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Scenario-based Method to Solve Optimal Reactive Power Dispatch using Modified Ant Lion Optimizer Considering Uncertainties in Load, Solar, and Wind Power

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Abstract- The dispatch of Optimal reactive power plays a vital role in power networks to maintain the desirable voltages at the buses. The power networks with conventional thermal generators are no longer being used, nowadays renewable energy sources have been incorporated to these networks due to their tremendous advantages. Therefore, this paper mainly focuses on solving the ORPD problem by integrating solar and wind plants. In the IEEE30 bus system, bus 5 and bus 8 thermal generators could be replaced with solar and wind power plants. In this regard, the Weibull probability density function, lognormal probability density function, and beta probability density function are used to solve some of the uncertainties including load demand, wind power, and solar power. The proposed method called a scenario-based method is used for representing uncertainties in which a set of 25 scenarios were created with the mixture of uncertainties in load demands and power of the solar and wind sources. This is delineated as an optimization problem by considering minimizing the power losses of transmission lines and voltage deviation as objectives. An analysis has been carried out using Modified Ant Line Optimizer (MALO) to examine the current approach to the modified IEEE 30-bus test system. Result: ORPD with uncertain demand, wind and solar power, the power losses are reduce to 2.567 MW , voltage deviation minimize to 0.0906 p.u.

Keywords True power loss, Reactive power dispatch, MALO, Solar power, Wind power.

Nomenclature-

ORPD: Optimal Reactive Power Dispatch	JA: Jaya Algorithm
ALO: Ant Line Optimizer	RER: Renewable Energy Resources
MALO: Modified Ant Line Optimizer	QPSODM: Quantum-behaved Particle Swarm Optimization Differential Mutation
IGSA: Improved Gravitational Search Algorithm	Ploss: Power Losse
CRO: Chemical Reaction Optimization	TVD: Total Voltage Deviation
BSO: Backtracking Search Optimizer	EVD: Expected Voltage Deviation
PSO: Particle Swarm Optimization	TEVD: Total Expected Voltage Deviation
HPSO: Hybrid PSO	EPL: Expected Power Losses
MSCA: Modified Sine Cosine Algorithm	TEPL: Total Expected Power Losses
OSSA: Oppositional Salp Swarm Algorithm	EMO: Expected Multi Objective

1. Introduction

The demand for Electricity in everyday life keeps on increasing due to population growth. This intern results, the electric power transmission operators facing many challenges in power sector[1]. The power system blackouts occurred in the system because of active flow of reactive power (VAr) along the transmission networks. Hence, the researchers of power systems are involved into the proper planning of reactive power. The researchers have been proposed a variety of solutions for reactive power planning problems in view of single and multi-objective functions, as well as reduced power loss, voltage deviation, and improved stability. Various control variables, including tap settings and generator output voltages, were selected to accomplish these objectives [2]. There are continuously and discretely variable ORPDs in this non-linear, non-convex model. The greater part of the published research articles on reactive power planning report the minimization of real power losses under the conditions of base load. Thus this objective paid a immense attention throughout the ORPD problem[3]. Generating power using thermal generators produce more emission. By incorporating renewable sources like solar and wind, the emission of the system can be minimized. This paper focuses on how to incorporate uncertainties related to solar power system and wind power system.

The ORPD difficulty involves non-convex, complex, and non-linear optimization involves number of techniques in order to reduce it, namely differential evaluation[4], Whale Optimization[5], Improved Gravitational Search Algorithm (IGSA) [6], Chemical Reaction Optimization (CRO) [7], Artificial Bee Colony Optimizer[8], Modified Harmony Search Algorithm [9], Ant Colony Optimization [10], Bat Algorithm [11], Firefly Algorithm [12], Hybrid Shuffled Frog Algorithm [13], Hybrid Tabu Search Algorithm [14], practical swam optimization algorithm [15], Cuckoo search algorithm [16], Evolutionary Programming[17], Efficient Hybrid Algorithm[18], Backtracking Search Optimizer (BSO) [19], Particle Swarm Optimization (PSO) [20], Hybrid PSO (HPSO) [21], diversity-enhanced (DEPSO) [22], Modified Sine Cosine Algorithm (MSCA) [23], Oppositional Salp Swarm Algorithm (OSSA) [24], opposition-based gravitational search algorithm[25], Jaya Algorithm (JA) [26], Ant Lion Optimizer (ALO) [27], Modified Ant Line Optimizer (MALO) applied to ORPD problem later Renewable Energy Resources (RER) are integrated with existing system.

Due to the continuous increment in electricity demand day-by-day, power sector is interfacing some challenges to maintain the balance between the power generation and demand with suffering from supply constraints and shortages in power [28]. To maintain the ratio of power generation and demand, moving from conventional sources to non-conventional sources is not only an option, it is a necessity [29]. So additionally (RER) have a number of issues arising from natural and continuous fluctuations including stochastics. Therefore, considering RER uncertainties is a major issue for effective planning, and several papers have been presented to diagnose the problem of uncertainty in power systems by adopting ORPD. Adaptive differential evolution was used in to address the ORPD, and scenario-based strategy was used to consider the loads. In practical IEEE 14-bus system and Adrars power system, Quantum-behaved Particle Swarm Optimization Differential Mutation (QPSODM) was used for solving ORPD considering the stochastic natural RERs and load [30]. The ORPD has been solved in the uncertainties of wind and load power. The uncertainty model of the load was used in [31] in solving the ORPD problem using the two-point estimation methods. ALO has been modified to MALO as a recent method to find the best position. In some cases, ALO may be tripped to a local optimization system. Hence, propose a modified ALO-based algorithm to solve the problem of stagnation.

