Optimisation of Economic and Environmental Dispatch of Power System with and without Renewable Energy Sources

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Abstract

Combined Economic and Environmental load dispatch is critical to the functioning of the power grid, and many models have been developed to address these issues using various techniques. Specially, soft computing methods have recently risen in popularity and have been used in a variety of popular and practical applications. The aim of this paper is to determine the benefits of applying Particle Swarm Optimization (PSO) to the Combined Economic and Environmental Dispatch (CEED) problem in particular. Here, an attempt has been made to find the minimum cost of generation of a system of thermal and solar power plants. The problem is multi-objective and is converted into a single objective function using weighted sum method. Analysis is also done

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with and without unit commitment using Priority List method and the results are compared. The analyses has been done in MATLAB tool using six thermal power generators and thirteen solar power plants.

Keywords: Optimisation, renewable energy sources, AHP, PSO, economic & environment.

Abbreviations

C_T	Total cost of generation
FLAPC	Full Load Average Production Cost
G_i	i^{th} Generator Unit
N_P	Population size
P_D	Power demand
P_{Gi}	Power generation
S_j	Total cost of power generated by a solar power plant
T	Number of iterations
V(t)	Velocity
W_i	Weight of i^{th} unit
X(t)	Position
λ	Lagrangian multiplier

1 Introduction

Optimisation is mathematical technique used to find the maximum or minimum value of a function of one or more variables subject to a set of constraints [1]. Electricity Generation Companies (EGC) optimize the ON/OFF status of the generator as well as the real power output while minimizing the device operating cost over the planning period under various physical operation and computation constraints [2]. 'Unit Commitment' and 'Economic Dispatch' are two interconnected optimisation issues to be resolved by EGC [1]. The process of determining when and which generating units at each power station will start-up and/or shut-down is known as Unit Commitment (UC). The method of determining what the individual power outputs of the scheduled generating units should be at each time-point is known as Economic Dispatch (ED). Due to the enormous number of possible combinations of the ON/OFF states of all the generating units in the power system at all time points during the study period, unit commitment is a difficult optimisation problem.

Thermal power plants are the backbone of generation of electricity in most of the developing countries like India. But these power plants are facing lot of challenges such as emission of green-house gases, rapidly depleting reserves of fossil fuels, the rise in fuel prices, and the environmental issues associated with thermal fuels. Steps should be taken to tackle these associated issues. Thus, the use of renewable energy sources along with thermal generation has gotten a lot of attention in recent decade to confront the issues associated with thermal plants [3]. The problem of optimization becomes more complex with the involvement of renewable energy sources participation for electricity generation and reduction of greenhouse gases [2]. This makes the Unit commitment (UC) a nonlinear mixed-integer optimization problem.

A bibliographical survey on ED and UC reveals that various numerical optimization techniques have been employed to approach these problems. ED has typically been solved using mathematical programming techniques such as lambda iteration [4], and others [5–8]. Intelligent approaches are also used to solve complex constrained ED. Genetic algorithm (GA) [9], evolutionary programming (EP) [10], dynamic programming (DP) [11], tabu search [12], hybrid EP [13], neural network (NN) [14], particle swarm optimization (PSO) [15] among others, are some of these methods. [16] uses stochastic fractal search algorithm (SFSA) for solving the economic emission dispatch (EED) problems. In [17], authors used carbon economic dispatch model of multi-energy combined system with wind power, photovoltaic, hydropower, thermal power, nuclear power, and energy storage. But most the paper discussed in the literature has not considered the impact of renewable energy sources.

In this paper, thermal generators and solar power plants of different capacities are taken into consideration. The data for the thermal generators are taken from IEEE 30-bus system, and the solar power plants are taken from [18]. The main objective of the research is to optimise CEED using a meta-heuristic algorithm – Particle Swarm Optimisation and compare it with the conventional economic dispatch technique – Lambda Iteration method. Main reason to select PSO algorithm is that it has successfully implemented for solving multimodal multi-objective problems [19]. It is also used to solve the real-world problems like structure optimization/motion characteristics of medical robotics [20], error correction in CCTV measurements [21] and load dispatch problem [22] etc. The above observations motivated the authors to consider the PSO for solving "Economic and Environmental Dispatch of Power System" problem. This paper also combines the Priority List method

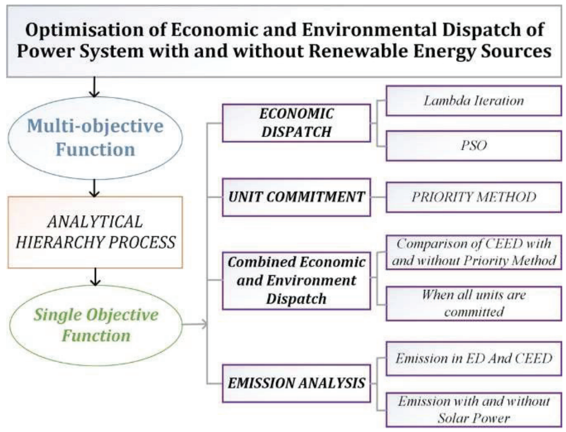

Figure 1 Graphical summary.

