Multi-Objective Optimal Power Flow for a Thermal-Wind-Solar Power System

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Abstract

This paper solves a novel multi-objective optimal power flow (MO-OPF) problem for a hybrid power system consisting the thermal generators, wind energy generators (WEGs) and solar photovoltaic (PV) units with battery energy storage (BES) system. In this paper, three objective functions, i.e., total generation cost, transmission losses and voltage stability enhancement index are considered to be optimized simultaneously. The total generation cost minimization objective include the cost of conventional thermal generators, wind and solar power purchasing from the private owners and to reduce the risk due to the wind and solar power uncertainties. Here, the power output from the wind and solar power outputs are determined based on the Weibull probability distribution function. This paper utilizes a particle swarm optimization (PSO) based fuzzy satisfaction maximization technique to solve the proposed MO-OPF problem of a hybrid power system. Here, a modified IEEE 30 bus system is used to demonstrate the effectiveness of the proposed approach. The proposed technique is robust and faster which modifies the control variables effectively. The proposed approach can be useful to the system operator as the decision supportive tool to handle the hybrid power systems.

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1 Introduction

During the last decade, renewable energy has been the world's fastest growing source to generate electricity. Renewable energy becomes popular as it is abundant, inexhaustible, inexpensive and environmental friendly. Rising energy prices and concern over greenhouse gas emission have focused attention on energy alternatives. Nowadays, participation of wind and solar energy in electricity market is common, in spite of its non-dispatchable/intermittent nature. Therefore, the wind and solar energy generators also submit their bids, saying how much power they want to sell and its price. However, there might be a chance of deviation from the amount of power it has been committed and it will lead to power imbalance in the system operation. Therefore, when the renewable power cannot produce according to the production forecast, other producers have to increase their power production in order to make sure the power balance. In such uncertain environment, the decision to be taken should be reasonable, economical and not risky [1].

Power systems are forever changing. The integration of stochastic weather-driven power sources (wind and solar photovoltaic (PV)) has resulted in larger uncertainties in the demand, that needs to be met by the dispatchable generation. The concerns brewing up over fossil fueled generating plants, and their part of play in global warming, has pushed energy based research towards utilization of green energy around the globe. Wind and solar energy resources are vital in this regard. Integration of these resources with the grid has seen a continuously increasing pattern. With the greater integration of renewable electricity generation like wind and solar PV power into existing grids, research efforts must be devoted to formulate generation scheduling problems taking into account the intrinsic variability and non-dispatchable characteristics of these resources. Further, future load is also uncertain and cannot be predicted accurately. System operator can predict the uncertainty of the wind and solar power/load demand by using wind/solar/load demand forecast data [2, 3].

Reference [4] presents a MO-OPF technique using particle swarm optimization (PSO) considering two conflicting objectives, i.e., generation cost, and environmental pollution, are minimized simultaneously. A new OPF model for wind, solar, and solar-thermal bundled power scheduling and dispatch is proposed in [5] to incorporate the deviation incentive/penalty

charges for renewable energy introduced in India. A Pareto-based approach using a hybrid algorithm based on PSO and Shuffled frog-leaping algorithms is used to optimize the fuel cost and emission is proposed in [6]. Reference [7] proposes a Multi-Objective Differential Evolution (MODE) algorithm to solve the MO-OPF problem considering fuel cost, emission and losses of FACTS device equipped power systems. An OPF approach considering the entire system to determine the optimal operating strategy and cost optimization scheme as well as the reduction of emissions for micro-grid is proposed in [8]. Reference [9] proposes the solution of multi-objective optimal dispatch problem of solar-wind-thermal system by improved stochastic fractal search algorithm. Reference [10] presents an application of a scenario-based method for risk constrained stochastic OPF problem in electricity utilities using a two-stage stochastic programming framework considering various uncertainties. Reference [11] presents a short-term optimal scheduling of stationary batteries considering the uncertainty of load, wind-based distributed generation and plug-in electric vehicles. Reference [12] presents an OPF problem with storage as a finite-horizon optimal control problem.

A literature review on trends in optimization techniques used for the design and development of solar PV–wind based hybrid energy systems is presented in [13]. In [14], a new multi-objective optimization (MOO) algorithm for a hybrid wind-solar generation microgrid system with hydrogen energy storage is proposed to minimize the annualized cost, loss of load expected and loss of energy expected. An optimal bid submission in a day-ahead electricity market for the problem of joint operation of wind with photovoltaic power systems having an energy storage device is proposed in [15]. Reference [16] proposes a price forecast algorithm which provides prices in a one-day horizon, based on price historical data and meteorological information. A stochastic programming model for the optimal operation scheduling of a distributed energy resource system with multiple energy devices including renewables, considering economic and environmental aspects is proposed in [17]. An approach to solve an OPF problem combining stochastic wind and solar power with conventional thermal power generators in the system is proposed in [18]. Reference [19] proposes a methodology for energy management system based on the multi-objective receding horizon optimization algorithm is proposed to find the optimal scheduling of hybrid renewable energy system. A new strategy for the optimal scheduling problem taking into account the impact of uncertainties in wind, solar PV and load demand forecasts is proposed in [20].