The paper contributes as:

- The modified version of traditional ALO was developed toward searchability.
- Apply the current algorithm to the problem of ORPD without solar and wind power.
- Despite of uncertainties of the demand for electricity, the problem of ORPD would be solved by using the sources of wind and solar PV sources.
- The scenario-based method is used in combination with a set of load, solar irradiance, and wind speed scenarios.
- This current technology algorithm has been applied to validate using modified IEEE 30-bus system.

2. Mathematical Formulation of ORPD Problems

Several classes of objectives can be assigned to the reactive power flow. The main intention of the work from an economic standpoint is to reduce the network active power losses. For the system security, contemplate voltage deviation as our objective.

2.1. Minimizing active power losses

Specifically, ORPD minimizes power losses by:

$$F_1 = Min(P_L) = \sum_{K=1}^{N_l} G_K[V_m^2 + V_n^2 - 2V_mV_n\cos(\delta_m - \delta_n)] \tag{1}$$

G_K represents the line conductance connected between m and n. Voltage magnitudes at the buses are denoted as V_m,V_n.δ_m,δ_n are the angles.

2.2. Voltage Deviation Minimization

As a result, swells should be reduced by properly maintaining the voltages. In addition, the voltage collapses must be reduced to avoid voltage swells. The voltage deviation can be reduced by using the following objective function:

$$F_2 = \sum_{i=1}^{N_B} \| V_m - 1 \| \tag{2}$$

V_m represents the bus voltage. m and N_B denotes the no.of buses.

The parameter considering both equality and inequality constraints, which can be used for solving the problem of ORPD.

$$P_{Gm} - P_{Dm} - V_m (G_{mn} \cos(\delta_m - \delta_n) + B_{mn} \sin(\delta_m - \delta_n)) = 0 \quad (3)$$

$$Q_{Gm} - Q_{Dm} - V_m (G_{mn} \cos(\delta_m - \delta_n) + B_{mn} \sin(\delta_m - \delta_n)) = 0 \quad (4)$$

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \quad \text{i=1,2,…,NG} \quad (5)$$

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max} \quad \text{i=1,2,…,NG} \quad (6)$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \quad \text{i=1,2,…,NG} \quad (7)$$

NG represents the number of generators.

$$T_i^{\min} \le T_i \le T_i^{\max} \quad \text{i=1,2,…,Nt} \quad (8)$$

N_t is the transformers number.

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max} \quad \text{i=1,2,…,Nc} \quad (9)$$

Nc is the number of capacitors.

3. Uncertainty Modelling

The study considers some uncertainties, such as load demand, PV and wind sources are affected by irradiance and wind speed. These uncertainties were modelled by using the probability density functions (PDF).

3.1. Uncertainty of Load Demand

As a result, swells should be reduced by properly maintaining the voltages. In addition, the voltage collapses must be reduced to avoid voltage swells. The voltage deviation can be reduced by using the following objective function.

$$PDF_L(P_L) = \frac{1}{\sigma_L \sqrt{2\pi}} \exp[-\frac{(P_L - \mu_L)^2}{2\sigma_L^{\ 2}}] \quad (10)$$

where σ represents the standard deviation & μ denotes the mean values. The values of the σ_L & μ_L are 70 & 10. Portability of the load demands & anticipated load scenarios can be attained as [32]:

$$\pi_{Li} = \int_{p_{Li}^{\min}}^{p_{Li}^{\max}} PDF_L(\mathrm{P}_L)\,\mathrm{dP}_L \quad (11)$$

$$P_{L,i} = \frac{1}{\pi_{L,i}} \int_{P_{L,i}^{\min}}^{P_{L,i}^{\max}} P_L \times PDF_L(P_L) dP_L \quad (12)$$

3.2. Uncertainty of the Wind Speed

Weibull PDF used in order to uncertain the wind speed as follows:

$$PDF_V(V) = \left(\frac{\beta}{\alpha}\right)\left(\frac{v}{\alpha}\right)^{(\beta-1)} \exp[-\left(\frac{v}{\alpha}\right)^{\beta}] 0 \le \mathrm{v} \le \infty \quad (13)$$

The Weibull PDF's shape and scale parametes are used in the following formula, where α is used with a value of 10.0434 and β is used with a value of 2.5034. Accordingly, the output power of wind turbine could be calculated as follows:

where πs,m denotes the probability of the solar irradiance of mth scenario. The scenarios & the corresponding irradiance

$$P_{wg}(V) = \begin{Bmatrix} 0 & for v < v_i \,\&\, v > v_0 \\ P_{WT}\left(\frac{v - v_{wi}}{v_{wr} - v_{wi}}\right) & for(v_i \le v \le v_r) \\ P_{WT} & for(v_r \le v \le v_0) \end{Bmatrix} \quad (14)$$

In this formula, PWT is the wind turbine's rated power, vi is the cut-in speed, v_r is its rated speed, and v_o is its cut-out speed. According to [32], obtain the following wind speed portability for each scenario:

$$\Pi_{W,\mathrm{k}} = \int_{v_k^{\min}}^{v_k^{\max}} PDF(v) dv \quad (15)$$

$$v_k = \frac{1}{\Pi_{L,i}} \int_{v_k^{\min}}^{v_k^{\max}} v \times PDF_v(v) dv \quad (16)$$

Where $\pi_{W,K}$ is the wind speed probability in scenario k; $V_k^{\min}$ and $V_k^{\max}$ denote at each scenario, the beginning and ending points of the interval for wind speed are indicated. Based on the equations outlined above, 25 scenarios are generated for wind speed. Table 1 shows the probabilities and wind speeds associated with various scenarios.

