Combined Economic and Emission Dispatch for a Wind Integrated System Using Particle Swarm Optimization

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Abstract—This paper deals with the problems of Economic Dispatch, Emission Dispatch and Combined Economic and Emission Dispatch problems for an integrated system having thermal and wind units. Particle Swarm Optimization and Genetic Algorithm methods are used to solve the problems of Economic dispatch, Emission dispatch and Combined Economic and Emission Dispatch problems. The effectiveness of PSO and GA methods are demonstrated by comparing the results obtained with both the methods.

Keywords —Emission level, Fuel cost, Particle Swarm optimization, Wind integration.

I. INTRODUCTION

A power system is a mix of different types of generations, out of which thermal, hydro and nuclear power generations have the maximum contribution. However, economic operation has conveniently been considered by proper scheduling of thermal and hydro-generation only. The nuclear stations are run at their base loads keeping safety in mind [13].

The purpose of economic dispatch is to find out the most economical schedule of the generating units while satisfying load demand and operational constraints. Economic dispatch is a familiar problem pertaining to the allocation of the amount of power to be generated by different units in the system on an optimum economy base [1]. This problem has been tackled by many researchers in the past. Recently the problem which has attracted much attention is pollution minimization due to pressing public demand for clean air. Environmental pollution is a direct consequence of industrial advancement. Technology, which has made economic development possible, produces enormous quantities of harmful by-products and wastes.

Thermal power stations are major causes of atmospheric pollution, because of high concentration of pollutants they cause. It is utmost important to protect our environment from harmful emissions out from thermal power plants. Power utilities using fossil fuels as a primary energy source, give rise to particulates and gaseous pollutants apart from heat. The particulates as also the gaseous pollutants such as carbon dioxide (CO₂), oxides of sulphur (SOₓ) and oxides of nitrogen (NOₓ) cause detrimental effects of CO₂ on the environment is not yet precisely known. Pollution control agencies (Municipal/Governmental regulatory bodies) restrict the amount of emission of pollutants depending upon their relative harmfulness to human beings [11]. So, the emission dispatch has been formulated. Of the pollutants emitted, NOₓ is of major concern and hence it has been considered. The objective of emission dispatch is to minimize the total environmental degradation or the total pollution emission due to burning of fuels for production to meet the load demand [14]. Hence, there is a need to formulate the combined emission and economic dispatch (CEED) problem. The idea behind combined emission and economic dispatch is to compute the optimal generation for individual units of the power system by minimizing the fuel cost and emission levels simultaneously,
subjected to the system constraints.

II. Problem formulation

A. Economic dispatch

The generation cost function is usually expressed as a quadratic polynomial and can be represented as below for an \( i \)th generator.

\[
F_i = a_i P_i^2 + b_i P_i + c_i \quad \text{Rs/hr} \quad (1)
\]

In the expression above, \( P_i \) is the output power in MW and \( a_i, b_i, c_i \) are the fuel cost-coefficients of the \( i \)th generating unit.

B. Emission Dispatch

Pollutant Emissions from the generating units such as oxides of nitrogen can be expressed as a quadratic polynomial and can be represented as below for an \( i \)th generator.

\[
E_i = a_i P_i^2 + b_i P_i + c_i \quad \text{Kg/hr} \quad (2)
\]

In the expression above, \( P_i \) is the output power in MW and \( a_i, b_i, c_i \) are the emission coefficients of the \( i \)th generating unit.

C. Constraints

1. Power Balance Constraint

\[
\sum_{i=1}^{ng} P_{gi} = P_D + P_L \quad (3)
\]

Where, \( ng \) = number of generating units, \( P_{gi} \) is the power generated by \( i \)th unit in MW, \( P_D \) is the wind power that is available in MW, \( P_L \) is the load demand in MW, \( P_L \) is the transmission loss in MW.

2. Generating Limits

\[
P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max} \quad (i=1,2,3,..ng)
\]

\( ng \) = number of generators.

D. CEED Cost Function

In this formulation both fuel cost objective and emission level objective are combined to form a single objective with the introduction of factor called ‘The Price Penalty Factor’, \( h_m \) (Rs/Kg).