The present paper aims at solving the MO-OPF problem of a hybrid power system considering the wind and solar PV power forecast uncertainties. The main contributions of this paper are:

- To develop and implement a new evolutionary based technique for solving the MO-OPF problem including the renewable energy resources (RERs) and battery energy storage.
- To integrate the wind energy generators (WEGs) and solar PV modules in the OPF model, which should handle both economical and reliability issues simultaneously.
- The uncertainties due to wind and solar powers are modeled using the Weibull probability distribution function.
- To evaluate different factors involved in the intermittency of renewable power.
- Three objective functions: total generation cost minimization, transmission losses minimization and voltage stability enhancement index are considered to solve the single and multi objective OPF problems.

The remainder of this paper is organized as follows: Section 2 describes the problem formulation of single and multi-objective OPF problems. Section 3 presents the modeling of wind, solar energy systems with battery energy storage. Solving the MO-OPF problem using PSO and fuzzy satisfaction maximization approach is described in Section 4. Section 5 presents the results obtained in this work along with a discussion about these results. Finally, the contributions with concluding remarks are drawn in Section 6.

2 Problem Formulation

This section presents the problem formulations of single and multi-objective optimization problems, and they are described next:

2.1 Single Objective OPF Problem

In single objective optimization, only one objective function is optimized at a time. This can be formulated as [21],

$$\text{minimize/maximize, } f(x, u) \quad (1)$$

$$\text{subjected to } g(x, u) = 0 \quad (2)$$

$$h(x, u) \leq 0 \quad (3)$$

where u is a vector of control variables, and x is a vector of state variables.

2.2 Multi-Objective OPF (MO-OPF) Problem

A general multi-objective optimization (MOO) problem has many objectives which are to be optimized simultaneously. The optimization problem is subjected to a number of equality and inequality constraints which the solution should satisfy. The MOO problem is formulated as [22],

$$\text{minimize/maximize, } f_i(x, u) \quad i = 1, 2, \dots, N_{obj} \quad (4)$$

$$\text{subjected to } g_j(x, u) = 0 \quad j = 1, 2, \dots, M_{eq} \quad (5)$$

$$h_k(x, u) \leq 0 \quad k = 1, 2, \dots, N_{ineq} \quad (6)$$

2.3 Objective Functions

2.3.1 Objective 1: Total generation cost minimization

This objective function is formulated as minimization of operating cost of conventional thermal generators, and the wind and solar power generation along with the factors involved due to the over/under estimation of wind and solar powers. This objective function is formulated as,

minimize, total generation cost (TGC), i.e.,
minimize,

$$\begin{aligned} TGC = & \sum_{i=1}^{N_G} C_{Gi}(P_{Gi}) + \sum_{j=1}^{N_W} C_{Wj}(P_{Wj}) + \sum_{k=1}^{N_S} C_{Sk}(P_{Sk}) \\ & + \sum_{j=1}^{N_W} C_{p,Wj}(P_{Wj,av} - P_{Wj}) + \sum_{j=1}^{N_W} C_{r,Wj}(P_{Wj} - P_{Wj,av}) \\ & + \sum_{k=1}^{N_S} C_{p,Sk}(P_{Sk,av} - P_{Sk}) + \sum_{k=1}^{N_S} C_{r,Sk}(P_{Sk} - P_{Sk,av}) \end{aligned} \quad (7)$$

The first term in the above equation is the operating cost of conventional thermal generators, and it is given by,

$$C_{Gi}(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 \quad (8)$$

where a_i , b_i and c_i are the cost coefficients for the i^{th} thermal generator, and P_{Gi} is the scheduled thermal power generation.

The second term is the operating cost for power drawn from the WEG. This cost depends upon the ownership of the wind farm. Suppose, if the wind farm is owned by the system operator (SO) itself, then this term may not exist.

If it is owned by the independent power producer (IPP), then the SO has to pay for the scheduled wind power (P_{Wj}). In this paper, a linear cost function is assumed for the scheduled wind power and it is given by,

$$C_{Wj}(P_{Wj}) = d_j P_{Wj} \quad (9)$$

where d_j is the direct cost coefficient of j^{th} WEG. Similarly, the third term is the operating cost of solar PV module, and it is given by,

$$C_{Sk}(P_{Sk}) = t_k P_{Sk} \quad (10)$$

where P_{Sk} is the scheduled power output from the solar PV module, and t_k is the direct cost coefficient of j^{th} WEG.

The fourth term in Equation (7) is the cost due to the under-estimation of wind power, and it is known as penalty cost. This cost function can be related with the variance of the probability distribution; normally produced above the scheduled value. This function is used to determine the excess power it might produce that the scheduled value, and it is given by [23],

$$C_{p,wj}(P_{wj,av} - P_{wj}) = K_{p,j} \int_{P_{wj}}^{P_{r,j}} (p^w - P_{wj}) f_p(p^w) dw \quad (11)$$

where p^w is the power output from the WEG, $P_{wj,av}$ is the available wind power from the j^{th} WEG. This is a random variable, with a range of $0 \leq P_{Wj,av} \leq P_{r,j}$. $f_p(p^w)$ is the probability density function (PDF) of WEG.