3.3. Modelling of Solar Irradiance Uncertainty

In order to model the solar irradiance (G) uncertainty, beta PDF is employed. It is explained as follows:

$$PDF_S(G) = \begin{cases} \frac{I\prime(\alpha+\beta)}{I\prime^{(\alpha)}+I\prime(\beta)} \times G^{\alpha-1} \\ \quad \times (1-G)^{\beta-1} otherwise \\ 0 \qquad if\ 0 \le\ G \le 1, 0 \le \alpha, \beta \end{cases} \quad (17)$$

The gamma PDF is calculated using (18) and (19) using the function Γ denoting the function of gamma along with α and β indicate the parameters of the beta PDF

$$\beta = (1-\mu_s) \times \left(\frac{\mu_s \times (1+\mu_s)}{\sigma_s^2}\right) - 1 \quad (18)$$

$$\propto = \left(\frac{\mu_s \times \beta}{(1-\mu_s)}\right) - 1 \quad (19)$$

where μs denotes the mean value, while σs is standard deviation. α and β have been selected as 6.38 and 3.43, respectively. Solar irradiance is a factor that determines the output power of a PV system, and also calculated using (17) as follows.

$$P_s(G) = \begin{cases} P_{sr}\left(\frac{G^2}{G_{std} \times X_c}\right) for\ 0 < G \le X_c \\ \quad P_{sr}\left(\frac{G}{G_{std}}\right) for G \ge\ X_c \end{cases} \quad (20)$$

A solar PV system's rated power is denoted by P_{sr}. The G_{std} indicates the standard solar irradiance of 1000 W/m^2. X_c which represents a certain irradiance point, set as 120 W/m^2.

The portability of solar irradiance can be calculated as:

$$\pi_{G,m} = \int_{G_m^{min}}^{G_m^{max}} PDF_s(G) dG \quad (21)$$

$$G_{,m} = \frac{1}{\pi_{s,m}} \int_{G_m^{min}}^{G_m^{max}} G \times PDF_s(G) dG \quad (22)$$

are depicted in Table 1. Through the combining of wind, solar irradiance, & load scenarios, obtain a set of scenarios based on their probabilities.

Table 1. The percentage of loads, solar irradiances, the wind speeds and their corresponding probabilities

Scenario number	% Loading Pd	Irradiance, G_s (W/m^2)	PV power (MW)	Wind speed v_w (m/s)	Wind power (MW)	Scenario probability, Δsc
1	105.784	1115.950	50.000	1.702	0.000	0.001
2	55.714	726.973	36.349	7.605	26.566	0.001
3	73.165	476.090	23.805	10.414	42.772	0.007
4	77.665	803.282	40.164	2.377	0.000	0.001
5	99.491	935.904	46.795	9.182	35.666	0.001
6	60.573	607.269	30.363	3.158	0.912	0.004
7	97.292	365.655	18.283	5.712	15.645	0.001
8	58.378	326.471	16.324	9.221	35.892	0.038
9	98.092	0.000	0.000	8.166	29.805	0.006
10	77.942	751.597	37.580	5.470	14.248	0.002
11	41.386	181.466	9.073	4.661	9.580	0.004
12	65.615	869.125	43.456	5.871	16.561	0.001
13	90.475	441.341	22.067	8.806	33.496	0.003
14	66.773	1103.501	50.000	10.001	40.393	0.001
15	61.498	551.278	27.564	8.628	32.470	0.009
16	68.935	0.000	0.000	6.229	18.629	0.478
17	67.603	138.834	6.942	9.084	35.103	0.093
18	71.770	379.832	18.992	9.678	38.528	0.044
19	79.921	672.788	33.639	5.271	13.102	0.004
20	72.351	411.201	20.560	7.880	28.152	0.037
21	78.322	201.152	10.058	4.813	10.458	0.048
22	66.073	95.657	3.813	11.743	50.441	0.027
23	74.465	229.271	11.464	2.538	0.000	0.071
24	63.754	518.084	25.904	3.245	1.416	0.012
25	67.487	275.124	13.756	14.439	65.994	0.106

4. Modified Ant Lion Optimizer (MALO) for the Problem of ORPD

Developed by Seydali Mirjalili, the ALO algorithm mimic random ants walking with antlions, being entrapped in pits of ants, finding prey by sliding towards ants, and then rebuilding the pit [33]. The elitism is utilized in order to ensure the best possible result is obtained across iterations, so the selected Ant Lions as well as the elite Ant Lions are saved, and it is assumed that these factors affect the random walk of ants on the search space [34]. An antlion pit is constructed, an ant is trapped in one, sliding towards an antlion, catching prey, re-constructing the pit, and entrapment is simulated in MALO.