with Particle Swarm Optimisation and finds the best ON/OFF statuses of thermal and solar plants. CEED is done for the units so committed and the results are compared with unit commitment without Priority List method. Two forms of PSO algorithms are used: Classical PSO and Binary PSO. These are combined together to optimise our objective function, which is known as Mixed-Integer Programming. The analysis consists of multiple objectives and constraints. In order to convert a multi-objective function into a single-objective function, a weighted sum method known as Analytical Hierarchy Process has been used. The paper also analyses the amount of green-house gas emission reduced due to environmental dispatch and the use of solar power. Summary of the contribution of the paper is depicted in Figure 1.

Rest of the paper is divided among different sections as defined, Section 2 explains the optimisation techniques used in this paper – both conventional and heuristic. Section 3 details the mathematical model formulated for this project. This also includes the weighted-sum method and its analysis. Section 4 illustrates and explains the results of various analysis carried out in this paper followed by conclusion.

2 Optimization Methods

This section will explain the implementation and operation of traditional approaches of ED and UC such as Lambda Iteration and Priority List

Method. The Lambda Iteration method is one of the methods for executing the economic load dispatch and Priority List Method is the simplest method for implementing UC of thermal generators. The algorithm/steps to be followed to implement these methods are explained in the subsequent sections. This section also explains the meta-heuristic approach – particle swarm optimisation.

2.1 Conventional Optimization Methods

Conventional approaches of ED and UC such as Lambda Iteration and Priority List Method is considered in this paper. Lambda Iteration method is for executing the economic load dispatch and Priority List Method is the simplest method for implementing UC of thermal generators. The algorithm/steps to be followed to implement these methods are explained in the subsequent sections.

2.1.1 Lambda iteration method

Lambda iteration method is an iterative computational technique. It is based on the principle of equal incremental cost. The optimum operating point of any generator set, within a specified limit, is found using this method. The incremental cost is also known as Lambda (λ) or Lagrange multiplier [23]. The inequality constraints should be satisfied in each iteration by the iterative method. This method requires an optimum operating point of any generator set within the specified limits, which can be found using Algorithm 1.

In ED, the total power demand (P_D) should be equal to the sum of all the power generated (P_{gi}) by the individual thermal generators considering that the sum of the real power generated by the individual thermal generators such that total thermal cost $(F(P_i))$ is the least. To understand this concept, consider n number of thermal generating units from G1 to Gn as shown in Figure 2.

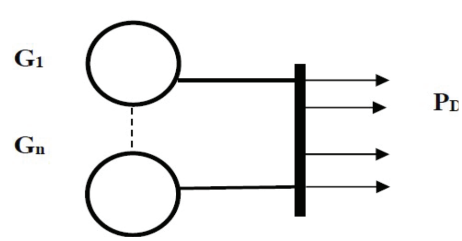

Figure 2 Illustration of power system network.

C1, C2,...,Cn are the generation cost of generators G1,G2...,Gn respectively.

The total cost of generation is given by Equation (1) [4]:

$$C_T = \sum_{i=1}^{n} C_i(P_{Gi}) \tag{1}$$

The equality constraint is represented by the power balance constraint, where the total power generation must cover the total power demand.

$$\sum_{i=1}^{n} P_{Gi} = P_D \tag{2}$$

Now,

$$C_T = C_1 + C_2 + \cdots + C_n \tag{3}$$

$$P_{GT} = P_{G1} + P_{G2} + \cdots + P_{Gn} = P_D \tag{4}$$

where C_T is the total generation cost of the generators, P_{GT} is the total power generated.

The Equation (3) is subjected to the equality constraint Equation (2) to obtain the auxiliary function (F) along with the Lagrangian multiplier, λ as

$$F = C_T + \lambda \left(P_D - \sum_{i=1}^{n} P_{Gi} \right) \tag{5}$$

Differentiating the objective function F with respect to the power generation P and equating to zero provides the optimal operation for the system.

$$\frac{\partial F}{\partial Pn} = \frac{\partial C_T}{\partial Pn} - \lambda = 0 \tag{6}$$

Since $C_T = C_1 + C_2 + C_3 + \cdots + C_n$, the Equation (5) can be written as

$$\frac{\partial C_T}{\partial P_n} = \frac{\partial C_n}{\partial P_n} = \lambda \tag{7}$$

The optimum condition for operation will be

$$\frac{\partial C_1}{\partial P_1} = \frac{\partial C_2}{\partial P_2} = \cdots = \frac{\partial C_n}{\partial P_n} = \lambda \tag{8}$$

The thermal fuel cost equation is given by Equation (9):

$$C_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \tag{9}$$

Differentiating the thermal fuel cost equation with respect to C_i to find the coordination equation:

$$\frac{\partial C_i}{\partial P_{Gi}} = b_i + 2a_i P_{Gi} = \lambda \tag{10}$$

$$P_{Gi}^K = \frac{\lambda^K - b_i}{2ai} \tag{11}$$

The Equation (11) is known as coordination equation [23].

