios to perform the optimization.

Now, the optimization algorithm is run for each scenario independently to minimize the objective functions of real power loss and aggregate voltage deviation, as applicable. The results and calculations of final objective values considering all the scenarios are presented in section 5. Section 4 describes the constraint handling technique and the algorithm employed for the study.

4. Constraint handling technique EC integrated with SHADE

In this section, constraint handling (CH) technique EC (ε -constraint) is described first, followed by an overview of SHADE algorithm. Finally, the integration approach of EC with SHADE is elaborated.

4.1 Epsilon constraint (ε -constraint) handling technique

When solving a constrained optimization problem using an evolutionary algorithm, it is essential to employ constraint handling method to effectively utilize the information present in the infeasible solutions so that the search process is driven towards global feasible optima. A constrained optimization problem with d parameters can be represented in the following form [32]:

$$\text{Minimize: } f(x), x = (x_1, x_2, \dots, x_d) \text{ and } x \in S \quad (20)$$

$$\text{subject to: } \begin{aligned} g_i(x) &\leq 0, & i &= 1, \dots, p \\ h_j(x) &= 0, & j &= p+1, \dots, m \end{aligned}$$

where S is the search space comprising p and $(m-p)$ number of inequality and equality constraints, respectively. $f(x)$ can be symbolized as the objective function of ORPD discussed in section 2.1. The equality constraints can be transformed into inequality constraints with the help of tolerance parameter δ and total constraint can be represented as:

$$G_i(x) = \begin{cases} \max[g_i(x), 0], & i = 1, \dots, p \\ \max[|h_i(x)| - \delta, 0], & i = p+1, \dots, m \end{cases} \quad (21)$$

After transforming the equality constraints into inequality constraints, the overall constraint violation of an individual is expressed as:

$$vio(x) = \frac{\sum_{i=1}^m w_i [G_i(x)]}{\sum_{i=1}^m w_i} \quad (22)$$

where $w_i (= 1/G_{i,max})$ is a weight parameter, $G_{i,max}$ is the maximum violation of constraint $G_i(x)$ obtained so far. Here, w_i is set as $1/G_{i,max}$, which varies during the evolution to balance the contribution of every constraint in the problem irrespective of the different numerical ranges of all constraints. The objective is to find an optimal feasible solution x^* with overall constraint violation $vio(x^*) = 0$ and minimum value of objective function $f(x^*)$.

In ε -constraint handling method (EC) [37], the relaxation of overall constraint violation is controlled by the ε -parameter. EC is more effective when the optimization problem contains active constraints. The search process to find feasible solutions can be efficiently handled by controlling the ε -parameter [37]. The parameter is updated according to the following equations.

$$\varepsilon(1) = vio(x_\theta) \quad (23)$$

$$\varepsilon(t) = \begin{cases} \varepsilon(1) * \left(1 - \frac{t}{T_c}\right)^{cp}, & 0 < t < T_c \\ 0, & t \geq T_c \end{cases} \quad (24)$$

where $\varepsilon(1)$ is the initial (generation, $t = 1$) epsilon parameter, x_θ is the top θ -th individual and $\theta = 0.05 * \text{population size } (Np)$, t is the generation counter. T_c is the number of generations up to which the ε -parameter is controlled and later it is set to zero. The recommended parameter ranges are [37]: $T_c \in [0.1T_{max}, 0.8T_{max}]$ and $cp \in [2, 10]$, where T_{max} is the maximum number of generations. In EC, comparison is done between a pair of solutions.

The solution x_i is considered superior to x_j when -

- x_i is feasible and x_j is infeasible.
- x_i and x_j are both feasible and x_i produces a smaller objective value (in a minimization problem) than what x_j does.
- x_i and x_j are both infeasible, but x_i results in a smaller overall constraint violation as computed by eq. (22).

A solution is regarded as feasible if its overall constraint violation is lower than $\varepsilon(t)$. During initial phase $\varepsilon(t)$ assumes a small value, and later the value is set to zero.

4.2 Success History based Adaptive Differential Evolution (SHADE)

Differential Evolution (DE) being a stochastic population-based optimization algorithm, it starts with randomly generated individuals that evolve through probabilistic operators like recombination and mutation. The performance of DE highly depends on the population size (Np), the chosen mutation and/or crossover strategies, the scale factor (F) associated with mutation and the crossover rate (CR) associated with recombination [38]. In order to do away with the tuning of parameters, adaptive mechanisms for online adjustment of the control parameters during the evolution have been investigated. In literature, JADE [39] where a novel mutation strategy is proposed and SHADE [26] where a history based parameter adaptation scheme is introduced, are considered to be effective on a wide variety of optimization problems. The current work employs a slightly modified version of original SHADE algorithm, with fine tuning of some parameters borrowed from L-SHADE [27]. The details of the SHADE algorithm applied is described herein. Like most population-based metaheuristics, standard DE algorithm starts with initialization followed by an iterative process involving mutation, crossover and selection.

4.2.1 Initialization

During initialization, a population of candidate solutions (decision vectors) is created with randomly assigned values. To ensure that the randomly generated values of the elements of the decision vectors lie within the defined upper and lower bounds, the j -th component of the i -th decision vector is generated as:

$$x_{i,j}^{(1)} = x_{min,j} + rand_{ij}[0,1](x_{max,j} - x_{min,j}) \quad (25)$$

where $rand_{ij}[0,1]$ is a uniform random number between 0 and 1 and superscript '1' represents initialization. If ' Np ' is the population size and ' d ' is the dimension of decision vector, then $i = 1, 2, \dots, Np$ and $j = 1, 2, \dots, d$.

4.2.2 Mutation

At a given generation t , mutation operator generates a donor/mutant vector $v_i^{(t)}$ corresponding to each population member $x_i^{(t)}$. Among the different DE mutation strategies, the current work employs 'current-to- $pbest/1$ ' [26] strategy given by:

$$v_i^{(t)} = x_i^{(t)} + F_i^{(t)} \cdot (x_{pbest}^{(t)} - x_i^{(t)}) + F_i^{(t)} \cdot (x_{r_1}^{(t)} - x_{r_2}^{(t)}) \quad (26)$$

where indices r_1^i & r_2^i are mutually exclusive integers randomly chosen from the population range; $x_{pbest}^{(t)}$ is randomly selected from best $Np \times p$ ($p \in [0,1]$) individuals of current generation. $F_i^{(t)}$ is a positive scale factor at t -th generation. After performing the mutation if an element $v_{i,j}^{(t)}$ violates the search boundaries $[x_{min,j}, x_{max,j}]$, it is corrected as:

$$v_{i,j}^{(t)} = \begin{cases} (x_{min,j} + x_{i,j}^{(t)})/2 & \text{if } v_{i,j}^{(t)} < x_{min,j} \\ (x_{max,j} + x_{i,j}^{(t)})/2 & \text{if } v_{i,j}^{(t)} > x_{max,j} \end{cases} \quad (27)$$