Minimize

\[
F_T = (a_i P_i^2 + b_i P_i + c_i) + h_m(a_i P_i^2 + \beta_i P_i + \gamma_i) \quad (4)
\]

Where, \( F_T \) is the total cost of generation(RS/hr).

E. Constraints

1. Power Balance Constraint

\[
\sum_{i=1}^{ng} P_{gi} = P_D + P_L \quad (5)
\]

Where, \( ng \) = number of generating units, \( P_{gi} \) is the power generated by \( i \)th unit in MW, \( P_D \) is the load demand in MW, \( P_L \) is the transmission loss in MW.

Losses can be calculated by B coefficients, which can be expressed as

\[
P_L = \sum_{i=1}^{ng} \sum_{j=1}^{ng} P_i B_{ij} P_j \quad (6)
\]

Where, \( B_{ij} \) is generation loss coefficient. \( P_i \) and \( P_j \) are the real power injections at \( i \)th and \( j \)th buses respectively.

2. Generating Limits

\[
P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max} \quad (i=1,2,3,..ng)
\]

\( ng \) = number of generators.

III. Wind Integration

This paper deals with a multi-objective generation dispatch problem that considers environment and fuel cost under substantial penetration of wind energy has been proposed [11]. Wind plants are different from conventional generation plants in that their fuel supply is neither steady nor controllable, and as a result, they exhibit greater uncertainty and variability in their output [10].

Wind plants naturally operate when the wind blows, and their power levels vary with the strength of the wind. The turbine power output is controlled by pitching the blades. With each new generation of wind turbines, the size has increased and reductions in the life-cycle cost of energy have been achieved through economies of turbine scale and a larger rotor to increase energy capture. However, there are constraints to this continued growth in size. At some point, it will cost more to build a larger turbine than the benefit of increased energy benefit is worth. In addition, land transport restrictions, cost as well as crane requirements, can impose size limits for wind turbines installed on land. A misconception about wind power [9] is that wind plants will cause the entire power system to collapse. But, because abrupt wind-related changes in plant output do not occur, this fear is unfounded. In fact, a modern wind plant will actually help a power system handle a major outage or contingency elsewhere on the system. Reactive-power control and low-voltage ride-through capabilities of modern wind plants actually improve system stability.

Wind-energy generation only occurs when the wind is...
blowing [12]. Wind power is therefore not dispatchable like conventional energy sources and delivers a variable level of power depending on the wind speed. Wind is primarily an energy resource and not a capacity resource. Its primary value is to offset fuel consumption and the resulting emissions. The output of output of wind power plant, or multiple wind power plants, is variable over time. Each megawatt generated by wind reduces the required generation of other units. Therefore, the remaining nonwind generation units only need to supply the load that is not supplied by the wind. This remaining load is often called the net load. Therefore, the non-wind portion of the power system is operated to the net load, which is the difference between load and wind. Although wind is a variable resource, operating experience and detailed wind integration studies have yet to find a credible and firm technical limit to the amount of wind energy that can be accommodated by electrical grids. Some countries already receive a significant amount of electricity from wind power. There is not a technical limit to increased penetration of wind energy but there might be an economic limit, a point at which it is deemed too expensive to accommodate more energy from wind in comparison with the value that it adds to the system.

IV. Problem formulation with Wind Integration

A. CEED problem formulation with WIND Integration

Minimize

\[ F_T = (a_i P_i^2 + b_i P_i + c_i), g_m (\alpha_i P_i^2 + \beta_i P_i + \gamma_i) \]

Where, \( F_T \) is the total cost of generation (RS/hr).

B. Constraints

1. Power Balance Constraint

\[ \sum_{i=1}^{ng} P_{si} + P_w = P_D + P_L \]

where, \( ng = \) number of generating units, \( P_{si} \) is the power generated by \( i^{th} \) unit in MW, \( P_w \) is the wind power that is available in MW, \( P_D \) is the load demand in MW, \( P_L \) is the transmission loss in MW.

