Comparative Study for Combined Economic and Emission Dispatch Problem Considering Valve Point Effect

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Abstract: *Nowadays, the attention to the problem of environmental pollution is increasing around the world. The problem of Combined Economic and Emission Dispatch (CEED) is a very important issue to minimize the production cost of electrical power in conjunction with reducing the emissions of the power plants while meeting the system constraints. The valve point loading effect is apparent in the fuel cost vs. power production curve as ripples resulting from sharp increase in losses which occur when each steam valve starts to open. The economic and emission dispatch problem considering valve point effect has been discussed in this paper using two efficient optimization methods, Simulated Annealing (SA) algorithm, and Particle Swarm Optimization (PSO) algorithm. The classical Lagrange's (LR) method is used to provide a primary solution to be compared with the solutions provided by the two methods. The proposed algorithms are tested on the IEEE 30-bus system with six generating units. Several cases are investigated to test and validate the consistency of detecting optimal or near optimal solution for each objective. The simulation is performed in Matlab environment. A comparison between the three methods is presented.*

Key words: *Environmental Economic Dispatch, Price Penalty Factor, Lagrange's method, Simulated Annealing (SA), Particle Swarm Optimization (PSO).*

1. Introduction.

Most large electric power plants today depend on fossil fuels. This causes the release of large amounts of emissions mainly composed of carbon dioxide (CO_2), sulphur dioxide (SO_2), and nitrogen oxides (NO_x). Those emissions results in the pollution of the surrounding environment which harmfully affect all forms of life. They also produce a global warming phenomenon, and therefore serious damages occur. The summation of these effects can be represented in a cost of environmental degradation. There has been a keen attention for emission control over environmental pollution caused by fossil-fired generating units and the enforcement of environmental regulations. Thus nowadays, the ED optimization technique should also consider this environmental pollution scenario.

In the context of smart gird, there is a smart grid control system, which consists of an intelligent Supervisory Control and Data Acquisition (SCADA) system, Solution Method Model (SMM), Monitoring System, and Generators Set Point Adjustment Controller (GSAC). The SCADA system is used to connect between thermal power stations and (SMM). Modern communication mediums such as wireless sensor networks are used to receive information from the generators and transmit the control signal. The predicted load curve is produced during monitoring of the network and the standard electrical needs of consumers, then main control centre of the power grid determines required megawatts and send it to SCADA system to provide adaptive economic dispatch solution for each hour of the day. The SMM is used to solve the economic dispatch problem. GSAC is used to detect the new operating set points of the generators using. Meanwhile, emissions are continuously measured throughout the day, and their levels (E_m) are sent to a monitoring system to compare between the total measured emission and maximum allowable emissions level (E_{limmit}). If the measured emissions level is greater than maximum allowable emissions level, then the GSAC adjusts the output power of the thermal units. Otherwise, the output power of the thermal units is the calculated values (the best solution). On the same time, the thermal power plants are controlled by the Local Control Center so as to start and stop, and monitor the performance of the thermal units. Figure 1 illustrates the procedure of the smart economic dispatch system.

2. Valve Point Effect Loading

The thermal plant consists of many components, but for the purpose of simplification, it can be considered as shown in Fig. 2. To control the steam passing through the steam turbine, it has a number of steam admission valves that are opened or closed sequentially during the operation of the thermal unit, in order to response to any changes in load demands. However, the change in the amount of steam passed to the turbine will not change the speed of the turbine; it will produce more/less power depending on the flow change. The valve point loading effect is considered where the fuel cost vs. power production curve is not linear but consists of ripples as a result of the sharp increase in losses due to the wire drawing effects which occur as each steam admission valve starts to open. In this case the cost function is obtained based on the ripple curve for more accurate modeling.