The fifth term is the reserve cost function, which represents the cost due to the available wind power being less than scheduled wind power. This cost function is used to determine the deficit power it might produce from the distribution function. This cost function is given by [24],

$$C_{r,wj}(P_{wj} - P_{wj,av}) = K_{r,j} \int_0^{P_{wj}} (P_{wj} - p^w) f_p(p^w) dw \quad (12)$$

where $K_{p,j}$, $K_{r,j}$ are the penalty and reserve cost coefficients for the j^{th} WEG.

Similarly, the sixth and seventh terms represents the under-estimation (penalty cost) and over-estimation (reserve cost) costs of solar power, respectively. The under-estimation cost of solar PV power is given by,

$$C_{p,sk}(P_{sk,av} - P_{sk}) = K_{p,k} \int_{P_{sk}}^{P_{r,k}^s} (p^s - P_{sk}) f_s(p^s) ds \quad (13)$$

where p^s is the power output from solar PV module, $P_{sk,av}$ is the available wind power from the k^{th} WEG. This is a random variable, with a range of $0 \leq P_{sk,av} \leq P_{r,k}^s$. $f_s(p^s)$ is the PDF of solar irradiation. The over-estimation cost of solar power is given by,

$$C_{r,sk}(P_{sk} - P_{sk,av}) = K_{r,k} \int_0^{P_{sk}} (P_{sk} - p^s) f_s(p^s) ds \quad (14)$$

2.3.2 Objective 2: Transmission Loss (TL) Minimization

The transmission loss in each line is calculated from the load flow solution. The net power loss is equal to the sum of power loss in each line, and it is formulated as [21],

minimize,

$$TL = \frac{1}{2} \sum_{i,j} [G_{ij} (V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j))] \quad (15)$$

2.3.3 Objective 3: Voltage Stability Enhancement Index (VSEI)/L-Index Minimization

To monitor the voltage stability in power system L-index/VSEI of the load buses is considered [25]. This L-index uses the information from a normal load flow and is in the range of 0 (no load) to 1 (voltage collapse). The control against voltage collapse is based on minimizing the sum of squared L-indices for a given system operating condition, and it is given by,

$$VSEI/L - index = \sum_{j=N_G+1}^n L_j^2 \quad (16)$$

where

$$L_j = \left| 1 - \sum_{i=1}^{N_G} F_{ij} \frac{V_i}{V_j} \right| \quad j = N_G + 1, \dots, n \quad (17)$$

The L-indices for a given load condition are computed for all load buses, and the maximum of L-indices gives the proximity of the system to voltage collapse.

2.4 Problem Constraints

2.4.1 Equality constraints

These are the typical power flow equations, and they are expressed as,

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^n V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) = 0 \quad (18)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^n V_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) = 0 \quad (19)$$

In the above Equations (18) and (19), $i = 1, 2, \dots, n$. Where n is the number of buses in the system. G_{ij} and B_{ij} are the real and imaginary parts of the element in the bus admittance matrix.

2.4.2 Thermal generators constraints

The active power outputs of thermal generators are restricted by their lower and upper limits, and it is expressed by,

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \quad (20)$$

The generator bus voltages are limited by,

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max} \quad (21)$$

2.4.3 Wind power constraint

For the WEG, the minimum output will be zero and maximum output is equal to the rated capacity of the WEGs (P_{Wj}^r). Therefore, the limits on wind power is expressed as,

$$0 \leq P_{Wj} \leq P_{Wj}^r \quad (22)$$

P_{Wj} is the amount of wind power generation and P_{Wj}^r is the maximum/rated power limit of j^{th} WEG.

2.4.4 Solar PV power constraint

The limits on solar PV power is expressed as,

$$0 \leq P_{Sk} \leq P_{Sk}^{max} \quad (23)$$

P_{Sk} is the amount of solar power generation and P_{Sk}^{max} is the maximum power limit of k^{th} solar PV unit.

