IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 23 June 2022, accepted 17 July 2022, date of publication 26 July 2022, date of current version 3 August 2022.

*Digital Object Identifier 10.1109/ACCESS.2022.3194012*

RESEARCH ARTICLE

# Economic Emission and Energy Scheduling for Renewable Rich Network Using Bio-Inspired Optimization

**MUHAMMAD WALEED TAHIR[1], GHULAM ABBAS[2], (Senior Member, IEEE), MUHAMMAD ARSALAN ILYAS[1], NASIM ULLAH[3], (Member, IEEE), AND S. M. MUYEEN[4], (Senior Member, IEEE)**

[1]Department of Technology, The University of Lahore, Lahore 54000, Pakistan
[2]Department of Electrical Engineering, The University of Lahore, Lahore 54000, Pakistan
[3]Department of Electrical Engineering, College of Engineering, Taif University, Taif 21944, Saudi Arabia
[4]Department of Electrical Engineering, Qatar University, Doha, Qatar

Corresponding authors: S. M. Muyeen (sm.muyeen@qu.edu.qa) and Ghulam Abbas (ghulam.abbas@ee.uol.edu.pk)

The publication of this article was funded by Qatar National Library. This work was also supported by Taif University, Taif, Saudi Arabia, under Taif University Researchers Supporting Project TURSP-2020/144.

**ABSTRACT** This paper deals with the combined economic emission load dispatch (CEELD) problem with and without the integration of renewable energy sources (RESs), in some more rational test scenarios of single CEELD and multi-objective CEELD (MO-CEELD) optimization. Hence, an efficient and coherent approach is presented to minimize the generation and emission cost using one of the bio-inspired metaheuristic algorithms named flower pollination algorithm (FPA). The evolution of a power system along with the integration of RESs demands equal advancement in the operation and control algorithms of the power grid. Therefore, the proposed approach in this paper offers an evolutionary single and multi-objective optimization process based on a bio-inspired FPA. Further, it has been validated by achieving the best compromise solution (BCS) using the Pareto categorizing process and fuzzy membership function. Moreover, different study cases comprising eleven and fifteen thermal units with and without considering RESs are tested with the proposed technique. Finally, the effectiveness of the proposed approach is tested by comparing the simulation results with some already existing techniques in terms of overall fuel and emission cost. Significantly, it has been noticed from the results that it outperforms all the previously presented approaches like PSO, DE, GSA, AEO, BA, and dBA, thus justifying its applicability.

**INDEX TERMS** Combined economic emission dispatch, fuzzy membership function, multi-objective flower pollination algorithm, Pareto categorizing process, price penalty factor approach.

## I. INTRODUCTION

In a conventional power grid, conventional generation (e.g. hydroelectric station, thermal power plant, etc.) supplies power to a variety of users and these conventional power grid focuses on electricity generation, transmission, distribution and control [1]. Today, the power system is facing serious environmental, financial and operational challenges. As the electricity demand has increased steadily for years, yet transmission system that transfers power from generation to user end has not been upgraded at the same pace. The result of this gap is that the power system has become overloaded, making it prone to blackouts [2] and other serious problems like voltage drop, line losses, decreased efficiency, frequency drop, increased electricity cost and more importantly the environmental deterioration due to the release of injurious pollutants from conventional thermal generators. To resolve these issues, a feasible solution is presented to encourage the consumers that they should revise their power demand plans depending upon the price-based

The associate editor coordinating the review of this manuscript and approving it for publication was Amjad Anvari-Moghaddam.

demand response programs [3]. Another attractive solution is to boost the power system stability, reliability, quality and economics by installing on-site distributed RESs. Also, outdated grids should be modernized using advance technologies to enhance the efficiency, quality, security and dependability of the delivered power significantly, called smart micro-grid (SMG). The micro-grid consists of energy storage resources and distributed generation (DG) units. As DG units, micro-grids can employ conventional generators or renewable energy sources. [4]. However, RESs have an advantage over traditional generators in terms of cost and environmental benefits, which makes them a better choice to be used in MG these days. The benefits of MG include improved power system dependability and quality, as well as lower power generation costs and carbon emissions. Therefore, it becomes essential to study and integrate the features of modern control technologies and distributed energy resources (DERs) into power system studies.

In recent times, satisfying the requirements of escalated power demand and limited reserves of fossil fuels is a challenge for the generation companies. This requires minimization in the cost of power generation, which is achievable by optimum generation scheduling. The optimal generation scheduling means to distribute a power demand between the available power generators in a cost-effective method. This problem is complex in economical, electrical and computational aspects [5]. Economically, it is the issue of economic load dispatch (ELD) [6]. Electrically, it is the problem of optimal power flow (OPF) [7] and computationally, it is the problem to find a feasible solution of different objectives of the power system which increases the system performance [8]. In modern power systems, ELD is one of the most complicated constrained optimization problem. The primary goal of ELD is to distribute the generated power among the loads to fulfill the load demand in a way that the generation cost is minimum while satisfying the system constraints. Factors that increase the complexity of ELD are system size, generator limits, system constraints and the fuel cost characteristics of generators that are usually non-convex. Constraints include power balance, valve point effect, security constraints, generator limits, transmission losses and emission constraints, etc. It can be observed from the literature that several researchers have utilized conventional algorithms to find the solution to the ELD problem while taking only thermal generators into account and considering fewer constraints. With the intervention of RESs, ELD problem becomes more complex.

The damage brought to the environment due to the utilization of fossil fuels in thermal generators has increased the attention of generation companies because of the release of poisonous and harmful gases in the environment. As far as the emission of poisonous gases is concerned, generation companies are responsible to maintain their specific levels [9]. The amount of harmful gases emitted can be minimized by installation of updated control equipment, utilizing an efficient generator and by emission dispatch [10], [11]. This problem in the power system operation and control is termed as emission dispatch (ED) problem. This problem is also complex in economical, electrical and computational aspects such as ELD. ED reduces the amount of harmful gases released into the air. By keeping in view of the ED, the operational policies of the thermal plants have to be modified to decrease the harmful pollutants in the air [12]. The emission of these gases into the environment is the main reason for global warming and an imbalance in ecology, which is one of the main environmental problems. Indeed, as per the US air act amendment of 1990, the electric utility industry will undoubtedly diminish its $NO_x$ discharge by 2 million tons/yr and $SO_2$ outflows by 10 million tons/yr, from the level in 1980 [13].

Economic dispatch by considering the integration of RESs and concurrent minimization of both emission of unsafe toxins and thermal cost while satisfying the system constraints is considered as a multi-objective optimization problem (MOO) in power system and is perceived by CEELD [14]. Multi-objective optimization (MOO) is definitely a hot issue among scholars and engineers right now. [15], [16] and MO-CEELD is a two-fold multi-objective optimization problem. Therefore, it's essential to reach the (BCS) using the Pareto categorizing process and membership function that can achieve minimized cost of fuel releasing the smallest amount of toxic gases in the environment while satisfying the system constraints.

Literature shows that the conventional algorithms are not satisfactory enough to guarantee the global optimal solution of multi-objective CEELD problems in the presence of RESs [17]. Also, because of the high integration of RESs, the power suppliers are facing some issues in managing the power demand therefore they depend upon the manual restrictions to manage the power [18]. In addition, the reserve capacity of the RESs has to be increased due to their uncertain and intermittent behavior, therefore it increases the electricity's marginal cost [19]. Due to these limitations, a bio-inspired FPA is suggested in this work to find the global optimal solution of the MO-CEELD problem. The suggested algorithm's performance was evaluated by comparing simulation results to those of other metahueristic population based algorithms used by other authors in the literature. The suggested FPA gives a more precise solution than existing approaches, as evidenced by all of the results.

## II. LITERATURE REVIEW

ELD has been studied since 1920 [20]. ELD and CEELD is an extensively-researched subject for the power system research community throughout the world. CEELD and ED are both nonlinear, complicated and computationally intensive power system operating challenges. They are a perfect choice for evolutionary optimization techniques to confront and verify their efficacy because of their mathematical complexity. [21]. Many conventional methods and modern meta-heuristic methods have been employed to solve these complex problems.

Traditional methods mainly rely on mathematical programming (e.g. quadratic programming, linear programming, dynamic programming technique and interior point method). There were only two optimization methods used till 1930, which were the best point loading and base load method. In the decade of 30s, better results were achieved with the help of equal incremental cost method [22]. Analog computers were the only source that was utilized for computations in those days. In 1954, the first computer was built for the calculation of transmission loss penalty factor. An electronic differential analyzer was established in 1955. The first-ever digital computer used for ED was in 1954 and they are still being utilized [23]. The algorithms developed using conventional techniques utilize step size, initial guess, estimations and engineering decisions to find the reasonable solution and have low convergence speed and sometimes may also halt in local optima due to wrong computational values, therefore the algorithm might become inaccurate and provide infeasible solutions. Furthermore, when control variables and constraints are increased these methods may cost computationally expensive. Due to these limitations, these methods are insufficient at a large scale as they depend on the initial guess. Lately, the non-linear and multi-modal nature of the CEELD problem is being dealt with through some modern population-based meta-heuristic and nature-inspired techniques. These methods are extremely capable to deal with the nonlinear and complex problems of the power system. [24]. They are adaptable and can return several solutions to a single problem in a single simulation run. Several well-known optimization techniques have attempted to overcome these issues, including: Genetic algorithm (GA) [25], moth swarm optimization algorithm (MSA) [26],differential evolution (DE) [27], [28],simulated annealing (SA) [29], particle swarm optimization (PSO) [30], [31], spider monkey optimization (SMO) [32], grey wolf optimizer (GWO) [33], gravitational search algorithm (GSA), [34],fire fly algorithm (FFA) [35], spiral optimization algorithm (SOA) [36], harmony search algorithm (HSA) [37], [38], harris hawks optimization (HHO) [39], squirrel search algorithm (SSA) [40], artificial bee colony (ABC) [41], sine-cosine algorithm (SCA) [42], differential evolution (DE) [43], bacterial forging algorithm (BFA) [44], Fluid search optimization (FSO) [45], improved ABC (IABC) [46], modified BFA (MBFA) [47], hybrid hierarchical evolution (HHE) [48], whale optimization algorithm (WOA) [49], chaos turbo PSO (CTPSO) [50], hybrid particle swarm gravitational search algorithm (PSOGSA) [51], multi-objective PSO (MOPSO) [52], new global PSO (NGPSO) [53], quantum inspired glowworm swarm optimization (QGSO) [54], multi-objective DE based PSO (MODE/PSO) [55], combination of continuous greedy randomized adaptive search procedure and modified differential evolution (CGRASP-MDE), combination of continuous greedy randomized adaptive search procedure and self-adaptive differential evolution (C-GRASP-SaDE) [56], successful history-based adaptive DE variants with linear population size reduction (L-SHADE) and improved L-SHADE (IL-SHADE) [57].

All the above mentioned algorithms are fixed population based algorithms and use two unique stages of search to discover the best optimal answer inside a search space: local and global search. [58]. Authors in [59] point out some disadvantages in GA, PSO and DE algorithms. The major disadvantage of GA is slow convergence and unguided mutation. A major disadvantage of DE is untimely convergence and the solution obtained is not global [59]. Similarly, PSO suffers from unstable convergence. Also, tuning of the control parameters of the aforementioned techniques takes time and adds complexity in the system [59]. Furthermore, EP, GSA and ABC algorithms are slow to converge and the exploration and exploitation processes are incompatible, thus the two abilities must be well balanced to achieve good optimization performance [60]. With various degrees of precision and convergence time, all of these methods were successful in solving the desired problem [61], but the research for an improved optimal solution is ongoing because novel and state of the art optimizing techniques being developed as highlighted by no free lunch theorem (NFL) [62]. Furthermore, with the advancement of measuring instruments and transducers more attention has been payed to the scheduling of non-dispatchable sources of energy. In this regards artificial intelligence (AI) and machine learning (ML) algorithms are considered in the ELD and optimal power flow (OPF) problems [63]. In this paper, we present a solution of MO-CEELD problem using FPA. FPA is meta-heuristic population based nature inspired algorithm that replicate the pollination process found in flowering plants. Different from other population methods, FPA contains only one critical parameter i.e. switch probability $S_p$, making it easy to apply and obtain the best solution quickly. Furthermore, by switching between local and global pollination, the local minimum solution can be avoided. So, the FPA is investigated in this paper to address the drawbacks of previous studies [60].

This paper considers a new way of tackling CEELD problems with RESs using the FPA methodology for single and multi-objective optimization. The overall theme and the strategy of the problem formulation and its solution is shown in Figure 1.