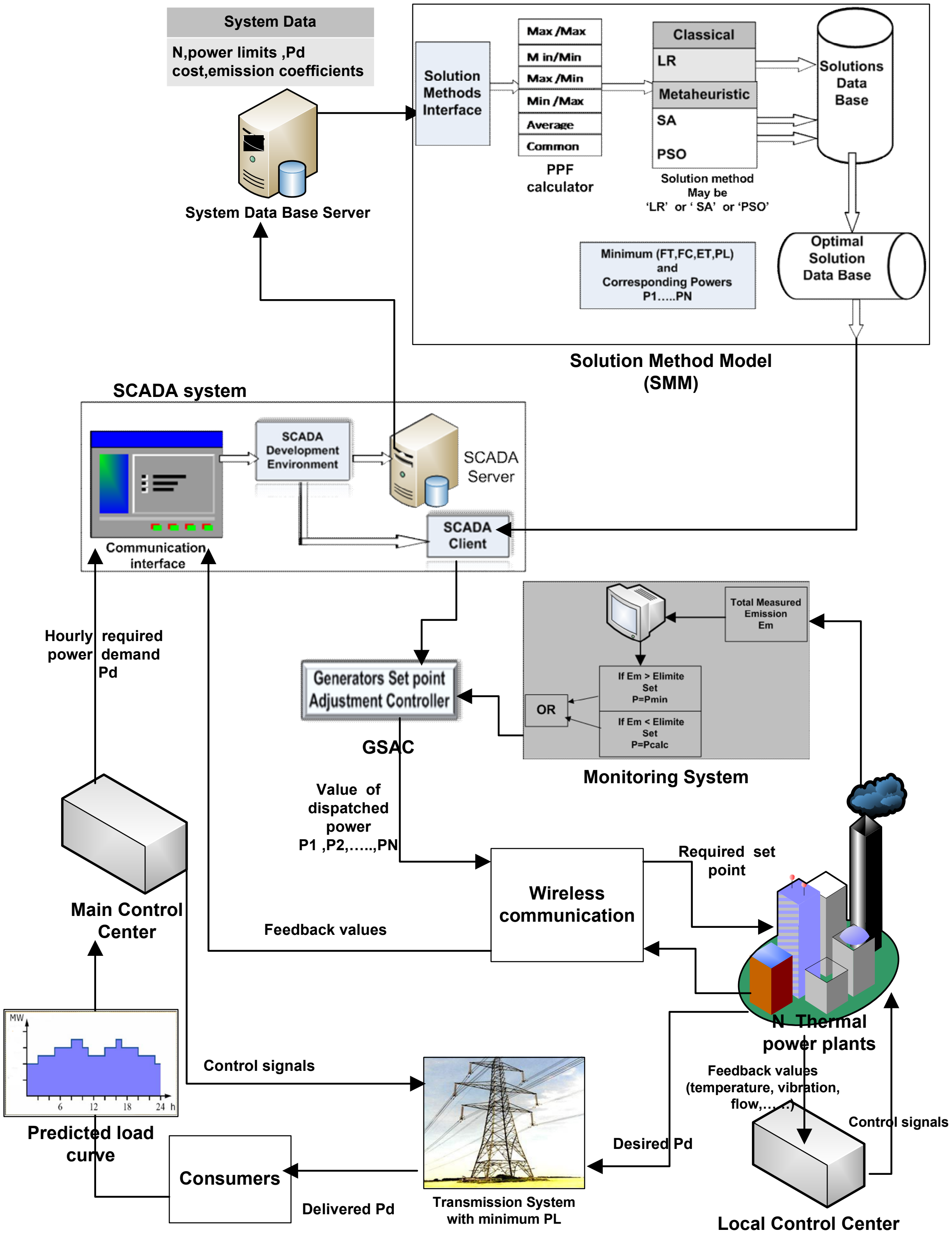

Fig.1. Smart economic dispatch system

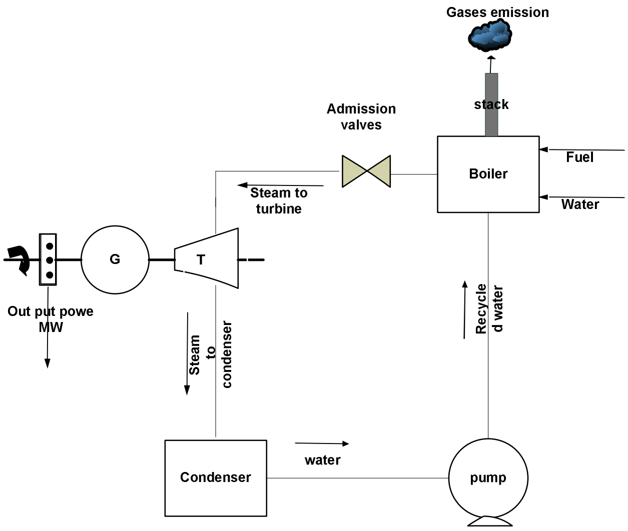

Fig.2. Schematic diagram of Thermal power station

The valve point loading effect has been modeled as a half wave rectifier output of sinusoidal function added to the smooth fuel cost curve given as shown in Fig. 3 [1]. It is clear that the solution of the ED problem will be more accurate when taking into account the valve point loading effect.