The Equation (2) can now be written using Equation (11) as:

$$\sum_{i=1}^{n} P_{Gi} = \frac{\lambda^K - b_i}{2ai} = P_D \tag{12}$$

From Equation (12), we can see that P_D is a function of λ:

$$f(\lambda) = P_D \tag{13}$$

In order to get a λ to satisfy the Equation (11) from an initial estimate $\lambda 0$, $\Delta\lambda 0$ is the correction factor to correct the solution.

Writing Taylor's series and neglecting higher order terms.

$$f(\lambda) = f(\lambda^0) + f'(\lambda^0)\Delta\lambda^0 = P_D \tag{14}$$

$$\Delta\lambda^0 = \frac{P_D - f(\lambda^0)}{f'(\lambda^0)} \tag{15}$$

From Equations (12) and (13),

$$f(\lambda^0) = \sum_{i=1}^{n} \frac{\lambda^0 - b_i}{2ai} \tag{16}$$

Differentiating Equation (16),

$$f'(\lambda^0) = \sum_{i=1}^{n} 1/2a_i \tag{17}$$

From Equations (15), (16) and (17), to obtain,

$$\Delta\lambda^0 = \frac{P_D - \sum_{i=1}^{n} \frac{\lambda^0 - b_i}{2a_i}}{\sum_{i=1}^{n} 1/2a_i} \tag{18}$$

Now for any iteration k,

$$\Delta\lambda^{k+1} = \lambda^k + \Delta\lambda^k \tag{19}$$

Lambda Iteration method is an ED method in which least cost of generation is obtained when the incremental costs of all the thermal generators are equal. Pseudo Code for ED using Lambda Iteration is given by Algorithm 1.

Algorithm 1 ED using lambda iteration

1: Read system data namely cost coefficients and the generation limits.
2: Set k = 0
3: Assume initial λ^K
4: Find power generated by individual generators by $P_{Gi}^T = \frac{\lambda^K - b_i}{2ai}$.
5: if $P_{\boldsymbol{Gi}}^k \leq P_{Gi}^{max}$ check step 6, if not update $P_{\boldsymbol{Gi}}^K = P_{Gi}^{max}$
6: if $P_{\boldsymbol{Gi}}^k \leq P_{Gi}^{min}$, compute $\Delta P^T = \sum_{i=1}^{k} P_{\boldsymbol{Gi}}^k - P_D$ if not update $P_{\boldsymbol{Gi}}^k = P_{Gi}^{max}$
7: if $|\Delta P^T| \leq \in$ is satisfied then print the schedule and stop
8: if it doesn't satisfy the step 7 compute $\Delta\lambda^k$ by $\Delta\lambda^k = \frac{\Delta P^k}{\sum_{i=1}^{N} 1/2a_i}$
9: After step 8 increment the λ^K by $\Delta\lambda^{k+1} = \lambda^k + \Delta\lambda^k$
10: Iteration k $= k + 1$

2.1.2 Priority List Method

Priority List Method is the simplest Unit Commitment solution method. In this method, the thermal power units are prioritized based on their Full Load Average Production Cost (FLAPC). The unit with the least FLAPC will be of highest priority.

The FLAPC is given by Equation (20) [12]:

$$FLAPC_i = \frac{a_i * P_{imax}^2 + b_i * P_{imax} + c_i}{P_{imax}} \frac{\$}{MWh} \tag{20}$$

where, a_i, b_i, c_i are fuel coefficients of ith Unit and P_{imax} is the maximum possible power that can be generated by the ith Unit.

The following assumptions are made in this paper when unit commitment is done while using priority method: (i) minimum Start-up time and Shut-down time are equal to zero, (ii) Ramp rate limits not considered, (iii) Minimum up-time and down-time are equal to zero.

2.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) belongs to a class of optimization algorithm called Metaheuristic algorithm initially introduced by Kennedy, Eberhart [23]. PSO analysis in this paper uses two types of variables:

- real-continuous variables thermal power to be generated by each thermal generator. Classical PSO deals with real-continuous variables.
- discrete-binary variables ON/OFF status of solar power plants have been considered. Binary PSO uses discrete-binary variables.

These two algorithms are combined in this paper to deal which is known as Mixed-Integer Programming. Mixed-Integer Programming takes the form [24]:

$$\min f(X,Y) \tag{21}$$

$$s.t \qquad X \in \{X|X \in R^n,\ X^L < X < X^H\}$$

$$Y \in \{Y|Y \in \{0,1\}^m\}$$

where, f (X,Y) is the objective function, X is a vector consisting of real-continuous variables and Y is a vector consisting of discrete binary variables.