4.2.3 Parameter Adaptation

At each generation t , each individual is assigned a scale factor $F_i^{(t)}$ and a crossover rate $CR_i^{(t)}$ which are used to generate new trial vectors. During evolution, the scale factor and the crossover rate are adapted as:

$$F_i^{(t)} = randc(\mu F_{r_i}^{(t)}, 0.1) \quad (28)$$

$$CR_i^{(t)} = randn(\mu CR_{r_i}^{(t)}, 0.1) \quad (29)$$

where $randc(\mu F_{r_i}^{(t)}, 0.1)$ generates a value through Cauchy distribution with location parameter $\mu F_{r_i}^{(t)}$ and scale parameter 0.1; $randn(\mu CR_{r_i}^{(t)}, 0.1)$ is a value sampled from Normal distribution with mean $\mu CR_{r_i}^{(t)}$ and variance 0.1. $\mu F_{r_i}^{(t)}$ is randomly chosen from a set of successful scale factors of previous generations stored in a memory M of size H ; $\mu CR_{r_i}^{(t)}$ is the one of the means of successful crossover rates from previous generations stored in the memory M [27]. During initialization, all μF and μCR are set to 0.5 and at the end of every generation the memory is updated at certain positions defined by indices k . In other words, at indices k , μF and μCR are modified using the weighted Lehmer mean, the detail of which can be referred in [26,27].

4.2.4 Crossover

At a given generation t , the decision variables of donor vector $v_i^{(t)}$ are combined with those of the target vector

1 $x_i^{(t)}$ to form the trial/offspring vector $u_i^{(t)} = (u_{i,1}^{(t)}, u_{i,2}^{(t)}, \dots, u_{i,d}^{(t)})$. The most commonly employed binomial
2 crossover operates on each variable based on the adapted crossover rate $CR_i^{(t)}$. The operation is described as:

$$u_{i,j}^{(t)} = \begin{cases} v_{i,j}^{(t)} & \text{if } j = j_{rand} \text{ or } rand_{i,j}[0,1] \leq CR_i^{(t)}, \\ x_{i,j}^{(t)} & \text{otherwise} \end{cases} \quad (30)$$

3 where j_{rand} is any randomly chosen natural number in $\{1, 2, \dots, d\}$, d being the dimension of the problem.

4 4.3 Integration of EC with SHADE algorithm

6 The selection of SHADE (and DE) is unconstrained. In SHADE-EC algorithm, the selection of individuals for the
7 next generation follows the rules of epsilon (ϵ) constraint handling technique. The description of SHADE-EC
8 algorithm is presented in Table 4 and in Fig. 6 with a flowchart. While the table describes the process in detail, the
9 flowchart gives an overview of the steps involved. The proposed algorithm is developed using MATLAB software
10 and simulations are carried out on a computer with Intel Core i5 CPU @2.7GHz and 4GB RAM. The user defined
11 input parameters for the algorithm are listed in Table 5. The population sizes are selected after several trials.

12

13 **Table 4.** SHADE-EC algorithm

SHADE-EC	
INPUT	<ul style="list-style-type: none"> • Dimension of the problem, d. • Population size, Np. • Stopping criterion, $maxeval$ i.e. maximum number of function evaluations. • Maximum and minimum values of d-decision variables, in vector form x_{max} and x_{min}. • $x_{max} = [x_{max,1}, \dots, x_{max,d}]$ and $x_{min} = [x_{min,1}, \dots, x_{min,d}]$.
INITIALIZATION	<ul style="list-style-type: none"> • Set generation counter, $t = 1$ and function evaluation counter $nfeval = 0$. • Set SHADE parameters: Memory (M) size $H = 5$, initialize $\mu F = 0.5$ and $\mu CR = 0.5$. • POP: Create population of Np individuals uniformly distributed within $[x_{min}, x_{max}]$.
EVALUATION	<ul style="list-style-type: none"> • Evaluate objective function, constraint function and constraint violation using eq. (20) to eq. (22) for each individual $x_i \forall i \in [1, Np]$ of POP. • Evaluate and set initial epsilon parameter $\epsilon(1)$ (see eq. (23)). • Increase function evaluation counter $nfeval$ by Np.
ALGORITHM LOOP:	
STEP 1	<ul style="list-style-type: none"> • Update epsilon (ϵ) parameter. • Generate mutant vector $v_i^{(t)}$ using eq. (26). Repair if necessary using eq. (27). • Generate trial vector element $u_{i,j}^{(t)}$ performing crossover according to eq. (30). • Formulate trial vector $u_i^{(t)}$ with all elements, this is OFS (offspring) vector x'_i obtained from parent POP.
STEP 2	<ul style="list-style-type: none"> • Compute objective function, constraint function and constraint violation using eq. (20) to eq. (22) for each individual $x'_i \forall i \in [1, Np]$ of OFS. • Increase function evaluation counter $nfeval$ by Np.
STEP 3	<ul style="list-style-type: none"> • In selection step, POP members for next generation are replaced with corresponding OFS members if OFS is better according to the rules of EC. An OFS is considered better if it yields lesser constraint violation than the respective old POP member. An OFS is also treated as better if it produces zero or less than calculated epsilon (ϵ) constraint violation (calculated by eq. (24)) in a generation alongwith smaller fitness value (minimization problem) than what the respective old POP member does. If OFS is worse, old POP member is retained. • If OFS is better, memory of μF and μCR is updated as described in section 4.2.3.
STEP 4	<ul style="list-style-type: none"> • Is stopping criterion, $maxeval$ reached? • If yes, STOP. • Else, increase generation counter by 1, i.e. $t = t + 1$. Go to algorithm loop STEP 1.

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Fig. 6. Flowchart for implementation of SHADE-EC algorithm

Table 5. Input parameters for SHADE-EC algorithm

Parameter	IEEE 30-bus	IEEE 57-bus
Dimension of optimization problem, d	19	27
Population size, Np	40	60
Constant, cp	5	5
Maximum no. of function evaluations, $maxeval$	30,000	36,000
Decision variable range $[x_{min}, x_{max}]$	Refer to result section	

5. Simulation results, analysis and comparison

Simulation results, detailed analysis and comparison are provided in this section for the two standard test systems and one adapted system. The deterministic ORPD cases for base configurations (only thermal generators) are discussed first, followed by stochastic ORPD solutions with renewable energy sources adopting scenario-based approach.

5.1. System 1: IEEE 30-bus test system (base case)

Case 1 and **Case 2** are for minimization of real power loss (P_{loss}) and aggregate voltage deviation (VD), respectively, for IEEE 30-bus system with all thermal generators. These two study cases consider more realistic mixed integer optimization problems where shunt VAR compensator ratings (capacitor banks) and transformer taps are treated as discrete variables. Capacitor can be switched in at discrete steps of 200 kVAr (i.e. 0.2 MVar) and transformer tap settings can be adjusted in steps of 0.02 p.u. Therefore, possible transformer taps are [0.90-0.92-0.94-...-1.08-1.10] p.u. To handle discrete variables, the algorithm performs rounding operation. During evolution, the control variables on shunt capacitor ratings and transformer taps are rounded off (upto required decimal points) to the nearest multiples of 0.2 (MVar) and 0.02 (p.u.), respectively. Further, as active power settings of generators (except swing generator) are vital for the optimization problem, the values are judiciously chosen within the defined ranges of the generators. The values of fixed active controls (i.e. active power of generators) are provided in Table A.1 in appendix.