The jth ant in ALO is given as

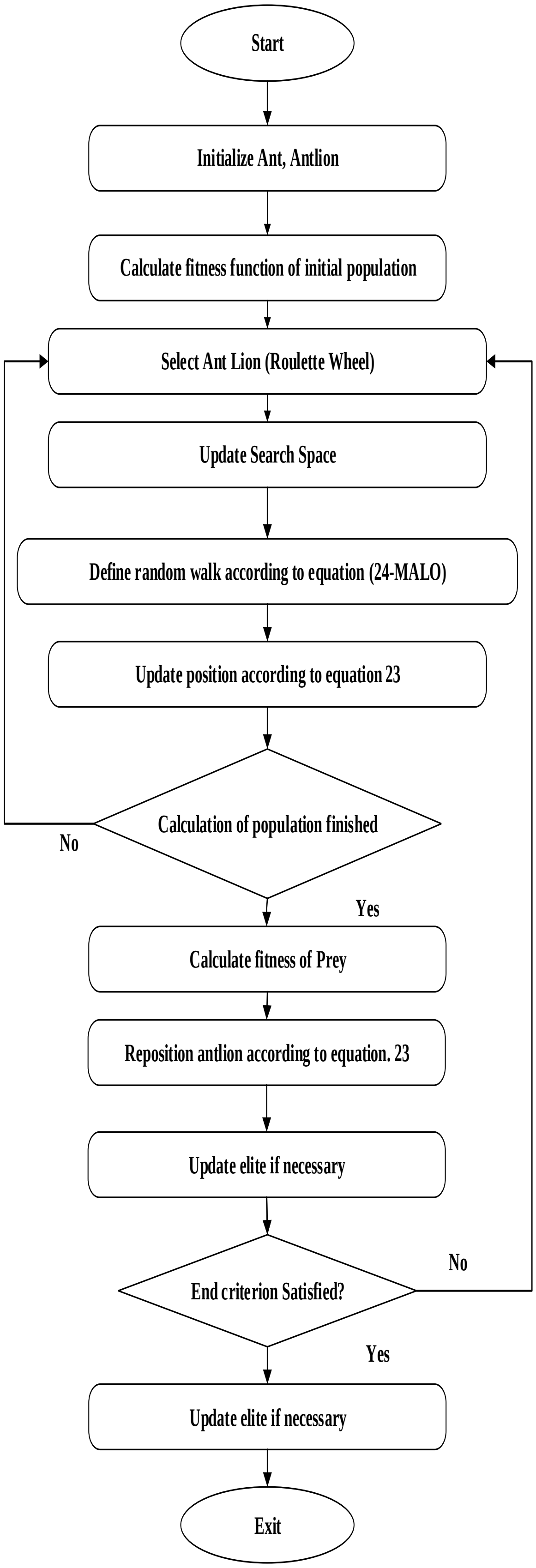
$$Ant_j^t = \frac{R_A^t + R_E^t}{2} \tag{23}$$

Antlions will randomly walk and elites are will walk for the next iteration, jth. The elites have been modified to be weighted elites in MALO. The equation 24 enumerates this

$$.MAnt_j^t = \frac{R_A^t * (2-W) + R_E^t * W}{2} \tag{24}$$

W is varying between 0 to 2. The ORPD variables are modified based on the equation stated above.

Flow chart for MALO:



5. Results and Discussion

It was tested on IEEE 30-bus system where the projected algorithm is applied for addresses of the ORPD. A Core I5 PC with 8GB of memory has been used to run the ORPD program written in MATLAB. Six thermal generation units are on each of the six buses of IEEE-30 bus system i.e., bus #1, bus #2, bus #5, bus #8, bus #11, and bus #13. This information is summarized in Table 2. In the case of adding together wind turbines at bus 5 and PV units at bus 8, the ORPD is solved with or without considering stochasticity or uncertainty of the RERs and load demands. All studied cases were examined with a search agent of 100 and a maximum number of iterations of 500, while a total of 30 trial runs were run. The following are the case studies examined.

5.1 *Case 1: A Solution to the ORPD Problem Without Solar and Wind*

Rather than considering RERs, the ORPD solution means minimizing power losses (PLoss) and summation voltage deviations (TVD). ALO and MALO optimization results are tabled in table 2, along with the best-fit variables. MALO and ALO result in power losses of 4.1428 MW and 4.59 MW, respectively. An example of how a number of optimization algorithms can yield comparable results for the reduction of power losses is shown in Figure 1. In comparison to the traditional ALO and other reported techniques, the proposed algorithm results in minimum power losses. ALO was found to result in 0.1199 p.u and MALO was found to result in 0.11936 p.u, respectively. Figure 1 shows the objective results of the MALO algorithm and other algorithms ae used for minimizing power loss. In comparison to traditional ALO and other algorithms, MALO has fewer power losses. Therefore, it shows MALO's effectiveness. For other case studies, MALO was thus applied.

Table 2. Simulation results for ORPD problem solution for case 1.

Control variables	P_{Loss} minimization		TVD minimization	
	MALO	ALO	MALO	ALO
V1 (p.u)	1.1000	1.100	0.9980	1.0299
V2 (p.u)	1.0952	1.0953	0.9885	1.0390
V5 (p.u)	1.0747	1.0767	1.0171	1.0110
V5 (p.u)	1.0825	1.0788	1.0156	1.0522
V11 (p.u)	1.1000	1.1000	1.0495	0.9854
V13 (p.u)	1.1000	1.1000	1.0444	0.9910
T6-9	0.9859	1.01	1.0194	1.9754
T6-10	1.0500	0.99	0.9055	0.4245
T4-12	1.0250	1.02	1.0278	2.2103

T27-28	1.0055	1.000	0.9543	2.8845
Q10 (p.u)	4.9242	4	1.2881	4.0412
Q12 (p.u)	3.7574	2	0.9755	3.2412
Q15 (p.u)	3.6568	4	0.9459	2.4120
Q17 (p.u)	4.7737	3	0.0117	2.6612
Q20 (p.u)	3.5424	2	4.7066	2.8456
Q21 (p u)	4.8584	4	0.7007	0.9721
Q23 (p.u)	0.4437	3	3.4206	0.8450
Q24 (p.u)	4.7621	5	3.9141	0.9144
Q29 (p.u)	3.3655	5	1.3718	0.9601
P_{Loss}	**4.1428**	**4.59**	**5.953**	**5.6980**
TVD (p.u)	**1.6435**	**2.569**	**0.11936**	**0.1199**

