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Multi-Objective Optimal Power Flow With Integration of Renewable Energy Sources Using Fuzzy Membership Function

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ABSTRACT In recent past, to meet the growing energy demand of electricity, integration of renewable energy resources (RESs) in an electrical network is a center of attention. Furthermore, optimal integration of these RESs make this task more challenging because of their intermittent nature. Therefore, in the present study power flow problem is treated as a multi-constraint, multi-objective optimal power flow (MOOPF) problem along with optimal integration of RESs. Whereas, the objectives of MOOPF are threefold: overall generation cost, real power loss of system and carbon emission reduction of thermal sources. In this work, a computationally efficient technique is presented to find the most feasible values of different control variables of the power system having distributed RESs. Whereas, the constraint satisfaction is achieved by using penalty function approach (PFA) and to further develop true Pareto front (PF), Pareto dominance method is used to categorize Pareto dominate solution. Moreover, to deal with intermittent nature of RES, probability density function (PDF) and stochastic power models of RES are used to calculate available power from RESs. Since, objectives of the MOOPF problem are conflicting in nature, after having the set of non-dominating solutions fuzzy membership function (FMF) approach has been used to extract the best compromise solution (BCS). To test the validity of developed technique, the IEEE-30 bus system has been modified with integration of RESs and final optimization problem is solved by using particle swarm optimization (PSO) algorithm. Simulation results show the achievement of proposed technique managing fuel cost value long with the optimal values of other objectives.

INDEX TERMS Fuzzy membership function, multi-objective optimal power flow problem, renewable energy sources.

I. INTRODUCTION

An electrical power system is comprised of generation sources, transmission lines and distribution system. Complexity of electrical power system is enhanced with the socio-economic growth of the modern society. With the exponential increase in consumers load, the energy demand increases day by day. In the meantime, rise in power demand and quick depletion of fossil fuels may pose serious challenges to utilities regarding supply and demand management. To deal with this issue, one attractive solution is to motivate consumers to reschedule their demand patterns using price based demand response programs [1] and second is to install on-site distributed RESs to enhance power system quality, reliability, stability and economics [2]. Evolution of traditional grid to smart grid drives to integrate information and communication technologies (ICTs) with the traditional grid [3]–[6]. In this regard, it is necessary to consider and incorporate the aspects

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of modern control technologies into optimal power flow (OPF) study. OPF is a key tool to measure the transmission and distribution system losses along with power generation cost [7], [9].

In power system operation and control, to ensure the stability and reliability of system OPF algorithms are considered a basic and vital tool for power system operator [10]. In order to optimize power system operation, OPF algorithms usually run after specific time intervals to tune the values of different control variables at optimal value [11]. From literature, it can be seen that various researchers have used classical OPF algorithms which consider the problem of economic environment dispatch EED, caters only thermal generators leading to CO_2 emissions [12], [13]. However, the OPF problem is complex in economical, and computational view point [9]. In regard of economically optimal power system, load flow can be seen as an economic load dispatch (ELD) problem, along with an objective to minimize the cost of thermal generators. However, ELD seems incapable in handling power flow constraints [14]. On the other hand, it is the load or power flow problem in which non-linearities of load, transmission loss, and generation capacity may increase the complexity of problem [15]. Computationally, the OPF is required to find optimal values of different control variables during its operation, which enhances the computational complexity [16].

Generally, in power flow studies, the reactive power, thermal limits of transmission system and security constraints are not considered. Therefore, the solution provided by these techniques may not be optimal and seems infeasible. Therefore, the objective of OPF is to find feasible solution for the selected objective i.e. (cost, power loss, voltage stability, etc.) without violating these constraints [17]. Where, the voltage, real and reactive power limits and transmission line capacity comprises the inequality constraints [18]. The objective function may include both, binary and continuous variables.

In the meantime, particular attention is given to the integration of variable energy resources into grid with the objective of de-carbonizing the electric power system [19]. Because of the concerns related to global warming due to climate change, solar photovoltaic and wind installations are steadily increasing. On the contrary, adaptation of fossil fuels based power generation sources are decreasing [20]. Recent studies show that variable energy resources such as solar and wind pose dynamics that span multiple time scales, hence affecting different layers of power system's control. These findings illustrate that traditional load flow studies are no longer sufficient to ensure reliability through optimal resource allocation, as penetration of RESs continue to grow [21]. It is also confirmed that due to high penetration of RESs, the operators face some problems in managing power demand and thus rely on manual curtailment to manage the demand [22]. In addition, the uncertainty and intermittency of variable energy resources are likely to increase the reserve capacity requirements, hence blackincreasing the marginal cost of electricity [23].

While the challenges of renewable energy integration and OPF may seem unrelated, their resolution is potentially synergistic. Along with the reduction in carbon emissions renewable energy technologies provide provision of easy storage. Therefore, it has potential to act as flexible energy source for both supply and demand sides of electricity system. On the other hand, power flow study is considered an efficient tool in managing supply-demand by considering control and other variables [24]–[26]. Therefore, to maintain reliability of the electric power system with the high penetration of RESs, it is required to have system operators to flexibly manage generation resources to handle uncertainty of solar and wind generation. In this context, this topic is novel in such a way that equilibrium states have been obtained through mathematical formulation.

A. CONTRIBUTION OF THE PAPER

The MOOPF problem is formulated such that it considered the integration of RESs in the power system. In this research study major contributions are as follows:

- The MOOPF problem is formulated to deal with three conflicting objectives of power generation cost, active power loss of power system and carbon emission of thermal generators.
- When the contribution of RESs varies (i.e., as they are weather dependent) real loss, overall cost and carbon emission also varies.
  Therefore, the major contribution of this work is that the proposed technique is able to find the BCS in all study cases presented in the paper while ensuring the intermittent nature of RESs. Additionally, to reduce the computational complexity of computer program, proposed technique is equipped with some common mathematical models.
- To calculate the optimal contribution of the RESs in the total generation the triangular FMF based model is used. This model helps to identify the ratio of RESs and thermal generators. This helps to identify the remaining demand which satisfied by most economical thermal generators to balance the power system economics.
- Moreover, Based on traditional stochastic model and PDF mechanism (section V), a novel computational mechanism is proposed to find most feasible values of control variables of power system presented in Table6. Overall cost function is formulated such that it considers the direct, penalty and reserve cost of RESs along with the generation cost of thermal generators (section IV-A).
- To guarantee the feasible solution, PFA is used for constraint handling because of its computational simplicity (section IV-E). Furthermore, to develop set of non-dominating solutions pareto dominance method is used to categorize the pareto dominate solution (section IV-F).
- In simulations PFs are plotted to show the conflicting nature of MOOPF problem objectives. FMF base

decision making approach is used to pull out the BCS form non-dominating solutions in different combinations of optimization cases (section VIII-D).

Simulations results from figure 5a to figure 6 show that the propose approach is capable to handle the complexity of MOOPF problem and to solve it efficiently. Furthermore, present study depicts the conflicting nature of different objectives related to OPF problem and a trade-off solution is presented in different test cases.

Paper is comprises as follows: Section II is of literature review. Motivation hs been address in section III. Mathematical modeling and problem formulation is presented in section IV. Power and stochastic models are reviewed in section V. Section VI describes the proposed approach. Section VII illustrate the experimental setup and section VIII narrate the results and discussion. Section IX concludes the paper.