2. Generating Limits

\[ P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \quad (i=1,2,3,..,ng) \]

\( ng = \) number of generators.

V. GENETIC ALGORITHM

The aim of optimization is to determine the best-suited solution to a problem under a given set of constraints. Since the beginning of the nineteenth century, a significant evolution in optimization theory has been noticed [15]. Classical linear programming and traditional non-linear optimization techniques such as Lagrange’s Multiplier was prevalent until this century. Unfortunately, these derivative based optimization techniques can no longer be used to determine the optima on rough non-linear surfaces. One solution to this problem has been put forward by the evolutionary algorithms research community. Genetic algorithm (GA), enunciated by Holland, is one such popular technique which comes under evolutionary algorithms. Genetic Algorithm consists of a string representation of points in the search space, a set of genetic operators for generating new search points, a fitness function to evaluate the search points and a stochastic assignment to control the genetic operations [12]. It typically consists of three phases.

1. Initialization
2. Evaluation
3. Genetic Operation

Initialization is the generation of initial population of chromosomes i.e. initial search points. Fitness function is so selected that the most fit solution is the nearest to the global optimum point. For minimization type problems, fitness function can be function of variables that bear inverse proportionality relationship with the objective function. The genetic operators are reproduction, crossover, and mutation. Reproduction is simply an operator where by an old chromosome is copied into a mating pool according to its fitness value. The commonly used method for selecting chromosomes for parents to cross over is Roulette Wheel selection, in roulette wheel selection technique, selection is usually implemented as a linear search through roulette wheel with slots weighted in proportion to string fitness values. The crossover is mainly responsible for the global search property of the GA. It is recombination operation. Here the gene information (information in a bit) contained in the two selected parents is utilized in certain fashion to generate two children who bear some of the useful characteristics of parents and expected to be more fit than parents. Usually, the probability of Crossover (P_C) is high and chosen to be in between (0.6 to 0.8). Mutation operator is capable of creation new genetic material in the population to maintain the population diversity. It is nothing but random alteration of a bit value at a particular bit position in the chromosome. Usually, the probability of Mutation (P_M) is very less and is chosen to be in between (0.001 to 0.01). We have another operator in GA, called Elitism. The copying of best population to next population is called Elitism. If the probability is high, then the convergence rate increases. Usually, the probability of Elitism (P_E) is chosen to be 0.15.
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A. Implementation of CEED with Genetic Algorithm:

Proposed Algorithm for solving CEED problem:

Step 1: Generate initial population of chromosome of binary bits using random generation technique.

Step 2: Implementation of a problem in a GA starts the parameter encoding. Proposed approach uses the equal system λ (equal system incremental cost) criterion as its basis[11]. The only encoded parameter is the normalized system incremental cost, λ_{min}. Decode the chromosomes of the population and determine normalized system incremental cost, λ_{min}.

Step 3: Calculate the actual system incremental cost λ_{d,e}

Initial point in search space, λ_{d,e} is calculated as,

\[
λ_{d,e} = λ_{min} + λ_{max}(λ_{max} - λ_{min})
\]  
(9)

Calculating λ_{min} and λ_{max} values:

\[
α(i) = b(i) + h_n \cdot β(i)
\]  
(10)

\[
β(i) = 2 \cdot (a(i) + h_m \cdot α(i))
\]  
(11)

\[
λ_{min} = α(i) + (β(i) \cdot p_{min}(i))
\]  
(12)

\[
λ_{max} = α(i) + (β(i) \cdot p_{max}(i))
\]  
(13)

The equivalent decimal integer of binary string λ is obtained from:

\[
y = \sum_{i=1}^{l} 2^{i-1} \cdot b_j \quad (j=1,2,…,L)
\]  
(14)

l=length if string.

b_j = i^th binary digit of j^th string.

L=population size.