### A. RESEARCH CONTRIBUTION

The following are the significant contributions of this study,

- A realistic approach is considered to obtain the dynamic scheduling of generation sources along with RESs using hourly metro-logical data in CEELD problem.
- The CEELD problem is additionally perceived by enhancing the exploitation and exploration characteristics using the Levy fight step size distribution of FPA algorithm.
- An improvement in the CEELD, bi-objective consolidation is attained using a PPF approach. Hence, PPFs are expressed as the ratio between cost and emissions of corresponding generator.
- An amelioration in the simultaneous optimization of conflicting objectives has been clinched by adopting

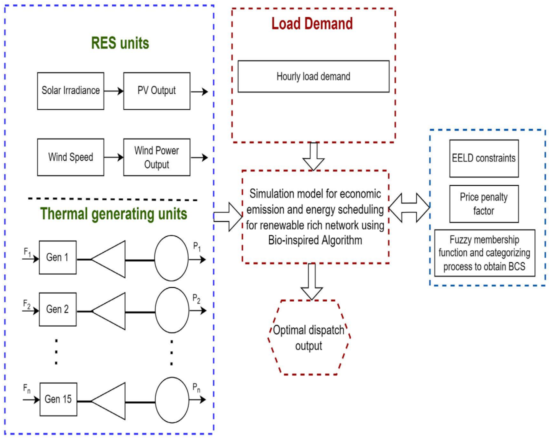


**FIGURE 1. Proposed methodology for CEELD/MO-CEELD.**

MOFPA approach. Hence, the conflicting nature of the two-fold objectives has been rectified.

- A coherent pareto front has been realised during crowding distance based non-dominating sorting and plotting process.
- BCS is secured using a triangular fuzzy membership function by computing the membership value of a decision pointer for non-dominating set of solutions.

Captivating simulation results in some realistic case studies revealed that the proposed approach outperform the former presented studies. No doubt, the convergence characteristics and position of pollinators at different iterations of the algorithm show that the FPA provides outstanding results as compared to other well-known meta-heuristic approaches like λ iteration, recursive, PSO, DE, GA similarity and GSA.

The remaining sections are organized as follows. Section III discusses the brief description and mathematical formulation of CEELD and MO-CEELD with the integration of RESs. Section IV discusses the theory of FPA. Section V describes the multiobjective FPA. The problem-solving approach is proposed and discussed in Section VI. Section VII covers the results and discussion. To end, the paper is concluded in Section VIII.

## III. PROBLEM FORMULATION

In many cases, an optimization problem may contain different objective functions which can be conflicting with each other. Thus, it is difficult to find the optimal solution of different objectives simultaneously. Therefore, such a problem can be converted into a multi-objective optimization problem (MOOP). In general, a MOOP with various constraints of equality and inequality can be expressed as follows [64].
*Minimize* :

$$f(y,z) = [f_1(y,z), f_2(y,z), \ldots, f_p(y,z)] \tag{1}$$

*subject to* :
*Inequality constraints*,

$$l_e(y,z) \geq 0, j = 1, 2 \ldots M \tag{2}$$

*Equality constraints*,

$$m_f(y,z) = 0, k = 1, 2 \ldots N \tag{3}$$

where, $y = (y^1, y^2, \ldots, y^n)^T$ shows a vector of independent decision variables and $z = (z^1, z^2 \ldots . z^n)^T$ depicts a vector of dependent variables. Inequality constraints are $l_e$ are M in numbers and equality constraints are $m_f$ which are N in numbers.

### A. OBJECTIVE FUNCTION FOR CONVENTIONAL EED PROBLEM

#### 1) FUEL COST FUNCTION OF THERMAL GENERATOR

Economic dispatch is mainly to minimize the fuel cost of thermal generators with the satisfaction of constraints and power demand of the power system. It is a quadratic function with a single polynomial. Eq. (4) describes the cost function in terms of real power output [65]:

$$F_i(P_i) = \sum_{i=1}^{N_t} (a_i P_{gi}^2 + b_i P_{gi} + c_i) \tag{4}$$

where $F_i(P_i)$ represents the cost of the fuel ($\$/h$) for $i^{th}$ unit, $N_t$ denotes the total generation units that takes part in scheduling, $a_i$, $b_i$ and $c_i$ represents cost coefficients.

#### 2) EMISSION FUNCTION OF THERMAL GENERATOR

The combustion of fossil fuels by conventional thermal generators emits a huge volume of lethal gases like as $CO_2$, $SO_x$, etc. Therefore, the release of these harmful gases from chimneys pollutes the environment. Hence, the role to minimize the emission function is to keep the level of emissions minimum. This emission function can be modeled as a combination of quadratic and exponential terms of generator power and mathematically can be stated as follows [66]:

$$E_i(P_i) = \sum_{i=1}^{N_t} [\alpha_i P_{gi}^2 + \beta_i P_{gi} + \gamma_i] \tag{5}$$

where $\alpha_i$, $\beta_i$, $\gamma_i$ are the coefficients of emission (Kg/h).

### B. OBJECTIVE FUNCTION FOR NON-CONVENTIONAL EED PROBLEM

#### 1) COST FUNCTION OF SOLAR

In most cases of MGs, the operation and control of RESs are the responsibility of some private bodies. As conventional fuel is not required for the operation and production of electricity from RESs. Yet, they define some maintenance and operation charges against their sources. As a result, the independent system operator (ISO) must pay in accordance with the contractually agreed planned power [67]. The output power produced by the solar plant is defined as follows [65]:

$$P_{PV} = PV_{rated} \times (1 + \phi(T_{var} - T_{fixed})) \times I_i \tag{6}$$

where $PV_{rated}$ is rated output power, $T_{fixed}$ denotes fixed temperature, $T_{var}$ represents variable temperature, $\phi$ represents temperature coefficient and $I_i$ is PV radiations incident on

PV panels. The share of solar of 'n' PV plants is defined as follows [68],

$$SolarShare = \sum_{k=1}^{n} (P_{PV_k} \times X_k) \tag{7}$$

where $P_{PV_k}$ denotes power available in $k^{th}$ PV plant and $X_k$ represents the ON/OFF state of $k^{th}$ PV unit, $X_k \in \{0, 1\}$.

From (6), it is obvious that output power generated by PV plant is dependent on $I_i$ and temperature but it is required that the plant must work at its rated power. To obtain the maximum advantage of PV plant, all PV units must be ON i.e. $X_k = 1$ for each $k^{th}$ unit, however the power available at the output varies with PV radiations and temperature, there incurs a penalty cost for each PV unit which is referred as per unit cost of each PV plant.

The operating cost of $k^{th}$ PV plant to generate PV power $P_{PV}$ is expressed in [68] as:

$$F_s(P_{PV}) = \sum_{k=1}^{n} (S_k \times P_{PV_k} \times X_k) \tag{8}$$

where $S_k$ represents the per unit solar cost coefficient. The unit of $S_k$ is given in \$/MWh. The operating cost is associated with each operational PV unit. It is obvious from 8 that operating cost can vary depending on the power output from PV plants and the per-unit cost coefficient of the solar plants [69].

### 2) COST FUNCTION OF WIND

A wind farm with 25 turbines is considered in this paper. Each turbine has a rated output of 3MW. As output power from a wind farm is dependent on wind speed, so as a function of wind speed, the real output power is calculated and is given as [70]:

$$P_w(v) = \begin{cases} 0 & \text{for } v < v_i \ \& \ v > v_o \\ p_{w_{rated}} \left( \dfrac{v - v_i}{v_r - v_i} \right) & \text{for } v_i \le v \le v_r \\ p_{w_{rated}} & \text{for } v_r < v \le v_o \end{cases} \tag{9}$$

where $p_{w_{rated}}$ denotes rated power of the wind turbine and $v_r$, $v$, $v_i$, $v_o$ represents the rated speed of wind, actual speed of wind, cut-in speed of wind and cut-out speed of wind respectively and their values are taken from [17], [24]. Direct cost of wind power from the wind farm as a function of scheduled power is represented as follows [17]:

$$F_w(P_w) = g_w P_w \tag{10}$$

where $g_w$ is the direct cost coefficient and $P_w$ is the actual output power obtained from a wind farm.

## C. CEELD BASED ON PRICE PENALTY FACTOR APPROACH

As mentioned above, the target of a MO-CEELD is to achieve the optimal generation schedule of electrical energy generation sources with the minimization of harmful pollutants. Hence, the cost of electricity generation and emission can be minimized for each ELD interval along with the satisfaction of power system constraints. Nevertheless, the generation cost of RESs is also added to the desired objective as per the cost models of wind and PV. Hence, the overall cost function can be formulated mathematically as:

$$\min G = \sum_{i=1}^{N_g} (F_i(P_i) + E_i(P_i) + F_s(P_{PV}) + F_w(P_w)) \tag{11}$$

where G is objective function to be minimized, $F_i(P_i)$ represents fuel cost, $E_i(P_i)$ denotes the emissions of $i^{th}$ generating unit, $F_s(P_{PV})$ represents the operational cost of solar plant to produce power $P_{(PV)}$ and $F_w(P_w)$ denotes the operational cost of wind plant to produce power $P_{(w)}$.

As discussed earlier, ELD and ED are two separate objectives to optimize. One is to deal with the minimization of the fuel cost of thermal generators, while the other is to minimize the emission volume of exhaust toxic gases. Therefore a compromise solution is required regarding cost and emission minimization.

Although, the thermal generators follow a unique cost and emission characteristics which are taken same from the earlier literature. Therefore, two optimization objectives are formulated to discussed all five study cases, presented later in the paper.

***Objective Function-1:***

Hence, the fuel cost and emission functions have been combined using the PPF is represented as follows:

$$F_T = \sum_{i=1}^{N_g} [F_i(P_i) + k_i E_i(P_i)] \tag{12}$$

where $k_i$ is the price penalty factor for each generator and explained briefly later in this section. The units of $F_T$ is $\$/hr$ and $k_i$ is $\$/Kg$.

## D. MO-CEELD BASED ON MULTI-OBJECTIVE APPROACH

In multi-objective approach, two conflicting objective functions such as cost and emission are optimized simultaneously and Pareto optimal set (POS) will find using the concepts of Pareto-dominance.

***Objective Function-2:***

Hence, MO-CEELD problem can be stated as follows [71]

$$F_T = \sum_{i=1}^{N_g} \min[F_i(P_i), E_i(P_i)] \tag{13}$$

## E. PRICE PENALTY FACTORS PPFs

In this optimization problem, the overall objective function is a bi-objective function combined using the PPF approach. The penalty factor $k_i$ is calculated using the different ratios of both objectives [59].

Equation (11) is converted into a single objective function by using the PPF approach. This approach has been adopted due to its simplicity in implementation. However, the selection of suitable PPF among different objectives is a major problem in this approach. In this study, to avoid this problem of selection of PPF, various types of penalty factors are computed and expressed as the ratio between fuel cost and emission of the corresponding generator in the case of maximum-maximum, maximum-minimum, minimum-minimum and minimum-maximum, respectively as:

$$k_i = \frac{F_i(P_i^{max})}{E_i(P_i^{max})} \tag{14}$$

$$k_i = \frac{F_i(P_i^{max})}{E_i(P_i^{min})} \tag{15}$$

$$k_i = \frac{F_i(P_i^{min})}{E_i(P_i^{min})} \tag{16}$$

$$k_i = \frac{F_i(P_i^{min})}{E_i(P_i^{max})} \tag{17}$$

where $F_i(P_i^{max})$ and $F_i(P_i^{min})$ is the maximum and minimum value of fuel cost respectively. While $E_i(P_i^{max})$ and $E_i(P_i^{min})$ is the maximum and minimum value of emission for the $i^{th}$ generator. The computed values of $k_i$ is given in Table 5.

### F. CONSTRAINTS OF MO-CEELD PROBLEM

Constraints are the limits on how much power may be produced in a given amount of time. The cost is kept as low as possible while considering all of the constraints because ignoring these constraints will result in non optimal solutions. In this research, the following constraints are taken into account.

#### 1) EQUALITY CONSTRAINTS

Equality constraints are considered as power-demand balance constraints, such that the generated power at any instant must equal the sum of load demand and real power loss of the system. Mathematically, can be expressed as [59],

$$P_{gen,i} = P_{load} + P_l \tag{18}$$

where $P_{gen,i}$ is the real power generated at $i^t h$ interval, $P_{load}$ load demand of consumers and $P_l$ is the real power loss of transmission network. In this research we are considering loss less transmission system.

#### 2) INEQUALITY CONSTRAINT

Inequality constraints are the limits on minimum and maximum power generation of generation sources. Therefore, generated power of thermal as well as wind and PV must lie between the maximum and minimum values [59].