2.2.1 Classical PSO

PSO algorithm is based upon handling a swarm of particles, which is the population of moving particles. These swarm particles transverse a multidimensional search space to figure out the most optimal solution. Every particle updates its position by the influence of the particle's own experience and the experience of the neighbouring particles. Each particle in the multidimensional search space alters its velocity by the knowledge of self and nearby particles.

Let Xi(t) and Vi(t) be the initial position and velocity of particle i in the n dimensional search space particular time t are represented as vectors. In addition to this, every particle has its memory of the best position. The Xi(t+1) and Vi(t+1) are the particle's updated position and velocity [25].

In Figure 3, Pi(t) is the best experience of particle i, g(t) is the global best experience of swarm particles. The particle moves parallel to its velocity for the new position, followed by moving parallel to its best experience and moving parallel to swarm particles' global best to find the new position.

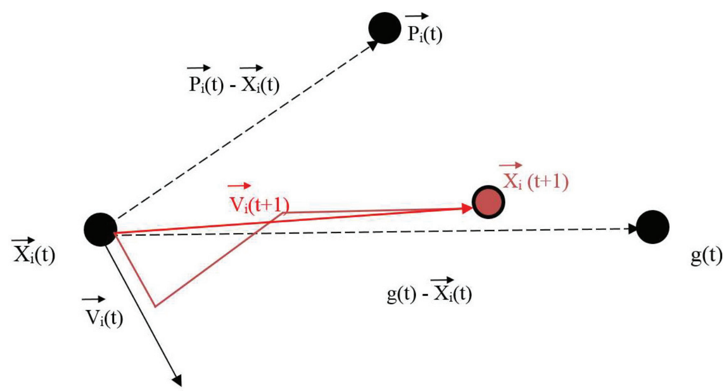

Figure 3 Illustration of position and velocity updates in PSO.

Equations for updating the position and velocity:

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{22}$$

$$V_i(t+1) = \omega * V_i(t) + c1 * rand * (p_i(t) - X_i(t)) + c2 * rand * (g(t) - X_i(t)) \tag{23}$$

where ω is the Inertia weight, c1 and c2 are the acceleration coefficients.

Using these three coefficients we can adjust the direction towards the original direction, personal best, global best respectively. The inertia weight changes the exploration and exploitation of the particle. Pseudo Code for ED using classical PSO is given by Algorithm 2.

2.2.2 Binary PSO

Kennedy and Eberhart also developed a unique algorithm based on the binary method with Particle Swarm Optimization. In this method, particles that move in the search space will provide results like yes and no, 0 and 1. In order to initialize the dimension of the particle as binary value, the probability of 0.5 is used as mentioned in [25]:

$$X_i = f(x) = \begin{cases} 1, & if\ rand > 0.5 \\ 0, & otherwise \end{cases} \tag{24}$$

Equation for updating the position [26]:

$$if\ rand(\ ) < S(V_i(t+1)) \begin{cases} then\ Xi\ (t+1) = 1 \\ else\ X_i(t+1) = 0 \end{cases} \tag{25}$$

Algorithm 2 Pseudo-code for classical PSO

```
Initialise:
    Np: Population size
    T: Number of Iterations
Generate the initial position and velocity with in the upper bound and lower bound.
Calculate the fitness function of every particle in the swarm using objective function.
Initialise pbest and gbest.
    for t = 1: max iteration (T) do
        w = w_max − (((w_max − w_min)/T) ∗ (T − t))
        c1 = 2.5 − (2 ∗ (t − T))
        c2 = 0.5 − (2 ∗ (t − T))
        for p = 1 : Np do
            update the velocity Vi of the particle i using the Equation (23)
            update the position Pi of the particle i using the Equation (22)
            calculate the fitness values of the new particle Xi using the objective function f.
            if f(p) < f_pbest(p) then
                update the personal best.
                if f_pbest(p) < f_gbest then
                    update the global best.
                end if
            end if
        end for
        t = t + 1
    end for
```

Equation for updating the velocity [25]:

$$sigmoid(V_i) = \frac{1}{(1 + e^{Vi})} \tag{26}$$

The algorithm of binary PSO is very similar to that of classical PSO in terms of updating velocity, personal best and global best. Initialisation, updating position and the discrete outputs are the aspects that differ from the classical PSO.

3 Mathematical Modeling

The objective of this paper is to minimise the total cost of generation of electric power produced by thermal and solar power plants. The thermal costs of generation are the cost of fuel and the cost of emission of green-house gases[27]. The thermal costs are functions of the amount of power generated by the generator. The solar cost of generation is the cost of installation which is normalised into cost per unit of solar power produced [28].