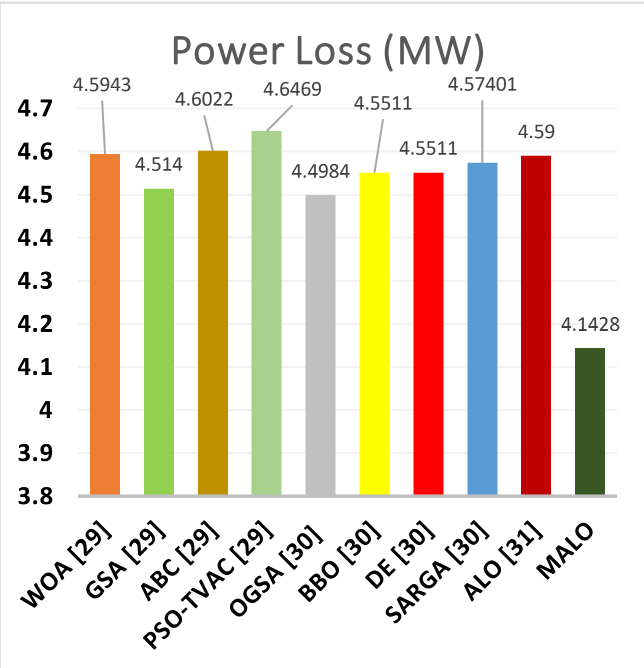


Fig. 1. Power loss values for different optimization techniques for ORPD

5.1. Case 2: An ORPD Solution Considering Load demand, Wind and Solar Powers Uncertainties

ORPD solves this problem by reducing the power losses under the load demand uncertainties, solar power, and wind power, which are based on the uncertainties of wind speed (v) and solar irradiance (G) [35]. Wind farm contains almost 25 turbines and the rated power of turbine is 3 MW, where its $v_{\omega r}$,$v_{\omega o}$ and $v_{\omega i}$ are 16 m/s, 25m/s, and 3m/s, approximately [36]. The PV system has a rated power of 50 MW and a Gstd is 1000 W/ m^2 [37].

The proposed method is used to combine of the probabilities of the solar irradiance, load, and wind speed. Below is a table of 25 scenarios with their probabilities. The primary goal for solving the ORPD is to minimize the resulting expected power losses, thereby calculation is as follows:

$$TEPL = \sum_{n=1}^{25} EPL_n = \sum_{n=1}^{25} \Delta_{SC,n} \times P_{Loss,n} \quad (25)$$

Where TEPL represents the total expected power losses; EPLn represents the expected power losses of ith scenario; indicate probabilities of n-th scenarios. For each scenario, table 3 outlines the solar and wind system output power, the power losses, EPL, voltage deviation, and EVD. TEPL gained by MALO equals 2.133022 MW, while TEPL without the inclusion of RERs is 4.1428MW.

$$TEVD = \sum_{n=1}^{25} EVD_n = \sum_{n=1}^{25} \Delta_{SC,n} \times VD_{sc,n} \quad (26)$$

Where TEVD denotes the total expected voltage deviation. The voltage deviation without inclusion RERs is 0.11936p.u while the TEVD that gained by MALO is 0.077977p.u.

We consider power loss and voltage deviation as one of objectives in the above two cases. They are combined to form the multi-objective case.

$$TEMO = \sum_{n=1}^{25} EMO_n = \sum_{n=1}^{25} \Delta_{SC,n} \times MO_{sc,n} \quad (27)$$

Table 4 shows a case study of multi-objective for the ORPD with uncertainty demand, wind and solar power, loss and expected loss of voltage deviation, power and expected voltage deviation for all scenarios. From this table it has been observed that TEPL is 2.567107844 MW, TEVD is 0.090613p.u. and multi-objective value is 3.473230543p.u. Here in this case both the voltage deviation & power losses are simultaneously optimized Therefore results are high compared to single objective optimization.

Figure 2, 3, and 4 show the voltage profile of the system for each scenario. For all scenarios, the profiles are within the allowable limits, which is [0.9-1.10] per unit. The figure depicts the optimal voltage settings for generator buss voltages for all scenarios in a multi objective case with solar and wind power. Both power losses and voltage deviations are minimized in this case, thus setting voltages at generator buss voltages between 0.90 to 1.10 p.u. Figure 3 shows the optimal generator bus voltage settings for all scenarios in the power loss minimization case with solar and wind power. The voltages are near their maximums because only power losses are optimized in this case. With solar and wind power, voltage deviation minimization is the main objective in this case, which is why voltage values are near 1 p.u. in this case. Figure 5 shows Voltage profile of load buses for a solar wind power system.

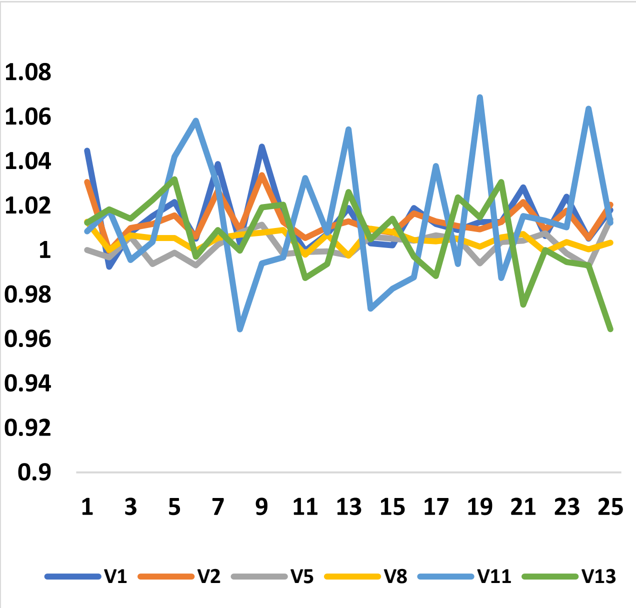


Fig. 2. Optimal settings of generator bus voltages for all scenarios in multi objective case with solar and wind power