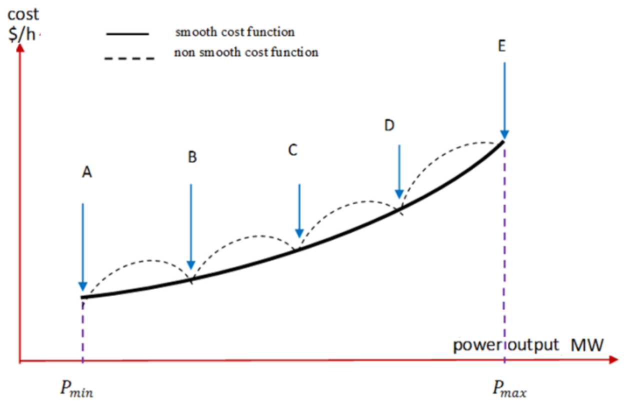

Fig.3. Fuel Cost considering valve-point effect

3. Literature Survey

Due to the importance of the ED of power system and its influence in the environment, there are several approaches developed by various researchers for the stabilization of the power systems. Many papers have focused on combined economic emission dispatch without considering valve point effect loading [2-4]. Recently the valve point effect loading pays great attention [5, 6]. Literally, the techniques used to solve combined economic emission dispatch (CEED) problem can be divided into two categories. The first one is the classical optimization techniques such as Lagrangian Relaxation Gradient and Dynamic programming method, Integer programming, Lambda-iteration, and Newton Raphson Method [7]. These techniques need derivative information of the objective function, give unsatisfactory results and require large computational time for non-linear complex problems. Linear programming method suffers from the limitation as it require piecewise linear cost approximation. Newton-based methods struggle with handling a large number of inequality constraints. In short, all these techniques suffer from: very slow convergence rate and inability to give the global solution of the nonlinear ED problem [8-12].

The second category is the metaheuristic optimization algorithms [13]. These algorithms are usually inspired by physics or biology. Many metaheuristic techniques have been used to solve ED problem, such as evolutionary programming (EP), simulated annealing (SA), tabu search (TS), genetic algorithm (GA), Differential Evolution (DE), particle swarm optimization (PSO), and Artificial Neural Networks (ANNs). The EP has the disadvantage that rather slow converging to a near optimum for some problems [3]. The TS is complicated in determining efficacious memory structures and strategies that depend on the problem [5]. GA sometimes does not have a strong ability to produce the best offspring and led to slow convergence near the global optimum, and sometimes may be to be trapped at a local optimum [2]. Differential Evolution (DE) is characterized as a very powerful algorithm, it has a small doubt but also it has the following disadvantage, which is the computing process to be trapped into local optima due to avarice updating principle and essential differential property [6]. The massive calculations due to excess numerical iterations are the most important disadvantages of artificial neural networks [4].

In this paper the classical Lagrange's method is compared with the SA, and PSO techniques for solving the CEED problem with valve point effect. The problem is solved with different types of price penalty factors (PPF) and different loading conditions.

SA algorithm is a hopeful heuristic algorithm for solving the non-convex optimization problems. SA's major advantage over other methods is an ability to avoid becoming trapped in local minima. It is relatively easy to code, even for complex problems. The result of the previous features, great results have emerged when applied SA algorithm to many of power system optimization problems [14]. The main drawback of this method is that it requires long CPU

time, due to the large number of iterations needed for the convergence of the algorithm [15].
PSO algorithm is widely applied into power system optimization problems. This is due to the advantages of PSO such as less complexity, fast convergence and free derivative algorithm [16,17]. PSO has a flexible and balanced mechanism to adapt the abilities of global and local search [18].
In [14] the SA algorithm was used to solve CEED problem, whereas in [19] the PSO algorithm was used to solve the same problem. In the two papers the problem was solved without considering the valve point loading effect. In this paper the valve point loading effect will be taken into consideration in solving the CEED problem. The curve fitting method will be used to simplify the complexity resulting from valve point loading effect. Also, the problem will be solved with different PPF and different loading conditions.