*Thermal generators real power limits:*

$$P_{gen,i}^{min} \leq P_{gen,i} \leq P_{gen,i}^{max} \tag{19}$$

*Solar real power limits:*

$$P_{PV,i}^{min} \leq P_{PV,i} \leq P_{PV,i}^{max} \tag{20}$$

*Wind real power limits:*

$$P_{W,i}^{min} \leq P_{W,i} \leq P_{W,i}^{max} \tag{21}$$

## IV. THEORY OF FPA

FPA was created by Yang in 2012 and influenced by the pollination process found in flowering plants. To solve problems of CEELD, this paper used the approach of FPA. Reproduction through pollination is the foremost aim of a flower. Flower pollination is tied up with the shift of pollens, which is commonly related to pollinators. The process of pollination takes place in two forms, the first is abiotic and the second is biotic. The biotic pollination process is used by most of the flowering plants in which pollens depend on pollinators to be transferred. Such flowering plants get assistance from the wind and diffusion in the process of pollination. Self-pollination and cross-pollination are the two ways to carry out the pollination process. The form of pollination in which the pollen grains are transferred from the male anther to the female stigma of the same flower is called self-pollination. The form of pollination in which pollen grains of the male anther of one flower is transferred to the female stigma of the other flower is called cross-pollination. The goal of flower pollination is to make possible the survival of the fittest and the flawless reproduction of the plants. This process can be thought of as the expansion process of plant species. All of these elements and operations of pollination produced the highest reproduction of the flowering plants. FPA progresses in the following way:

**Step 1:**

Biotic and cross-pollination can be viewed as processes of universal pollination and pollinators that are carrying pollen progress in a way that follows Levy flights [72].

**Step 2:**

For local pollination, abiotic and self pollination process are considered [72].

**Step 3:**

Flower constancy is defined as the chance of reproduction being proportionate to the resemblance of the two flowers involved [72].

**Step 4:**

The shifting between local pollination to global pollination or vice versa is controlled by a probability switch $p \in [0, 1]$ [72].

The rules mentioned above have to be transformed into actual updating equations. For example, pollinators such as insects or birds carry flower pollen gametes over a large distance since insects can frequently fly and in a much longer range. Accordingly, rule 1 and rule 3 can be stated mathematically as follows [60],

$$x_i^{t+1} = x_i^t + \gamma L(\lambda)(m_* - x_i^t) \tag{22}$$

where $m_*$ is current best solution, $x_i^t$ is pollen $i$ at iteration $t$. Here, $\gamma$ is a scaling factor to control the step size. The parameter $L(\lambda)$ relates to the strength of the pollination and it should be greater than zero. Since insects can move over vast distances with varying distance steps, a levy flight can be utilised to effectively replicate this behaviour i.e. $L > 0$ is drawn from a Levy distribution as follows [60]:

$$L = \frac{\lambda\Gamma(\lambda)\sin(\pi\lambda/2)}{\pi}\frac{1}{s^{1+\lambda}}, (s \gg s_0 > 0) \tag{23}$$

Here $\Gamma(\lambda)$ is the standard gamma distribution and only applicable for large steps $s > 0$.

For the mathematical modeling of local pollination, both Rule 2 and Rule 3 can be stated as follows [60]:

$$x_i^{t+1} = x_i^t + \epsilon(x_j^t - x_k^t) \tag{24}$$

where $x_j^t$ and $x_k^t$ in 24 represents the pollen from various flowers of the same plant species. For a random local walk $x_j^t$ and $x_k^t$ comes from the same species then $\epsilon$ is drawn from a uniform distribution as [0,1].

In theory, pollination can take place at any scale. Local flower pollen is more likely to fertilize nearby flower than those who are far away. To do this, a switch probability (Step 4) can be used to switch between local and global pollination. One can begin by using the naive value of $p = 0.5$. According to a preliminary parameterization, $p = 0.8$ would be preferable for the majority of applications. [72]

## V. MULTI-OBJECTIVE FPA

In this section, the FPA approach is extended to solve the multi-objective optimization problems. In this approach a Pareto-optimal categorizing mechanism and fuzzy-based clustering mechanism are to be adopted to find the BCS of highly complex MO-CEELD problems.

### A. PARETO OPTIMAL CATEGORIZING METHOD

As there is only one objective in a single-objective problem, there is only one solution. Secondly, relational operators like $<$, $\leq$, $>$ or $\geq$ make it simple to compare solutions. However, when comparing solutions to multi objectives, relational operators are ineffective, because several objectives are taken into account in a multi-objective problem, so there is no single ideal solution. The solution to a multi-objective problem is a set of answers that comprises the best trade-offs between objectives. For minimization problems, the most popular operator in the literate is Pareto optimal dominance, which is defined mathematically as [24]:

$$\forall i \in \{1, 2, \ldots, m\} : f_i(y_1, z) \leq f_i(y_2, z)$$
$$\exists i \in \{1, 2, \ldots, m\} : f_i(y_1, z) < f_i(y_2, z)$$

This equation indicates that a solution in multi-objective search space is better than another if it is equal in all objectives and better in at least one of them. Pareto optimum dominance is denoted with $\prec$ and $\succ$. Solutions can be easily compared and discriminated using these two operators. When using Pareto dominance, Pareto optimality refers to the best solutions. Non-dominated solutions are another name for them. Every multi-objective problem has a set of best non-dominated solutions known as the real Pareto optimum solution set (POSS). This set is mathematically defined as follows [73]:

$$POSS = \{y, z \in R \mid \nexists y \prec z\} \tag{25}$$

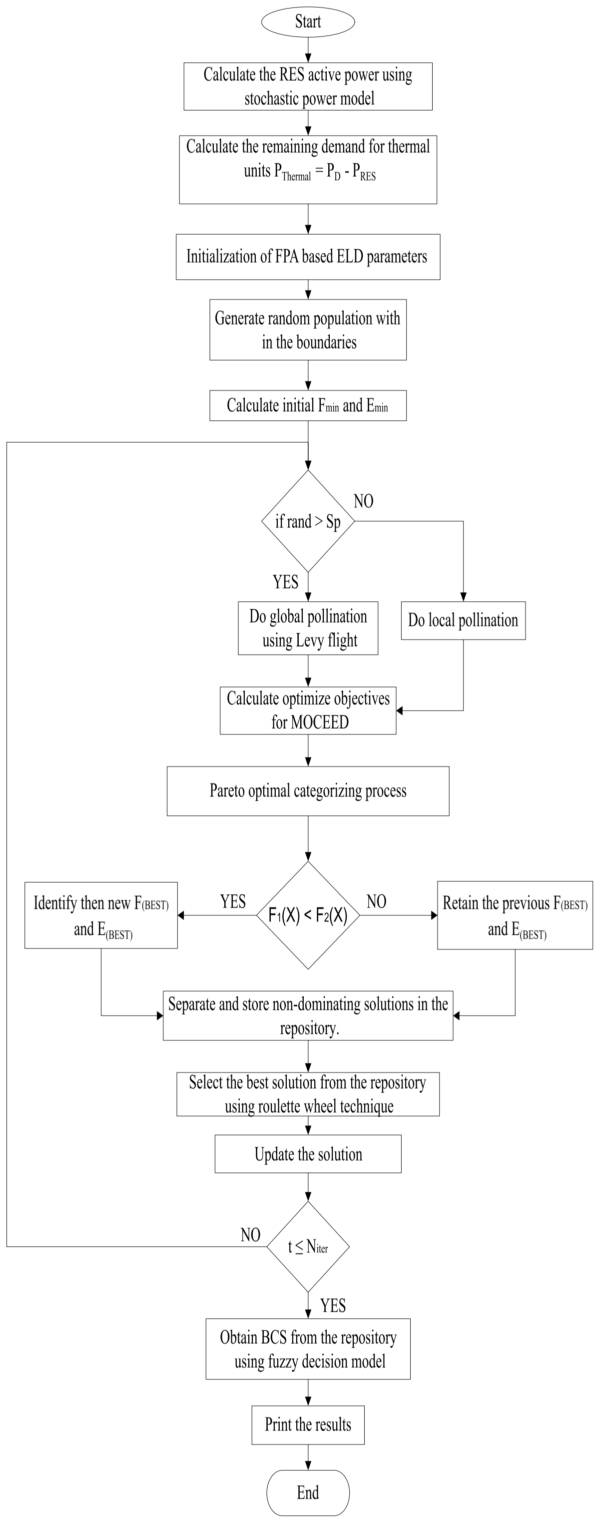


**FIGURE 2.** FPA-based multi-objective CEELD process chart.

POSS is the Pareto optimal solution set, while $R$ denotes a set of solutions. The Pareto optimum solution set, according to 25, is a set in which no solution is dominated by another which means all of the solutions in this collection are non-dominated. Finding this non-dominating set is the

**Algorithm 1** FPA-Based Multi-Objective CEELD Pseudocode

Initialize the parameters for CEELD problem.
Total Demand, cost and emission coefficients and limits of decision variables.
Initialize PV and Wind plant parameters and operation status.
Calculate the available PV power using stochastic equations and solar profile.
Calculate the available wind power using stochastic equations and wind speed profile.
Calculate the part of conventional thermal generators in total demand.
Initializing the FPA-based CEELD parameters as given in Table 4.
Initialization of bounded population matrix of $15 \times 40$.
Minimization of objective function ($F_{min}$) from the fitness vector.
Find the initial best solution (best) from the initial population.
**while** $t \le T_{max}$ **do**
    **for** $i = 1 : n$ **do**
        **if** $rand > S_p$ **then**
            Make a vector $L_d$ that obey levy distribution using Eq (23).
            Calculate the step increment.
            Global pollination using eq (22)
        **else**
            Drawing $\epsilon$ from uniform distribution.
            Do local pollination using Eq (24)
        **end if**
        **if** $LB \le pop \le UB$ **then**
            Calculate the fitness of each objective.
        **else**
            Limit the pollinators within their define bonds.
        **end if**
        Evaluate fitness of each objective.
        **if** Fitness better **then**
            Update the population.
        **end if**
        Perform fast non-dominating sorting.
        Update the repository based on crowding distance and then rank the solutions.
    **end for**
**end while**
Extract the best trade-off solution.
Print the best-fit dispatch schedule.
**end**

primary goal of a multi-objective optimization problem. Pareto front (PF) is the set of these non-dominating solutions.

### B. FUZZY BASED CLUSTERING MECHANISM

A fuzzy decision model is proposed in order to obtain BCS from a non-dominated Pareto-front solution. The linear membership function $\beta_i^k$ is introduced for every solution in $j^{th}$ Pareto-front and defined as follows [74]:

$$\beta_i^j = \begin{cases} 1 & \text{for } f_i \le f_i^{min} \\ \dfrac{f_i^{max} - f_i}{f_i^{max} - f_i^{min}} & \text{for } f_i^{min} < f_i < f_i^{max} \\ 0 & \text{for } f_i \ge f_i^{max} \end{cases} \tag{26}$$

where $f_i^{min}$ and $f_i^{max}$ are the objective function's minimum and maximum values respectively and $j$ is the unique non-dominating solution in the Pareto front space. The preference value of each non dominating solution $j$ can be calculated using normalized membership value $\mu_k$ and is represented as follows [74]:

$$\mu_k = \frac{\sum_{i=1}^{m} \mu_i^k}{\sum_{k=1}^{S_{nd}} \sum_{i=1}^{m} \mu_i^k} \tag{27}$$

where $S_{nd}$ denotes total number of non-dominating solutions in a solution set. The highest value of the $\mu_k$ will have the BCS.