II. LITERATURE REVIEW

About half a century ago in 1962 Carpentier formulated the first OPF problem. Since its formulation, OPF remains a widely-cultivated topic for power system research community across the globe. The OPF problem can be divided into two methods: conventional methods and modern metaheuristic methods. Conventional methods are based on mathematical programming (e.g. linear programming and quadratic programming, interior point method, and dynamic programming technique, etc.). In these methods, initial guess, step size, approximations, and engineering judgments are used to find a feasible solution. But algorithms based on these techniques may have slow convergence characteristics and sometimes get stuck in the local optima due to the inappropriate initial guess, step size, and approximation, thus suffers from inaccuracy and provide infeasible solutions. In recent past researchers have developed some modern metaheuristic techniques to deal with the non-linear and multi-modal (more than one local optimum) nature of the OPF problem [27]. These methods are quite competent to handle the nonlinear and multimodal nature of the OPF problem. They are versatile and can find multiple solutions in a single run simulation. Still some disadvantages are associated with these intelligent methods like large dimensionality and the choice of training methodology. Some common examples of these methods which are generally found in the literature are: differential evolution (DE), non-dominating sorting genetic algorithm (NSGA), and particle swarm optimization algorithm (PSO).
The Basic Jaya algorithm is modified to solve multi-objective OPF (MOOPF); a novel quasi-oppositional based (QOB) modified Jaya algorithm is introduced in [28]. By deploying the QOB learning strategy the exploration capability of Jaya is improved. To compare the best and worst solution fuzzy decision-making approach is used. The crowding distance approach is to maintain the diversity of PF. The IEEE 30-bus system is used to validate the QOB modified Jaya algorithm. A modified firefly algorithm is proposed in [29] for the solution of MOOPF problem non-dominating sorting, and for well distributed PF crowding distance approach is utilized along with integration of fuzzy affiliation for picking BCS. IEEE 30 and 57-bus test models, are used to validate the results by considering nine different cases.

A Pareto dominance-based approach is used to guarantee the non-violation of the constraints. The single objective OPF problem is transformed into MOOPF by weighted sum approach the suggested algorithm is implemented using Differential search algorithm (DSA) as applied in [30]. Different OFs are optimized and the superiority of DSA is validated from the obtained results. The multi-objective multi-hive bee algorithm (MHBA), which is the extension of basic bee algorithm (BA), is used in [31] for solving MOOPF problem. By incorporating an external archive the basic BA is modified for solution of the MOO problem. For the determination flight behavior of bees, the comprehensive learning method is utilized. By using the weighted sum approach, modified artificial bee colony (ABC) algorithm is used to solve MOOPF problem in [32]. The optimization of different objectives reveals the dominance of ABC over other algorithms. Objective functions of cost, power loss and emission are considered to solve the MOOPF problem in [33]. By applying dynamic population-based ABC (ABC-DP) approach, a comparison is made with multi-objective ABC and NSGA-II. Better performance of ABC-DF has been demonstrated by the simulation results. Multi-objective cuckoo search (CS) and QOB multi-objective CS (QOB-MOCS) are introduced in [34] to solve MOOPF problem. The QOB learning strategy is deployed in the CS to speed up the convergence, and crowding distance approach is applied for PF dominance. To ensure the feasibility of solution, the feasibility prior domination rule is considered. The PFs obtained by QOB-MOCS out perform the PFs of other algorithms.

Improved differential evolution (DE) with a self-adaptive strategy and mixed crossover operator is considered in [35] for single objective OPF and MOOPF problem. The simulation results prove the competency of enhanced DE algorithm. In [36] multi-objective DE algorithm is used for the solution of multi-objective reactive power dispatch. The basic DE algorithm is modified by integrating crowding distance with a combination of non-dominated sorting approach. The PF solution obtained from multi-objective DE outperforms the strength Pareto evolutionary (SPEA) algorithm. Metaheuristic algorithm with incremental power flow (IPF) model for the solution of MOOPF is presented in [37]. The IPF model is used to decrease the computation time by reducing the number of power flow computations. Results validate the effectiveness and robustness of the proposed algorithm. The imperialist competitive algorithm (ICA), which is based on imperialistic competition, is modified, and MO-ICA is developed and successfully deployed for the solution of MOOPF problems in [38]. All metaheuristic techniques have their limitations to provide an optimal solution for these objectives due to the inconsistency of the solution. So, there is always a room available to develop a new algorithm that solves this multi-objective problem efficiently. It is required to solve the conflicting objective simultaneously in the real world OPF problem. For this multi-objective optimization (MOO) problem there are two approaches: a priori and posteriori approach [39]. In a priori approach, MOO problem is converted into a single objective optimization (SOO) problem by using weighted sum by assigning weight to different objectives and summing them together. The choice of weighting coefficients is essential to assign a preference order by the decision marker to the multiobjective. In second MOO approach, weighting coefficients are defined by an expert. For weighting coefficients variety of solutions are presented, and the PF is approximated even in a single run [40], [41].

III. MOTIVATION

It is quit clear by reviewing of literature in section II, that all the matahuristic techniques are efficient to solve the MOOPF problem with conventional generators, when dealing with the minimization of generation cost of a system having only conventional fossil fuel generators. It has recently been studied in a few literatures, that unconventional generation sources e.g. wind and solar power plants are also incorporated in power system. In [42] Gbest guided artificial bee colony (GABC) has been used to solve the OPF problem. In [43] OPF is formulated with the integration of doubly fed induction generator (DFIG) model and Modified bacteria foraging algorithm (MBFA) is used to find feasible solution. Ref [44] proposed a modified power system having wind and conventional generators and the load flow problem is solved using ant colony optimization (ACO). A model of wind mill is proposed by authors in [45]. Carbon emission, valve point effect of steam turbine are incorporated in [46] as dynamic ED problem. An hybrid model of solar PV, diesel generator and battery is presented in [22] to manage the power flow. System constraints are considered in literature [47], but constraints validation have been not explicitly addressed.
Although above methods are perfect candidates for solving MOPs, but when it comes to a larger system having uncertain RESs, other techniques are required to solve constrained MOOPF problem. This is due to the fact of their computational complexity and large dimensionality [48]. To the best of our knowledge most of the reported algorithms and techniques do not investigate the integration of intermittent RESs while investigating the optimal power flow rather they considered conventional thermal generators only. Moreover it has been found that optimal power flow problem has not been addressed as MOOPF problem along with RESs. Hence, there is always an opportunity to enhance the efficiency and to reduce the complexity of computer program while soving MOOPF problem for a power system having distributed RESs. In summary, further attention is required to solve the MOOPF problem. Therefore A multi-constraint multi-objective optimal power flow MOOPF problem is formed for power system operation with intermittent RESs, and afterwards is solved by the particle swarm optimization(PSO) algorithm hybrid with the probability density function (PDF), penalty function approach (PFA), fuzzy membership function (FMF). The idea behind the work is different from those mention earlier and it is mainly established on the interpretation of RESs estimated output power (section V).
The same idea which is used in [21] has been adopted, in which RESs are incorporated to investigate the cost, loss and emission profile of modified power system. In the present study, first we calculate the estimated available power from RESs using PDF and stochastic models. Then most economical thermal generators are found and placed in IEEE modified 30-bus system. Afterwards, developed optimization problem is solved as MOOPF problem using PSO base ELD algorithm. A set of non-dominating solution is developed using categorizing process (section IV-F). Moreover, proposed technique is equipped with the PFA to avoid constraint violation (section IV-E). FMF is used to assign different weight to RESs contribution to investigate the conflicting objectives variations (section IV-D). Finally, table 7 presents the results obtained using proposed mechanism are compared with the existing results from literature to validate the key findings.

IV. PROBLEM FORMULATION

In mathematics and computational science, any multi-objective optimization problem can be generally expressed as follow:

$$minimize : f(x, v) = [f1(x, v), f2(x, v), \dots, fp(x, v)] \quad (1)$$

subjected to :

$$g_j(x, v) \geq 0, \quad j = 1, 2 \dots M \quad (2)$$

$$h_k(x, v) = 0, \quad k = 1, 2 \dots N \quad (3)$$

where, in Equation (1), $x = x^1, x^2, \dots, x^{n^T}$ represents a vector of independent decision variables, and $v = (v^1, v^2 \dots v^n)^T$ represents a vector of dependent decision variables. Inequality, constraints are $g_j j = 1, 2, \dots, M$, and equality constraints are $h_k(x)k = 1, 2, \dots, N$. In this problem formulation variables can be classified as follow [49]:
The control (independent) Variables are gives as:

P_{Gb} : Real power at generator buses except the slack bus.
V_{Gb} : Voltage magnitude at generator buses.

And state(dependent) Variables:

P_{G1} : Slack bus real power
V_L : Load bus voltage magnitude.
Q_G : Generator bus reactive power.
S_l : Line burden.

A. OBJECTIVES OF OPTIMIZATION

In this work, three minimization objectives are formulated. First objective is to minimize the fuel cost with and without valve point effect along with RESs cost, second objective is consists of real power loss minimization and third objective is to minimize the carbon emission.