4. Problem Formulation

The main objective of solving the economic dispatch problem in electric power system is to determine the generation levels for all on-line units which minimize the total fuel cost and minimizing the emission level of the system, while satisfying a set of constraints.
When considering the valve point loading effect, the CEED problem turns into a non-convex multi objective optimization problem.

A. Multi-objective Function

The main objective of the CEED problem is to minimize the two objectives given as fuel cost and emission simultaneously to ensure optimal output of generated power whilst satisfying the equality and inequality constraints. The amount of pollutants is converted into emission cost in the objective function by using a price penalty factor. The multi-objective CEED problem is formulated as [19, 20]:

$$Min(F_T) = F_{C+} h_{T*} E_T \quad (1)$$

Where: F_T, F_C represent the total cost and total fuel cost in \$/hr, E_T is the total emission rate in kg/h, and h_T is the total price penalty factor in \$/kg, expressed as the summation of penalty factors of thermal units.

$$h_{T=} \left(\sum_{i=1}^{N} h_i\right) \quad (2)$$

In general the economic dispatch problem can be solved in three ways according to two weight factors w_1 and w_2 [19]:

$$F_T = w_1 F_{C+} w_2 (h_{T*} E_T) \quad (3)$$

- If $w_1 = 1$ and $w_2 = 0$, the problem is a classic economic dispatch problem.
- If $w_1 = 0$ and $w_2 = 1$, the problem is an emission dispatch problem.
- If $w_1 = 1$ and $w_2 = 1$, the problem is a combined economic and emission dispatch problem.

The CEED problem without valve point effect is determined by the following objective function:

$$F_T = \sum_{i=1}^{N}(a_i.P_i^2 + b_i.P + c_i) + h_i.(\alpha_i * P_i^2 + \beta_i.P_i + \gamma_i) \quad (4)$$

where a_i, b_i, and c_i are the coefficients of i^{th} generating unit, N is total number of generating units committed to the system, in \$/MW^2 h, \$/MWh and \$/h respectively, α_i, β_i, and γ_i are the emission coefficients of generator i in kg/MW^{2}h, kg/MWh and kg/h respectively, and d_i and, e_i are valve point effect coefficients
Whereas, the CEED problem with valve point effect is determined by the following objective function:

$$F_T = \sum_{i=1}^{N} (a_i.P_i^2 + b_i.P_i + c_i + \left|d_i.\sin(e_i.(P_i^{min} - P_i)\right| + h_i (\alpha_i.P_i^2 + \beta_i.P_i + \gamma_i) \quad (5)$$

Owing to valve-point effect exhibited by multi-valve steam turbines, the cost function is non-convex. The Maclaurin series-based Lagrangian method is proposed to solve complicated, non-convex and non-linear ED problems [22]. The main drawback of that method is the use of many approximations due to neglecting the higher order terms in Maclaurin sine series expansion. Theses approximations lead to a noticeable decrease in the accuracy of the obtained solution. In this paper a new proposed methods is used to solve the CEED problem. This method is based on converting valve point effect part to second order equation using curve fitting technique as explained by the following equations.

$$\left|d_i.\sin(e_i.(P_i^{min} - P_i)\right| = r_i.P_i^2 + s_i.P_i + u_i \quad (6)$$

$$F_T = \sum_{i=1}^{N}(A_i.P_i^2 + B_i.P + C_i) + h_i (\alpha_i.P_i^2 + \beta_i.P_i + \gamma_i) \quad (7)$$

where

$\mathrm{A_i = (a_i + r), B_i = (b_i + s_i)}$ and $\mathrm{C_i = (c_i + u_i)}$

The CEED optimization with two objective functions can be converted into a single objective function problem by using a price penalty factor h_i as will be explained later.

B. Problem Constraints

The objective function in (1) is subjected to the following equality and inequality constraints.

B.1 Power balance constraints

The total generation must supply the demand [19].

$$\sum_{i=1}^{N} P_i - P_d - P_L = 0\,, \quad i = 1,2,3,\ldots,N \qquad (8)$$

Where: P_d is the total demand in MW, and P_L is total transmission loss of the system in MW, and N is the number of generation units. The transmission loss is expressed as [19]:

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i \,.\, B_{ij} .\, P_j \; + \sum_{i=1}^{N} B_{0i} \,.\, P_i + B_{00} \qquad (9)$$

where P_i, P_j are active powers generation of unit i and unit j ,and B_{ij} , B_{0i}, B_{00} are transmission loss coefficients.