2.4.5 Transformer constraints

Transformer taps have minimum and maximum setting limits, and they are limited by,

$$T_i^{min} \leq T_i \leq T_i^{max} \quad (24)$$

2.4.6 Switchable VAR sources

The switchable VAR sources have restrictions as follows,

$$Q_{ci}^{min} \leq Q_{ci} \leq Q_{ci}^{max} \quad (25)$$

2.4.7 Security constraints

These include the limits on the load bus voltage magnitudes (V_{Di}) and line flow (S_{Li}) limits. These are expressed as,

$$V_{Di}^{min} \leq V_{Di} \leq V_{Di}^{max} \quad i = 1, 2, \dots, N_D \quad (26)$$

$$S_{Li} \leq S_{Li}^{max} \quad i = 1, 2, \dots, N_{line} \quad (27)$$

3 Modeling of Wind and Solar Energy Systems with Battery Storage

3.1 Modeling of Wind Power

Wind velocity has great impact on wind power generation. Wind speeds vary both in time and space. Power output from the WEG is calculated using [23, 26],

$$P_W = \begin{cases} 0 & v < v_{ci} \\ av^3 - bP_W^r & v_{ci} < v < v_r \\ P_W^r & v_r < v < v_{co} \\ 0 & v > v_{co} \end{cases} \quad (28)$$

where $a = P_W^r / (v_r^3 - v_{ci}^3)$, $b = v_{ci}^3 / (v_r^3 - v_{ci}^3)$. v_{ci} , v_{co} and v_r are the cut-in, cut-out and rated speed of WEG. Wind speed distribution is modeled as Weibull PDF, and it is given by [1],

$$f_v(v) = \left(\frac{k}{c}\right) \left(\frac{v}{c}\right)^{(k-1)} \exp \left[-\left(\frac{v}{c}\right)^k \right] \quad 0 < v < \infty \quad (29)$$

The Weibull distribution parameters (c and k) should be greater than zero, and they are referred to as scale factor and shape factor, respectively. The Weibull PDF of wind power output is given by [24],

$$f_p(p) = \frac{k(v_r - v_i)}{c^k * p_r} \left[v_i + \frac{p}{p_r} (v_r - v_i)^{k-1} \right] \exp \left[- \left[\frac{v_i + \frac{p}{p_r} (v_r - v_i)}{c} \right]^k \right] \text{ for } v_i \leq v \leq v_r \quad (30)$$

3.2 Modeling of Solar PV Power with Battery Storage

The solar energy system with battery energy storage (BES) connected to the grid is depicted in Figure 1. The power output from the solar energy system is given by [27],

$$P_S = P_{PV} + P_b - P_u \quad (31)$$

where P_u is the spillage power from solar PV unit. The power output from the solar PV generator (P_{PV}) depends on the solar irradiance (G), and it is expressed using [27],

$$P_{PV} = \begin{cases} P_S^r \left(\frac{G^2}{G_{std} R_c} \right) & \text{for } 0 < G < R_c \\ P_S^r \left(\frac{G}{G_{std}} \right) & \text{for } G > R_c \end{cases} \quad (32)$$

Figure 1 Solar Energy System with Battery Energy Storage (BES).

P_b is the amount of power output from the BES system and it is given by [28],

$$P_b = \frac{(C_{init} - C)V_b}{\eta_b \Delta t} \quad (33)$$

where C_{init} and C are the aggregated battery state of charge of all batteries at the beginning and the end of the scheduling period. η_b is the efficiency of battery.

Generally, the distribution of hourly irradiation at a particular location follows a bimodal distribution, which can be seen as a linear combination of two unimodal distribution functions. The unimodal distribution functions can be modeled by Beta, Weibull, and Log-normal PDFs. In this paper, the Weibull PDF is employed, and it is expressed as [29],

$$f(G) = \omega \left(\frac{k_1}{c_1} \right) \left(\frac{G}{c_1} \right)^{k_1-1} e^{-\left(\frac{G}{c_1} \right)^{k_1}} + (1 - \omega) \left(\frac{k_2}{c_2} \right) \left(\frac{G}{c_2} \right)^{k_2-1} e^{-\left(\frac{G}{c_2} \right)^{k_2}} \quad 0 < G < \infty \quad (34)$$

where G is the solar irradiance, ω is weight factor ($0 < \omega < \infty$). c_1 , c_2 , k_1 and k_2 are scale and shape factors, respectively.

4 MO-OPF Using PSO and Fuzzy Satisfaction Maximization Approach

Though the multi-objective optimization (MOO) offers a set of solutions which are all optimal, the user needs only one final optimal solution. The user needs some higher level information to choose one solution from the set of optimal [30] solutions. Higher level information is usually taken from domain expertise. The principle of an ideal MOO procedure is to find multiple trade-off optimal solutions with a wide range of values for objectives, and then to choose one of the solutions using the higher level information [22].

In this paper, the Particle swarm optimization (PSO) algorithm is used for solving the MOO of conflicting objectives presented in Section 2.3. The reader may refer References [31, 32] for solving the single objective OPF problem using PSO. Fuzzy satisfaction maximization approach [33] is used to determine the best compromise solution. To minimize $[f_1(x), f_2(x)]$ objectives simultaneously, while satisfying the set of equality and inequality constraints, let the optimal control vector with f_1 as objective function be x_1^* and with f_2

as objective function be x_2^* . Here, the objective is to find an optimal control vector x^* , such that $f_1(x_1^*) < f_1(x^*) < f_1(x_2^*)$ and $f_2(x_2^*) < f_2(x^*) < f_2(x_1^*)$.