Algorithm 3 Pseudo-code for BPSO

Initialise:
  Np: Population size
  T: Number of Iterations
Initialise position vector for BPSO according to the Equation (24)
Initialise velocity vector is set as *zero* for BPSO.
Calculate the fitness function of every particle in the swarm using objective function.
Initialise pbest and gbest.
  for t = 1: max iteration (T) **do**
    $w = w_{max} - ((\frac{(w_{max} - w_{min})}{T}) * (T - t))$
    $c1 = 2.5 - (2 * (t - T))$
    $c2 = 0.5 - (2 * (t - T))$
    for $p = 1 : Np$ **do**
      update the velocity Vi of the particle i using the Equation (25)
      update the position Pi of the particle i using the Equation (26)
      calculate the fitness values of the new particle X_i using the objective function f.
      if $f(p) < f\_pbest(p)$ **then**
        update the personal best.
        if $f\_pbest(p) < f\_gbest$ **then**
          update the global best.
        end if
      end if
    end for
    $t = t + 1$
  end for

3.1 Objective Function

The objective of this paper is to minimise the total cost of generation of electric power produced by thermal and solar power plants.

$$\min C = \sum_{i=1}^{n} F(P_i) + \sum_{i=1}^{n} E(P_i) + \sum_{j=1}^{m} S_j \tag{27}$$

The Objective function is subject to the following constraints:

$$P_i^L \leq P_i \leq P_i^H$$

$$P_D = \sum_{i=1}^{n} P_i + \sum_{j=1}^{m} P_j \tag{28}$$

where, P_i^L and P_i^H are the minimum and maximum power that can be generated by the ith thermal plant, P_D is the power demand at a time interval, P_j is the power produced by solar plant j at the same time interval.

The fuel cost of a coal-fired Thermal Power Plant is given by Equation (29) [18]:

$$F(P_i) = (a_i * P_i^2 + b_i * P_i + c_i)\ \$/h \tag{29}$$

where, a_i, b_i, c_i are fuel coefficients of ith Thermal Unit and P_i is the power generated by the ith Thermal Unit.

The amount green-house gas emission from a coal-fired Thermal Power Plant per hour is also a monotonically increasing convex function of the generator's MW output is given by Equation (30) [18]:

$$E(P_i) = (\propto_i * P_i^2 + \beta_i * P_i + \gamma_i)\ kg/h \tag{30}$$

where, $\propto_i$, β_i, γ_i are fuel coefficients of ith Thermal Unit and P_i is the power generated by the ith Thermal Unit.

The amount of emission is converted into emission cost by introducing a price penalty factor given by Equation (31):

$$h_i = \frac{a_i * P_{imax}^2 + b_i * P_{imax} + c_i}{\propto_i * P_{imax}^2 + \beta_i * P_{imax} + \gamma_i} \tag{31}$$

where P_{imax} is the maximum possible power that can be generated by the ith thermal generator.

The power generated by one solar power plant is given by Equation (32) [18]:

$$P_{sj} = P_{jrated}\{1 + (T_{amb} - T_{ref})\} * \propto * \frac{S_h}{1000}\ MW \tag{32}$$

where, P_{rated} is the rated power, T_{amb} is the ambient temperature at hour h, $T_{ref} = 25$°C, $\propto$ is the temperature coefficient and S_i is the solar irradiance (in W/m2) of jth solar plant at hour h.

The total solar share is given by Equation (33):

$$P_{gs} = \sum_{j=i}^{m} P_{sj} * U_j\ MW \tag{33}$$

where, U_j is the ON/OFF status of jth solar plant.

The total cost of power generated by a solar power plant is given by Equation (34):

$$S_j = \sum_{j=1}^{m} PUcost_j * P_{sj} * U_j\ \$/h \tag{34}$$

where, $PUcost_j$ is the per unit cost of jth solar plant.

3.2 Analytical Hierarchy Process

In this paper the defined multi-objective function is being converted to single objective function using weighted-sum method. The weights of each attribute is calculated by a method known as the Analytical Hierarchy Process (AHP). Among the numerous procedures with several parameters and several characteristics, AHP is one of the most used methods in decision-making, and it is providing several benefits: simplicity, adaptability, and clarity that allow for comparing and assessing different alternatives [29]. The implementation procedure of the AHP is given in Algorithm 4.

Algorithm 4 Implementation of analytical hierarchy process

1: Set the number of attributes
2: Create a pair-wise comparison matrix by giving ranks
3: Normalise the Matrix by dividing each element by the sum of its corresponding column
4: Find the value of λ from Equation (35)

$$\lambda = \frac{\textit{Weighted sum of each row}}{\textit{Weight of attribute}} \tag{35}$$

5: Find average of all values of λ –> λ_{avg}
6: Find the value of CI from Equation (36)

$$\textit{Consistency Index } (CI) = \frac{\lambda_{avg} - n}{n - 1} \tag{36}$$

7: Find the value of CR from Equation (37)

$$\textit{Consistency Ratio } (CR) = \frac{CI}{RI} \tag{37}$$

8: **if** CR<0.1 **then**
9: Weights are consistent; Proceed with optimisation
10: **else**
11: Go to step 2
12: **end if**

Several combinations of weights were analysed to find the combination that gives the least total cost of power production as shown in Table 1. Let f1, f2 and f3 represent the thermal fuel cost, thermal emission cost and solar cost respectively and let w1, w2 and w3 be their respective weights.