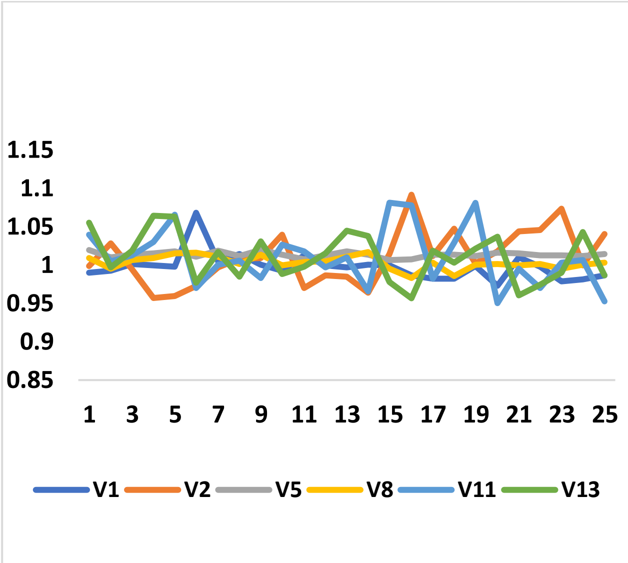


Fig. 4. Optimal settings of generator bus voltages for all scenarios in voltage deviation minimization case with solar and wind power

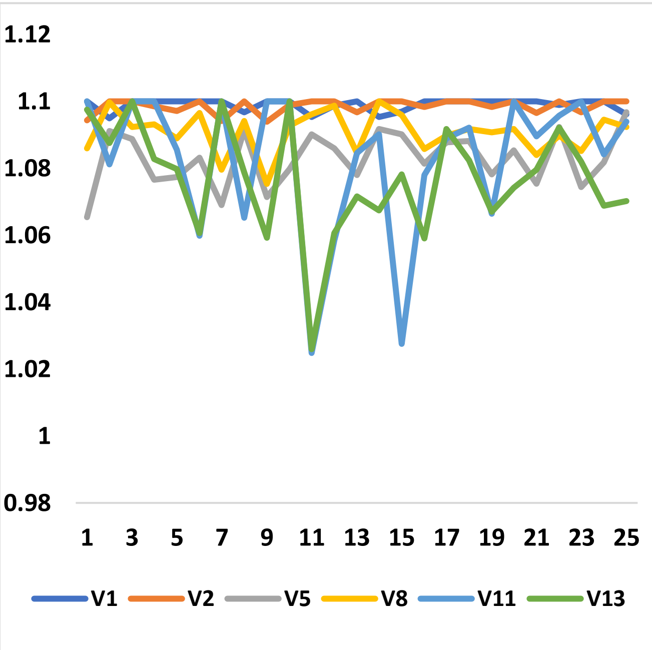


Fig. 3. Optimal settings of generator bus voltages for all scenarios in power loss minimization case with solar and wind power

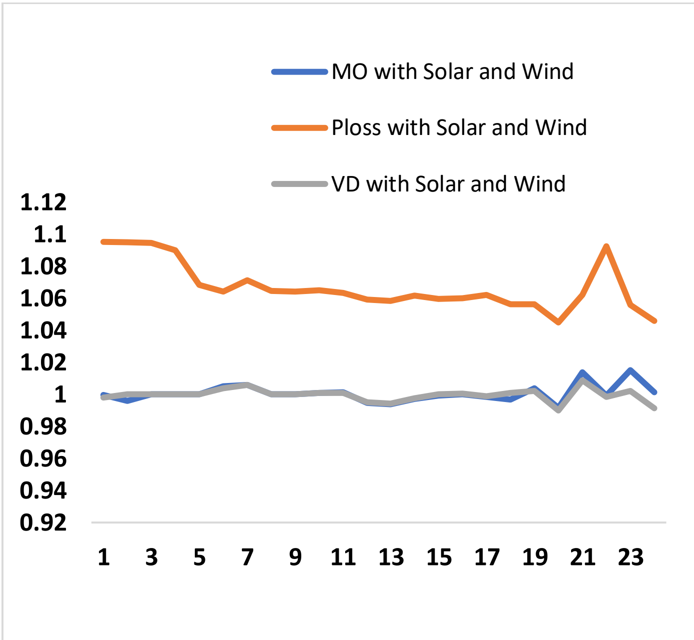


Fig. 5. Voltage profile of load buses

Uncertainties in solar power and load consider in study 1, in this case only solar power is considered to in operate in the system at bus 8. In study 2 only wind power is incorporated into the system at bus 5, in study 3 both solar and wind powers are incorporated at bus 8 and bus 5 respectively. Table 5 presents the single-objective ORPD case study with uncertain demand and RERs, the power losses and the expected power losses for all scenarios.Table 6 presents the single-objective ORPD case study with uncertain demand and RERs, the voltage deviation, and the expected voltage deviation for all scenarios.

From the table 5 it has been observed that total expected power losses by considering only solar is 5.445235 MW, by considering only wind power power losses are 2.52077 MW, but with the use of both solar and wind power, power losses reduced to 2.133022MW.From the table 6 it has been observed that total expected voltage deviation by considering only solar is 0.101031p.u, by considering only wind power voltage deviation is 0.11194p.u, but with the use of both solar and wind power voltage deviation reduced to 0.077977p.u. therefore it is concluded that with the help of solar and wind power generation the power losses and voltage deviation getting reduced.

Table 3. The power generation of wind and solar, the Voltage deviation and the expected Voltage deviation for all scenarios.