**TABLE 1.** Study cases.

| Cases | Scenario |
|---|---|
| Case 1 | Single objective optimization with RES |
| Case 2 | Single objective optimization without RES |
| Case 3 | Bi-objective optimization using PPF |
| Case 4 | Multi-objective optimization with RES |
| Case 5 | Multi-objective optimization without RES |

## VI. PROPOSED FPA BASED OPTIMIZATION APPROACH

This section discusses the computational flow of the suggested approach. The algorithms that are discussed in the literature review section have their limitations while finding the global solution of the MO-CEELD problem, so there always exists a research gap for the new algorithm to find best optimal solution. Also, the CEELD with the intervention of RESs is a challenging optimization problem. Random decision variables are continuous in thermal generators. Random decision variables for solar or wind power plants are binary, with a value of either 0 or 1. A novel approach will be developed to find the best-compromised solution of two conflicting objectives of the power system i.e., cost and emission minimization. In this work, we will find the global optimal solution of the MO-CEELD problem using a novel FPA. Firstly, we will calculate the stochastic power from the solar and wind plant by considering their power models. This provides information that how much of the total demand is fulfilled by renewable sources. After this, the remaining demand is fulfilled by thermal generators in optimal manner to reduce the overall price of generation. Then emission function of each generator is calculated from the optimal values of the generation units. The penalty factor approach will be used to combine the two conflicting objectives and finally the optimal value of the objective function is calculated for the said demand. After this, both objectives are simultaneously optimized using MO-FPA technique and

**TABLE 2.** Cost and emission coefficients of thermal generators [75], [76].

| Thermal Generators | Pmin (MW) | Pmax (MW) | a ($/MW$^2$) | b ($/MW) | c ($) | $\alpha$ (Kg/MW$^2$h) | $\beta$ (Kg/MWh) | $\gamma$ (Kg/h) |
|---|---|---|---|---|---|---|---|---|
| G1 | 150 | 455 | 0.000299 | 10.1 | 671 | 0.0296 | -4.18 | 300 |
| G2 | 150 | 455 | 0.000183 | 10.2 | 574 | 0.0512 | -3.34 | 520 |
| G3 | 20 | 130 | 0.001126 | 8.8 | 374 | 0.0496 | -3.55 | 510 |
| G4 | 20 | 130 | 0.001126 | 8.8 | 374 | 0.0496 | -3.55 | 510 |
| G5 | 150 | 470 | 0.000205 | 10.4 | 461 | 0.0151 | -2.68 | 220 |
| G6 | 135 | 460 | 0.000301 | 10.1 | 630 | 0.0151 | -2.66 | 222 |
| G7 | 135 | 465 | 0.000364 | 9.8 | 548 | 0.0151 | -2.68 | 220 |
| G8 | 60 | 300 | 0.000338 | 11.2 | 227 | 0.0151 | -2.68 | 220 |
| G9 | 25 | 162 | 0.000807 | 11.2 | 173 | 0.0145 | -2.22 | 290 |
| G10 | 25 | 160 | 0.001203 | 10.7 | 175 | 0.0145 | -2.22 | 285 |
| G11 | 20 | 80 | 0.003586 | 10.2 | 186 | 0.0138 | -2.26 | 295 |
| G12 | 20 | 80 | 0.005513 | 9.9 | 230 | 0.0138 | -2.26 | 295 |
| G13 | 25 | 85 | 0.000371 | 13.1 | 225 | 0.0132 | -2.42 | 310 |
| G14 | 15 | 55 | 0.001929 | 12.1 | 309 | 0.0132 | -2.42 | 310 |
| G15 | 15 | 55 | 0.004447 | 12.4 | 323 | 1.842 | -1.11 | 360 |

**TABLE 3.** Load variations for 24 hours [77].

| T(h) | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| Load(MW) | 1650 | 1680 | 1680 | 1700 | 1700 | 1700 |
| T(h) | 7 | 8 | 9 | 10 | 11 | 12 |
| Load(MW) | 2000 | 2000 | 2500 | 2500 | 2700 | 2800 |
| T(h) | 13 | 14 | 15 | 16 | 17 | 18 |
| Load(MW) | 2900 | 3000 | 3000 | 3000 | 3000 | 2800 |
| T(h) | 19 | 20 | 21 | 22 | 23 | 24 |
| Load(MW) | 2500 | 2000 | 1800 | 1750 | 1700 | 1700 |

**TABLE 4.** Control parameter setting.

| **Parameters** | **Value** |
|---|---|
| Total number of iterations | 2000 |
| Switch probability | 0.8 |
| Population size | 40 |
| Step size parameter $\lambda$ | 1.5 |
| Step size scaling factor $\gamma$ | 0.01 |
| Uniform distribution $\epsilon$ | [0,1] |
| Temperature coefficient $\phi$ | -0.0025 |
| Ambient temperature | 25°C |

**TABLE 5.** Computed PPFs.

| **PPF Type** | **Min-Min** | **Max-Max** | **Min-Max** | Max-Min |
|---|---|---|---|---|
| $k_1$ | 6.468223 | 1.177276 | **0.484469** | 15.718 |
| $k_2$ | 1.800271 | 0.547177 | **0.219596** | 4.485812 |
| $k_3$ | 1.199657 | 1.733348 | **0.620757** | 3.349816 |
| $k_4$ | 1.199657 | 1.733348 | **0.620757** | 3.349816 |
| $k_5$ | 12.84065 | 2.349437 | **0.882239** | 34.19515 |
| $k_6$ | 14.47518 | 2.434258 | **0.911297** | 38.6661 |
| $k_7$ | 14.07548 | 2.315397 | **0.83868** | 38.85909 |
| $k_8$ | 7.927235 | 4.667639 | **1.16157** | 31.8547 |
| $k_9$ | 1.861963 | 6.460572 | **1.458692** | 8.246667 |
| $k_{10}$ | 1.858012 | 6.371418 | **1.472598** | 8.03897 |
| $k_{11}$ | 1.533113 | 5.060984 | **1.932818** | 4.014376 |
| $k_{12}$ | 1.684965 | 5.220636 | **2.12426** | 4.141012 |
| $k_{13}$ | 2.14445 | 6.716985 | **2.768227** | 5.203416 |
| $k_{14}$ | 1.774439 | 4.521216 | **2.264143** | 3.543338 |
| $k_{15}$ | 0.673002 | 0.173472 | **0.086868** | 1.343959 |

a set of non-dominating solutions are obtained using Pareto optimal categorizing process and PF curve is plotted. After this fuzzy clustering mechanism is used to find the BCS from POSS. Figure 2 shows the flow chart of the proposed technique and pseudo-code is shown in Algorithm 1.

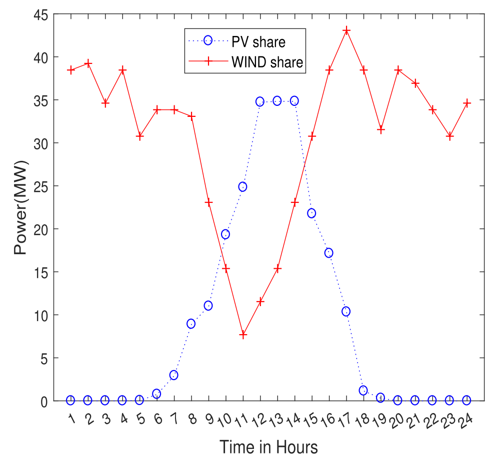


**FIGURE 3.** RE share.

## VII. RESULTS AND DISCUSSION

To prove the prominence of the proposed FPA, four study cases are investigated on a high dimensional system consisting of fuel-based thermal generating units along with the intervention of RESs. To validate the effectiveness, efficiency and robustness of the proposed MOFPA, it has been compared with other population based metaheuristic approaches which have already been investigated by other authors in literature using MATLAB 2017a on an Intel core i5 processor with 6 GB RAM. Furthermore, simulation parameters used in the MATLAB program are specifically defined and have not been changed unless mentioned. Parameter settings for FPA and solar plants are presented in Table 4. Furthermore, simulation parameters used in the MATLAB program are specifically defined and have not been changed unless mentioned. Parameters are adjusted several times to find ideal combinations.

**TABLE 6.** Generation sources schedule with RES.

| Time (h) | P1 (MW) | P2 (MW) | P3 (MW) | P4 (MW) | P5 (MW) | P6 (MW) | P7 (MW) | P8 (MW) | P9 (MW) | P10 (MW) | P11 (MW) | P12 (MW) | P13 (MW) | P14 (MW) | P15 (MW) | Wind (MW) | Solar (MW) | Emission (Kg/h) | Cost ($/h) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1.0 | 180.4 | 150.2 | 130.0 | 130.0 | 150.0 | 194.6 | 465.0 | 60.0 | 25.0 | 25.0 | 20.1 | 26.2 | 25.0 | 15.0 | 15.0 | 38.5 | 0.0 | 8517.0 | 21801.4 |
| 2.0 | 204.9 | 150.0 | 130.0 | 130.0 | 150.0 | 196.6 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 29.3 | 25.0 | 15.0 | 15.0 | 39.2 | 0.0 | 8693.6 | 22101.2 |
| 3.0 | 209.0 | 150.0 | 130.0 | 130.0 | 150.0 | 198.8 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 27.6 | 25.0 | 15.0 | 15.0 | 34.6 | 0.0 | 8736.6 | 22141.0 |
| 4.0 | 206.8 | 150.0 | 130.0 | 130.0 | 150.0 | 214.9 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 29.8 | 25.0 | 15.0 | 15.0 | 38.5 | 0.0 | 8773.2 | 22312.3 |
| 5.0 | 213.0 | 150.3 | 130.0 | 130.0 | 150.0 | 216.3 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 29.6 | 25.0 | 15.0 | 15.0 | 30.8 | 0.0 | 8834.3 | 22378.3 |
| 6.0 | 217.9 | 150.0 | 130.0 | 130.0 | 150.0 | 208.9 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 28.6 | 25.0 | 15.0 | 15.0 | 33.8 | 0.8 | 8846.1 | 22345.6 |
| 7.0 | 321.9 | 238.4 | 130.0 | 130.0 | 150.0 | 307.8 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 35.2 | 25.0 | 15.0 | 15.0 | 33.8 | 2.9 | 12034.1 | 25405.4 |
| 8.0 | 308.2 | 239.7 | 130.0 | 130.0 | 150.0 | 314.5 | 465.0 | 60.0 | 25.0 | 25.0 | 20.3 | 35.3 | 25.0 | 15.0 | 15.0 | 33.1 | 8.9 | 11908.0 | 25360.2 |
| 9.0 | 451.2 | 454.6 | 130.0 | 130.0 | 150.0 | 454.0 | 465.0 | 60.0 | 25.0 | 25.0 | 24.3 | 41.8 | 25.0 | 15.0 | 15.0 | 23.1 | 11.0 | 22680.9 | 30593.3 |
| 10.0 | 453.9 | 454.0 | 130.0 | 130.0 | 150.0 | 450.7 | 465.0 | 60.0 | 25.0 | 25.0 | 24.0 | 42.7 | 25.0 | 15.0 | 15.0 | 15.4 | 19.3 | 22679.4 | 30588.0 |
| 11.0 | 455.0 | 455.0 | 130.0 | 130.0 | 304.5 | 460.0 | 465.0 | 60.0 | 25.0 | 25.0 | 46.2 | 56.8 | 25.0 | 15.0 | 15.0 | 7.7 | 24.8 | 23454.8 | 32703.0 |
| 12.0 | 455.0 | 455.0 | 130.0 | 130.0 | 385.2 | 460.0 | 465.0 | 60.0 | 25.0 | 25.0 | 51.0 | 57.5 | 25.0 | 15.0 | 15.0 | 11.5 | 34.7 | 24074.6 | 33634.3 |
| 13.0 | 455.0 | 455.0 | 130.0 | 130.0 | 469.6 | 460.0 | 465.0 | 60.0 | 25.0 | 25.0 | 58.1 | 62.1 | 25.0 | 15.0 | 15.0 | 15.4 | 34.8 | 24929.3 | 34656.6 |
| 14.0 | 455.0 | 455.0 | 130.0 | 130.0 | 470.0 | 460.0 | 465.0 | 60.0 | 25.0 | 77.1 | 80.0 | 80.0 | 25.0 | 15.0 | 15.0 | 23.1 | 34.8 | 24881.7 | 35662.5 |
| 15.0 | 455.0 | 455.0 | 130.0 | 130.0 | 470.0 | 460.0 | 465.0 | 60.0 | 25.0 | 82.5 | 80.0 | 80.0 | 25.0 | 15.0 | 15.0 | 30.8 | 21.7 | 24882.6 | 35712.5 |
| 16.0 | 455.0 | 455.0 | 130.0 | 130.0 | 470.0 | 460.0 | 465.0 | 60.0 | 25.0 | 79.6 | 79.9 | 80.0 | 25.0 | 15.0 | 15.0 | 38.5 | 17.1 | 24882.3 | 35683.8 |
| 17.0 | 455.0 | 455.0 | 130.0 | 130.0 | 470.0 | 460.0 | 465.0 | 60.0 | 25.0 | 81.6 | 80.0 | 80.0 | 25.0 | 15.0 | 15.0 | 43.1 | 10.3 | 24882.6 | 35704.2 |
| 18.0 | 455.0 | 455.0 | 130.0 | 130.0 | 390.1 | 460.0 | 465.0 | 60.0 | 25.0 | 25.0 | 50.4 | 59.8 | 25.0 | 15.0 | 15.0 | 38.5 | 1.1 | 24117.9 | 33693.9 |
| 19.0 | 454.6 | 455.0 | 130.0 | 130.0 | 150.0 | 450.0 | 465.0 | 60.0 | 25.0 | 25.0 | 25.0 | 43.6 | 25.0 | 15.0 | 15.0 | 31.5 | 0.3 | 22727.1 | 30613.0 |
| 20.0 | 316.6 | 228.2 | 130.0 | 130.0 | 150.0 | 320.5 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 36.2 | 25.0 | 15.0 | 15.0 | 38.5 | 0.0 | 11832.7 | 25390.8 |
| 21.0 | 265.5 | 150.0 | 130.0 | 130.0 | 150.0 | 256.3 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 31.2 | 25.0 | 15.0 | 15.0 | 36.9 | 0.0 | 9531.0 | 23349.7 |
| 22.0 | 238.3 | 150.0 | 130.0 | 130.0 | 150.0 | 237.0 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 30.9 | 25.0 | 15.0 | 15.0 | 33.8 | 0.0 | 9147.2 | 22863.9 |
| 23.0 | 217.8 | 150.0 | 130.0 | 130.0 | 150.0 | 209.6 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 31.9 | 25.0 | 15.0 | 15.0 | 30.8 | 0.0 | 8842.6 | 22378.7 |
| 24.0 | 210.6 | 150.0 | 130.0 | 130.0 | 150.0 | 215.7 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 29.1 | 25.0 | 15.0 | 15.0 | 34.6 | 0.0 | 8808.7 | 22345.5 |
| **Total Emission (Kg/day)** | | | | | | | | | | | | | | | | | | **388698.2** | |
| **Total Generation Cost ($/day)** | | | | | | | | | | | | | | | | | | | **669418.8** |