From Table 1, it can be inferred that the combination that gives the least Total Cost of Production is w3>w2>w1. Hence, this combination was chosen for the assigning weights for the different objectives. In the first 3 rows, total cost of generation was calculated by considering only one objective each. The weights are calculated such that their sum is equal to one. The implementation of AHP is explained for this combination in Tables 2–4.

Table 1 Total generation cost for different combinations of weights

	w_1	w_2	w_3	Total Cost ($/h)
Only f_1	1	0	0	1,35,946.32
Only f_2	0	1	0	1,42,035.47
Only f_3	0	0	1	1,22,336.60
$\mathbf{w_1{=}w_2{>}w_3}$	0.4285	0.4285	0.1430	1,25,668,94
$\mathbf{w_1{=}w_2{<}w_3}$	0.2257	0.2257	0.5485	1,17,646.50
$\mathbf{w_1{>}w_2{>}w_3}$	0.623	0.2409	0.1373	1,29,206.57
$\mathbf{w_1{>}w_3{>}w_2}$	0.623	0.1373	0.2409	1,22,145.66
$\mathbf{w_2{>}w_1{>}w_3}$	0.2409	0.623	0.1373	1,21,828.52
$\mathbf{w_2{>}w_3{>}w_1}$	0.1373	0.623	0.2409	1,24,809.43
$\mathbf{w_3{>}w_1{>}w_2}$	0.2409	0.1373	0.623	1,16,955.19
$\mathbf{w_3{>}w_2{>}w_1}$	**0.1373**	**0.2409**	**0.623**	**1,13,946.24**

Table 2 Pair-wise comparison matrix

	Fuel Cost	Emission Cost	Solar Cost
Fuel Cost	1	0.5	0.25
Emission Cost	2	1	0.33
Solar Cost	4	3	1
Sum	7	4.5	1.583

Table 3 Normalised matrix

	Fuel Cost	Emission Cost	Solar Cost	Weights
Fuel Cost	0.1429	0.11	0.158	0.1373
Emission Cost	0.2857	0.22	0.21	0.2409
Solar Cost	0.5714	0.66	0.6317	0.623

Table 4 Lambda value and Eigen value computation to check consistency

	Fuel Cost	Emission Cost	Solar Cost	Weighted Sum	λ
Fuel Cost	1	0.5	0.25	0.4135	3.012
Emission Cost	2	1	0.33	0.6712	2.79
Solar Cost	4	3	1	1.8949	3.04

In Table 2, each of the three attributes are given a ranking pair-wise according to Saaty Table [29]. Since the combination where w3>w2>w1> gives the least cost (Table 1), ranks are given accordingly.

In Table 3, each element of Pair-wise Comparison Matrix is divided by the sum of elements of their respective column. The average of the elements of each row of this normalised matrix is the weight of the respective attribute.

Therefore, the weights for Total Thermal Fuel Cost, Total Thermal Emission cost and Total Solar costs are 0.1373, 0.2409 and 0.623 respectively.

Now, in order to check for the consistency of the weights, weighted sum of each row of the pair-wise comparison matrix is found as shown in Table 4. Then, using Equation (35), λ is computed for each attribute. The average of the λ values is then computed. λavg was found to be 2.95.

The above results were checked for consistency by using Equations (35)–(37). The absolute value of CR was found to be 0.05 which is less than 0.1 and hence the weights determined are consistent.

3.3 Objective Function with Weights

From Section 3.2, it is found that the weights used for the analysis are 0.625, 0.2409 and 0.1373 for fuel, emission and solar costs respectively. Therefore, the final objective function with weights is given by Equation (38):

$$\min C = 0.625 * \sum_{i=1}^{n} F(P_i) + 0.2409 * \sum_{i=1}^{n} E(P_i) + 0.1373 * \sum_{j=}^{m} S_j \tag{38}$$

In the analyses without solar power, fuel cost comparison between Lambda iteration and PSO (Section 4.1) and Emission Analysis without solar power (Sub-section 4.4.2), the weights are taken as 0.5 for both fuel and emission costs as given by Equation (39).

$$\min C = 0.5 * \sum_{i=1}^{n} F(P_i) + 0.5 * \sum_{i=1}^{n} E(P_i) \tag{39}$$

This is because in [30], it was found that the combination of weights that gave the least Total Thermal Cost was 0.5 and 0.5 respectively.

4 Results and Discussions

A comparison between Lambda Iteration Method and Particle Swarm Optimization is discussed in this section along with the comparison between CEED with FLAPC and without FLAPC. Emission Analysis gives the amount of emission reduced with CEED and Solar Power. This section finally gives the cost analysis with and without solar power.