Cost of electricity production is mainly dependent upon operating cost which majorly consist of fuel cost of thermal generators. It can be explain by the quadratic equation with single polynomial. Cost function with regard to real power output is described in equation (4).

$$f_{cost} = \sum_{i=0}^{N_g}(a_i + b_iP_{gi} + c_iP_{gi}^2)\$/h \quad (4)$$

where, f_{cost} denotes the total fuel cost, N_g gives the total number of generators, a_i, b_i and c_i are the coefficients of generators cost function connected to i^{th} bus, respectively. Finally, P_{gi} gives the real power of the i^{th} generator.
Cost function in terms of valve-point effect can be express through Equation (5).

$$f_{cost_{vp}} = \sum_{i=0}^{N_g}(a_i + b_iP_{gi} + c_iP_{gi}^2|d_i \times sin(e_i \times (P_{gi}^{min} - P_{gi}))|)\ \$/h \quad (5)$$

where, total fuel cost with valve-point effect is represented by $f_{cost_{vp}}$, cost coefficients with valve-point effect of generator connected to i^{th} bus are shown by d_i and e_i. Real power limit of the i^{th} generator is given by P_{gi}^{min}. Generally, Private bodies own RESs and they are responsible to operate and control them. As RESs do not require any conventional fuel for electricity generation. Yet, they charge maintenance and operation cost. Therefore, due to the contractually agreed scheduled power, the independent system operator (ISO) must pay, accordingly [50]. Therefore, the direct cost of all RESs i.e., wind, solar and small hydro units can be stated as follows:

$$C_w(P_w) = g_wP_w \quad (6)$$
$$C_{pv}(P_{pv}) = h_{pv}P_{pv} \quad (7)$$
$$C_h(P_h) = g_hP_h \quad (8)$$

where, P_w, P_{PV} and P_h represent the scheduled output power from wind farm, solar photovoltaic and small hydro, respectively. Where, g_w, h_{pv} and g_h represent direct cost coefficients of RESs. The actual power produced by RESs varies because of ever changing and rendom behaviour of these sources. Therefore, this variable provides the opportunity to ISO to have reserve generation capacity for fulfilling load demand. Reserve cost model for these sources are taken from the [51] and described as follows;

$$C_{W_{R,i}}(\Delta P) = k_{rw,i}(\Delta P) \quad (9)$$
$$\Delta P = P_{Wsh,i} - P_{Wac,i} \quad (10)$$
$$C_{W_{R,i}}(\Delta P) = k_{rw,i}\int_0^{P_{Wsh,i}}(P_{Wsh,i} - p_{wac,i})f_w(p_{w,i})dp_{w,i} \quad (11)$$

where, $P_{Wsh,i}$ & $P_{Wac,i}$ denote scheduled and available power capacities from wind power source, $f_w(p_{w,i})$ gives the PDF of wind source and $k_{rw,i}$ denotes the reserve cost coefficient for wind. If the excess power available from RESs is not used by ISO, then it will pay penalty cost as per following penalty cost function:

$$C_{W_{P,i}}(\Delta P) = k_{Pw,i}(\Delta P) \quad (12)$$

$$C_{W_{P,i}}(\Delta P) = k_{Pw,i}\int_0^{P_{Wsh,i}}(P_{Wac,i} - p_{wsh,i})f_w(p_{w,i})dp_{w,i} \quad (13)$$

where, $k_{Pw,i}$ denotes penalty cost coefficient for i^{th} wind mill. Similarly, reserve and penalty cost of solar and small hydro ($C_{PV_{R,i}}, C_{PV_{P,i}}, C_{H_R}, C_{H_P}$) power sources can also be calculated. The cost coefficient values are given in table 1.

TABLE 1. Cost coefficients for RESs.

Direct cost coefficient	
Wind	$g_w = 1.6$
Solar	$g_s = 1.6$
Small hydro	$g_h = 1.5$
Reserve cost coefficient	
Wind	$k_{rw} = 3$
Solar	$k_{rs} = 3$
Small hydro	$k_{rh} = 3$
Penalty cost coefficient	
Wind	$k_{pw} = 1.5$
Solar	$k_{ps} = 1.5$
Small hydro	$k_{ph} = 1.5$

Mathematically, the cumulative cost function can be written as:

$$\begin{aligned} OF1: f_{cost} &= f_{cost_{vp}} + [C_w(P_w) + C_{PV}(P_{PV}) + C_H(P_H)] \\ &+ [C_{W_{R,i}}(\bigtriangleup P) + C_{PV_{R,i}}(\bigtriangleup P) + C_{H_{R,i}}(\bigtriangleup P)] \\ &+ [C_{W_{P,i}}(\bigtriangleup P) + C_{PV_{p,i}}(\bigtriangleup P) + C_{H_{p,i}}(\bigtriangleup P)]\ \$/h \end{aligned} \quad (14)$$

Transmission system losses because of resistive nature of the transmission lines. When electrical power flow in a branch from one node to another, power dissipate in form of heat. When this loss occur it effects the node voltages and it can be explain in terms of node voltage magnitude and its angle. Hence, Second objective function to minimize real power loss of transmission network can be expressed as equation (15).

$$OF2: f_{Ploss} = \sum_{l=1}^{N_l} C_l[V_i^2 + V_j^2 - 2V_iV_jcos\delta_ij]MW. \quad (15)$$

where, total active power loss is denoted by f_{Ploss}, N_l represents total number of branches power system, conductance of the l^{th} line from i to j node is represent by C_l. Where as, V_i & V_j represent voltage magnitudes of bus i and j, respectively. Moreover, δ_{ij} gives the voltage angle difference between bus i and j. Finally, angle the δ_{ij} gives the voltage angle difference between bus i and j.

Similarly, the third objective function is introduced to minimize carbon emission caused by sulphur and nitrogen oxides particles. In fossil fuel plants due to the combustion of fuel, flue gases emits from chimney and pollutes the environment. Main objective is to distribute the power demand among the schedule generator so that the volume of emission is kept at minimum level. Volume of this carbon emissions can be modeled as a combination of quadratic and exponential function in terms of generator power [52], and mathematically can be stated as the equation (16).

$$OF3 : f_{emission} = \sum_{i=1}^{N_g}[\alpha_i P_{gi}^2 + \beta_i P_{gi} + \gamma_i + \omega_i e^{(\mu_i P_{gi})}]ton/h \tag{16}$$

where, the coefficients of carbon emission for i^{th} generator are α_i, β_i, γ_i, ω_i and μ_i.

B. EQUALITY CONSTRAINTS

a) Active power balance at the i^{th} bus is given as follows:

$$P_{Gi} - P_{Di} - P_{Loss} = 0 \quad i\epsilon N \tag{17}$$

where, real power loss is given as:

$$P_{Loss} = V_i \sum_{j=1}^{NB} V_j[G_{ij}cos(\delta_{ij}) + B_{ij}sin(\delta_{ij})] = 0 \tag{18}$$

b) Reactive power balance at the i^{th} bus is given as:

$$Q_{Gi} - Q_{Di} - Q_{Loss} = 0 \quad i \in N \tag{19}$$

$$Q_{Loss} = V_i \sum_{j=1}^{NB} V_j[G_{ij}cos(\delta_{ij}) + B_{ij}sin(\delta ij)] = 0 \tag{20}$$

where, elements of the Y Bus matrix are calculated as,

$$Y_{ij} = G_{ij} + B_{ij} \tag{21}$$

Equality constraints shown in equations 17-20 are discussed in detail in [29]. The convergence process of running load flow will eventually minimized the equality constraints in the allowable boundaries.

C. INEQUALITY CONSTRAINTS

a) Real power generation limits of generators are,

$$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max} \quad for\ i = 1, 2, \ldots, NG \tag{22}$$

b) Reactive power generation limits of generators is written as,

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max} \quad for\ i = 1, 2, \ldots, NG \tag{23}$$

c) Generation bus voltage limits are given as,

$$V_i^{min} \leq V_i \leq V_i^{max} \quad for\ i = 1, 2, \ldots, NG \tag{24}$$

d) Power flow limit of all branches is given as,

$$P_{ij} < TL_{ij} \tag{25}$$

where, TL_{ij} gives thermal limit of the power flow line from node i to j. The specific meaning of each variable in equations (22−25) is given in [29]. The optimization algorithm picks the feasible value of dependent variables to satisfy the inequality constraints from their allowable limits.