S. No	% Loading Pd	PV power (MW)	Wind power (MW)	Scenario probability, Δsc	Scenario based VDscn(p.u.)	EVD: ∑Δsc,n × VDscn	Scenario based Ploss,n(MW)	EPL: $\sum \Delta_{sc,n} \times P_{Loss,n}$
1	105.784	50.000	0.000	0.001	0.1305	0.00013	7.495617	0.007496
2	55.714	36.349	26.566	0.001	0.0685	6.85E-05	0.852461	0.000852
3	73.165	23.805	42.772	0.007	0.0794	0.000556	1.281879	0.008973
4	77.665	40.164	0.000	0.001	0.0956	9.56E-05	3.102854	0.003103
5	99.491	46.795	35.666	0.001	0.1202	0.00012	3.72553	0.003726
6	60.573	30.363	0.912	0.004	0.0770	0.000308	1.634924	0.00654
7	97.292	18.283	15.645	0.001	0.0936	9.36E-05	6.089844	0.00609
8	58.378	16.324	35.892	0.038	0.0622	0.002365	0.819095	0.031126
9	98.092	0.000	29.805	0.006	0.0928	0.000557	6.375345	0.038252
10	77.942	37.580	14.248	0.002	0.0966	0.000193	2.413721	0.004827
11	41.386	9.073	9.580	0.004	0.0409	0.000164	0.763031	0.003052
12	65.615	43.456	16.561	0.001	0.0518	5.18E-05	1.347643	0.001348
13	90.475	22.067	33.496	0.003	0.0948	0.000284	3.519081	0.010557
14	66.773	50.000	40.393	0.001	0.0632	6.32E-05	0.982333	0.000982
15	61.498	27.564	32.470	0.009	0.0591	0.000532	0.931932	0.008387
16	68.935	0.000	18.629	0.478	0.0768	0.036693	2.393426	1.144058
17	67.603	6.942	35.103	0.093	0.0743	0.006912	1.444153	0.134306
18	71.770	18.992	38.528	0.044	0.0813	0.003579	1.386092	0.060988
19	79.921	33.639	13.102	0.004	0.1067	0.000427	2.848342	0.011393
20	72.351	20.560	28.152	0.037	0.0715	0.002645	1.724556	0.063809
21	78.322	10.058	10.458	0.048	0.0776	0.003725	3.622915	0.1739
22	66.073	3.813	50.441	0.027	0.0798	0.002154	1.122843	0.030317
23	74.465	11.464	0.000	0.071	0.1200	0.008522	3.649632	0.259124
24	63.754	25.904	1.416	0.012	0.0885	0.001062	1.945618	0.023347
25	67.487	13.756	65.994	0.106	0.0630	0.006675	0.910082	0.096469
26	**-**	**-**	**-**	**-**	**EVD:**	**0.077977**	**EPL:**	**2.133022**

Table 4. Case study of a multi-objective ORPD with uncertain demand, wind and solar power, the power losses and the expected power losses, voltage deviation, and expected voltage deviation for all scenarios.

S. No	Scenario-based Ploss,sc (MW)	EPL: ∑Δsc × Ploss,sc	Scenario based VDsc (p.u.)	EVD: ∑Δsc × VDsc	Scenario-based Multi. Obj MO sc(1*PL+10*VD)	EMO=∑Δsc × MOsc
1	8.767089	0.008767089	0.169881	0.00017	10.46589	0.010465889
2	1.058242	0.001058242	0.060606	6.06E-05	1.664267	0.001664267
3	1.562011	0.010934074	0.084977	0.000595	2.411756	0.016882294

4	3.730001	0.003730001	0.115026	0.000115	4.880258	0.004880258
5	4.306263	0.004306263	0.159632	0.00016	5.902551	0.005902551
6	1.98351	0.007934042	0.080693	0.000323	2.790415	0.011161659
7	7.022073	0.007022073	0.144945	0.000145	8.471523	0.008471523
8	1.043268	0.039644196	0.071806	0.002729	1.761325	0.066930335
9	7.256562	0.043539373	0.152814	0.000917	8.7847	0.052708198
10	2.921337	0.005842673	0.108076	0.000216	4.002089	0.008004178
11	0.896717	0.003586867	0.063975	0.000256	1.536436	0.006145745
12	1.653008	0.001653008	0.085256	8.53E-05	2.505562	0.002505562
13	4.100488	0.012301465	0.118177	0.000355	5.282249	0.015846747
14	1.220224	0.001220224	0.087298	8.73E-05	2.093183	0.002093183
15	1.138394	0.010245549	0.080896	0.000728	1.947349	0.017526142
16	2.848485	1.361575634	0.091355	0.043668	3.762029	1.798249675
17	1.752354	0.162968927	0.089213	0.008297	2.644457	0.245934465
18	1.71173	0.07531614	0.093241	0.004103	2.64414	0.116342164
19	3.346273	0.013385092	0.132197	0.000529	4.668238	0.018672953
20	2.09092	0.077364034	0.105779	0.003914	3.1487	0.116501898
21	4.352828	0.208935761	0.093654	0.004495	5.289328	0.253887763
22	1.32817	0.035860603	0.071673	0.001935	2.044852	0.055211013
23	4.339656	0.30811556	0.099852	0.007089	5.338173	0.379010306
24	2.30855	0.027702599	0.083919	0.001007	3.147719	0.037772627
25	1.265079	0.134098358	0.081473	0.008636	2.079803	0.220459148
26	**EPL**	**2.567107844**	**EVD**	**0.090613**	**EMO**	**3.473230543**

Table 5. A single-objective ORPD case study with uncertain demand and RERs, the power losses, and the expected power losses for all scenarios.