**TABLE 7.** Generation sources scheduling without RES.

| Time (h) | P1 (MW) | P2 (MW) | P3 (MW) | P4 (MW) | P5 (MW) | P6 (MW) | P7 (MW) | P8 (MW) | P9 (MW) | P10 (MW) | P11 (MW) | P12 (MW) | P13 (MW) | P14 (MW) | P15 (MW) | Emission (Kg/h) | Cost ($/h) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1.0 | 204.1 | 150.0 | 130.0 | 130.0 | 150.0 | 207.3 | 465.0 | 60.0 | 25.0 | 25.0 | 20.1 | 28.6 | 25.0 | 15.0 | 15.0 | 8724.7 | 22132.8 |
| 2.0 | 221.4 | 150.0 | 130.0 | 130.0 | 150.0 | 220.4 | 464.9 | 60.0 | 25.0 | 25.0 | 20.0 | 28.2 | 25.0 | 15.0 | 15.0 | 8921.2 | 22439.6 |
| 3.0 | 222.7 | 150.3 | 130.0 | 130.0 | 150.0 | 217.2 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 29.8 | 25.0 | 15.0 | 15.0 | 8921.1 | 22439.6 |
| 4.0 | 226.0 | 150.0 | 130.0 | 130.0 | 150.0 | 233.2 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 30.7 | 25.0 | 15.0 | 15.0 | 9013.5 | 22644.3 |
| 5.0 | 233.3 | 150.0 | 130.0 | 130.0 | 150.0 | 226.4 | 465.0 | 60.0 | 25.0 | 25.0 | 20.1 | 30.3 | 25.0 | 15.0 | 15.0 | 9052.7 | 22644.3 |
| 6.0 | 228.6 | 150.0 | 130.0 | 130.0 | 150.0 | 230.4 | 465.0 | 60.0 | 25.0 | 25.0 | 20.1 | 30.9 | 25.0 | 15.0 | 15.0 | 9024.5 | 22644.3 |
| 7.0 | 319.7 | 257.7 | 130.0 | 130.0 | 150.0 | 328.5 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 34.2 | 25.0 | 15.0 | 15.0 | 12572.5 | 25725.0 |
| 8.0 | 327.0 | 255.1 | 130.0 | 130.0 | 150.0 | 323.0 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 34.8 | 25.0 | 15.0 | 15.0 | 12583.5 | 25725.0 |
| 9.0 | 455.0 | 455.0 | 130.0 | 130.0 | 153.0 | 459.9 | 465.0 | 60.0 | 25.0 | 25.0 | 36.1 | 50.9 | 25.0 | 15.0 | 15.0 | 22829.6 | 30893.5 |
| 10.0 | 455.0 | 455.0 | 130.0 | 130.0 | 150.0 | 459.9 | 464.9 | 60.0 | 25.0 | 25.0 | 39.0 | 51.0 | 25.0 | 15.0 | 15.0 | 22820.3 | 30893.5 |
| 11.0 | 454.9 | 455.0 | 130.0 | 130.0 | 334.7 | 460.0 | 465.0 | 60.0 | 25.0 | 25.0 | 46.6 | 58.8 | 25.0 | 15.0 | 15.0 | 23662.4 | 32993.5 |
| 12.0 | 454.9 | 454.9 | 130.0 | 130.0 | 426.3 | 460.0 | 465.0 | 60.0 | 25.0 | 25.0 | 51.8 | 62.1 | 25.0 | 15.0 | 15.0 | 24456.7 | 34049.1 |
| 13.0 | 455.0 | 455.0 | 130.0 | 130.0 | 470.0 | 460.0 | 465.0 | 60.0 | 25.0 | 35.8 | 80.0 | 79.2 | 25.0 | 15.0 | 15.0 | 24906.4 | 35113.6 |
| 14.0 | 455.0 | 455.0 | 130.0 | 130.0 | 470.0 | 460.0 | 464.9 | 60.0 | 25.0 | 135.0 | 80.0 | 80.0 | 25.0 | 15.0 | 15.0 | 24931.7 | 36203.9 |
| 15.0 | 455.0 | 455.0 | 130.0 | 130.0 | 470.0 | 460.0 | 465.0 | 60.0 | 25.1 | 134.9 | 80.0 | 80.0 | 25.0 | 15.0 | 15.0 | 24931.5 | 36203.9 |
| 16.0 | 455.0 | 455.0 | 130.0 | 130.0 | 470.0 | 460.0 | 465.0 | 60.0 | 25.0 | 135.0 | 80.0 | 80.0 | 25.0 | 15.0 | 15.0 | 24930.6 | 36203.9 |
| 17.0 | 455.0 | 455.0 | 130.0 | 130.0 | 470.0 | 460.0 | 465.0 | 60.1 | 25.0 | 134.9 | 80.0 | 80.0 | 25.0 | 15.0 | 15.0 | 24932.0 | 36203.9 |
| 18.0 | 455.0 | 455.0 | 130.0 | 130.0 | 425.9 | 460.0 | 465.0 | 60.0 | 25.0 | 25.0 | 54.3 | 59.8 | 25.0 | 15.0 | 15.0 | 24459.1 | 34049.1 |
| 19.0 | 455.0 | 455.0 | 130.0 | 130.0 | 151.4 | 460.0 | 465.0 | 60.0 | 25.0 | 25.1 | 38.4 | 50.1 | 25.0 | 15.0 | 15.0 | 22825.6 | 30893.5 |
| 20.0 | 326.1 | 255.0 | 130.0 | 130.0 | 150.0 | 323.0 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 35.8 | 25.0 | 15.0 | 15.0 | 12565.9 | 25725.0 |
| 21.0 | 269.2 | 167.6 | 130.0 | 130.0 | 150.0 | 268.7 | 464.9 | 60.0 | 25.0 | 25.0 | 20.1 | 34.4 | 25.0 | 15.0 | 15.0 | 9862.5 | 23669.4 |
| 22.0 | 247.5 | 150.0 | 130.0 | 130.0 | 150.0 | 260.5 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 32.0 | 25.0 | 15.0 | 15.0 | 9353.4 | 23156.6 |
| 23.0 | 229.9 | 150.0 | 130.0 | 130.0 | 150.0 | 230.0 | 465.0 | 60.0 | 25.0 | 25.0 | 20.2 | 30.0 | 25.0 | 15.0 | 15.0 | 9035.9 | 22644.3 |
| 24.0 | 229.3 | 150.8 | 130.0 | 130.0 | 150.0 | 228.4 | 465.0 | 60.0 | 25.0 | 25.0 | 20.0 | 31.5 | 25.0 | 15.0 | 15.0 | 9031.6 | 22644.3 |
| | | | | | | | | | | | | | | | **Total Emission (Kg/day)** | **394349.0** | |
| | | | | | | | | | | | | | | | **Total Generation Cost ($/day)** | | **677935.94** |

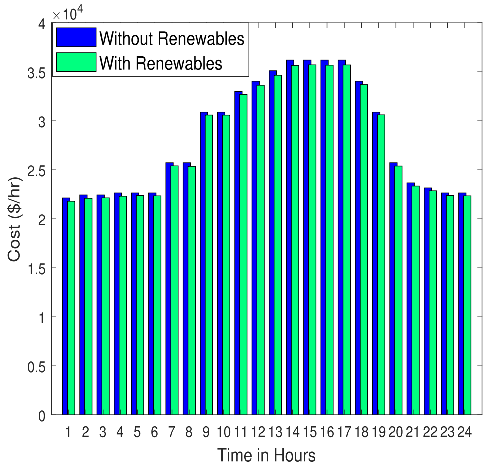


**FIGURE 4.** Cost offered with and without renewables.

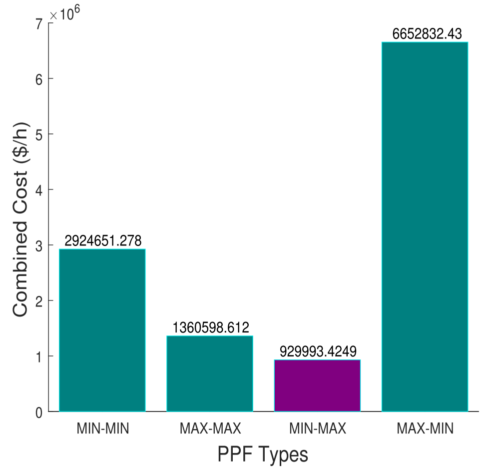


**FIGURE 5.** Comparison of different PPF.

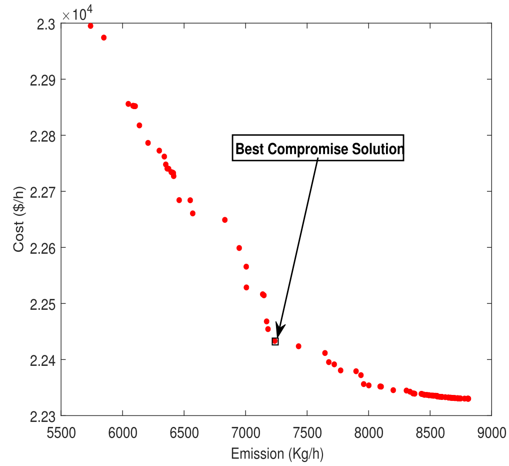


**FIGURE 6.** Pareto front with RES.

The study cases that are used to testify the performance of the proposed algorithm are discussed in Table 1.

### A. TEST SYSTEMS

The test system model used in this study consists of high dimensional 15 thermal generators having non-convex fuel cost curves, 13 PV units and a wind farm of 75 MW. The input data of cost and emission for thermal units along with the maximum and minimum power limits has been taken from [75] and [76] respectively and is presented in the Table 2. Table 3 shows the load variation for a complete 24 hour period [77]. The renewable share forecasting over a complete 24 hours is shown in Fig 3. The power ratings and per-unit costs of different PV units used in this research are taken from [65]. In this work, PV plants are considered to be operated from 5:00 to 17:00 h. The switching status of solar units and data for a wind farm is taken from [69]. Price penalty factors for this system are computed using equations (14-17) and are presented in Table 5.

#### 1) CASE 1

To verify the computational performance and efficacy of the proposed FPA for the identification of total cost and total emission in the presence of RESs for a 24-h dispatch period, simulations have been executed and are presented in Table 6. In this case, cost and emission objectives are treated independently. It is clear from the results that all constraints are well satisfied and all generators are operating within the limits while satisfying the load demand of that particular hour. The optimal fuel cost along with optimal emission obtained by FPA is 669418.8 $\$/day$ and 388698.2 $Kg/day$ respectively.

#### 2) CASE 2

In this case, simulations have been carried out by considering the cost and emission objectives independently and the demand is fulfilled by thermal generators only. Simulation results in terms of operating cost and emissions for a 24-h period are shown in Table 7. It can be seen from the results that the proposed algorithm is well behaved with no constraints violation. The total operating cost for the 24 h dispatch period is 677935.94 $/day and the total emission is 39439.0 $Kg/day$. The results from the Tables 6 and 7 depict that RESs integration not only saves the overall cost, but also the emission levels are minimized. There is a saving of $\mathbf{8517.14\ \$/day}$ and $\mathbf{5650.8\ Kg/day}$. Reduction in cost and emission is due to the integration of nature friendly RESs and this is shown in Figure 4 clearly.

#### 3) CASE 3

In this case study cost function and emission function are converted into a single objective function using Equation 12. Simulation results in terms of total operating cost by using different types of PPF are shown in Figure 5. It is clear from the results that Min-Max PPF yields the best result i.e. $\mathbf{929993.4\ \$/day}$.