D. FMF

The aggregate power from RESs is calculated by using FMF which is obtain from fuzzy decision making approach. The use of FMF provides the true variation in the contribution of RESs real power, in this way its helps to investigate the variation in real power loss, over all cost and carbon emission. When different coefficients have been assigned to RESs, system losses vary but proposed technique is able to find the most feasible contribution ratio of RESs where losses, generation cost and emission can be compromise and a trade off solution has been achieved during run of OPF program. The FMF values μ for RESs contribution are computed and defined as (26):

$$\mu_j(y_j) = \begin{cases} 0 & \text{for } y_j \leq y_1 \\ (y_j - y_1)/(y_2 - y_1) & \text{for } y_1 < y_j < y_2 \\ 1 & \text{for } y_j \geq y_2 \end{cases} \tag{26}$$

Here, y_j denotes the value of contributing index. In this work, y_1 and y_2 are considered as 0 and 1.25 respectively [53]. Where, cumulative active power from RESs is expressed through equation (27):

$$RE_{TP} = \{\mu_w \times P_w\} + \{\mu_{pvh} \times (P_{pv} + P_{hyd})\} \tag{27}$$

E. CONSTRAINTS HANDLING APPROACH (CHA)

When equality constraints violates their specified ranges, they are repaired in process of load flow program as follows in (28):

$$c_i = \begin{cases} c_{imin} & \text{if } c_i < c_{imin} \\ c_i & \text{if } c_{imin} < c_i < c_{imax} \\ c_{imax} & \text{if } c_i > c_{imax} \end{cases} \tag{28}$$

It is also worth noting here that when optimization algorithms are used to solve any type of objective function, it is difficult to handle all respective constraints of diverse nature. So, there must be some mechanism to deal with constraints handling task. For this purpose, penalty function approach (PFA) is considered as a widely adopted method *i.e.* to allow the search process to reach global feasible optima, while discarding the infeasible solution. The proposed technique is equipped with PFA to convert the constrained MOOPF problem into the unconstrained optimization problem, as given bellow in 29:

$$minf_{i,pf} = \begin{cases} f_o & \text{where } f_o \in F \\ min(f_i + penalty) & \text{otherwise} \end{cases} \tag{29}$$

$$penalty = K_V \sum_{i=1}^{N_{pq}}(V_{li} - V_{Li}^{lim}) + K_Q \sum_{i=1}^{N_g})(Q_{gi} - Q_{gi}^{lim}) + K_P \sum_{i=1}^{N_g}(P_{gref} - P_{gref}^{lim}) + K_S \sum_{i=1}^{N_l}(S_i - S_i^{lim}) \tag{30}$$

where, f_i is the i^{th} objective function, K_v, K_q, K_p, K_s are the penalty factors and *lim* shows the maximum limit of the specified dependent variable. If no violation occurs, then penalty will be considered zero and positive otherwise.

F. CATEGORIZING PROCESS

To further categorize the obtained solution, we have used the Pareto dominance method. Mathematically, it is stated as in Equation 31:

$$x_1 \prec x_2 \text{ iff } \begin{cases} f_i(x_1, v) \leq f_i(x_2, v) & \forall i \in \{1, 2, \ldots, m\} \\ f_j(x_1, v) < f_j(x_2, v) & \exists j \in \{1, 2, \ldots, m\} \end{cases} \quad (31)$$

Let the solution space for P objectives be R^P and the decision variable search space be Ω, for all $x \in \Omega$ and $f(x, v) \in R^P$. If we consider two objective functions f_i and f_j, which map in the solution space R^P through decision variable vectors x_1 and x_2. Then x_1 Pareto dominates x_2, when both conditions in above equation are satisfied. This relationship shows that (x_1, v) is a Pareto optimal point and can not be further improved i.e. there is a trade off between one objective and deterioration of any other objective. The set of such Pareto optimal points in known as set of ''non dominating solution''. The surface defined by these non-dominating set of solutions is called the PF.

V. POWER AND STOCHASTIC MODELS OF RESs

The uncertainty of RESs is incorporated as per following PDF models:

A. MODEL OF WIND GENERATOR

In this section the wind generator model is discussed.

1) POWER MODEL

In this work, we consider a wind farm having 25 turbines which is connected at bus 13. The rated power of each turbine is 3MW. However, the output power obtained from a wind farm depends on wind speed. So, the real output power as a function of wind speed is described in as [21]. So, the real output power of each turbine is dependent on wind speed. Mathematically textcolorblackexpressed as Equation (32)::

$$P_w(v) = \begin{cases} 0 & \text{for } v < v_{in} \,\&v > v_{out} \\ p_{wr}\left(\dfrac{v - v_{in}}{v_r - v_{in}}\right) & \text{for } v_{in} \leq v \leq v_r \\ p_{wr} & \text{for } v_r < v \leq v_{out} \end{cases} \quad (32)$$

where, p_{wr} gives rated power of the wind turbine and v, v_r, v_{in}, v_{out} are the actual speed of wind, rated speed of wind, cut-in speed of wind and cut-out speed of wind, respectively. In the proposed work, the rated values are considered as, $v_r = 16m/s$, $v_{in} = 3m/s$, and $v_{out} = 25m/s$.

2) STOCHASTIC MODEL

Probabilistic models can be used to estimate the real output power of the wind farm. The wind speed at certain locations follows a specific pattern. So, it is required to use prediction or estimation theory to better estimate the value. In this regard, the Weibull PDF stochastic model is considered best for wind speed approximation [21], which is given as;

$$f_v(v) = (k/c)(v/c)^{(k-1)} e^{[-(v/c)^k]} \quad \forall\, 0 < v < \infty \quad (33)$$

Mean value of a Weibull distribution is define as:

$$M_{wb} = c * \Gamma(1 + k^{-1}) \quad (34)$$

Gamma function $\Gamma < x >$ is stated bellow;

$$\Gamma < x >= \int_0^{\infty} \exp^{-t} t^{x-1} dt \quad (35)$$

The Weibull curve shape and scale parameters are represented by k and c, respectively. The shape parameters k and c are selected in such a way that maximum Weibull mean value remains nearly equal to 10. Whereas, the PDF parameters used in this study are given in Table 2. The actual maximum Weibull mean calculated in this study is $v = 8.862m/s$. Unless mentioned, we use this value in current case study.

B. MODEL OF PHOTOVOLTAIC GENERATION

In this section the photovoltaic generation model is discussed.

1) POWER MODEL

For solar power, energy conservation function is given in [21] expressed through Equation (36):

$$P_s(G) = \begin{cases} P_{sr}\dfrac{G^2}{G_{std}R_c} & \text{for } 0 \leq G \leq R_c \\ P_{sr}\dfrac{G}{G_{std}} & \text{for } G \geq G \end{cases} \quad (36)$$

where, G, G_{std}, R_c, and P_{sr} are forecasted solar irradiation, solar irradiation at STP, actual solar irradiation and solar rated output power, respectively. In this article the $G_{std} = 800\ W/m^2$, $R_c = 120W/m^2$ values are used.

2) STOCHASTIC MODEL

For solar irradiance, it is also possible to predict the solar radiations through stochastic model. In [21], solar irradiance is given by log-normal PDF, where μ is mean and σ is standard deviation:

$$f_g(G) = [1/G\sigma\sqrt{2\pi}]e^{-(\ln(x)-\mu)^2/2\sigma^2} \quad for\ G > 0 \quad (37)$$

Mean of lognormal distribution is stated bellow:

$$M_{lgn} = e^{(\mu + \frac{\sigma^2}{2})} \quad (38)$$

C. MODEL OF SMALL HYDRO PLANT

1) POWER MODEL

For small hydro power plant, a mathematical function is given in [50], [51]. Where, the river flow rate and effective head of water determine the electrical output from run-off of the river.

$$P_H(Q_h) = \rho\varepsilon Q_h H_h \quad (39)$$

where, $\rho, \varepsilon, g, Q_h$ and H_h denote density of water, efficiency, gravitational acceleration, flow rate and effective pressure head, respectively. Here, $\varepsilon = 0.85$ and $H_h = 25m$ values are used for experimental purpose.