	Only Solar Power with uncertain demand		**Only Wind Power with uncertain demand**		**Both Solar and Wind Power with uncertain demand**	
S. No	**Scenario based Ploss,sc (MW)**	**EPL: ∑Δsc × Ploss,sc**	**Scenario based Ploss,sc (MW)**	**EPL: ∑Δsc × Ploss,sc**	**Scenario based Ploss,sc (MW)**	**EPL: ∑Δsc × Ploss,sc**
1	3.374104	0.003374	8.788069	0.008788	7.495617	0.007496
2	3.860193	0.00386	0.891343	0.000891	0.852461	0.000852
3	4.480446	0.031363	1.239458	0.008676	1.281879	0.008973
4	3.698757	0.003699	3.447672	0.003448	3.102854	0.003103
5	3.502775	0.003503	4.336394	0.004336	3.72553	0.003726
6	4.148552	0.016594	1.693899	0.006776	1.634924	0.00654
7	4.763423	0.004763	5.467843	0.005468	6.089844	0.00609

8	4.802022	0.182477	0.822028	0.031237	0.819095	0.031126
9	5.932378	0.035594	8.546119	0.051277	6.375345	0.038252
10	3.792081	0.007584	2.656703	0.005313	2.413721	0.004827
11	5.238261	0.020953	0.984581	0.003938	0.763031	0.003052
12	3.548384	0.003548	1.490898	0.001491	1.347643	0.001348
13	4.611669	0.013835	3.187491	0.009562	3.519081	0.010557
14	3.306719	0.003307	0.98141	0.000981	0.982333	0.000982
15	4.201396	0.037813	0.944057	0.008497	0.931932	0.008387
16	5.916328	2.828005	2.668054	1.27533	2.393426	1.144058
17	5.386396	0.500935	1.108573	0.103097	1.444153	0.134306
18	4.694574	0.206561	1.254687	0.055206	1.386092	0.060988
19	4.062343	0.016249	2.998935	0.011996	2.848342	0.011393
20	4.63908	0.171646	4.601267	0.170247	1.724556	0.063809
21	5.21125	0.25014	4.888698	0.234658	3.622915	0.1739
22	5.593716	0.15103	2.887544	0.077964	1.122843	0.030317
23	5.152213	0.365807	3.058008	0.217119	3.649632	0.259124
24	4.332786	0.051993	1.899418	0.022793	1.945618	0.023347
25	5.005666	0.530601	1.902653	0.201681	0.910082	0.096469
26	**Total EPL**	**5.445235**	**Total EPL**	**2.52077**	**Total EPL**	**2.133022**

Table 6. A single-objective ORPD case study with uncertain demand and RERs, the voltage deviation, and the expected voltage deviation for all scenarios.

	Only Solar Power with uncertain demand		**Only Wind Power with uncertain demand**		**Both Solar and Wind Power with uncertain demand**	
S. No	**Scenario based VDsc (p.u.)**	**EVD: ∑Δsc × VDsc**	**Scenario based VDsc (p.u.)**	**EVD: ∑Δsc × VDsc**	**Scenario based VDsc (p.u.)**	**EVD: ∑Δsc × VDsc**
1	0.124761	0.000125	0.13464	0.000135	0.1305	0.00013
2	0.118709	0.000119	0.095722	9.57E-05	0.0685	6.85E-05
3	0.114908	0.000804	0.135978	0.000952	0.0794	0.000556
4	0.133713	0.000134	0.117612	0.000118	0.0956	9.56E-05
5	0.138918	0.000139	0.141998	0.000142	0.1202	0.00012
6	0.101389	0.000406	0.094994	0.00038	0.0770	0.000308
7	0.120339	0.00012	0.132102	0.000132	0.0936	9.36E-05
8	0.101066	0.003841	0.106262	0.004038	0.0622	0.002365
9	0.114058	0.000684	0.127052	0.000762	0.0928	0.000557
10	0.105915	0.000212	0.130271	0.000261	0.0966	0.000193
11	0.087694	0.000351	0.073758	0.000295	0.0409	0.000164
12	0.101937	0.000102	0.100762	0.000101	0.0518	5.18E-05
13	0.116693	0.00035	0.127199	0.000382	0.0948	0.000284
14	0.110631	0.000111	0.104287	0.000104	0.0632	6.32E-05

15	0.096	0.000864	0.097397	0.000877	0.0591	0.000532
16	0.09625	0.046008	0.107907	0.05158	0.0768	0.036693
17	0.085322	0.007935	0.10768	0.010014	0.0743	0.006912
18	0.118354	0.005208	0.115846	0.005097	0.0813	0.003579
19	0.124803	0.000499	0.097619	0.00039	0.1067	0.000427
20	0.095429	0.003531	0.084926	0.003142	0.0715	0.002645
21	0.099161	0.00476	0.152065	0.007299	0.0776	0.003725
22	0.119785	0.003234	0.116168	0.003137	0.0798	0.002154
23	0.122941	0.008729	0.12928	0.009179	0.1200	0.008522
24	0.08883	0.001066	0.102949	0.001235	0.0885	0.001062
25	0.110394	0.011702	0.114085	0.012093	0.0630	0.006675
26	**Total EVD**	**0.101031**	**Total EVD**	**0.11194**	**Total EVD**	**0.077977**

6. Conclusion

The optimal reactive power dispatch solution was presented in the first section of the paper for IEEE 30 bus systems with the help of thermal generators only. It has achieved the lowest amount of power losses and minimum voltage deviations by applying the proposed MALO with ALO and other reported optimization techniques. A stochastic load demand, wind and solar power model is used in ORPD to describe the uncertainties appropriately. The model considers several scenarios. To select representative scenarios, stochastic programming is used and then calculate the expected power loss (EPL) and voltage deviation (EVD) using optimized network parameters under various load demands, and wind and solar power availability scenarios.

By adopting a scenario-based approach, a stochastic ORPD solution accommodates uncertain load demand, and wind, and solar power formulation. The optimization tasks are based on the MALO algorithm. PV system was used in place of the conventional thermal generator at bus 8 and wind power plant output was used in place of the thermal generator at bus 5. The ORPD problem was solved by considering only solar power, only wind power replacement, and both wind and solar power replacement. When solar and wind power are used together, power losses and voltage deviations are lower than when only solar power or only wind power is used. Additionally, the renewable energy penetration in the system reduces the power loss and voltage deviation in the given ORPD problem. FACTS will be used for multi-objective optimization in the future. Additionally, voltage stability was considered as another objective for improving the stability of the system in the future.

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