Table 5 Results of Lambda Iteration for different loads

DEMAND (MW)	700	750	800	850	900	950	1000	1088	1155	1244
P1 (MW)	25	26.86	28.75	30.65	32.51	34.305	36.1	42.204	47.71	73.78
P2 (MW)	10	10	10	10	10.81	13.398	15.98	24.77	32.69	70.22
P3 (MW)	102.79	112.95	123.236	133.52	143.64	153.39	163.155	196.34	226.26	250
P4 (MW)	110.74	118.76	126.89	135.03	143.03	150.74	158.45	184.69	208.34	210
P5 (MW)	232.86	246.34	260	273.66	287.1	300.05	313.008	325	325	325
P6 (MW)	219.25	235.07	251.11	267.13	282.9	298.1	313.3	315	315	315
TOTAL COST (1000$/h)	36.0	38.3	40.7	43.1	45.5	47.9	50.4	54.8	58.3	63.3

Table 6 Results of PSO for different loads

DEMAND (MW)	700	750	800	850	900	950	1000	1088	1155	1244
P1 (MW)	56.38	36.05	27.83	60.304	67.61	51.85	20.208	47.76	57.02	87.78
P2 (MW)	32.28	23.05	59.82	241.703	38.27	51.54	71.298	25.58	74.97	84.67
P3 (MW)	73.62	129.44	150.56	174.21	179.64	171.32	182.477	173	213.07	247.14
P4 (MW)	140.45	145.32	135.78	143.44	157.077	143.44	188.267	203.21	181.47	205.62
P5 (MW)	228.66	216.88	263.43	256.72	240.41	287.65	263.53	324.95	313.46	305.12
P6 (MW)	168.6	199.24	162.58	191.15	216.99	244.18	274.194	313.41	315	313.66
TOTAL COST (1000$/h)	36.0	38.3	40.7	43.1	45.5	47.9	50.4	54.8	58.3	63.3

4.1 Economic Dispatch

4.1.1 Lambda iteration results For ED

Based on the steps defined in Algorithm 1 using Lambda Iteration method, Table 5 gives the power generated by the 6 thermal units and the total cost of fuel.

When the generators have equal incremental costs, that is, when the total cost of power generation is least, the power generated by each thermal unit is shown for 10 different load demands with its corresponding total cost of production.

4.1.2 PSO Results for ED

The PSO algorithm as shown in Algorithm 2, was executed for 10 different load demands and the power generated by each thermal unit and the total generating cost is shown in table 6.

4.1.3 Fuel cost comparison

Table 7 shows the comparison between the total fuel cost of the 6 thermal units for different demand in terms of dollars per hour.

Table 7 Fuel cost comparison between lambda iteration and PSO

	Cost ($/h)		
Demand (MW)	LI	PSO	Difference in Cost
700	3.60E+04	3.60E+04	4.50E+00
750	3.83E+04	3.83E+04	5.60E+00
800	4.07E+04	4.07E+04	3.78E+00
850	4.31E+04	4.31E+04	2.67E+00
900	4.55E+04	4.55E+04	3.68E+00
950	4.79E+04	4.79E+04	4.90E+00
1000	5.04E+04	5.04E+04	4.44E+00
1088	5.48E+04	5.48E+04	4.32E+00
1155	5.83E+04	5.83E+04	4.11E+00
1244	6.33E+04	6.33E+04	4.40E+00
Average difference in cost			4.24E+00

Table 8 Priority of Thermal Units based on FLAPC

Units	FLAPC ($/MWh)	$P_{\min}$ (MW)	$P_{\max}$ (MW)
6	48.244	125	315
5	48.292	130	325
3	51.37	35	250
4	51.574	35	210
1	63.634	10	125
2	65.058	10	150

It can be inferred from the table that the total fuel cost of 6 thermal units is lesser when PSO algorithm is used. Difference in cost has an estimated average benefit of 4.24 dollars per hour when the load distribution has been done using PSO. This is the significant saving in cost for the large grid.

4.2 Unit Commitment Scheme Using Priority Method

Using Equation (20) the 6 thermal units are prioritized as shown in Table 8 and a commitment scheme for different ranges of demand is prepared in Table 9.

It can be observed from Table 8 that Generator 6 is having the highest priority due to its least FLAPC.

According to the priority list, the commitment scheme is prepared as shown in Table 9. Assuming the load demand as 200 MW, it is seen that only generator 6 has to be committed. On the other hand, if the demand is 900 MW, then generators 6,5,3 and 4 would be committed. It can also be

Table 9 Commitment Scheme using FLAPC

Units Committed	Demand (MW)
6	125 – 315
6, 5	315 – 640
6, 5, 3	640 – 865
6, 5, 3, 4	865 – 1100
6, 5, 3, 4, 1	1100 – 1225
6, 5, 3, 4, 1, 2	1225 – 1375