2) STOCHASTIC MODEL

Form literature [54]–[56], it is found that Gumbel distribution curve is considered best to estimate the river flow rate Q_h, which follows distribution curve with scale parameter γ and location parameter β;

$$f_H(Q_h) = [1/\gamma]e^{(Q_h-\beta)/\gamma)} \times e^{(-(Q_h-\beta)/\gamma)} \tag{40}$$

TABLE 2. Parameters for stochastic models.

Generating Units	Cumulative Power	Stochastic Parameters
Wind Farm @ bus 11	75MW	Weibull PDF: c=10 and k=2
Soalr park @ bus 13	60MW	Lognormal PDF: $\sigma = 0.6$ and $\mu = 6$
Small hydro @ bus 13	5MW	Gumbel PDF: $\beta = 15$ and $\gamma = 1.2$

D. CALCULATION OF WIND POWER PROBABILITIES

Referring to Section III-A, it can be seen that there are two regions in which wind power is discrete, this is due to wind speed variation. The wind power is zero when the wind speed is below and above the cut-in and cut-out values. However, it is equal to rated power of wind mill when wind speed is in between the rated and cut-out speed. Probabilities of these discrete zones are calculated as [46]:

$$f_w(p_w)\{p_w = 0\} = 1 - e^{[-(v_{in}/c)^k]} + e^{[-(v_{out}/c)^k]} \tag{41}$$
$$f_w(p_w)\{p_w = p_{wr}\} = e^{[-(v_r/c)^k]} - e^{[-(v_{out}/c)^k]} \tag{42}$$

It is also observed that other then these two regions, the output power of wind turbine is continuous in between cut-in and rated speed [46]. The probability of wind power in continuous region is calculated using ;

$$\begin{aligned} f_w(p_w) = &\frac{k(v_r - v_{in})}{c^k \times p_{wr}}\left[v_{in} + \frac{p_w}{p_{wr}}(v_r - v_{in})\right]^{k-1} \\ &\times exp\left(-(\frac{v_{in} + \frac{p_w}{p_{wr}}(v_r - v_{in})}{c})^k\right) \end{aligned} \tag{43}$$

E. CALCULATION OF OVER AND UNDER ESTIMATION COST FOR SOLAR PV

As discussed before, scheduled power can be any amount of active power as per mutual agreement between ISO and solar park owner. When available power varied from the scheduled power, it can be a case of over or under estimation, which are further described in the following section [57], [58].

1) OVERESTIMATION COST

If the available power P_{sn} remains shorter than the scheduled power P_{ss} (i.e., the case of overestimation) and occurrence frequency for particular schedule power is given by f_{sn}, then the reserve cost can be calculated as:

$$C_{R,s}(\triangle P) = k_{rs}(P_{ss} - P_{sav}) = k_{rs}\sum_{n=1}^{N^-}[P_{ss} - P_{sn}] * f_{sn} \tag{44}$$

where, k_{rs} gives the reserve cost coefficient, N^- is the number of pairs of $(P_{sn,f_{sn}})$ generated for PDF.

2) UNDERESTIMATION COST

Similarly if the available power P_{sp} increases to the scheduled power P_{ss} (i.e., the case of underestimation) and occurrence frequency for particular schedule power is given by f_{sp}, then the penalty cost can be calculated as:

$$C_{P,s}(\triangle P) = k_{ps}(P_{sav} - P_{ss}) = k_{ps}\sum_{n=1}^{N^+}[P_{sp} - P_{ss}] * f_{sp} \tag{45}$$

where, k_{ps} denotes the penalty cost coefficient, and N^+ gives the number of pairs of $(P_{sp,f_{sp}})$ generated for PDF.

VI. PROPOSED MOOPF APPROACH

This section describes the overview and computational flow of the proposed technique.

Limitations are always associated with the optimization techniques to find the global optimum solution of the MOOPF problem. However, there is always a room to improve the working of any algorithm such that to find the optimal solution of the MOOPF problem. In this work, rather than using true Pareto base optimization, we have developed a computationally efficient approach which finds the global optimal solution of MOOPF problem by using split approach. Initially, we split the aggregate demand in optimal ratio which lowers the overall generation cost of the power system. Then, we accommodate the remaining demand from RE sources. In this case, the sharing of power demand on RE sources is further calculated by using a PDF models of RESs and FMF. This allows us to integrate the RESs in such a way that the active power loss of the power system can be lowered. As the MOOPF problem has threefold objective: cost, loss and carbon emission minimization. Therefore, there is always a trade-off solution exists among these three objectives. Hence, upon having a set of non-dominating solutions PFs are plotted and BCS has been picked.

A. EVOLUTION OF TRADITIONAL GRID

In the traditional power system, thermal generators consume fossil fuel, but increase in electrical demand may also increases the pollution index. This would certainly motivate the researchers to adopt renewable energy sources RESs to cater the environmental concerns. Furthermore, the integration of RESs such as wind and solar greatly reduces the carbon emission and global warming [1].

B. FMF

As it is easy to take decision for human in real world but when it comes to machines it is difficult to take decision due to the fuzziness of available knowledge. In order to calculate the real contribution of RESs in total generation, preference order is assigned to each RES. Furthermore, to extract the BCS from set of non dominated solution FMF has also been used in this article [59].

In this proposed technique triangular FMF based mathematical model has been used to calculate the true membership of RESs in the total generation of power system. The main advantage of this model is to analyze the variations in different conflicting objectives of MOOPF problem. Therefore, contribution indexes have been assigned to the estimated produce power from RESs. Upon having the estimated power of RESs, a set of different combination indexes has been generated to create a pool of distributed RESs. Furthermore, remaining demand has been satisfied with the most economical thermal generators. In this way before going into the categorizing process a reasonable set of trade-off solution has been achieved. Optimal combination of generation sources is shown in figure 7. Moreover, after the categorizing process a confident solution from the set of non-dominating solutions has been picked with the highest value of membership (section VIII-D). It is worth mentioning that the hypothesis which is built in this work to use FMF to investigate the variations in defined objectives has not been found in literature.

C. ELD USING PARTICLE SWARM OPTIMIZATION (PSO)

PSO is a nature inspired population based matahuristic technique that is developed to solve the engineering and scientific optimization problems. In this technique, individuals change their state (position) as the algorithm converge. Initially a swarm of random particles is created and random velocities are assign to them, when they move through the search space best position or fitness stored as "pbest". In the global version of PSO, another value is tracked by the algorithm which is "gbest". Position of each particle is effected by the best fit particle in the entire swam. Information regarding best solution is shared throughout the swarm by using star social topology. The loop is ended when a pre-define stopping criterion is met or convergence results are obtained [60].

D. PROPOSED TECHNIQUE FOR MOOPF

In the proposed technique, we calculate the available power from RESs using stochastic and PDF models. Calculate the preference order of RESs to contribute in the power generation and then split the demand to calculate the thermal generation. Then, we compute the fitness value of the objective functions. Afterwards, we calculate the constraint violation penalty and add that value in objective function to avoid the infeasible solution. Moreover, we developed a non-dominated set of solutions using Pareto dominance method to plot the PFs for different study cases. To analysis all possible operating values of control variables load flow program has been used as a deterministic tool in algorithm loop. Once non-dominated solutions from pareto-optimal set are obtained, one BCS is extracted in all study cases. Flow chart which depicts the proposed idea of the proposed technique is shown in figure 1, and pseudo code is given in algorithm 1.