Step 4: Calculate the generation output of all the units for each chromosome from its λ_{d,e} value and enforce P_{i} limits.

\[
P_i = \frac{(b_i + h_n \cdot α_i) \sum_{j=1}^{m} b_j \cdot p_j}{2α_i + 2h_mα_i}
\]  
(15)

Step 5: Calculate transmission losses using B-coefficient equation (5) and compute the error ε

\[
ε = |P_{D} - P_{L} - \sum_{i=1}^{m} P_{Bi}|
\]  
(16)

Step 6: Calculate the fitness value of the chromosome, using the equation

\[
fitness = 1 / (1 + 50 \cdot ferror)
\]  
(17)

\[
ferror = \text{abs}(P_{G} \cdot P_{D} \cdot P_{loss})
\]  
(18)

Step 7: Repeat the procedure from Step 2 until chromosome count > population size.

Step 8: Sort the chromosomes and all their related data in the descending order of fitness.

Step 9: Check if the error is less than ε. If yes, go to Step 15.

Step 10: Copy the P_{k} % chromosomes of old population to new population starting from the best ones from the top.

Step 11: Perform crossover on selected parents and generate new child chromosomes, repeat it to get required number of chromosomes.

Step 12: Add all the generated child chromosomes to new population.

Step 13: Perform mutation on all chromosomes.

Step 14: Replace old population with new population.

Step 15: Calculate the total cost, fuel cost, emission release, emission cost, power generated by units.

VI. Particle Swarm Optimization

The aim of optimization is to determine the best-suited solution to a problem under a given set of constraints. Since the beginning of the nineteenth century, a significant evolution in optimization theory has been noticed [15]. Classical linear programming and traditional non-linear optimization techniques such as Lagrange’s Multiplier was prevalent until this century. Unfortunately, these derivative based optimization techniques can no longer be used to determine the optima on rough non-linear surfaces. One solution to this problem has been put forward by the evolutionary algorithms. Genetic algorithm (GA), enunciated by Holland, is one such popular algorithm which is a guided search technique. When it comes to evolutionary programming, techniques like Particle Swarm optimization (PSO) and Differential Evolution (DE) have been proposed. These algorithms are inspired by biological and sociological motivations and can take care of optimality on rough, discontinuous and multimodal surfaces. Particle Swarm Optimization (PSO) has been developed through simulation of simplified social models [2]. This algorithm is motivated by the behavior of organisms such as bird flocking and fish schooling and it utilizes a population based search procedure. The algorithm searches a space by adjusting the trajectories of individual vectors, called “particles” as they are conceptualized as moving points in multidimensional space. The individual particles are drawn stochastically towards the positions of their own previous best
performance and the best previous performance of their neighbors. The particles are thought of as collision-proof birds and the original intent is to graphically simulate the graceful but unpredictable choreography of a bird flock.

PSO is initialized with a group of random particles and then searches for optima by updating generations. Each particle in PSO represents a feasible solution. In other words, each particle represents a point in multi-dimensional search space, in which optimal point is to be determined. Each particle changes its state by ‘flying’ around the multi-dimensional search space until a relatively unchanged state (optimal state) has been obtained. Every generation, each particle is updated by following two “best” values. The first one is the best solution it has achieved so far. This value is called “localbest”. Another “best” value that is tracked by the particle swarm optimizer is a global best and called “globalbest”.

In PSO, the coordinates of each particle represent a possible solution that has two vectors associated with it, position \((x_i)\) and velocity \((v_i)\) vectors [16]. The size of the vectors \(x_i\) and \(v_i\) is equal to the problem space dimension. Each particle updates its position based on its own best exploration, best swarm overall experience, and its previous velocity vector according to the following equations:

\[
v_{i}^{k+1} = w v_{i}^{k} + c_1 r_1 (\text{localbest}_i - x_{i}^{k}) + c_2 r_2 (\text{globalbest}_i - x_{i}^{k}) \tag{19}
\]
\[
x_{i}^{k+1} = x_{i}^{k} + v_{i}^{k+1} \tag{20}
\]

where, \(c_1\) and \(c_2\) are two positive constants, \(r_1\) and \(r_2\) are two randomly generated numbers with a range of \([0,1]\). The first term of right-hand side of (19) corresponds to global search. The second and third terms of equation (19) corresponds to local search. Hence, this method has a well-balanced mechanism to utilize global and local search efficiently [2].