Due to the imprecise nature of decision maker's judgment, the objective functions are treated as fuzzy membership functions with linearly decreasing membership function. The degree of membership is assigned as 0 if ($f_i \geq f_i^{\max}$). The degree of membership is assigned as 1 if ($f_i \leq f_i^{\min}$), and if ($f_i^{\min} < f_i < f_i^{\max}$), a linearly decreasing membership is assigned, and it is expressed as [22, 25],

$$\mu_i = \begin{cases} 1 & f_i \leq f_i^{\min} \\ \frac{f_i^{\max} - f_i}{f_i^{\max} - f_i^{\min}} & f_i^{\min} < f_i < f_i^{\max} \\ 0 & f_i \geq f_i^{\max} \end{cases} \quad (35)$$

For the two objective optimization problem, the following data will be available at the operating point x_1^* and x_2^* .

- At x_1^* , $f_1(x_1^*)$ and $f_2(x_1^*)$, with $f_1(x_1^*)$ at optimized value and corresponding $f_2(x_1^*)$.
- At x_2^* , $f_1(x_2^*)$ and $f_2(x_2^*)$, with $f_2(x_2^*)$ at optimized value and corresponding $f_1(x_2^*)$.

Then, $f_1^{\min} = f_1(x_1^*)$ and $f_1^{\max} = f_1(x_2^*)$. Similarly, $f_2^{\min} = f_2(x_2^*)$ and $f_2^{\max} = f_2(x_1^*)$.

If the problem is to optimize three objectives simultaneously, then x_1^* , x_2^* and x_3^* represent optimal values corresponding to three objectives considered. Correspondingly, $f_1(x_1^*)$, $f_2(x_1^*)$, $f_3(x_1^*)$, $f_1(x_2^*)$, $f_2(x_2^*)$, $f_3(x_2^*)$, $f_1(x_3^*)$, $f_2(x_3^*)$ and $f_3(x_3^*)$ are to be evaluated. Then,

$$f_1^{\min} = f_1(x_1^*), f_1^{\max} = \max[f_1(x_2^*), f_1(x_3^*)] \quad (36)$$

$$f_2^{\min} = f_2(x_2^*), f_2^{\max} = \max[f_2(x_1^*), f_2(x_3^*)] \quad (37)$$

$$f_3^{\min} = f_3(x_3^*), f_3^{\max} = \max[f_3(x_1^*), f_3(x_2^*)] \quad (38)$$

Therefore, in the case of two objective optimization problem [22, 34],

$$\mu_1 = \begin{cases} 1 & f_1 \leq f_1(x_1^*) \\ \frac{f_1(x_2^*) - f_1}{f_1(x_2^*) - f_1(x_1^*)} & f_1(x_1^*) < f_1 < f_1(x_2^*) \\ 0 & f_1 \geq f_1(x_2^*) \end{cases} \quad (39)$$

$$\mu_2 = \begin{cases} 1 & f_2 \leq f_2(x_2^*) \\ \frac{f_2(x_1^*) - f_2}{f_2(x_1^*) - f_2(x_2^*)} & f_2(x_2^*) < f_2 < f_2(x_1^*) \\ 0 & f_2 \geq f_2(x_1^*) \end{cases} \quad (40)$$

The above Equations (39) and (40) give the membership values of two objective functions. The final objective is to maximize the fuzzy satisfaction parameter. The fuzzy satisfaction parameter (λ) is obtained as the intersection of the two degrees of membership i.e., minimum of (μ_1, μ_2). This would be minimum of (μ_1, μ_2, μ_3) for the case of three objective optimization. The solution with maximum overall satisfaction is the best compromise solution. Effectively, this approach uses the PSO algorithm for deciding the two extremes of the objective functions (i.e., single objective optimization problem) that are to be optimized simultaneously. Then, the PSO is used for generating the optimal trade-off between the two extremes of the objective function values and for maximization of overall fuzzy satisfaction parameter (λ) [22]. Figure 2 depicts the flow chart of multi-objective PSO using fuzzy satisfaction maximization approach.

4.1 Algorithm for Solving the MO-OPF Problem

Step 1: Read the system data.

- a) Data required for PSO.
(Swarm size, particle size, number of generators, generator voltage magnitudes, transformers with taps and shunts, number of discrete control steps for shunts and taps, cost coefficients, maximum and minimum power output of generators, voltage limits of buses, maximum and minimum values of taps, and shunts, line flow limits, $c_1 = 2.05$, $c_2 = 2.05$, itermax).
- b) Data required for load flow solution.
(n, NL, nslack, max iterations, epsilon, line data, bus data, shunts, line flow limits).

Step 2: Form Y_{bus} using sparsity technique.

Step 3: Form constant slope matrices and decompose using cholesky decomposition.

Step 4: Set discrete tap control vector ttap.

ttap(1) = t_{min} ; (min tap value)

ttap(i) = ttap(i-1) + 0.0125; for i = 1: number of discrete control steps for taps.

Figure 2 Flow chart of Multi-objective PSO using Fuzzy satisfaction maximization approach.