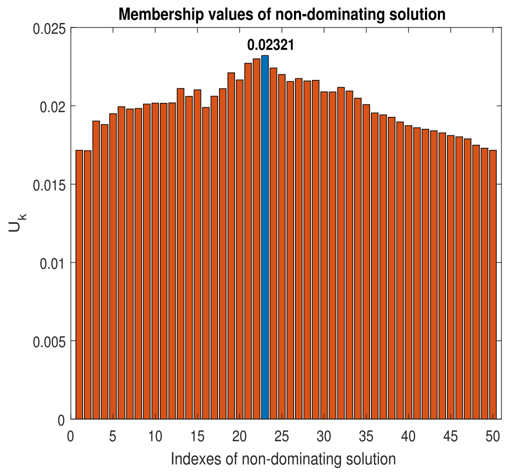


**FIGURE 7.** Membership values against non-dominating solutions with RES.

#### 4) CASE 4

In this case, the CEELD objectives are treated simultaneously in the presence of RESs and are solved by MOFPA approach. The Pareto dominance concept is employed to determine POSS and then external depository archive is used to store non-dominating solutions from POSS. Furthermore, a triangular fuzzy clustering mechanism is used to find the BCS. Pareto front curve and BCS computed by the suggested algorithm is shown in Figure 6. It is clear that the compromised cost is $2.2432 \times 10^4$ $\$/h$ and the total emission is 7240.8 $Kg/h$. Hence, the membership values against the BCS is plotted in Figures 7. Here, the highest value of the membership function shows that the BCS lies at the knee of the PF curve.

#### 5) CASE 5

In this case, PF is plotted in Figure 8 to show the conflicting nature of objectives of CEELD problem without the intervention of RESs. The figure shows that there is a trade-off between the required objectives. Furthermore, a fuzzy clustering mechanism is used to extract the BCS from the non-dominating solutions. The BCS obtained by the proposed approach is $3.52436 \times 10^4$ $\$/h$ and $1.90658 \times 10^4$ $Kg/h$. Further, the membership values against the BCS is plotted in Figure 9.

### B. CHARACTERISTICS OFFERED BY FPA

Figures 10–13 show different characteristics of FPA for selected test cases. The algorithm has been run as per parameters defined in Table 4. Figures 10-11 show the position of pollinators at the start and after 2000 iterations, respectively. As clear from the results that pollinators start at a random position and converge to the optimal solution after 2000 iterations. Also almost all the pollinators advanced towards the best solution, signifying that the solution is much closer to a global solution. Figures 12-13 shows the convergence characteristics offered by FPA. As clear from the convergence characteristics curve the fitness (cost) value decreases gradually as the iterations proceeds. It increases the probability of the solution approaching the global best position.

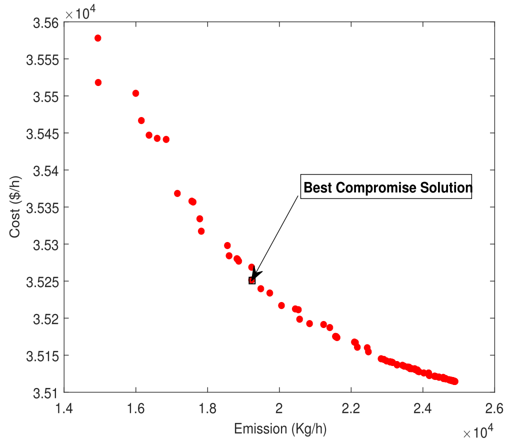


**FIGURE 8.** Pareto front without RES.

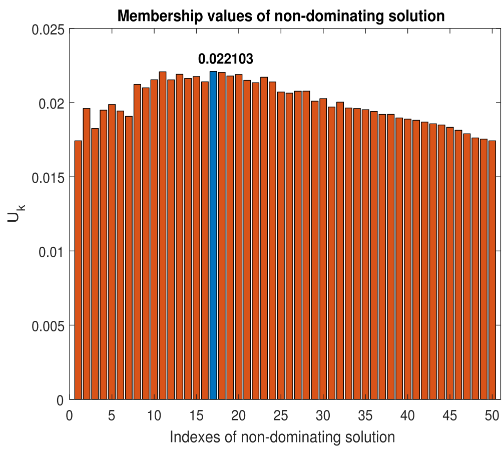


**FIGURE 9.** Membership values against non-dominating solutions without RES.

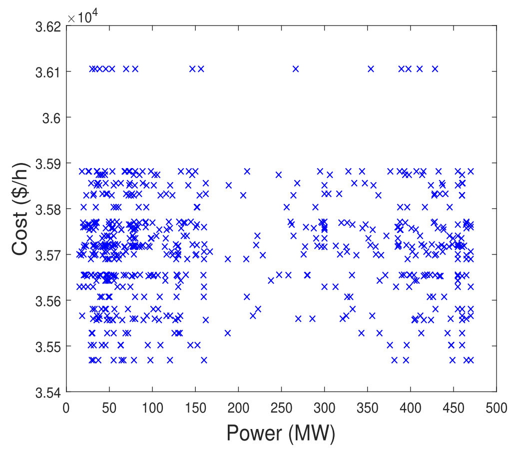


**FIGURE 10.** Position of pollinators after $1^{st}$ iteration.

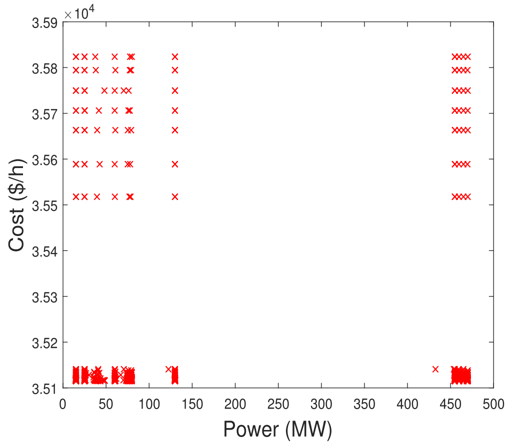


**FIGURE 11.** Position of pollinators after 2000 iteration.

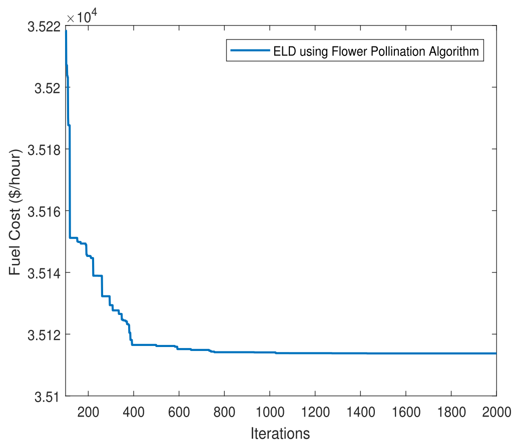


**FIGURE 12.** Convergence characteristics without RES.

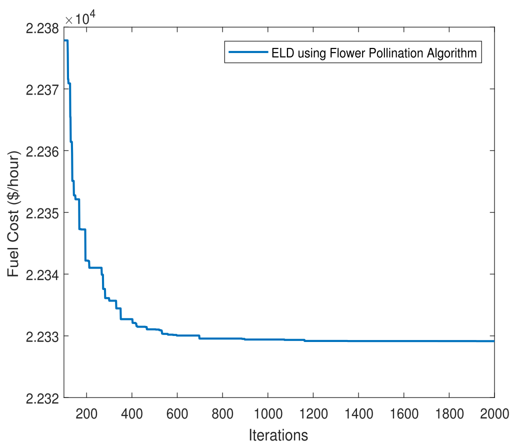


**FIGURE 13.** Convergence characteristics with RES.

### C. COMPARISON OF PROPOSED TECHNIQUE WITH EXISTING TECHNIQUES

To validate the effectiveness, efficiency and robustness of the proposed technique, it has been compared with other population based metaheuristic approaches which have already been tested and reported by other authors in literature. A test system is considered consisting of eleven thermal generating units having quadratic emission and cost function. This test systems is widely used as benchmarks in the power system field for solving the CEELD problem. The input data for this system is taken from [73] and total load demand is set as 2500 MW without considering the transmission losses. Maximum iterations are set to 1000 for all techniques to compare the results on single scale. From the findings presented in Table 8, it is clear that the proposed algorithm has performed best in finding the BCS in comparison with other metaheuristic algorithms reported in [73], [78]. Also from the pareto optimal front curve shown in figure 14, the fuel cost and emission obtained by the proposed algorithm is $\mathbf{12409\ \$/h}$ and $\mathbf{2002.945\ Kg/h}$ respectively. On the other hand, the robustness of FPA is also tested in a case of 3000 MW demand with 15 units of thermal generators without RESs and compared with BA, dBA, PSO and GA in Table 9. Here, it is clear that FPA gives better cost as compared to other techniques. It is worth mentioning here that the overall cost per day is reduced by approximately 101$ [77]. However, it is worth noting that the idea behind the work is different from those mentions earlier and it is mainly established on the interpretation of RESs estimated output power, while extracting a best compromise solution in terms of fuel cost of thermal generators and carbon

**TABLE 8.** Comparison with other techniques in terms of BCS.

| Reference | Technique | Fuel Cost ($/h) | Total Emission (Kg/h) |
|---|---|---|---|
| [78] | $\lambda$ Iteration | 12424.94 | 2003.301 |
| [78] | Recursive | 12424.94 | 2003.3 |
| [78] | PSO | 12428.63 | 2003.72 |
| [78] | DE | 12425.06 | 2003.35 |
| [78] | Simplified recursive | 12424.94 | 2003.3 |
| [73] | GA similarity | 12423.77 | 2003.10 |
| [73] | GSA | 12422.66 | 2003.024 |
| [73] | AEO | 12424.90013 | 2003.420114 |
| [73] | CAEO4 | 12424.77517 | 2003.613181 |
| Proposed technique | MOFPA | **12409.682** | **2002.945** |

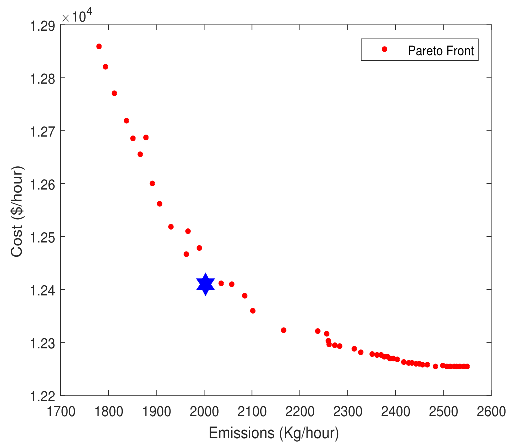


**FIGURE 14.** Pareto front curve.

**TABLE 9.** Overall fuel cost comparison without RES [77].

| Reference | Technique | Fuel Cost ($/h) |
|---|---|---|
| [77] | GA | 36490 |
| [77] | PSO | 36299 |
| [77] | BA | 36242 |
| [77] | dBA | 36204.07 |
| Proposed | FPA | 36203.96 |

emission. Therefore, along with the RESs no comparable literature is available in terms of BCS and overall cost. Still, in comparison to other metaheuristic approaches like BA, PSO and GA, simulation findings reveal that FPA provides promising outcomes in terms of quality and convergence characteristics without being caught in a local optimal solution.

## VIII. CONCLUSION

This has been observed in a literature review that there is room to apply a new bio-inspired algorithm to solve the economic emission dispatch problem along with the integration of renewable energy sources. Therefore, this study is carried out to check the effectiveness of the bio-inspired flower pollination algorithm (FPA) to solve the constrained economic emission dispatch problem. Further, in problem formulation, the scenario has been made more complex by integrating RESs along with the conventional thermal generators. So, the energy dispatch problem is presented as a combined economic emission dispatch with non-synchronous energy sources. In addition to this, the conflicting objectives of cost and emission have been combined using the price penalty factor approach. Finally, the combined objective function has been optimized using the FPA. In the end, it has been observed that FPA outperforms the different meta-heuristic techniques i.e. GA, PSO, BA, DBA, $\lambda$ iteration, GSA, AEO and CAEO4. The statistical and graphical comparison is presented in the result section. To justify the performance of the presented approach, two different scenarios were considered with and without renewable energy sources. In both cases, results are tabulated and it has been noticed that a prominent difference is achieved in the overall generation cost. On the other hand, with the aid of levy-flights-based step size, the FPA outperformed all other algorithms with comparatively fast convergence. Additionally, much better convergence characteristics are achieved due to the long flight nature of insects. Hence, the FPA is found better than all other algorithms regarding a premature convergence problem. Lastly, the study is extended to illustrate the conflicting nature of the objectives. Therefore, a Pareto front is plotted to show the tread-off characteristics. Hence, from the set of non-dominating solutions, a trade-off solution is extracted during the simultaneous optimization. Nevertheless, the presented approach is far better than the others but in the future, it can be made more efficient by fine-tuning the algorithm parameters and could be applied to the more lifelike scenarios of ELD problems. Therefore, the author suggests that the presented study could be implemented in some more constrained situations including multi-fuel generators, transmission line losses, battery storage systems and optimal power flow problems along with different RESs. Furthermore, the study can be extended to some more rational situations doubly-fed induction generator for a wind turbine, stand-alone PV system with and without maximum power point tracker (MPPT) and FACT devices.