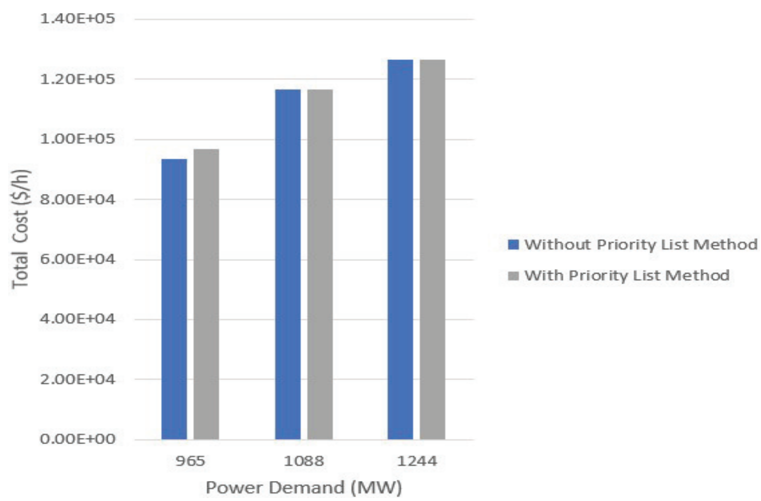

Figure 4 Comparison between costs when all units are committed with or without priority method.

inferred from the table that the maximum capacity of the system of 6 thermal units is 1375 MW, and the minimum is 125 MW.

4.3 CEED with Solar Power

The analysis for the CEED now includes 13 large scale solar PV power plants along with the 6 thermal units [18].

4.3.1 Comparison of CEED with and without priority method

Figure 4 shows the comparison of total cost, which includes fuel, emission and solar cost, between the scenario when all units are committed at the same time and when units are committed using Priority method for 3 different load demands.

Table 10 Thermal power generated for demand of 1088 MW

Thermal Units	Power Generated (MW)
P1	73.896
P2	108.596
P3	121.926
P4	169.702
P5	237.880
P6	276.025

Table 11 Results for solar Power for demand of 1088 MW at 11:00 hour

S1 S2…S13	0000010001100
Solar Share (MW)	99.954

Table 12 Costs for demand of 1088 MW

Fuel Cost ($/h)	51,091.623
Emission Cost ($/h)	39,199.340
Solar Cost ($/h)	26,900.643
Total Cost ($/h)	1,17,191.606

It can be inferred for Figure 4 that the total cost of generation is less when all units are committed when compared to fewer units committed as per priority method.

4.3.2 When all units are committed

Tables 10, 11 and 12 show the results obtained for CEED with Solar power when all 6 thermal units are committed.

When CEED was executed using PSO according to Algorithm 2 and 3, the power generated by the six thermal units when the demand is 1088 MW is shown is Table 10.

It can be seen from Table 11 that solar units S6, S10 and S11 are committed and the rest are not committed (1 – committed; 0 – not committed). The lesser number of units are committed due to higher weightage given for reducing solar cost in the objective function as explained in Section 3.2.

When CEED for six thermal units and 13 solar plants was performed for 1088 MW, the total costs and individual share of the cost of each attribute are shown in Table 12.

4.4 Emission Analysis

This section gives analysis and comparison of the amount of greenhouse gas emissions (kg/h) under various conditions.

Table 13 Comparison of emission between ED and CEED

	Emission (kg/h)		
Demand (MW)	ED	CEED	Difference
965	691.02	662.76	28.26
1088	772.76	728.65	49.41

Table 14 Emission with and without solar power

	Emission (kg/h)		
Demand (MW)	Without Solar	With Solar	Difference
965	764.80	662.76	102.04
1088	1022.17	728.65	298.84

4.4.1 Emission in ED and CEED

Table 13 gives the comparison between the analysis when only Economic Dispatch is done and when Combined Economic and Environmental Dispatch is done. The Comparison is shown for two demands.

It can be inferred from Table 13 that a significant amount of green-house gas emission is reduced when CEED is performed. For example, 49.41 kg of green-house gas emission is reduced at the hour when the demand is 1088 MW.

4.4.2 Emission with and without solar power

Table 14 shows the comparison between the amount of greenhouse gas emitted with and without solar power.

It can be inferred from the table that a considerable amount of greenhouse gas emissions is reduced when solar power plant is included in the power system. For example, 298.84 kg green-house gas emission is reduced at an hour when the demand is 1088 MW. This shows that the contribution of renewable energy sources is significant in reducing environmental pollution.

5 Conclusion

This paper experimented optimization of unit commitment and combined economic and environmental dispatch using conventional methods such as Lambda iteration and priority list method along with a meta-heuristic approach called Particle Swarm Optimization. Thermal power plants and solar power plants were used for the analysis. Particle Swarm Optimisation, a meta-heuristic approach, gives better results when compared to the conventional Lambda Iteration method. All thermal units committed at the same time gives better results than when unit commitment is done using Priority List method followed by economic dispatch using PSO. The PSO program has to be run multiple times to get best results. This increases the computation time and the complexity. In contrast, Lambda Iteration is simple and faster. A significant amount of green-house gas emissions, can reduced by environmental dispatch and by introducing solar power into the grid. Solar Power contributes more towards the cost than the thermal power.

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