Step 5: Set discrete shunt control.

sshunt(1) = sshunt(min tap value)
sshunt(i) = sshunt(i-1) + 0.01; for i = 1: number of discrete control steps for shunts.

Step 6: Randomly initialize the swarm of particles.

Step 7: Randomly initialize velocities of all particles.

Step 8: Initialize G_{best} and P_{best} particles to zero.

Step 9: Set iteration count = 1.

Step 10: Set particle count ($k = 1$).

Step 11: Use control variables from particle and modify Y_{bus} elements due to taps and shunts.

Step 12: Run load flow analysis. From converged load flow solution compute slack bus power, fuel cost, line losses, and voltage stability evaluation index.

Step 13: Check for limits on load bus voltage magnitudes, generator reactive power limits, slack bus power limit, and line flow limit.

Step 14: Calculate penalty factor for violated functional constraints.

Step 15: Compute the augmented objective function.

Step 16: Calculate fitness of the particle considering selected objective function f_1 .

Step 17: Compute P_{best} particle.

Step 18: Check if $G_{best} < P_{best}(k)$
if yes, set $G_{best} = P_{best}(k)$.

Step 19: Based on P_{best} particle and G_{best} particle compute velocities of particles. Calculate new positions for particles and enforce the limits on all the control variables.

Step 20: Check if ($k < \text{number of particles}$)
if yes, increment particle count, $k = k + 1$, and go to Step 11.

Step 21: Check if (iteration < itermax) if yes, increment iteration count by 1 and go to Step 10.

Step 22: Repeat Steps 6 to 21 for selected second objective function f_2 .

Step 23: Identify the boundaries of the optimal front considering both the optimal objective function values, and repeat Steps 6 to 12.

Step 24: Evaluate fuzzy satisfaction parameter (λ) as minimum of fuzzy membership values of f_1 and f_2 .

Step 25: Assign fitness to each particle as λ .

Step 26: Repeat steps 17 to 20.

Check if (iteration < itermax)

if yes, increment iteration count by 1 and go to Step 10.

Step 27: Print out the best compromise solution as the one with maximum satisfaction parameter (λ).

5 Results and Discussion

The proposed MOO approach is demonstrated on a modified IEEE 30 bus, 41 branch system. The network parameters of the system are taken from [35, 36]. The network consists of 6 generating units, 21 load buses and 41 branches, of which 4 branches are tap setting transformer branches. Buses 10, 12, 15, 17, 20, 21, 23, 24 and 29 have been selected as shunt compensation buses [25]. In this paper, the standard IEEE 30 bus system is modified to include wind and solar energy generators [27]. It is assumed that out of six generating units, four are considered as the conventional thermal generating units located at buses 1, 2, 5 and 8; and one wind farm is located at bus 11, and one solar PV module (including BES system) is located at 13th bus. In this paper, 25 control variables are considered: Three thermal generator active power outputs, one WEG active power output, one solar PV unit power output, one active power output of BES system, six generator-bus voltage magnitudes, four transformer-tap settings, nine bus shunt susceptances. In this paper, the reserve cost coefficients (k_r) is selected as 1\$/MW and the penalty cost coefficients (k_p) is selected as 5\$/MW. The generator data considered for the modified IEEE 30 bus system is presented in Table 1.

Table 1 Generator data for the modified IEEE 30 bus test system

Bus No.	P_{Gi}^{min} (MW)	P_{Gi}^{max} (MW)	Q_{Gi}^{min} (MVAR)	Q_{Gi}^{max} (MVAR)	a (\$/hr)	b (\$/MWh)	c (\$/MW ² h)
1	50	200	-20.0	200.0	0.0	3.00	0.0250
2	20	100	-20.0	100.0	0.0	3.50	0.0625
5	10	70	-15.0	80.0	0.0	3.25	0.00834
8	15	70	-15.0	60.0	0.0	3.50	0.00375
11	0	40	-10.0	50.0	0.0	2.75	0.0
13	0	40	-15.0	60.0	0.0	2.75	0.0

The objective here is to determine the set of control variables, which minimize all the objective functions considered. In this paper, the PSO parameters considered are: Swarm size is 60, size of particles is 25, maximum number of generations is 200, acceleration constants (c_1 and c_2) are 2.05, inertia weight (ω) is 1.2 and the constriction factor (χ) is 0.7295.

The OPF problem with different objectives is formulated as a multi-objective optimization (MOO) problem. The problem is first treated as two objective optimization problem with total generation cost and transmission losses; total generation cost and VSEI objectives. The OPF problem is then treated as three objective optimization problem with the above mentioned three objectives as competing objectives. As mentioned earlier, in this paper, the MOO is performed using the PSO and fuzzy satisfaction maximization approach. In this paper, 6 case studies are performed and they are:

- **Case 1:** OPF with total generation cost minimization as objective.
- **Case 2:** OPF with transmission losses minimization as objective.
- **Case 3:** OPF with VSEI/L-index minimization as objective.
- **Case 4:** MO-OPF with total generation cost and transmission loss minimization as objectives.
- **Case 5:** MO-OPF with total generation cost and L-index minimization as objectives.
- **Case 6:** MO-OPF with total generation cost, transmission losses and L-index minimization as objectives.