Case 1a and **Case 2a** are additional study cases with objectives of minimization of real power loss (P_{loss}) and aggregate voltage deviation (VD), respectively and are performed here for a valid comparison with past studies. These cases consider all continuous variables with distribution of generation (except swing) fixed at the values given in [7] and also provided in Table A.1.

Table 6 lists the optimum settings of all control variables and calculated state variables with their allowable ranges to minimize the respective objective functions of case studies related to IEEE 30-bus system. The state variables on generator reactive power are listed here to show compliance with the limits of these constraining variables. The negative reactive power signifies absorption of reactive power (i.e. VAR consumption) by the generator. As it transpires, some of the values of reactive power are at the limits (either upper or lower). So, the designer must be careful of this constraint while performing the optimization study. In last row of the table, the typical CPU execution time of a single run in a case study is provided. The run time is about 150 seconds for the cases of IEEE 30-bus system. The constraint on load bus voltage is also critical as the allowable operating range for the bus voltage is narrow and the buses are often found to be operating near to the limits. The voltage profiles of load buses for the study cases are presented in Fig. 7. In order to attain minimum power loss, voltages of few load buses are pushed to the upper limit. **Case 2** (and **Case 2a**) of minimizing voltage deviation (VD) will not lead to overvoltage as the objective is to maintain system voltage around 1 p.u. However, this objective may influence the generators to an extent to breach the reactive power limits. The reduced voltage level (in **Case 2** and **Case 2a**) throughout the system escalates the currents and losses. Further, change in reactive power demand may entice the nearby generators to deliver/absorb additional VAR. Power flow is a complex phenomenon in the electrical network, and supply and consumption of VAR depend on many factors such as locations of loads, types of loads, voltages of buses, parameters of lines etc. However, the facts and observations in the study cases presented here reiterate the need of verifying state of the constraints in a constrained optimization problem such as ORPD. The superiority of a proper constraint handling (CH) technique like EC lies in the fact that the search process is systematically guided towards the feasible region of solutions. In general, no additional measures are needed to look for or check feasibility of the optimal solutions. Fig. 8 shows convergence characteristics of SHADE-EC algorithm for the study cases 1 and 2. The algorithm converges to optimal solution within 12000 function evaluations. The minimum loss achieved in **Case 1** is **4.4126 MW**, while the optimal value of voltage deviation in **Case 2** is **0.08886 p.u.**

Table 6. Simulation results of case studies for IEEE30-bus system

Parameters	Min	Max	Case 1 (Min. P_{loss})	Case 1a (Min. P_{loss})	Case 2 (Min. VD)	Case 2a (Min. VD)
V_1 (p.u.)	0.95	1.10	1.0694	1.0720	1.0045	1.0031
V_2 (p.u.)	0.95	1.10	1.0609	1.0628	1.0019	0.9986
V_5 (p.u.)	0.95	1.10	1.0375	1.0405	1.0203	1.0162
V_8 (p.u.)	0.95	1.10	1.0434	1.0406	1.0063	1.0084
V_{11} (p.u.)	0.95	1.10	1.0918	1.0923	1.0268	1.0674
V_{13} (p.u.)	0.95	1.10	1.0508	1.0526	1.0222	1.0206
T_{11} (p.u.)	0.90	1.10	1.04	1.0624	1.04	1.0918
T_{12} (p.u.)	0.90	1.10	0.96	0.9153	0.9	0.9000
T_{15} (p.u.)	0.90	1.10	0.98	0.9873	1	1.0067
T_{36} (p.u.)	0.90	1.10	0.98	0.9752	0.96	0.9697
Q_{C10} (MVar)	0.0	5.0	2.8	0	4.6	5
Q_{C12} (MVar)	0.0	5.0	0.4	2.8322	0.2	4.1036
Q_{C15} (MVar)	0.0	5.0	4.2	4.0992	5	5
Q_{C17} (MVar)	0.0	5.0	5	5	0.2	0
Q_{C20} (MVar)	0.0	5.0	4	3.9847	5	5
Q_{C21} (MVar)	0.0	5.0	5	5	5	5
Q_{C23} (MVar)	0.0	5.0	3	2.7884	5	5
Q_{C24} (MVar)	0.0	5.0	5	5	5	5
Q_{C29} (MVar)	0.0	5.0	2.6	2.4367	2	2.62
P_{loss} (MW)			4.4126	4.8612	5.4495	6.0099
VD (p.u.)			0.9029	0.9205	0.08886	0.08724
Q_{G1} (MVar)	-20	150	-0.2645	0.0754	-20	-20
Q_{G2} (MVar)	-20	60	15.7848	16.4707	-9.8371	-20
Q_{G5} (MVar)	-15	62.5	24.9606	24.3843	61.4656	53.4571
Q_{G8} (MVar)	-15	48.7	29.1134	29.6861	48.7	48.7
Q_{G11} (MVar)	-10	40	24.6734	27.2998	13.7823	34.9661
Q_{G13} (MVar)	-15	44.7	1.1666	2.2413	10.2631	8.8982
CPU Time (s)			149.6	151.2	148.4	146.7

Fig. 7. Voltage profiles of load buses for the case studies of IEEE 30-bus system

Fig. 8. Convergence of SHADE-EC algorithm for Case 1 and Case 2 of IEEE 30-bus system

Table 7 presents the comparison of results obtained in present study by SHADE-EC with some recently reported results on ORPD. It is worthwhile to mention that barring ref. [7] no other reference papers in the table explicitly mentioned about active power settings of individual generators. It is assumed that all have followed the data given in [7]. While active control settings in **Case 1** lead to the lowest loss (by SHADE-EC), the loss achieved by the algorithm with settings of **Case 1a** is apparently bettered by quite a few algorithms. However, a more detailed and in-depth analysis is necessary in this regard. In comparison of objective of power loss minimization, the reported VD values in [3], [5] and [11] render the solutions infeasible. Under no circumstances the VD value shall be higher than 1.2 p.u. for the 30-bus system to maintain its load bus voltages within [0.95 p.u.-1.05 p.u.]. For the system under study, a total of 24 load buses (PQ bus) are present. Theoretically, if all these buses operate at the limits, the maximum possible cumulative sum of voltage deviations (VD in eq. (3)) would be 1.2 p.u. (i.e. 24×0.05 p.u.). Among the references listed in comparison table, except ref. [8], all have used penalty function method to handle system constraints. As mentioned before, the static penalty function approach is sensitive to selection of penalty coefficient and inconsiderate selection may lead to violation of system constraints, possibly without the cognizance of the designer. Refs. [6] and [13] did not report the voltage profile or VD value. The control variable settings, specifically, the generator voltages in [6] and [7] (not listed here) are all near to 1.1 p.u. While the condition helps minimize current (hence loss) in the network, it makes impossible for the system to maintain all load bus voltages (especially the load buses near to the generators) below 1.05 p.u. The shunt compensation in [14] is very low (total about only 0.2 MVar). To minimize loss, voltage in the network should be maintained high enough to reduce current (and hence loss). With compensation being so low, it is not possible to achieve minimum loss. A different approach to constraint handling (CH) is noted in [8]. It adopted a concept similar to superiority of feasible