VII. Algorithm for solving Combined Economic and Emission Dispatch problem using PSO

Power outputs from each generator are taken as the particles of the PSO [2]. The PSO algorithm for dispatch problems is stated as follows:

Step1: The particles are randomly generated between the maximum and minimum operating limits of the generators.

Step2: The particle velocities are generated randomly.

Step3: Objective function values of the particles are evaluated. Penalties are given for violations of demand constraint (2). These values are set the localbest value of the particle.

Step4: The best value among all the localbest values (globalbest) is identified.

Step5: New velocities for the particles are calculated using (19).

Step6: The positions for each particle are updated using (20).

Step7: New objective function values are calculated for new positions of the particles. If the new value is better than the previous localbest, the new value is set to localbest. If the stopping criterion is met, the positions of the particles represent the optimum solution. If the stopping criteria is not met, the procedure is repeated from Step4.

VIII. Results

In GA, the population size is taken as 60, String length = 16, \(P_c = 0.70\), \(P_m = 0.01\), \(P_e = 0.15\)

In the PSO technique, the population is taken as 40 and the values of \(c_1\) and \(c_2\) are \(c_1 = 2\) and \(c_2 = 2\).

The techniques are tested on IEEE 30-bus system [17], having 6 generators and a total demand of 900MW. The cost coefficients for the generators and their capacities, the corresponding emission coefficients for the generators and the B-coefficients considered in [17], are mentioned in the appendix. The Economic Dispatch problem is solved using GA and PSO and the results are tabulated in Table I. The Emission Dispatch problem is solved using GA and PSO and the results are tabulated in Table II. Later, CEED problem is solved using GA and PSO and the results are tabulated in Table III.

The CEED problem is solved using PSO taking into account wind integration [11]. For a total demand of \(P_d = 900\)MW, the Transmission losses, Fuel Costs, Emission release and Total cost are calculated without and with wind integration. Results are compared in Table IV. The parameters mentioned above are calculated with increasing wind penetration and the results are tabulated in Table V.

Computations have been carried out in MATLAB 7.5 environment.

Table I. Results comparing GA and PSO for Economic Dispatch problem

<table>
<thead>
<tr>
<th>Method</th>
<th>Transmission losses (MW)</th>
<th>Fuel cost (Rs/hr)</th>
<th>Emission release (Kg/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA</td>
<td>27.0153</td>
<td>50691.60</td>
<td>793.319</td>
</tr>
<tr>
<td>PSO</td>
<td>20.5518</td>
<td>45464.00</td>
<td>708.54</td>
</tr>
</tbody>
</table>
Table II. Results comparing GA and PSO for Emission Dispatch problem

<table>
<thead>
<tr>
<th>Method</th>
<th>Transmission losses (MW)</th>
<th>Emission release (Kg/hr)</th>
<th>Fuel cost (Rs/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA</td>
<td>26.12</td>
<td>647.11</td>
<td>49634.30</td>
</tr>
<tr>
<td>PSO</td>
<td>16.96</td>
<td>646.13</td>
<td>48069.00</td>
</tr>
</tbody>
</table>

Table III. Results comparing GA and PSO for Combined Economic and Emission Dispatch problem

<table>
<thead>
<tr>
<th>Method</th>
<th>Transmission losses (MW)</th>
<th>Fuel cost (Rs/hr)</th>
<th>Emission release (Kg/hr)</th>
<th>Total cost (Rs/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA</td>
<td>23.41</td>
<td>48029.00</td>
<td>687.52</td>
<td>78983.7</td>
</tr>
<tr>
<td>PSO</td>
<td>20.55</td>
<td>45464.00</td>
<td>603.61</td>
<td>72651.0</td>
</tr>
</tbody>
</table>

Table IV: Results comparing without and with wind integration.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Without wind integration</th>
<th>With P_W = 90 MW</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transmission losses (MW)</td>
<td>20.55</td>
<td>16.728</td>
</tr>
<tr>
<td>Fuel Cost(Rs/hr)</td>
<td>45464.00</td>
<td>41150.00</td>
</tr>
<tr>
<td>Emission release(Kg/hr)</td>
<td>603.61</td>
<td>452.228</td>
</tr>
<tr>
<td>Total cost (Rs/hr)</td>
<td>72651.00</td>
<td>61518.00</td>
</tr>
</tbody>
</table>

Table V: Results with increasing wind penetration.