5.1 Case 1: OPF with Total Generation Cost Minimization as Objective

In this case, the total generation cost (i.e., Equation (7)) minimization is considered as a single objective function to be optimized using the PSO algorithm. Table 2 presents the optimum control variables settings and objective function values for Case 1. When the total generation cost minimization objective is optimized independently, then the obtained optimum cost is 1532.22\$/hr, which includes the cost of conventional thermal generators, WEGs, solar PV plants and the cost due to over-estimation and under-estimation of wind and solar powers. From the simulation results, it can be observed that the obtained total cost is optimum, but the system transmission losses and VSEI/L-index are deviated from the optimum. Therefore, there is a requirement for the MOO to obtain the best-compromised solution.

Table 2 Optimum control variables and objective function values for single objective OPF of hybrid power system using PSO

Control Variables and Objective Function Values	Case 1	Case 2	Case 3
P_{G1} (in MW)	126.18	75.96	86.90
P_{G2} (in MW)	53.26	86.45	77.01
P_{G5} (in MW)	28.78	28.95	32.79
P_{G8} (in MW)	26.34	25.93	40.73
P_{W11} (in MW)	30.80	37.63	21.03
P_{S13} (in MW)	24.98	33.98	30.75
V_{G1} (in p.u.)	1.0724	1.0371	1.0500
V_{G2} (in p.u.)	1.0671	1.0918	1.0529
V_{G5} (in p.u.)	1.0871	1.0394	1.0776
V_{G8} (in p.u.)	1.0472	1.0635	1.0771
V_{W11} (in p.u.)	1.0617	1.0476	1.0606
V_{S13} (in p.u.)	1.0853	1.0865	1.0806
$T_{6,9}$ (in p.u.)	0.9750	1.075	1.0625
$T_{6,10}$ (in p.u.)	0.9125	0.9875	1.025
$T_{4,12}$ (in p.u.)	1.025	1.0125	0.900
$T_{28,27}$ (in p.u.)	1.0125	0.9875	0.950
$b_{sh,10}$ (in p.u.)	0.05	0.04	0.00
$b_{sh,12}$ (in p.u.)	0.02	0.05	0.03
$b_{sh,15}$ (in p.u.)	0.05	0.02	0.05
$b_{sh,17}$ (in p.u.)	0.01	0.00	0.04
$b_{sh,20}$ (in p.u.)	0.02	0.01	0.02
$b_{sh,21}$ (in p.u.)	0.05	0.02	0.03
$b_{sh,23}$ (in p.u.)	0.02	0.02	0.04
$b_{sh,24}$ (in p.u.)	0.02	0.03	0.01
$b_{sh,29}$ (in p.u.)	0.00	0.01	0.03
Thermal Generation Cost (in \$/hr)	1330.91	1357.76	1448.546
Wind and Solar Generation Cost (in \$/hr)	153.40	196.91	161.6355
Total Generation Cost (in \$/hr)	1539.22	1640.72	1673.10
Transmission Loss (in MW)	6.94	5.49	5.81
VSEI/L-Index	0.1923	0.1840	0.1392

5.2 Case 2: OPF with Transmission Losses Minimization as Objective

In this case, the total transmission losses (i.e., Equation (15)) minimization is considered as a single objective function to be optimized using the PSO algorithm. Table 2 also presents the optimum control variables settings and objective function values for Case 2. The optimum losses obtained in this case is 5.49MW, but the total generation cost and VSEI are deviated from the optimum. The total generation cost is 6.6% more than the Case 1 and the VSEI is 32.2% more than the Case 3. Therefore, this paper presents the MOO based OPF for the hybrid thermal-wind-solar power system.

5.3 Case 3: OPF with VSEI/L-Index Minimization as Objective

In this case, the VSEI/L-index (i.e., equation (16)) minimization is considered as a single objective function to be optimized using the PSO algorithm. Table 2 also presents the optimum control variables settings and objective function values for Case 3. In this case, the obtained VSEI/L-index is 0.1392, which is optimum compared to Cases 1 and 2. But, the total generation cost and transmission losses are deviated from the optimum. The total generation cost is 8.7% more than the Case 1 and the transmission losses are 5.8% more than the Case 2.

5.4 Case 4: MO-OPF with Total Generation Cost and Transmission Loss Minimization as Objectives

For solving the Case 4, for simultaneous minimization of total generation cost and total transmission losses, the two extremes solutions from the Cases 1 and 2 are selected from Table 2. The total generation cost (i.e., maximum) value from Case 2 is 1640.72\$/hr, and the minimum total generation cost is 1539.22\$/hr from Case 1. On the similar lines, the optimum loss obtained from Case 2 is 5.49MW, and the maximum loss obtained from Case 1 is 6.94MW. With these extreme values PSO is used to generate optimal front with 50 particles.