solutions (SF) [40] to handle system constraints. However, the range of load bus voltage used in the study (0.94 p.u. to 1.06 p.u.) is different from others. In comparison of study **Case 2** (and **Case 2a**), many algorithms reported much lower VD values. Unfortunately, no publication listed here verified the status of the actual reactive power generation or voltage profile of load buses. We investigate the control variables listed in [13] and [14]. Almost zero compensation (about 0.14 MVar) and generator voltage settings of about 1 p.u. in [14] lead to undervoltage in many load buses. In comparison between refs. [13] and [14], ref. [13] proposed a total shunt compensation of about 21.5 MVar against 0.14 MVar in [14]. With so much difference in compensation, the VD values cannot be similar as reported. Further, verification of actual reactive power generation is also desirable. In summary, the performance comparison between a pair of algorithms merely on numerical values of results is invalid and unjustified for a constrained optimization problem. The effectiveness of the adopted constraint handling techniques must be assessed, moreover, the feasibility of the solutions must be checked.

Table 7. Comparison of results of case studies for IEEE 30-bus system

Case no.	Algorithm	Power loss P_{loss} (MW)	Voltage dev. VD (p.u.)
Case 1	SHADE-EC	4.4126	0.9029
Case 1a	SHADE-EC	4.8612	0.9205
	DE [3]	4.5550	1.9589 ^b
	QOTLBO [5]	4.5594	1.9057 ^b
	MFO [6]	4.5128	-
	EMA [7]	4.4978	0.8123
	IGSA-CSS [8]	4.7660 ^a	-
	OGSA [9]	4.4984	0.8085
	HFA [11]	4.529	1.625 ^b
	FAHCLPSO [13]	4.4877	-
	NGBWCA [14]	4.4801	0.8413
Case 2	SHADE-EC	5.4495	0.08886
Case 2a	SHADE-EC	6.0099	0.08724
	QOTLBO [5]	6.4962	0.0856
	MFO [6]	-	0.12154
	EMA [7]	6.241	0.06131
	IGSA-CSS [8]	-	0.08968 ^a
	OGSA [9]	6.9044	0.0640
	HFA [11]	5.75	0.0980
	FAHCLPSO [13]	-	0.04315
	NGBWCA [14]	6.3142	0.0458

^aHigher ranges for load bus voltage and generator reactive power are considered

^bInfeasible solution, constraint on load bus voltage is violated

5.2. System 2: IEEE 57-bus test system (base case)

The minimization of real power loss (P_{loss}) and aggregate voltage deviation (VD) for IEEE 57-bus system are formulated in **Case 11** and **Case 12**. The rationale behind the study cases is about giving due consideration to discrete steps of shunt VAR compensators and transformer taps in real-word applications. The discrete steps are same as mentioned for the equipment in 30-bus system. These cases also consider more practical settings of active power for the generators (except swing generator). Table A.2 in appendix lists the generator active power used for the case studies of 57-bus system. In **Case 11** and **Case 12**, no generator real power is set to zero unlike **Case 11a** and **Case 12a**. **Case 11a** and **Case 12a** are performed with same data set as in reference papers and with all continuous (control) variables. The real power settings of 3-generators are zero in **Case 11a** and **Case 12a**. This signifies that these generators are not producing any real power; they are either consuming VAR or delivering VAR (as synchronous condenser). Though theoretically it is very much possible by controlling excitation of the generators, the practice is not so common. Hence, more practical case studies - **Case 11** and **Case 12** are performed in our work. Like 30-bus system, all control variables and state variables on generator reactive power alongwith their operating ranges are provided in Table 8 for the case studies of IEEE 57-bus system. The typical CPU time for one run in a case study of the system, provided in last row of the table, is about 60 seconds higher than the run time of an equivalent case study of the IEEE 30-bus system. The difference in time is primarily due to execution of repetitive power flow of a larger system (IEEE 57-bus) with more components. Only a fraction (about 10%) of the increment in time can be attributed to the higher number of function evaluations of the larger dimensional problem of IEEE 57-bus system. The load bus voltage profiles for the case studies of the test system are displayed in Fig. 9. Clearly all constraints are diligently satisfied by the epsilon constraint (EC) handling method. The convergence curves of SHADE-EC algorithm are drawn in Fig. 10 for **Case 11** and **Case 12**. The algorithm converges to an optimal solution within 20000 function evaluations.

Table 8. Simulation results of case studies for IEEE 57-bus system

Parameters	Min	Max	Case 11 (Min. P_{loss})	Case 11a (Min. P_{loss})	Case 12 (Min. VD)	Case 12a (Min. VD)
V_1 (p.u.)	0.95	1.10	1.0848	1.0875	1.021	1.02
V_2 (p.u.)	0.95	1.10	1.0782	1.0768	1.0172	1.0116
V_3 (p.u.)	0.95	1.10	1.0661	1.0653	1.0158	1.0107
V_6 (p.u.)	0.95	1.10	1.0584	1.0562	1.0005	1.0034
V_8 (p.u.)	0.95	1.10	1.0731	1.0746	1.0064	1.0297
V_9 (p.u.)	0.95	1.10	1.0464	1.0428	0.9945	1.007
V_{12} (p.u.)	0.95	1.10	1.048	1.0455	1.0246	1.036
T_{19} (p.u.)	0.90	1.10	1.06	0.9729	0.96	0.9653
T_{20} (p.u.)	0.90	1.10	0.94	1.0085	1.04	0.9942
T_{31} (p.u.)	0.90	1.10	1	1.0054	0.98	0.9714
T_{35} (p.u.)	0.90	1.10	0.96	1.0302	1.04	1.0541
T_{36} (p.u.)	0.90	1.10	1.04	0.989	0.98	1.0876
T_{37} (p.u.)	0.90	1.10	1	1.0044	1	1.0039
T_{41} (p.u.)	0.90	1.10	1	0.9968	0.98	1.0017
T_{46} (p.u.)	0.90	1.10	0.96	0.9524	0.94	0.918
T_{54} (p.u.)	0.90	1.10	0.94	0.9094	0.9	0.9001
T_{58} (p.u.)	0.90	1.10	1	0.9894	0.94	0.9303
T_{59} (p.u.)	0.90	1.10	0.98	0.9712	0.96	0.9849
T_{65} (p.u.)	0.90	1.10	0.98	0.9749	1	1.0072
T_{66} (p.u.)	0.90	1.10	0.94	0.9416	0.9	0.9
T_{71} (p.u.)	0.90	1.10	0.98	0.971	0.98	0.9589
T_{73} (p.u.)	0.90	1.10	1	0.9848	0.98	1.0082
T_{76} (p.u.)	0.90	1.10	0.98	0.959	0.9	0.9
T_{80} (p.u.)	0.90	1.10	1	0.9845	0.98	0.987
QC_{18} (MVar)	0	20	5.2	8.148	13.8	0.0075
QC_{25} (MVar)	0	20	14.2	14.4048	18.4	19.9909
QC_{53} (MVar)	0	20	13.6	13.2747	20	19.9974
P_{loss} (MW)			18.4000	23.3031	21.6013	27.7317
VD (p.u.)			1.5207	1.7322	0.62632	0.59673
Q_{G1} (MVar)	-140	200	51.2244	52.0795	0.5534	-14.9401
Q_{G2} (MVar)	-17	50	50	50	50	49.9403
Q_{G3} (MVar)	-10	60	41.9006	48.3738	60	59.993
Q_{G6} (MVar)	-8	25	-8	-1.2067	-8	-7.9852
Q_{G8} (MVar)	-140	200	58.7302	67.037	12.4105	51.2724
Q_{G9} (MVar)	-3	9	9	8.9997	9	8.9798
Q_{G12} (MVar)	-150	155	52.9306	46.6327	138.7671	154.8363
CPU Time (s)			209.9	215.6	208.7	212.3