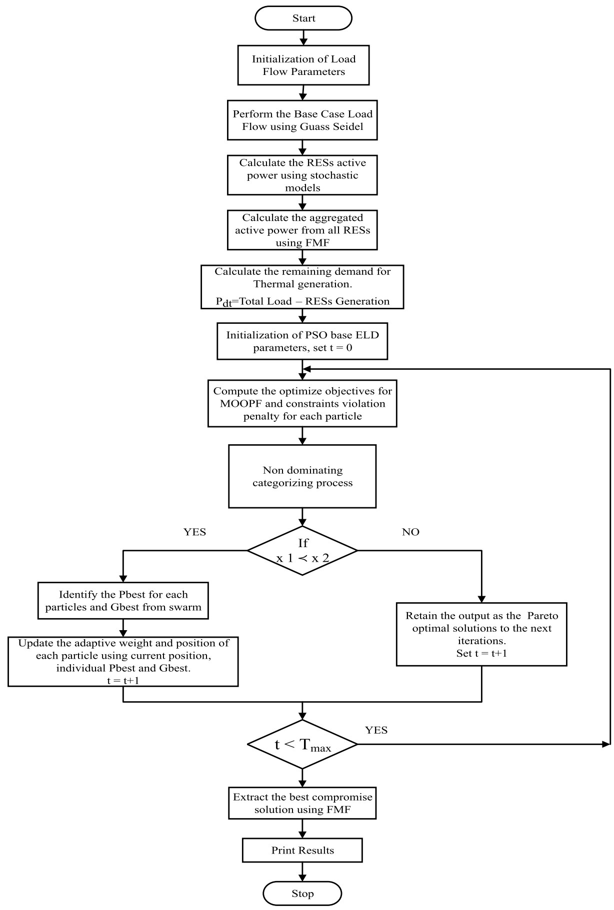


FIGURE 1. Process Flow Chart.

VII. EXPERIMENTAL SETUP

The proposed technique has been developed to solve the multi-objective and non-linear constrained optimization problem. A sequential procedure is adopted to search the feasible solution at each phase of the optimization algorithm. This procedure guarantees the feasibility of non-dominated solutions. To meet the load demand efficiently by OPF, a mathematical formulation of a system model is proposed with thermal generators and RESs. The proposed algorithm based on MOOPF problem has been applied on a modified IEEE 30-bus system as shown in figure 2. The proposed system is modified as per details given in Table 3.

VIII. RESULTS AND DISCUSSIONS

This section described the results of formulated multi-objective and non-linear constrained optimization problem. A sequential procedure is used to find an optimal solution at each phase of the search algorithm. This procedure guarantees the feasibility of non-dominated solutions. Modified IEEE 30-bus system is used as a test bench. To implement and check the validity of proposed technique, a PC of 2.

Algorithm 1 Pseudo Code for MOOPF

Initialization of load flow parameters.
Base case load flow analysis.
Calculate the RESs active power using stochastic models.
Calculate the aggregated active power from all RESs using FMF.
Calculate the remaining demand for thermal generation.
Initialization of PSO base ELD parameters, set t = 0.
while $t \leq Tmax$ maximum iteration **do**
  Set the penalty factors as per PFA for constraints handling.
  Calculate the fitness of objective functions.
  Compute the constraint violation penalty and add to objective function.
  for $i = 1$ *to* N_p **do**
    for $j = 1$ *to* N_p **do**
      if $x1old \prec x2old$ **then**
        Algorithm loop.
        if $x1new \prec x2old$ **then**
          select $x1new$ as a new solution in PF;
        end if
      else
        Sort and extract the BCS using FMF approach.
      end if
    end for
  end for
  $t++$;
end while
end

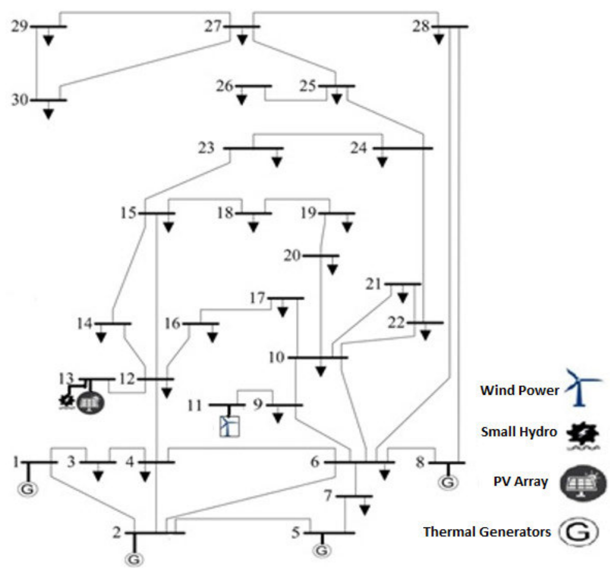


FIGURE 2. Modified IEEE 30-Bus system with RESs.

13×2.13 GHz clock CPU with 4GB volatile memory and 64-bit windows 7 has been used. And to reveal the results of developed technique 64-bit MATLAB 2018a software has been used. It is also required to consider the conflicting nature of the three objective functions as explained in Section II. Therefore, five cases are considered to exemplify the conflicting nature of the MOOPF problem.

TABLE 3. Data for the modified IEEE 30-bus network.

Items	Quantity	Details
Buses	30	6 Generator buses and 24 load buses
Branches	41	
Thermal Generators Buses	4	Bus 1 is slack bus and @ bus number 2,5 and 8
Solar + Small Hydro	1	@ bus 13
Wind	1	@ bus 11
Connected load		283.4MW, 102.5MVAr

TABLE 4. Different combinations of conflicting objective functions.

Study Cases	Objectives' combinations
1	$min\ f_{cost}$ & f_{Ploss}
2	$min\ f_{cost\_vp}$ & f_{Ploss}
3	$min\ f_{cost\_vp}$ & $f_{emission}$
4	$min\ f_{cost}$ & f_{Ploss} & $f_{emission}$
5	$min\ f_{cost\_vp}$ & f_{Ploss} & $f_{emission}$

TABLE 5. Different parameters of algorithm.

Parameters	Values
y_1	0
y_2	1.25
Population size	50
Numbers of iterations for PSO convergence	500
Inertia of particles	0.9
Weight of particles	0.4
Base MVA	100
Accuracy	0.001
Acceleration	1.8
Max Iteration for load flow convergence	200
a_i	320, 310, 370
b_i	11.5, 12, 11.7
c_i	0.00211, 0.00200, 0.00623
d_i	18, 16, 12
e_i	0.037, 0.038, 0.045
P_{gmin}	20, 20, 25
P_{gmax}	130, 110, 200

A. PARAMETERS SETTING

Parameters of Fuzzy function, ELD, power system model and thermal generators are adjusted as given in Table5. Parameters are tuned many times to get the suitable combination.

TABLE 6. BCS for all study cases.

Variables Names	Study Case 1	Study Case 2	Study Case 3	Study Case 4	Study Case 5
TG1	139.9998	140	140	140	139.9999
TG1	51.46717	52.244	53.79177	58.886	52.91711
TG1	18.8946	20.40975	23.44755	34.41584	22.02893
WFg	30.64751	33.09879	38.00135	55.16033	35.55007
S+Hg	56.66667	51.94444	42.5	9.444444	47.22222
V@bus1	1.06	1.06	1.06	1.06	1.06
V@bus2	1.043	1.043	1.043	1.043	1.043
V@bus5	1.01	1.01	1.01	1.01	1.01
V@bus8	1.01	1.01	1.01	1.01	1.01
V@bus11	1.081998	1.081998	1.081998	1.081998	1.081998
V@bus13	1.070998	1.070998	1.070998	1.070998	1.070998
Q@bus1	55.34849	55.34849	55.34849	55.34849	55.34849
Q@bus2	-16.7187	-16.7187	-16.7187	-16.7187	-16.7187
Q@bus5	-25.1761	-25.1761	-25.1761	-25.1761	-25.1761
Q@bus8	25.83227	25.83227	25.83227	25.83227	25.83227
Q@bus11	28.40549	28.40549	28.40549	28.40549	28.40549
Q@bus13	23.46115	23.46115	23.46115	23.46115	23.46115
Total Cost ($\hr)	**676.4**	**704.8**	**715.8**	**724.7**	**710.3**
Total Loss (MW)	**13.95**	**13.85**		**13.73**	**13.77**
Total Emission (ton/hr)			**10.43**	**10.43**	**10.43**

B. VARIATION OF GENERATION COST OF RESs

In this section, the simulation results of cost variation of wind and solar power plant are discussed. The Weibull parameters are taken as described in Table2. The scheduled power of wind and solar is varied from zero to the rated power and variation in direct, penalty, reserve and total cost is shown in Fig. 3 and 4. Moreover, with the increase of scheduled power, reserve cost is escalates due to large spinning reserve requirement. In addition, the direct cost increases linearly with the scheduled power. Whereas, the penalty cost decreases monotonically with the increase of scheduled power.