## REFERENCES


[1] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart grid—The new and improved power grid: A survey," *IEEE Commun. Surveys Tuts.*, vol. 14, no. 4, pp. 944–980, 4th Quart. 2012.

[2] M. Amin and P. F. Schewe, "Preventing blackouts," *Sci. Amer.*, vol. 296, no. 5, pp. 60–67, May 2007.

[3] M. Rasheed, N. Javaid, A. Ahmad, Z. Khan, U. Qasim, and N. Alrajeh, "An efficient power scheduling scheme for residential load management in smart homes," *Appl. Sci.*, vol. 5, no. 4, pp. 1134–1163, Nov. 2015.

[4] N. I. Nwulu and X. Xia, "Optimal dispatch for a microgrid incorporating renewables and demand response," *Renew. Energy*, vol. 101, pp. 16–28, Feb. 2017.

[5] M. Abdullah, N. Javaid, I. U. Khan, Z. A. Khan, A. Chand, and N. Ahmad, "Optimal power flow with uncertain renewable energy sources using flower pollination algorithm," in *Advanced Information Networking and Applications*, vol. 926, L. Barolli, M. Takizawa, F. Xhafa, and T. Enokido, Eds. Cham, Switzerland: Springer, 2019, pp. 95–107.

[6] A.-A. A. Mohamed, Y. S. Mohamed, A. A. M. El-Gaafary, and A. M. Hemeida, "Optimal power flow using moth swarm algorithm," *Electr. Power Syst. Res.*, vol. 142, pp. 190–206, Jan. 2017.

[7] P. K. Roy, S. P. Ghoshal, and S. S. Thakur, "Multi-objective optimal power flow using biogeography-based optimization," *Electr. Power Compon. Syst.*, vol. 38, no. 12, pp. 1406–1426, 2010.

[8] S. S. Reddy and P. R. Bijwe, "Efficiency improvements in meta-heuristic algorithms to solve the optimal power flow problem," *Int. J. Elect. Power Energy Syst.*, vol. 82, pp. 288–302, Nov. 2016.

[9] A. A. El-Keib, H. Ma, and J. L. Hart, "Environmentally constrained economic dispatch using the LaGrangian relaxation method," *IEEE Trans. Power Syst.*, vol. 9, no. 4, pp. 1723–1729, Nov. 1994.

[10] S. F. J. Brodsky and R. W. Hahn, "Assessing the influence of power pools on emission constrained economic dispatch," *IEEE Trans. Power Syst.*, vol. 1, no. 1, pp. 57–62, Feb. 1986.

[11] J. S. Heslin and B. F. Hobbs, "A multiobjective production costing model for analyzing emissions dispatching and fuel switching (of power stations)," *IEEE Trans. Power Syst.*, vol. 4, no. 3, pp. 836–842, Aug. 1989.

[12] R. Ramanathan, "Short-term energy and emission trading analysis," *IEEE Trans. Power Syst.*, vol. 10, no. 2, pp. 1118–1124, May 1995.

[13] M. Sudhakaran, S. Slochanal, R. Sreeram, and N. Chandrasekhar, "Application of refined genetic algorithm to combined economic and emission dispatch," *IE (I) J.-EL*, vol. 85, pp. 115–119, Sep. 2004.

[14] M. A. Abido, "Environmental/economic power dispatch using multiobjective evolutionary algorithms," *IEEE Trans. Power Syst.*, vol. 18, no. 4, pp. 1529–1537, Nov. 2003.

[15] M. B. R. Rodríguez, J. L. M. Rodríguez, O. C. Fonticiella, and E. M. F. Donéstevez, "Tube and Shell heat exchanger optimization taking into account Mechanical restrictions," *ITEGAM-JETIA*, vol. 1, no. 3, pp. 1–8, 2015.

[16] R. Azzouz, S. Bechikh, and L. B. Said, "Dynamic multi-objective optimization using evolutionary algorithms: A survey,"ÂÎ in *Recent Advances in Evolutionary Multi-Objective Optimization* (Adaptation, Learning, and Optimization), vol. 20, S. Bechikh, R. Datta, and A. Gupta, Eds. Cham, Switzerland: Springer, 2017, pp. 31–70.

[17] P. P. Biswas, P. N. Suganthan, and G. A. J. Amaratunga, "Optimal power flow solutions incorporating stochastic wind and solar power," *Energy Convers. Manage.*, vol. 148, pp. 1194–1207, Sep. 2017.

[18] H. Tazvinga, B. Zhu, and X. Xia, "Optimal power flow management for distributed energy resources with batteries," *Energy Convers. Manage.*, vol. 102, pp. 104–110, Sep. 2015.

[19] K. Kusakana, "Optimal scheduled power flow for distributed photovoltaic/wind/diesel generators with battery storage system," *IET Renew. Power Gener.*, vol. 9, no. 8, pp. 916–924, Nov. 2015.

[20] T. N. Malik, "Economic dispatch using hybrid approaches," Ph.D. thesis, Univ. Eng. Technol. Taxila, Taxila, Pakistan, 2009.

[21] S. Fayyaz, M. K. Sattar, M. Waseem, M. U. Ashraf, A. Ahmad, H. A. Hussain, and K. Alsubhi, ‘‘Solution of combined economic emission dispatch problem using improved and chaotic population-based polar bear optimization algorithm,’’ *IEEE Access*, vol. 9, pp. 56152–56167, 2021.

[22] S. Krishnamurthy and R. Tzoneva, ‘‘Comparison of the Lagrange’s and particle swarm optimisation solutions of an economic emission dispatch problem with transmission constraints,’’ in *Proc. IEEE Int. Conf. Power Electron., Drives Energy Syst. (PEDES)*, Dec. 2012, pp. 1–8.

[23] H. H. Happ, ‘‘Optimal power dispatch—A comprehensive survey,’’ *IEEE Trans. Power App. Syst.*, vol. 96, no. 3, pp. 841–854, May 1977.

[24] M. A. Ilyas, G. Abbas, T. Alquthami, M. Awais, and M. B. Rasheed, ‘‘Multi-objective optimal power flow with integration of renewable energy sources using fuzzy membership function,’’ *IEEE Access*, vol. 8, pp. 143185–143200, 2020.

[25] H. R. E. H. Bouchekara, A. E. Chaib, and M. A. Abido, ‘‘Optimal power flow using GA with a new multi-parent crossover considering: Prohibited zones, valve-point effect, multi-fuels and emission,’’ *Electr. Eng.*, vol. 100, no. 1, pp. 151–165, Mar. 2018.

[26] E. E. Elattar, ‘‘Optimal power flow of a power system incorporating stochastic wind power based on modified moth swarm algorithm,’’ *IEEE Access*, vol. 7, pp. 89581–89593, 2019.

[27] M. Niu, N. Z. Xu, H. N. Dong, Y. Y. Ge, Y. T. Liu, and H. T. Ngin, ‘‘Adaptive range composite differential evolution for fast optimal reactive power dispatch,’’ *IEEE Access*, vol. 9, pp. 20117–20126, 2021.

[28] B. Qiao and J. Liu, ‘‘Multi-objective dynamic economic emission dispatch based on electric vehicles and wind power integrated system using differential evolution algorithm,’’ *Renew. Energy*, vol. 154, pp. 316–336, Jul. 2020.

[29] C. A. O. De Freitas, R. C. L. de Oliveira, D. J. A. Da Silva, J. C. Leite, and J. D. A. B. Junior, ‘‘Solution to economic—Emission load dispatch by cultural algorithm combined with local search: Case study,’’ *IEEE Access*, vol. 6, pp. 64023–64040, 2018.

[30] G. Abbas, J. Gu, U. Farooq, M. U. Asad, and M. El-Hawary, ‘‘Solution of an economic dispatch problem through particle swarm optimization: A detailed survey—Part I,’’ *IEEE Access*, vol. 5, pp. 15105–15141, 2017.

[31] M. M. Iqbal, I. Ali Sajjad, A. Manan, M. Waseem, A. Ali, and A. Sohail, ‘‘Towards an optimal residential home energy management in presence of PV generation, energy storage and home to grid energy exchange framework,’’ in *Proc. 3rd Int. Conf. Comput., Math. Eng. Technol. (iCoMET)*, Jan. 2020, pp. 1–7.

[32] A. S. Tomar, H. M. Dubey, and M. Pandit, ‘‘Combined economic emission dispatch using spider monkey optimization,’’ in *Advanced Engineering Optimization Through Intelligent Techniques*. Singapore: Springer, 2020, pp. 809–818.

[33] M. Waseem, Z. Lin, S. Liu, I. A. Sajjad, and T. Aziz, ‘‘Optimal GWCSO-based home appliances scheduling for demand response considering end-users comfort,’’ *Electr. Power Syst. Res.*, vol. 187, Oct. 2020, Art. no. 106477.

[34] Y. Yang, B. Wei, H. Liu, Y. Zhang, J. Zhao, and E. Manla, ‘‘Chaos firefly algorithm with self-adaptation mutation mechanism for solving large-scale economic dispatch with valve-point effects and multiple fuel options,’’ *IEEE Access*, vol. 6, pp. 45907–45922, 2018.

[35] M. Nasir, A. Sadollah, İ. B. Aydilek, A. Lashkar Ara, and S. A. Nabavi-Niaki, ‘‘A combination of FA and SRPSO algorithm for combined heat and power economic dispatch,’’ *Appl. Soft Comput.*, vol. 102, Apr. 2021, Art. no. 107088.

[36] Y. Cao, H. Nikafshan Rad, D. Hamedi Jamali, N. Hashemian, and A. Ghasemi, ‘‘A novel multi-objective spiral optimization algorithm for an innovative solar/biomass-based multi-generation energy system: 3E analyses, and optimization algorithms comparison,’’ *Energy Convers. Manage.*, vol. 219, Sep. 2020, Art. no. 112961.

[37] M. A. Al-Betar, M. A. Awadallah, A. T. Khader, A. L. Bolaji, and A. Almomani, ‘‘Economic load dispatch problems with valve-point loading using natural updated harmony search,’’ *Neural Comput. Appl.*, vol. 29, no. 10, pp. 767–781, May 2018.

[38] H. Rezaie, M. H. Kazemi-Rahbar, B. Vahidi, and H. Rastegar, ‘‘Solution of combined economic and emission dispatch problem using a novel chaotic improved harmony search algorithm,’’ *J. Comput. Des. Eng.*, vol. 6, no. 3, pp. 447–467, Jul. 2019.

[39] M. Rizwan, L. Hong, M. Waseem, S. Ahmad, M. Sharaf, and M. Shafiq, ‘‘A robust adaptive overcurrent relay coordination scheme for wind-farm-integrated power systems based on forecasting the wind dynamics for smart energy systems,’’ *Appl. Sci.*, vol. 10, no. 18, p. 6318, Sep. 2020.

[40] V. P. Sakthivel, M. Suman, and P. D. Sathya, ‘‘Combined economic and emission power dispatch problems through multi-objective squirrel search algorithm,’’ *Appl. Soft Comput.*, vol. 100, Mar. 2021, Art. no. 106950.

[41] T. K. Panigrahi, A. K. Sahoo, and A. Behera, ‘‘A review on application of various heuristic techniques to combined economic and emission dispatch in a modern power system scenario,’’ *Energy Proc.*, vol. 138, pp. 458–463, Oct. 2017.

[42] T. Guesmi, A. Farah, I. Marouani, B. Alshammari, and H. H. Abdallah, ‘‘Chaotic sine–cosine algorithm for chance-constrained economic emission dispatch problem including wind energy,’’ *IET Renew. Power Gener.*, vol. 14, no. 10, pp. 1808–1821, 2020.

[43] A. A. A. El Ela, M. A. Abido, and S. R. Spea, ‘‘Differential evolution algorithm for emission constrained economic power dispatch problem,’’ *Electr. Power Syst. Res.*, vol. 80, no. 10, pp. 1286–1292, Oct. 2010.

[44] L. Tan, H. Wang, C. Yang, and B. Niu, ‘‘A multi-objective optimization method based on discrete bacterial algorithm for environmental/economic power dispatch,’’ *Natural Comput.*, vol. 16, no. 4, pp. 549–565, Dec. 2017.