Fig. 9. Voltage profiles of load buses for the case studies of IEEE 57-bus system

Fig. 10. Convergence of SHADE-EC algorithm for Case 11 and Case 12 of IEEE 57-bus system

The comparison of results of study cases related to IEEE 57-bus system with some recently reported results is provided in Table 9. SHADE-EC algorithm achieves the best results among the results of all algorithms listed in the table. The algorithm duly satisfies all constraints. The optimum real power loss in **Case 11a** is **23.3031 MW** and the minimum VD attained in **Case 12a** is **0.59673 p.u.** However, as already mentioned, comparison on apparent numerical results of a constrained optimization problem is flawed. One must verify the feasibility of the solutions. The proper constraint handling technique like EC initially guides the search process towards feasible region, thereafter, improves the solution with the aid of a compatible evolutionary algorithm.

Table 9. Comparison of results of study cases for IEEE 57-bus system

Case no.	Algorithm	Power loss P_{loss} (MW)	Voltage dev. VD (p.u.)
Case 11	SHADE-EC	18.4000	1.5207
Case 11a	SHADE-EC	23.3031	1.7322
	MFO [6]	24.2529	-
	IGSA-CSS [8]	22.2718 ^a	-
	OGSA [9]	23.43	1.1907
	ICA [10]	24.1607	-
	PSO-ICA [10]	24.1386	-
	MICA-IWO [12]	24.2568	-
Case 12	SHADE-EC	21.6013	0.62632
Case 12a	SHADE-EC	27.7317	0.59673
	IGSA-CSS [8]	-	0.60347 ^a
	OGSA [9]	32.34	0.6982
	ICA [10]	-	0.6137
	PSO-ICA [10]	-	0.6031

^aDifferent ranges for generator reactive power are used

5.3. System 3: Adapted IEEE 30-bus test system incorporating wind and solar power

This section deals with the modified IEEE 30-bus system where the thermal generators at bus 5 and bus 8 are replaced with a wind generator and a PV unit, respectively. The load is variable based on the scenario. Shunt VAR compensators and transformer taps are considered discrete as in Cases 1 and 2. Thermal generator settings (except swing generator) are provided in Table A.1 in appendix. The wind generator power and PV output are variables under different scenarios as discussed in section 3. Therefore, the swing generator must be capable of delivering the balance active power if there is a deficit in supply of active power from these renewable energy units. The maximum real power output of swing generator is considered high enough (200 MW) in this study so that the generator can mitigate the load demand even if the real power output from both the renewable energy sources is zero. The reactive power output range of the wind generator and the PV unit is considered approximately between -0.4 p.u. to 0.5 p.u. throughout their active power output range. The justification for such assumption is provided in [23]. Numerical values of these reactive power are provided in Table A.1 in appendix. The ORPD objectives of power loss and voltage deviation are optimized individually, and thereafter, collectively as a multi-objective optimization.

5.3.1. Single objective stochastic optimal reactive power dispatch

The scenario-based approach to stochastic ORPD with uncertain wind power was proposed in [20-22]. The authors took same approach in calculating expected power loss (*EPL*) and expected voltage deviation (*EVD*) in all these reference papers. The control variables on generator bus voltages and transformer tap settings (termed as ‘*here and now*’ control variables) are consider same and fixed for all scenarios. Uncertain wind generator active power is variable (for different scenarios) and power loss is optimized for different scenarios by adjusting shunt VAR compensation (termed as ‘*wait and see*’ control variable). However, the authors did not provide explanation on why the control variables were segregated. One possible reason is that the optimal settings of ‘*here and now*’ control variables are not hugely different across the scenarios. But, if shunt VAR compensation and slack generator active power are adjusted, generator bus voltage can also be adjusted by changing excitation of the generator. Online alteration of tap changer is also plausible. Therefore, we consider optimization of all control variables to minimize power loss under all scenarios with respective values of load demand and renewable power (i.e. active power at bus 5 and bus 8). In reality, OPF is run at certain time intervals to optimize various objectives in the network. Hence, running ORPD to optimize settings of all control variables for different scenarios is a realistic proposition in calculating probabilistic loss and voltage deviation. To elaborate further, the minimization of *EPL* in **Case 21** requires running the optimization algorithm 25 times for 25 scenarios. For each scenario, the optimized value of power loss ($P_{loss,sc}$) is provided in Table 10. If probability of the scenario is Δ_{sc} and optimized power loss for the scenario is $P_{loss,sc}$, the expected power loss (*EPL*) is calculated over all scenarios as:

$$EPL: \sum_{sc=1}^{N_{sc}} \Delta_{sc} \times P_{loss,sc} \quad (31)$$

where N_{sc} is the total number of selected scenarios. In similar manner, voltage deviation (*VD*) for each scenario is optimized in **Case 22** and the optimal values of voltage deviations for all scenarios (VD_{sc}) are presented in Table 10. The expected value of voltage deviation (*EVD*) over all scenarios is expressed as:

$$EVD: \sum_{sc=1}^{N_{sc}} \Delta_{sc} \times VD_{sc} \quad (32)$$

Table 10. Single-objective ORPD case studies with uncertain demand and renewable power

Scenario number	% Loading	Wind power (MW)	PV power (MW)	Scenario probability, Δ_{sc}	Scenario based $P_{loss,sc}$ (MW)	Scenario based VD_{sc} (p.u.)
1	105.784	0	50	0.001	7.9319	0.12220
2	55.714	26.566	36.349	0.001	0.9004	0.04330
3	73.165	42.772	23.805	0.007	1.3633	0.05884
4	77.665	0	40.164	0.001	3.3351	0.07177
5	99.491	35.666	46.795	0.001	3.8883	0.09801
6	60.573	0.912	30.363	0.004	1.7466	0.04863
7	97.292	15.645	18.283	0.001	6.4390	0.10849
8	58.378	35.892	16.324	0.038	0.8527	0.04432
9	98.092	29.805	0	0.006	6.6330	0.10172
10	77.942	14.248	37.580	0.002	2.5992	0.06973
11	41.386	9.580	9.073	0.004	0.7832	0.03318
12	65.615	16.561	43.456	0.001	1.4177	0.05160
13	90.475	33.496	22.067	0.003	3.6836	0.08605
14	66.773	40.393	50	0.001	1.0216	0.05144
15	61.498	32.470	27.564	0.009	0.9400	0.04610
16	68.935	18.629	0	0.478	2.5207	0.05619
17	67.603	35.103	6.942	0.093	1.5320	0.05284
18	71.770	38.528	18.992	0.044	1.4708	0.06316
19	79.921	13.102	33.639	0.004	3.0025	0.07099
20	72.351	28.152	20.560	0.037	1.8219	0.05902
21	78.322	10.458	10.058	0.048	3.8375	0.07098
22	66.073	50.441	3.813	0.027	1.1676	0.05110
23	74.465	0	11.464	0.071	3.8974	0.07095
24	63.754	1.416	25.904	0.012	2.0554	0.05748
25	67.487	65.994	13.756	0.106	0.9567	0.05678
Case 21 - <i>EPL</i>: $\sum \Delta_{sc} \times P_{loss,sc} = 2.2515$ MW						
Case 22 - <i>EVD</i>: $\sum \Delta_{sc} \times VD_{sc} = 0.05794$ p.u.						