Similarly, the variation in cost of solar power plant is shown in Fig. 4 for the over/under estimation cases. It is quit visible that total cost of solar power is not monotonically increasing, actually it is decreasing near 15MW and then increases again with the increase in scheduled power. Cost coefficients are using the same parametric values as given in table 1. Log-normal PDF parameters are used same as given in table 2.

C. PF COMPUTATION

Simulation results of three different combinations of optimization objectives which are shown in Table 4 are expressed in this section. PFs are developed to analyze the different solutions upon having non-dominated solutions. From these a best compromise solution is extracted.

- *Case 1* ($minf_{cost}$ & f_{Ploss}): When the generation capacity increases cost also increases due to the proportional relation. Moreover, voltage difference between the buses decreases when the generation on generator buses increase, which becomes the cause in the reduction of power loss. Therefore, at the same time when cost is increase power loss decreases. This conflicting nature can be seen from figure 5a which is obtained after running the optimization algorithm.
- *Case 2* ($minf_{(cost\_vp)}$ & f_{Ploss}): For study case 2 PF is shown in figure 5b. Similar, from *case 1* cost and loss shows same relation but due to the sinusoidal effect of valve opening overall cost increases. This can be noted in figure when cost with valve point effect increase from 715$/hr to 720$/hr and power loss remains almost constant while it follows same pattern in study case 1 when cost increase from 690$/hr to 695$/hr.
- *Case 3* ($minf_{(cost\_vp)}$ & $f_{emission}$): PF obtain in Figure 5c shows conflicting nature of emission and cost with valve point due to the characteristics of objective function equations. It can be seen from

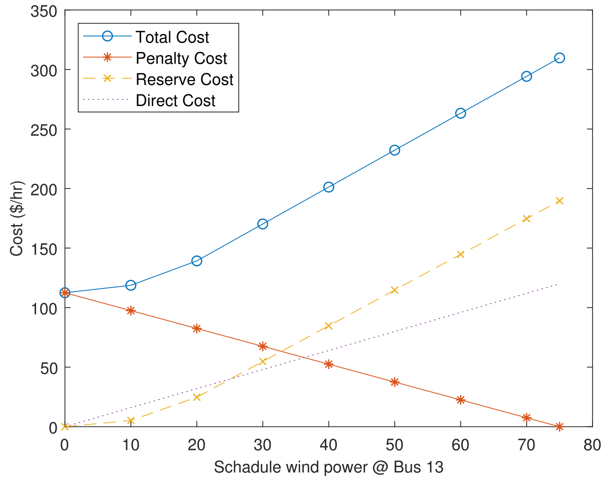


FIGURE 3. **Wind power cost variation vs schedule power.**

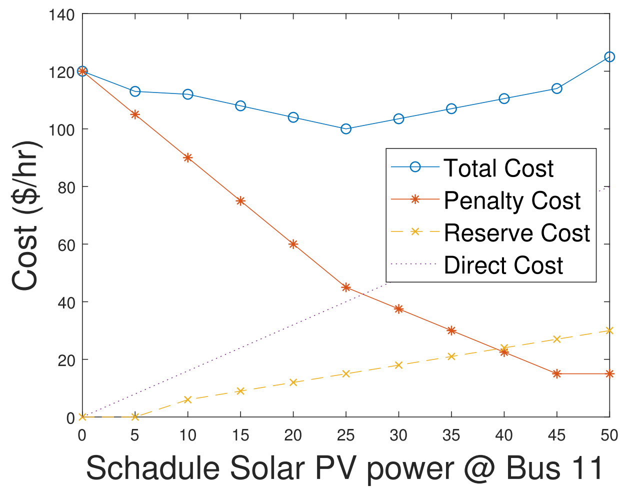
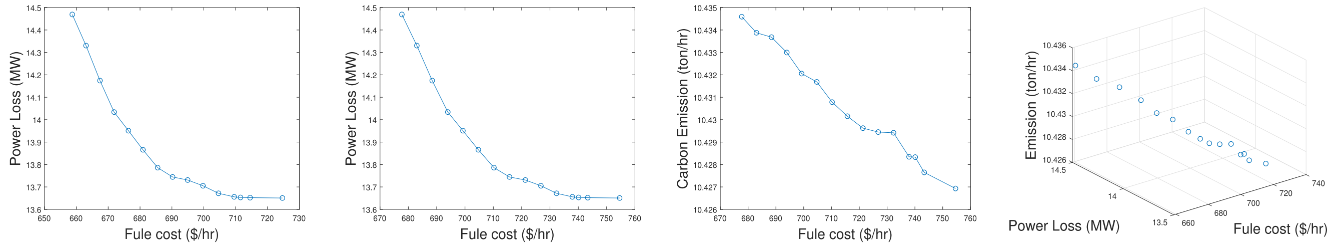


FIGURE 4. **PV power cost variation vs schedule power.**



(a) Test Case 1:Pareto Front for Bi-objective (b) Test Case 2:Pareto Front for Bi-objective (c) Test Case 3:Pareto Front for Bi-objective (d) Test Case 4:Pareto Front for Tri-objective

FIGURE 5. Analyzing the impact Pareto Front for different objective functions.

the figure that there is a trade-off between the said objectives. It can be seen that the PF forms almost straight line due to the fact that there is little variation in thermal generation. This is due to the intervention of RESs which are inherently green in nature.

- *Case 4* ($minf_{cost}$ & f_{Ploss} & $f_{emission}$) and *Case 5* ($minf_{(cost\_vp)}$ & f_{Ploss} & $f_{emission}$): To show the results of *case 4* and *case 5* PFs for tri-objective optimization are shown in figure 5d and figure 6 respectively, tri-objective are simultaneously optimized and set of non-dominating solutions are plotted to form the PFs. Smooth PF is obtained despite the non linear effect of valve point.

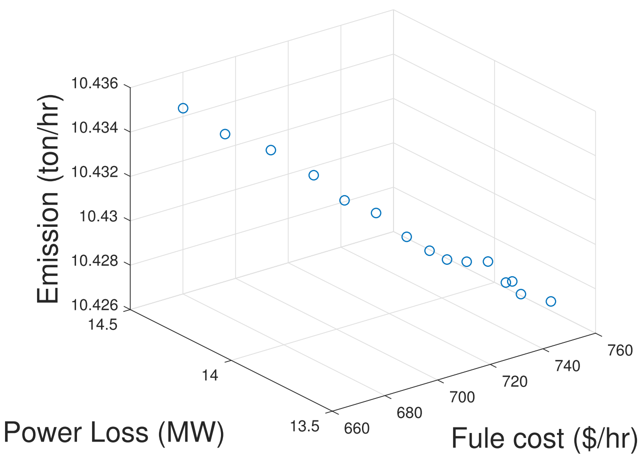


FIGURE 6. Test Case 5:Pareto Front for Tri-objective.

To minimize total generation cost given by Equation 16 for all generators PSO based ELD optimization algorithm is integrated with the proposed technique. Cost and PDF coefficients are same as provided in table 1 and 2 respectively. The convergence of PSO based ELD is plotted in figure 8. It can be seen that the optimized cost is achieved after the 50^{th} iteration due to fixed value. Figure 7 shows the contribution of generation sources in all case studies.

To validate the findings of proposed technique on the bases of BCS, a detailed comparison of bi-objective and tri-objectives cases obtained by $MOPSO_{FMF}$, $NSGA-II$, $MOEA_D$, WA, $MOEA_{D-SF}$, $MOFA_{CPA}$, and $MOFA_{PFA}$ is presented in table 7. From this comparison table it can be seen that the optimal BCS picked by MOPSO/FMF is $710.3\$/hr$, 13.77 MW and 0.1043 ton/hr, which is quite low in terms of cost and emission. Reduction in carbon emission level is observed this is due to the penetration of inherently clean RESs. Moreover, optimum generation combination of the renewable sources reduces the overall generation cost to a good extant, which is 902.54 \$/hr and 878.13 \$/hr in MOEA/D and MOFA-CPA algorithms respectively. It is worth mentioning that the numbers of trial in these algorithms are also double than the proposed one, hence reducing the computational complexity of proposed technique, which is also an objective of this work. Although, in terms of losses of power system BCS is at higher side than that of compared ones. But the fact is, this is all because of low reactive power generation capabilities of RESs, which are replaced by the conventional thermal generators on the generator buses as shown in table 2, figure 2. While the other algorithms only considered thermal generators in their system models. Moreover, It is noticeable here that the comparison of MOPSO/FMF between other algorithms is only given for conventional thermal generators because no comparable literature is available for the case of multi-objectives optimal power flow with RESs. Moreover, an extension of this work in the future can be to compensate these losses by optimal placement of reactive power compensation devices.