[45] R. Dong and S. Wang, ‘‘New optimization algorithm inspired by fluid mechanics for combined economic and emission dispatch problem,’’ *Turkish J. Elect. Eng. Comput. Sci.*, vol. 26, no. 6, pp. 3305–3318, 2018.

[46] D. Aydin, S. Özyön, C. Yaşar, and T. Liao, ‘‘Artificial bee colony algorithm with dynamic population size to combined economic and emission dispatch problem,’’ *Int. J. Electr. Power Energy Syst.*, vol. 54, pp. 144–153, Jan. 2014.

[47] P. K. Hota, A. K. Barisal, and R. Chakrabarti, ‘‘Economic emission load dispatch through fuzzy based bacterial foraging algorithm,’’ *Int. J. Elect. Power Energy Syst.*, vol. 32, no. 7, pp. 794–803, Sep. 2010.

[48] M. Pandit, L. Srivastava, M. Sharma, H. M. Dubey, and B. K. Panigrahi, ‘‘Large-scale multi-zone optimal power dispatch using hybrid hierarchical evolution technique,’’ *J. Eng.*, vol. 2014, no. 3, pp. 71–80, 2014.

[49] S. M. Abd Elazim and E. S. Ali, ‘‘Optimal network restructure via improved whale optimization approach,’’ *Int. J. Commun. Syst.*, vol. 34, no. 1, p. e4617, 2021.

[50] J.-B. Park, Y.-W. Jeong, J.-R. Shin, and K. Y. Lee, ‘‘An improved particle swarm optimization for nonconvex economic dispatch problems,’’ *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 156–166, Feb. 2010.

[51] J. Radosavljević, ‘‘A solution to the combined economic and emission dispatch using hybrid PSOGSA algorithm,’’ *Appl. Artif. Intell.*, vol. 30, no. 5, pp. 445–474, May 2016.

[52] M. A. Abido, ‘‘Multiobjective particle swarm optimization for environmental/economic dispatch problem,’’ *Electr. Power Syst. Res.*, vol. 79, no. 7, pp. 1105–1113, Jul. 2009.

[53] D. Zou, S. Li, Z. Li, and X. Kong, ‘‘A new global particle swarm optimization for the economic emission dispatch with or without transmission losses,’’ *Energy Convers. Manage.*, vol. 139, pp. 45–70, May 2017.

[54] M. Moradi-Dalvand, B. Mohammadi-Ivatloo, A. Najafi, and A. Rabiee, ‘‘Continuous quick group search optimizer for solving non-convex economic dispatch problems,’’ *Electr. Power Syst. Res.*, vol. 93, pp. 93–105, Dec. 2012.

[55] D.-W. Gong, Y. Zhang, and C.-L. Qi, ‘‘Environmental/economic power dispatch using a hybrid multi-objective optimization algorithm,’’ *Int. J. Elect. Power Energy Syst.*, vol. 32, no. 6, pp. 607–614, 2010.

[56] J. X. V. Neto, G. Reynoso-Meza, T. H. Ruppel, V. C. Mariani, and L. D. S. Coelho, ‘‘Solving non-smooth economic dispatch by a new combination of continuous GRASP algorithm and differential evolution,’’ *Int. J. Electr. Power Energy Syst.*, vol. 84, pp. 13–24, Jan. 2017.

[57] M. Hamdi, L. Idomghar, M. Chaoui, and A. Kachouri, ‘‘An improved adaptive differential evolution optimizer for non-convex economic dispatch problems,’’ *Appl. Soft Comput.*, vol. 85, Dec. 2019, Art. no. 105868.

[58] M. Rizwan, L. Hong, M. Waseem, and W. Shu, ‘‘Sustainable protection coordination in presence of distributed generation with distributed network,’’ *Int. Trans. Electr. Energy Syst.*, vol. 30, no. 3, Mar. 2020, Art. no. e12217.

[59] B. Dey, S. K. Roy, and B. Bhattacharyya, ‘‘Solving multi-objective economic emission dispatch of a renewable integrated microgrid using latest bio-inspired algorithms,’’ *Eng. Sci. Technol., Int. J.*, vol. 22, no. 1, pp. 55–66, Feb. 2019.

[60] A. Y. Abdelaziz, E. S. Ali, and S. M. Abd Elazim, ‘‘Implementation of flower pollination algorithm for solving economic load dispatch and combined economic emission dispatch problems in power systems,’’ *Energy*, vol. 101, pp. 506–518, Apr. 2016.

[61] M. K. Sattar, A. Ahmad, S. Fayyaz, S. S. Ul Haq, and M. S. Saddique, ‘‘Ramp rate handling strategies in dynamic economic load dispatch (DELD) problem using grey wolf optimizer (GWO),’’ *J. Chin. Inst. Eng.*, vol. 43, no. 2, pp. 200–213, Feb. 2020.

[62] S. S. Ul Haq, A. Ahmad, F. Ikram, T. Nawaz, A. Majeed, M. S. Saddique, and M. K. Sattar, "A novel binary variant model of swarm inspired polar bear optimization algorithm employed for scalable unit commitment," *Int. Trans. Electr. Energy Syst.*, vol. 31, no. 2, Feb. 2021, Art. no. e12711.

[63] M. A. Ilyas, T. Alquthami, M. Awais, A. H. Milyani, and M. B. Rasheed, "(DA-DOPF): A day-ahead dynamic optimal power flow with renewable energy integration in smart grids," *Frontiers Energy Res.*, vol. 9, p. 424, Aug. 2021.

[64] H. Qin, J. Zhou, Y. Lu, Y. Wang, and Y. Zhang, "Multi-objective differential evolution with adaptive Cauchy mutation for short-term multi-objective optimal hydro-thermal scheduling," *Energy Convers. Manage.*, vol. 51, no. 4, pp. 788–794, 2010.

[65] N. A. Khan, A. B. Awan, A. Mahmood, S. Razzaq, A. Zafar, and G. A. S. Sidhu, "Combined emission economic dispatch of power system including solar photo voltaic generation," *Energy Convers. Manage.*, vol. 92, pp. 82–91, Mar. 2015.

[66] T. Niknam, H. D. Mojarrad, and B. B. Firouzi, "A new optimization algorithm for multi-objective economic/emission dispatch," *Int. J. Electr. Power Energy Syst.*, vol. 46, pp. 283–293, Mar. 2013.

[67] C.-L. Chen, T.-Y. Lee, and R.-M. Jan, "Optimal wind-thermal coordination dispatch in isolated power systems with large integration of wind capacity," *Energy Convers. Manage.*, vol. 47, nos. 18–19, pp. 3456–3472, Nov. 2006.

[68] C. Shilaja and K. Ravi, "Optimization of emission/economic dispatch using Euclidean affine flower pollination algorithm (eFPA) and binary FPA (BFPA) in solar photo voltaic generation," *Renew. Energy*, vol. 107, pp. 550–566, Jul. 2017.

[69] A. Abid, T. N. Malik, and M. M. Ashraf, "Combined emission economic dispatch of power system in presence of solar and wind using flower pollination algorithm," *Mehran Univ. Res. J. Eng. Technol.*, vol. 38, no. 3, pp. 581–598, 2019.

[70] R. Farmani and J. A. Wright, "Self-adaptive fitness formulation for constrained optimization," *IEEE Trans. Evol. Comput.*, vol. 7, no. 5, pp. 445–455, Oct. 2003.

[71] P. K. Roy and S. Bhui, "Multi-objective quasi-oppositional teaching learning-based optimization for economic emission load dispatch problem," *Int. J. Elect. Power Energy Syst.*, vol. 53, pp. 937–948, Dec. 2013.

[72] X.-S. Yang, "Flower pollination algorithm for global optimization," in *Proc. Int. Conf. Unconventional Comput. Natural Comput.* Berlin, Germany: Springer, 2012, pp. 240–249.

[73] M. H. Hassan, S. Kamel, S. Q. Salih, T. Khurshaid, and M. Ebeed, "Developing chaotic artificial ecosystem-based optimization algorithm for combined economic emission dispatch," *IEEE Access*, vol. 9, pp. 51146–51165, 2021.

[74] K. Mahesh, P. Nallagownden, and I. Elamvazuthi, "Advanced Pareto front non-dominated sorting multi-objective particle swarm optimization for optimal placement and sizing of distributed generation," *Energies*, vol. 9, no. 12, p. 982, Nov. 2016.

[75] L. D. S. Coelho and C.-S. Lee, "Solving economic load dispatch problems in power systems using chaotic and Gaussian particle swarm optimization approaches," *Int. J. Electr. Power Energy Syst.*, vol. 30, no. 5, pp. 297–307, Jun. 2008.

[76] A. Chatterjee, S. P. Ghoshal, and V. Mukherjee, "Solution of combined economic and emission dispatch problems of power systems by an opposition-based harmony search algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 39, no. 1, pp. 9–20, Jul. 2012.

[77] F. Tariq, S. Alelyani, G. Abbas, A. Qahmash, and M. R. Hussain, "Solving renewables-integrated economic load dispatch problem by variant of Metaheuristic bat-inspired algorithm," *Energies*, vol. 13, no. 23, p. 6225, Nov. 2020.

[78] R. Balamurugan and S. Subramanian, "A simplified recursive approach to combined economic emission dispatch," *Electr. Power Compon. Syst.*, vol. 36, no. 1, pp. 17–27, Dec. 2007.



**MUHAMMAD WALEED TAHIR** received the bachelor's degree in electrical engineering from the Sharif College of Engineering and Technology, Lahore, Pakistan, in 2015, and the M.S. degree in electrical engineering from The University of Lahore, Lahore, in 2021. He has been with the Department of Technology, The University of Lahore, since 2016. His research interests include power systems scheduling, smart grid, and optimization techniques.



**GHULAM ABBAS** (Senior Member, IEEE) received the B.E. degree from the University of Engineering & Technology Lahore, Lahore, Pakistan, in 2004, and the M.E. and Ph.D. degrees from the Institut National des Sciences Appliquées de Lyon (INSA Lyon), France, in 2008 and 2012, respectively, all in electrical engineering. He is currently working as an Associate Professor with the Department of Electrical Engineering, The University of Lahore, Lahore. He has published a number of papers in various international and national IEEE conferences and journals of repute, such as IEEE, Elsevier, and MDPI. His research interests include analog and digital controller designs for power switching converters, soft computing, and power system optimization. He is a Reviewer of a number of premier conferences and journals, including the IEEE Transactions on Industrial Informatics, *Asian Journal of Control*, *Engineering Optimization*, and IEEE Access. He has served several *Computer & Electrical Engineering* journals as a Guest Editor.



**MUHAMMAD ARSALAN ILYAS** received the bachelor's and master's degrees in electrical engineering from The University of Lahore, Lahore, Pakistan, in 2010 and 2020, respectively. He was a Plant Engineer in coal gasifier at Batala Steel Mills, from 2010 to 2015. He is currently working as a Lecturer with the Faculty of Engineering and Technology, The University of Lahore. His research interests include power flow study, power system operation and control, power system protection, and mathematical optimization.



**NASIM ULLAH** (Member, IEEE) received the Ph.D. degree in mechatronics engineering from Beihang University, Beijing, China, in 2013. From September 2006 to September 2010, he was a Senior Design Engineer with IICS, Pakistan. He is currently working as a Full Professor in electrical engineering with Taif University, Saudi Arabia. His research interests include renewable energy, flight control systems, integer and fractional order modeling of dynamic systems, integer/fractional-order adaptive robust control methods, fuzzy/NN, hydraulic and electrical servos and epidemic, and vaccination control strategies.



**S. M. MUYEEN** (Senior Member, IEEE) received the B.Sc. (Eng.) degree from the Rajshahi University of Engineering and Technology (RUET), Bangladesh, formerly known as the Rajshahi Institute of Technology, in 2000, and the M.Eng. and Ph.D. degrees from the Kitami Institute of Technology, Japan, in 2005 and 2008, respectively, all in electrical and electronic engineering. He is currently working as a Full Professor with the Electrical Engineering Department, Qatar University. He has been a keynote speaker and an invited speaker at many international conferences, workshops, and universities. He has published more than 250 articles in different journals and international conferences. He has also published seven books as an author or an editor. His research interests include power system stability and control, electrical machine, FACTS, energy storage systems (ESS), renewable energy, and HVDC systems. He is a fellow of Engineers Australia. He is serving as an Editor/an Associate Editor for many prestigious journals from IEEE, IET and other publishers, including IEEE Transactions on Energy Conversion, IEEE Power Engineering Letters, *IET Renewable Power Generation*, and *IET Generation, Transmission & Distribution*.