The *EPL* achieved in **Case 21** is **2.2515 MW** and *EVD* in **Case 22** is **0.05794 p.u.** In Table 10, the scenario based optimal losses ($P_{loss,sc}$) can be easily interpreted. The lowest value of loss is realized when network loading is minimum (scenario 11). Minimum loading signifies lowest current (hence low loss) in the network. On contrary,

the loss is the highest when network loading is maximum with no available wind power (scenario 1). The non-availability of wind power requires the swing generator to supply additional power to relatively remote load points. The voltage in some section of the network is also not well supported. The combined effect of high load current and low voltage level raises the network losses. Results of voltage deviation can also be analyzed in similar way. With minimum loading (scenario 11), the voltage profile of the network can be maintained throughout very close to the desired 1 p.u. Again, low current (for minimum loading condition) means small voltage drop. Hence, scenario 11 leads to the minimum aggregate voltage deviation. On the other hand, maximum loading and zero wind power (scenario 1) results in the highest aggregate voltage deviation of the system. The control variables for these extreme scenarios are provided in Table S.2 (in the supplementary document) for both the study cases. The control variables on generator bus voltages for different scenarios are presented in Fig. 11 and Fig. 12 for all scenarios in **Case 21** and **Case 22**, respectively. In general, the voltage levels of generator buses in **Case 21** are higher than those in **Case 22**. In the former case, power loss is minimized. Hence, bus voltages are to be maintained at a higher level to reduce load current that incurs power loss. Voltage setting of generator bus 11 is higher than the other generator buses, especially in **Case 22**. Bus 11 is connected to neighboring load buses without any shunt compensation. A little higher voltage setting of this generator bus facilitates sustainment of steady voltage at the load buses in the proximity. The settings of other control variables on transformer taps and shunt VAR compensators are provided in stacked column charts in Fig. S.1, Fig. S.2, Fig. S.3 and Fig. S.4 in the supplementary document.

Fig. 11. Optimal settings of generator bus voltages for all scenarios in Case 21

Fig. 12. Optimal settings of generator bus voltages for all scenarios in Case 22

Due to highly non-linear nature of ORPD problem, it is difficult to decipher any specific pattern of change in control variables under different scenarios of network loading, wind and solar power. However, in no scenario of a case study, the voltage levels of load buses violate the allowable limits. This is insured by the CH technique in optimization algorithm. It is not practical to indicate voltage profiles for all scenarios here. The profiles of extreme scenarios (scenario 1 and scenario 11) are drawn in Fig. 13 for both the cases. Load bus voltage levels are justifiably nearest to the peak to lower load current (hence loss) in scenario 11 of **Case 21** when the network loss is minimum. The load bus voltage profile is closest to 1 p.u. in scenario 11 of **Case 22** when the aggregate voltage deviation (VD) is the least. Fig. 14 shows maximum and minimum reactive power contributions of all the generators across all scenarios for **Case 21** of minimum EPL . Similar bar chart is drawn for **Case 22** (of minimum EVD) in Fig. 15. 'Allow Max' and 'Allow Min' are the maximum and minimum allowable values of generator reactive power, respectively. The actual values of maximum and minimum reactive power superimposed in these diagrams confirm compliance to reactive power limits under all scenarios.

Fig. 13. Load bus voltage profiles under extreme scenarios in Case 21 and Case 22

Fig. 14. Minimum and maximum reactive power of the generators over all scenarios in Case 21

Fig. 15. Minimum and maximum reactive power of the generators over all scenarios in Case 22

5.3.2. Multi-objective stochastic optimal reactive power dispatch

Stochastic ORPD with the objectives of power loss and voltage deviation is performed in the previous section where each objective is optimized individually. In multi-objective optimization of ORPD (MO-ORPD), both the objectives need to be considered simultaneously in optimization. A popular method of optimizing a multi-objective problem (MOP) with a single objective optimization algorithm is to convert the MOP into a single objective one adopting weighted sum approach [5,19,41]. In this method, each objective is multiplied with a predetermined weight factor before adding the objectives. The weight factors are carefully selected such that all the effective objective values (i.e. products of the respective weight factors and objectives) become of the same order [41-42]. The optimization objective for MO-ORPD can be written as:

$$LVD_{obj} = \lambda_l P_{loss} + \lambda_{vd} VD \quad (33)$$

where P_{loss} and VD are calculated using eq. (2) and eq. (3), respectively. The selected weight factors are $\lambda_l = 1$ and $\lambda_{vd} = 10$.

A case study (Case 23) with above-mentioned objective is performed on the adapted IEEE 30-bus system. The conditions of this study are same as in Cases 21 and 22. The objective values (LVD_{obj}), scenario-based losses ($P_{loss,sc}$) and voltage deviations (VD_{sc}) are listed in Table 11. In Case 23, EPL and EVD values are higher than those in Case 21 and Case 22, respectively. The fact can be readily justified as multi-objective optimization results in a compromise solution of the constituting objectives. The load bus voltage profiles for extreme scenarios (Fig. S.5) and a diagram on minimum and maximum reactive power data (Fig. S.6) over all scenarios are provided in the supplementary document. It is evident from the results that all constraints are duly satisfied by the algorithm. In addition, control variables on generator bus voltages (Fig. S.7), transformer taps (Fig. S.8) and VAR compensator settings (Fig. S.9) are also provided in the supplementary document for information.