Fuzzy satisfaction maximization approach converts the objective function values of each particle into fuzzy membership functions. Fuzzy satisfaction parameter is defined as the intersection of these fuzzy membership values. The solution with maximum overall satisfaction parameter is the best compromise solution. The best compromise solution obtained has the total generation cost of 1588.04\$/hr and the transmission losses of 6.13MW. The corresponding control variable settings for this case are presented in Table 3.

Table 3 Optimum control variables and optimal objective function values for MO-OPF of hybrid power system using PSO and fuzzy satisfaction maximization approach

Control Variables and Objective Function Values	Case 4	Case 5	Case 6
P_{G1} (in MW)	122.45	131.51	106.87
P_{G2} (in MW)	56.89	51.92	57.03
P_{G5} (in MW)	25.54	33.74	32.79
P_{G8} (in MW)	32.25	30.39	34.41
P_{W11} (in MW)	20.87	20.07	28.05
P_{S13} (in MW)	31.53	27.01	30.75
V_{G1} (in p.u.)	1.0689	1.0534	1.0500
V_{G2} (in p.u.)	1.0758	1.0653	1.0529
V_{G5} (in p.u.)	1.0323	1.0629	1.0776
V_{G8} (in p.u.)	1.0413	1.0417	1.0770
V_{W11} (in p.u.)	1.0435	1.0254	1.0606
V_{S13} (in p.u.)	1.0506	1.0371	1.0805
$T_{6,9}$ (in p.u.)	0.925	0.975	1.0625
$T_{6,10}$ (in p.u.)	0.975	1.0125	1.0250
$T_{4,12}$ (in p.u.)	0.9875	1.0875	0.975
$T_{28,27}$ (in p.u.)	0.975	1.0625	0.950
$b_{sh,10}$ (in p.u.)	0.02	0.05	0.00
$b_{sh,12}$ (in p.u.)	0.02	0.04	0.03
$b_{sh,15}$ (in p.u.)	0.00	0.00	0.05
$b_{sh,17}$ (in p.u.)	0.01	0.02	0.04
$b_{sh,20}$ (in p.u.)	0.04	0.03	0.02
$b_{sh,21}$ (in p.u.)	0.02	0.02	0.03
$b_{sh,23}$ (in p.u.)	0.03	0.05	0.04
$b_{sh,24}$ (in p.u.)	0.05	0.00	0.01
$b_{sh,29}$ (in p.u.)	0.05	0.01	0.03
Thermal Generation Cost (in \$/hr)	1382.88	1406.83	1405.32
Wind and Solar Generation Cost (in \$/hr)	144.16	129.48	161.70
Total Generation Cost (in \$/hr)	1588.04	1601.26	1620.15
Transmission Loss (in MW)	6.13	6.42	6.50
VSEI/L-Index	0.1851	0.1511	0.1532

5.5 Case 5: MO-OPF with Total Generation Cost and L-Index Minimization as Objectives

Considering Case 5, for simultaneous minimization of total generation cost and VSEI/L-index, the two extremes of total generation cost and VSEI are selected from Table 2. The maximum value of total generation cost is selected as 1673.10 \$/hr and the minimum value of total generation cost is 1539.22\$/hr. Index maximum value is chosen as 0.1923 and index minimum value is chosen as 0.1392. Now, the PSO-fuzzy satisfaction maximization approach gives the best compromise solution has the total generation cost of 1601.26\$/hr and the L-index of 0.1511. The corresponding control variable settings are presented in Table 3.

5.6 Case 6: MO-OPF with Total Generation Cost, Transmission Losses And L-Index Minimization as Objectives

Case 7 considers the MOO of total generation cost, transmission loss and VSEI simultaneously. The minimum and the maximum values of total generation cost, transmission loss and VSEI are selected from Table 3. The maximum and minimum values of total generation cost are 1673.10\$/hr and 1539.22\$/hr, maximum and minimum values of transmission losses are 6.94MW and 5.49MW, whereas the maximum and minimum values for L-index are 0.1923 and 0.1392, respectively. The best compromise solution obtained using PSO and fuzzy approach has the total generation cost, transmission loss and VSEI are 1620.15\$/hr, 6.50MW and 0.1532, respectively.

6 Conclusions

This paper solves the multi-objective optimal power flow (MO-OPF) problem for a hybrid power system with thermal generators, wind energy generators and solar PV farms with battery energy storage. It gives the optimal generation schedules by optimizing the three different objective functions, i.e., total generation cost, transmission losses and voltage stability enhancement index. The total generation cost minimization objective include the cost of conventional thermal generators, wind and solar power purchasing from private owners and to reduce the risk due to the wind and solar power uncertainties. Here, the stochastic nature of wind and solar power outputs are modeled using the Weibull probability distribution function. This paper utilizes a particle swarm optimization based fuzzy satisfaction maximization technique to solve the proposed MO-OPF problem of a hybrid power system. Here, a modified

IEEE 30 bus system is used to demonstrate the effectiveness of the proposed approach.

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Biography

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