D. EXTRACTION OF BCS

From the set of non-dominating solutions, one confident solution has been extracted by using FMF. This post-optimal process is used to extract the non-inferior solution from the pareto optimal front. As the judgment in decision making is imprecise in nature, the membership of individual solution is given by the following Equation 46:

$$\mu_i^k = \begin{cases} 1 & \text{for } f_i \leq f_(i, min) \\ \dfrac{f_{(i,max)}-f_i}{f_{(i,max)} - f_{(i,min)}} & \text{for } f_{(i,min)} < f_i < f_{(i,max)} \\ 0 & \text{for } f_i \geq f_{(i,max)} \end{cases} \tag{46}$$

where, $f_{i,min}$ and $f_{i,max}$ denote the minimum and maximum values of the objective function, and k represents the specific

TABLE 7. A comparison of BCS obtained with some existing results.

Reference	Techniques	Pop Size	Max #s of Iteration	Trials	CHA	Total Cost ($/hr)	System Loss (MW)	Total Emission (p.u)
Proposed	$MOPSO_{FMF}$	50	500	15	PFA	710.3	13.77	0.1043
[30]	$MOFA_{CPA}$	100	300	30	CPA	878.13	3.9232	0.2171
[30]	$MOFA_{PFA}$	100	300	30	PFA	879.91	4.2179	0.2165
[73]	$MOEA_{SF}^{D}$	300	100000	50	SF	881.012	4.1441	0.2164
[74]	$NSGA-II$	20	1000	-	-	837.416	5.2397	-
[75]	$MOEA_{D}$	100	500	31	PFA	902.54	3.4594	0.2107
[76]	WA	80	300	-	-	897.2797	4.6211	0.2175

TABLE 8. A comparison of Fuzzy based control schemes used in literature.

Reference	Technique	Objective	Remarks
[69]	Barrier Lyapunov functions-based command filtered output feedback control for full-state constrained nonlinear systems	An adaptive output feedback control via command filtered backstepping is proposed for class of uncertain nonlinear systems with full-state constraints	As the load flow problem is highly complex , nonlinear and constraint optimization problem, so PF problem can be model as control system problem and can be solved as in [69]
[70]	Adaptive H∞ sliding mode control of uncertain neutralâĂŘtype stochastic systems based on state observer	This paper is focused on the problem of adaptive sliding mode control design for uncertain neutral-type stochastic systems under a prescribed H∞ performance	When RESs are integrate to the existing power system problem of rotor speed and system frequency arises. Parameters of power system can be tune to stabilize the system
[71]	Passivity-based robust sliding mode synthesis for uncertain delayed stochastic systems via state observer	In this paper, a new methodology of the observer-based SMC for uncertain DSS has been proposed. A novel linear sliding surface has been presented based on the designed observer. A new sufficient exponential stability condition with passivity for the closed-loop system during the predefined sliding surface has been derived by employing the stochastic stability theory and linear matrix inequality approach	On the front of power system quality fault analysis of power system can be observe and investigate using the system model
[72]	Adaptive neural command filtering control for nonlinear MIMO systems with saturation input and unknown control direction	A command ïňĄltered adaptive neural networks (NNs) control method is presented with regard to the MIMO systems by designing the virtual controllers and error compensation signals	Moreover, to forecast the wind speed and solar irradiance NN based virtual controllers and error compensator can be designed

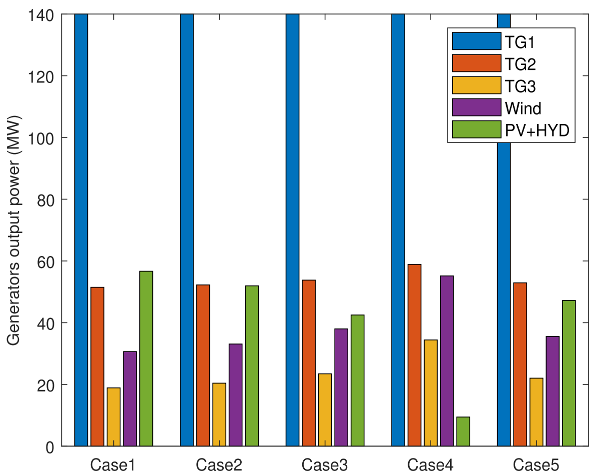


FIGURE 7. Contribution of generation sources.

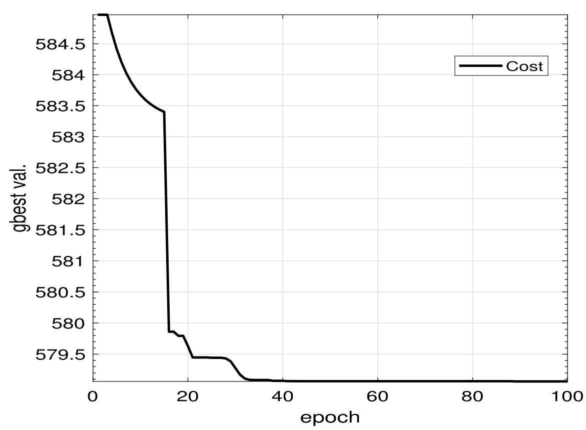


FIGURE 8. Convergence graph of PSO based ELD.

non-dominating solution in the Pareto front space. The normalization of k^{th} individual is given by following equation 47.

$$\mu_k = \frac{\sum_{i=1}^{m} \mu_i^k}{\sum_{k=1}^{S_{nd}} \sum_{i=1}^{m} \mu_i^k} \tag{47}$$

where, S_{nd} represents the numbers of non-dominating solutions. The largest value of the μ_k will have the best compromise solution. Table 6 is presented to exemplify the BCS found in the Pareto front space in all cases. It can be seen that the carbon emission is constant for cases 3,4 and 5. Because, the overall thermal generation is nearly constant. Other than emission it can be seen that there is always a trade-off between the objectives of optimization. Table also shows the values of generator bus voltage and reactive power limits which are well truly in allowable ranges.

IX. CONCLUSION

In this research work, OPF problem is formulated as MOOPF problem. A new and slightly different technique is developed to find the optimal values of different control variables in the presence of distributed RESs. To deal with the intermittent nature of RESs, PDF and stochastic models are used to calculate the available power. Optimization of overall cost is achieved in both; under and overestimation scenarios. Moreover, to address the conflicting nature of formulated objectives, PFs are plotted for different case studies. Pareto dominance method is used to categorize the pareto dominate solution. Where, not only PFs are obtained but BCS is also extracted from the set of non-dominating solutions using FMF approach. For different combination of objectives, trade-off solutions are also presented. During the implementation of multi-objective optimization problem, PFA method is used in order to avoid violation of physical and security constraints. As a response, a closed form optimal solution the solution is obtained. Moreover, computational requirements are significantly reduced due to simplest form of mathematical models to achieve the BCS in different trials. To validate the effectiveness of developed technique IEEE 30-bus system is modified to incorporate the RESs and simulations are performed in MATLAB 2018a software. The future scope on MOOPF front, author propose the possible induction of battery storage system, pumped or small hydro in the power system with more number of buses. Doubly fed induction generator for wind turbine, stand alone PV system with and without maximum power point tracker (MPPT) and FACT devices can also be incorporated to extend the research study.

Moreover, author suggest future direction on front of control system, power system stability and data science, many stochastic system model control, adaptive fuzzy control and neural networks methods have been recently developed to determine the state of control variable in table 8. As the power flow (PF) problem is highly complex, nonlinear and constraint optimization problem, so PF problem can be model as control system problem and can be solved as in [61]. When RESs are integrate to the existing power system problem of rotor speed and system frequency arises. Parameters of power system can be tune to stabilize the system using [62]. On the front of power system quality fault analysis of power system can be observe and investigate using the system model in [63]. Moreover, to forecast the wind speed and solar irradiance NN based virtual controllers and error compensators can be design as in [64]. So in future we will use these modern technique of control system and neural network (NN) to predict and to solve optimal power flow.

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