Table 11. A multi-objective ORPD case study with uncertain demand and renewable power

Scenario number	Scenario probability, Δ_{sc}	Objective value, LVD_{obj}	Scenario based $P_{loss,sc}$ (MW)	Scenario based VD_{sc} (p.u.)
1	0.001	9.9126	8.5860	0.13266
2	0.001	1.4696	1.0163	0.04533
3	0.007	2.2020	1.5661	0.06359
4	0.001	4.4898	3.7099	0.07799
5	0.001	5.3527	4.3057	0.10470
6	0.004	2.4850	1.9574	0.05276
7	0.001	8.1078	7.0178	0.10899
8	0.038	1.4477	0.9683	0.04794
9	0.006	8.3367	7.1858	0.11508
10	0.002	3.6216	2.9037	0.07179
11	0.004	1.2534	0.8988	0.03546
12	0.001	2.1555	1.5905	0.05650
13	0.003	4.9813	4.0937	0.08876

Scenario number	Scenario probability, Δ_{sc}	Objective value, LVD_{obj}	Scenario based $P_{loss,sc}$ (MW)	Scenario based VD_{sc} (p.u.)
14	0.001	1.7090	1.1554	0.05536
15	0.009	1.5654	1.0656	0.04998
16	0.478	3.4557	2.8076	0.06481
17	0.093	2.3239	1.7266	0.05973
18	0.044	2.3243	1.6722	0.06521
19	0.004	4.1182	3.3354	0.07827
20	0.037	2.7394	2.0471	0.06923
21	0.048	5.0376	4.2296	0.08080
22	0.027	1.8860	1.3308	0.05552
23	0.071	5.0343	4.3202	0.07141
24	0.012	2.8764	2.3010	0.05755
25	0.106	1.6348	1.0887	0.05461

Case 23 - EPL: $\sum \Delta_{sc} \times P_{loss,sc} = 2.5113$ MW

EVD: $\sum \Delta_{sc} \times VD_{sc} = 0.06396$ p.u.

6. Conclusion

In the first section of this paper, deterministic optimal reactive power dispatch (ORPD) solutions for two standard bus systems with only thermal generators are performed. Subsequently, stochastic ORPD formulation and solution incorporating uncertain load demand, wind and solar power are presented by adopting scenario-based approach. SHADE algorithm is applied for the optimization tasks in all cases. The algorithm is successfully integrated with a proper constraint handling technique (ε -constraint) of evolutionary algorithms (EAs). The usefulness of a proper constraint handling (CH) technique is established with study cases using basic configurations of the two test systems. The status of all network constraints is verified, and results are critically analyzed against constraint violation in comparison with past studies. Besides, the proposed SHADE-EC is an effective algorithm for constrained optimization problems. It quickly drives the search process towards feasible region and thereafter ensures fast convergence to global optima. In ORPD with stochastic load demand, wind and solar power, the uncertainties are appropriately modeled with suitable probability density functions (PDFs). Numerous scenarios are created running Monte Carlo simulations. A representative set of scenarios is selected employing appropriate scenario reduction method of stochastic programming. Expected power loss (EPL) and expected voltage deviation (EVD) values are calculated with optimization of network parameters under various scenarios of load demands, available wind and solar power. In future, the study can be further extended with accurate models of PV inverters and wind generators to take into account the actual reactive power capabilities of these devices. Multi-objective optimization using multi-objective evolutionary algorithm (MOEA) and inclusion of voltage stability as the objective also remain a work front for the future.

Appendix:

Table A.1. Generator data for IEEE 30-bus system

Bus no.	P_G^{min} (MW)	P_G^{max} (MW)	Q_G^{min} (MVar)	Q_G^{max} (MVar)	Settings of thermal units, P_G (MW)		
					Case 1, 2	Case 1a, 2a	Case 21, 22
1	50	200	-20	150	Swing	Swing	Swing
2	20	80	-20	60	75	80	75
5 (thermal)	15	50	-15	62.5	40	50	-
5 (wind)	0	75	-30	35	-	-	Variable
8 (thermal)	10	35	-15	48.7	30	20	-
8 (PV)	0	50	-20	25	-	-	Variable
11	10	30	-10	40	25	20	25
13	12	40	-15	44.7	30	20	30

Table A.2. Generator data for IEEE 57-bus system

Bus no.	P_G^{min} (MW)	P_G^{max} (MW)	Q_G^{min} (MVar)	Q_G^{max} (MVar)	Settings of thermal units, P_G (MW)	
					Case 11, 12	Case 11a, 12a
1	0	576	-140	200	Swing	Swing
2	30	100	-17	50	50	0
3	40	140	-10	60	60	40
6	30	100	-8	25	50	0
8	100	550	-140	200	400	450
9	30	100	-3	9	50	0
12	100	410	-150	155	300	310

Supplementary document:

This paper has a supplementary downloadable PDF file with relevant data and figures.

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References

- [1]. Grudin, N. (1998). Reactive power optimization using successive quadratic programming method. *IEEE Transactions on Power Systems*, 13(4), 1219-1225.
- [2]. Ramos, J. M., Exposito, A. G., & Quintana, V. H. (2005). Transmission power loss reduction by interior-point methods: implementation issues and practical experience. *IEE Proceedings-Generation, Transmission and Distribution*, 152(1), 90-98.
- [3]. El Ela, A. A., Abido, M. A., & Spea, S. R. (2011). Differential evolution algorithm for optimal reactive power dispatch. *Electric Power Systems Research*, 81(2), 458-464.
- [4]. Basu, M. "Quasi-oppositional differential evolution for optimal reactive power dispatch." *International Journal of Electrical Power & Energy Systems* 78 (2016): 29-40.
- [5]. Mandal, B., & Roy, P. K. (2013). Optimal reactive power dispatch using quasi-oppositional teaching learning based optimization. *International Journal of Electrical Power & Energy Systems*, 53, 123-134.
- [6]. Mei, R. N. S., Sulaiman, M. H., Mustaffa, Z., & Daniyal, H. (2017). Optimal reactive power dispatch solution by loss minimization using moth-flame optimization technique. *Applied Soft Computing*, 59, 210-222.
- [7]. Rajan, A., & Malakar, T. (2016). Exchange market algorithm based optimum reactive power dispatch. *Applied Soft Computing*, 43, 320-336.
- [8]. Chen, G., Liu, L., Zhang, Z., & Huang, S. (2017). Optimal reactive power dispatch by improved GSA-based algorithm with the novel strategies to handle constraints. *Applied Soft Computing*, 50, 58-70.
- [9]. Shaw, B., Mukherjee, V., & Ghoshal, S. P. (2014). Solution of reactive power dispatch of power systems by an opposition-based gravitational search algorithm. *International Journal of Electrical Power & Energy Systems*, 55, 29-40.
- [10]. Mehdinejad, M., Mohammadi-Ivatloo, B., Dadashzadeh-Bonab, R., & Zare, K. (2016). Solution of optimal reactive power dispatch of power systems using hybrid particle swarm optimization and imperialist competitive algorithms. *International Journal of Electrical Power & Energy Systems*, 83, 104-116.
- [11]. Rajan, A., & Malakar, T. (2015). Optimal reactive power dispatch using hybrid Nelder-Mead simplex based firefly algorithm. *International Journal of Electrical Power & Energy Systems*, 66, 9-24.
- [12]. Ghasemi, M., Ghavidel, S., Ghanbarian, M. M., & Habibi, A. (2014). A new hybrid algorithm for optimal reactive power dispatch problem with discrete and continuous control variables. *Applied soft computing*, 22, 126-140.
- [13]. Naderi, E., Narimani, H., Fathi, M., & Narimani, M. R. (2017). A novel fuzzy adaptive configuration of particle swarm optimization to solve large-scale optimal reactive power dispatch. *Applied Soft Computing*, 53, 441-456.
- [14]. Heidari, A. A., Abbaspour, R. A., & Jordehi, A. R. (2017). Gaussian bare-bones water cycle algorithm for optimal reactive power dispatch in electrical power systems. *Applied Soft Computing*, 57, 657-671.
- [15]. Nuaekaw, K., Artrit, P., Pholdee, N., & Bureerat, S. (2017). Optimal Reactive Power Dispatch Problem using a Two-Archive Multi-Objective Grey Wolf Optimizer. *Expert Systems with Applications*.
- [16]. Chen, G., Liu, L., Guo, Y., & Huang, S. (2016). Multi-objective enhanced PSO algorithm for optimizing power losses and voltage deviation in power systems. *COMPEL: The International Journal for Computation and Mathematics in Electrical and Electronic Engineering*, 35(1), 350-372.
- [17]. Shargh, S., Mohammadi-ivatloo, B., Seyed, H., & Abapour, M. (2016). Probabilistic multi-objective optimal power flow considering correlated wind power and load uncertainties. *Renewable Energy*, 94, 10-21.
- [18]. Mohseni-Bonab, S. M., Rabiee, A., Mohammadi-Ivatloo, B., Jalilzadeh, S., & Nojavan, S. (2016). A two-point estimate method for uncertainty modeling in multi-objective optimal reactive power dispatch problem. *International Journal of Electrical Power & Energy Systems*, 75, 194-204.
- [19]. Liang, R. H., Wang, J. C., Chen, Y. T., & Tseng, W. T. (2015). An enhanced firefly algorithm to multi-objective optimal active/reactive power dispatch with uncertainties consideration. *International Journal of Electrical Power & Energy Systems*, 64, 1088-1097.
- [20]. Mohseni-Bonab, S. M., Rabiee, A., & Mohammadi-Ivatloo, B. (2016). Voltage stability constrained multi-objective optimal reactive power dispatch under load and wind power uncertainties: A stochastic approach. *Renewable Energy*, 85, 598-609.
- [21]. Mohseni-Bonab, S. M., & Rabiee, A. (2017). Optimal reactive power dispatch: a review, and a new stochastic voltage stability constrained multi-objective model at the presence of uncertain wind power generation. *IET Generation, Transmission & Distribution*, 11(4), 815-829.
- [22]. Mohseni-Bonab, S. M., Rabiee, A., & Mohammadi-Ivatloo, B. (2017). Multi-objective Optimal Reactive Power Dispatch Considering Uncertainties in the Wind Integrated Power Systems. In *Reactive Power Control in AC Power Systems* (pp. 475-513). Springer International Publishing.
- [23]. Biswas, P. P., Suganthan, P. N., & Amaratunga, G. A. (2017). Optimal power flow solutions incorporating stochastic wind and solar power. *Energy Conversion and Management*, 148, 1194-1207.
- [24]. Chang, T. P. (2010). Investigation on frequency distribution of global radiation using different probability density functions. *International Journal of Applied Science and Engineering*, 8(2), 99-107.