<table>
<thead>
<tr>
<th>WindPower integrated(MW)</th>
<th>P_W = 90</th>
<th>P_W = 120</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transmission losses (MW)</td>
<td>16.728</td>
<td>15.533</td>
</tr>
<tr>
<td>Fuel Cost(Rs/hr)</td>
<td>41150.00</td>
<td>39732.00</td>
</tr>
</tbody>
</table>

IX. Conclusions

In this paper, GA and PSO techniques are used to solve the Economic Dispatch problem, the Emission Dispatch problem and the Combined Economic and Emission Dispatch problems. The results showed that in Economic Dispatch problem, the objective being to reduce the fuel cost, the emission level was higher, also, PSO yielded in better results when compared with GA. Similarly, in Emission Dispatch problem, the objective being to reduce the pollution level, the fuel cost was higher, also, PSO yielded in better results when compared to GA. Hence, the CEED problem is formulated whose objective is to reduce both fuel cost and emission release. Results have shown that PSO yielded in better results when compared to GA.

Later, when wind integration was taken into account, the results have shown that the transmission losses, fuel cost, emission levels and total cost can be reduced. Also, it was observed that the transmission losses, fuel cost, emission level and total cost can be reduced further with increase in wind penetration level.

However, there may be a limit for the amount of wind power that can be integrated to a system.

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APPENDIX

Fuel Cost Coefficients and Generator Capacity Limits

<table>
<thead>
<tr>
<th>Generator</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>P_{min} (MW)</th>
<th>P_{max} (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.1524</td>
<td>38.5397</td>
<td>756.798</td>
<td>10</td>
<td>125</td>
</tr>
<tr>
<td>2</td>
<td>0.1058</td>
<td>46.1591</td>
<td>451.325</td>
<td>10</td>
<td>150</td>
</tr>
<tr>
<td>3</td>
<td>0.0280</td>
<td>40.3965</td>
<td>1049.99</td>
<td>35</td>
<td>225</td>
</tr>
<tr>
<td>4</td>
<td>0.0354</td>
<td>38.3055</td>
<td>1243.53</td>
<td>35</td>
<td>210</td>
</tr>
<tr>
<td>5</td>
<td>0.0211</td>
<td>36.3278</td>
<td>1658.55</td>
<td>130</td>
<td>325</td>
</tr>
<tr>
<td>6</td>
<td>0.0179</td>
<td>38.2704</td>
<td>1356.65</td>
<td>125</td>
<td>315</td>
</tr>
</tbody>
</table>

Emission Coefficients

<table>
<thead>
<tr>
<th>Generator</th>
<th>α</th>
<th>β</th>
<th>γ</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.00419</td>
<td>0.3276</td>
<td>13.85932</td>
</tr>
<tr>
<td>2</td>
<td>0.00419</td>
<td>0.3276</td>
<td>13.85932</td>
</tr>
</tbody>
</table>

The Transmission loss coefficients matrix

\[
\begin{bmatrix}
0.00014 & 0.000017 & 0.000015 & 0.000019 & 0.000026 & 0.000022 \\
0.00017 & 0.000060 & 0.000013 & 0.000016 & 0.000015 & 0.000020 \\
0.00015 & 0.000013 & 0.000065 & 0.000017 & 0.000024 & 0.000019 \\
0.00019 & 0.00016 & 0.000017 & 0.000071 & 0.000030 & 0.000025 \\
0.00026 & 0.00015 & 0.000024 & 0.000030 & 0.000069 & 0.000032 \\
0.00022 & 0.00020 & 0.000019 & 0.000025 & 0.000032 & 0.000085
\end{bmatrix}
\]