- [25]. Biswas, P. P., Suganthan, P. N., Qu, B. Y., & Amaratunga, G. A. (2018). Multiobjective economic-environmental power dispatch with stochastic wind-solar-small hydro power. *Energy*, 150, 1039-1057.
- [26]. Tanabe, R., & Fukunaga, A. (2013, June). Success-history based parameter adaptation for differential evolution. In *Evolutionary Computation (CEC), 2013 IEEE Congress on* (pp. 71-78). IEEE.
- [27]. Tanabe, R., & Fukunaga, A. S. (2014, July). Improving the search performance of SHADE using linear population size reduction. In *Evolutionary Computation (CEC), 2014 IEEE Congress on* (pp. 1658-1665). IEEE.
- [28]. Awad, N. H., Ali, M. Z., Liang, J. J., Qu, B. Y., & Suganthan, P. N. (2016). Problem definitions and evaluation criteria for the CEC 2017 special session and competition on single objective bound constrained real-parameter numerical optimization. In *Technical Report*. Nanyang Technological University Singapore.
- [29]. Biswas, P. P., Suganthan, P. N., & Amaratunga, G. A. (2017, June). Optimal placement of wind turbines in a windfarm using L-SHADE algorithm. In *Evolutionary Computation (CEC), 2017 IEEE Congress on* (pp. 83-88). IEEE.
- [30]. Biswas, P. P., Suganthan, P. N., Wu, G., & Amaratunga, G. A. (2018). Parameter estimation of solar cells using datasheet information with the application of an adaptive differential evolution algorithm. *Renewable Energy*, 132, 425-438.
- [31]. Biswas, P. P., Suganthan, P. N., & Amaratunga, G. A. (2017). Minimizing harmonic distortion in power system with optimal design of hybrid active power filter using differential evolution. *Applied Soft Computing*, 61, 486-496.
- [32]. Mallipeddi, R., Jeyadevi, S., Suganthan, P. N., & Baskar, S. (2012). Efficient constraint handling for optimal reactive power dispatch problems. *Swarm and Evolutionary Computation*, 5, 28-36.
- [33]. Bjelogrić, M., Calović, M. S., Ristanović, P., & Babić, B. S. (1990). Application of Newton's optimal power flow in voltage/reactive power control. *IEEE Transactions on Power Systems*, 5(4), 1447-1454.
- [34]. Alsac, O., & Stott, B. (1974). Optimal load flow with steady-state security. *IEEE transactions on power apparatus and systems*, (3), 745-751.
- [35]. R.D. Zimmerman, C.E. Murillo-Sánchez, R.J. Thomas, Matpower (Available at:) <http://www.pserc.cornell.edu/matpower>
- [36]. Growe-Kuska, N., Heitsch, H., & Romisch, W. (2003, June). Scenario reduction and scenario tree construction for power management problems. In *Power tech conference proceedings, 2003 IEEE Bologna* (Vol. 3, pp. 7-pp). IEEE.
- [37]. Takahama, T., & Sakai, S. (2010, July). Constrained optimization by the ϵ constrained differential evolution with an archive and gradient-based mutation. In *Evolutionary Computation (CEC), 2010 IEEE Congress on* (pp. 1-9). IEEE.
- [38]. Mallipeddi, R., Suganthan, P. N., Pan, Q. K., & Tasgetiren, M. F. (2011). "Differential evolution algorithm with ensemble of parameters and mutation strategies." *Applied Soft Computing*, 11(2), 1679-1696.
- [39]. Zhang, J., & Sanderson, A. C. (2009). JADE: adaptive differential evolution with optional external archive. *IEEE Transactions on evolutionary computation*, 13(5), 945-958.
- [40]. Deb, K. (2000). An efficient constraint handling method for genetic algorithms. *Computer methods in applied mechanics and engineering*, 186(2), 311-338.
- [41]. Biswas, P. P., Suganthan, P. N., Mallipeddi, R., & Amaratunga, G. A. (2018). Optimal power flow solutions using differential evolution algorithm integrated with effective constraint handling techniques. *Engineering Applications of Artificial Intelligence*, 68, 81-100.
- [42]. Srinivas, N., & Deb, K. (1994). Multiobjective optimization using nondominated sorting in genetic algorithms. *Evolutionary computation*, 2(3), 221-248.