B.2 Power generation limits

The maximum power generation of a thermal power plant is limited by thermal consideration and also minimum power generation is limited by the flame instability of a boiler. The power generation of unit i should be between its minimum and maximum limits [20].

$$P_i^{min} \leq P_i \leq P_i^{max} \qquad (10)$$

where P_i^{min} , P_i^{max} are minimum, and maximum limits of power generated from the i^{th} unit in MW.

B.3 Emission constraints

According to the value of the measured emission recorded by monitoring system (explained in Fig. 1) for each thermal plant the value of the generating power by each plant can be detected according to the following equation:

$$P_i = \begin{cases} P_{i\,min} & if\ E_m \geq E_{limit} \\ P_{i\,calculated} & if\ E_m < E_{limit} \end{cases} \qquad (11)$$

Where E_m is the total measured emission and E_{limmit} is the maximum allowance level of emissions. P_i calculated is the value of the power generation of unit i results from solving the optimization problem. This value is then sent to the GSPAC which in turns sends a command to the thermal unit operators.

5. Price Penalty Factor

In CEED problem the price penalty factor (PPF) is used to convert bi-objective function into a single objective function. PPF is the ratio of fuel cost, f_i to emission cost, E_i for each generating unit There are many formulas used for calculating the price penalty factors for CEED problem such as Max-Max, Min-Min, Min-Max, Max-Min, Average and Common [19,23]. These formulas can be expressed as:

$$max/\max h_i = \frac{f_i\,(p_i^{max})}{\mathrm{E_i}\,(\mathrm{p_i^{max}})}$$

$$min/\min h_i = \frac{f_i\left(p_i^{min}\right)}{\mathrm{E_i}\,(\mathrm{p_i^{min}})}$$

$$min/\max h_i = \frac{f_i\left(p_i^{min}\right)}{\mathrm{E_i}\,(\mathrm{p_i^{max}})}$$

$$max/\min h_i = \frac{f_i\,(p_i^{max})}{\mathrm{E_i}\,(\mathrm{p_i^{min}})}$$

$$average\ h_i = average\ of\ the\ above\ factors$$

$$common\ h_i = \sum_{i=1}^{N} (\,average\ PPF)\,/\mathrm{N}$$

6. Solution Algorithms

In this paper the classical Lagrange's method is compared with the SA, and PSO techniques for solving the CEED problem with valve point effect. The problem is solved with different types of PPF and different loading conditions.

A. Classical method (Lagrange's method)

The Lagrange multipliers method is a mathematical optimization technique; it provides a strategy for finding the local maxima and minima of a function subject to equality constraints [24]. Lagrange method is used to solve the CEED by using a Lagrange function based on a Lagrange's multiplier λ.

$$L = F_T + \lambda\,(P_d + P_L - \sum_{i=1}^{N} P_i\,) \qquad (12)$$

Then, the CEED problem is solved as a problem for minimizing L according to P_i, and maximizing of L according to λ, under the predefined constraints.

According to equation (7), Lagrange function will be in the following form:

$$\mathrm{L} = \sum_{i=1}^{N} \Big(A_i . P_i^2 + B_i . P_i + C_i + h_i \,.(\alpha_i . P_i^2 + \beta_i . P + \gamma_i) \Big) + \lambda\Big(P_d + \sum_{i=1}^{N} \sum_{j=1}^{N} P_i \,.\, B_{ij} .\, P_j + \sum_{i=1}^{N} B_{0\,i} \,.\, P_i + B_{00} - \sum_{i=1}^{N} P_i \Big) \qquad (13)$$

B. Simulated Annealing algorithm

Simulated annealing algorithm (SA) was inspired from the solid annealing principle [25]. It is a successful application in the combinatorial optimization problems. The SA technique simulates the physical annealing process for the determination of global or near-global optimal solutions of the difficult combinatorial optimization problems involving non-linear objective functions and complex constraints [26]. There are four control parameters in the SA algorithm; the Initial Temperature, Final Temperature, Rate of Temperature Decrement and Iteration at each Temperature [27-28]. Those parameters should be set well for the successful application of the SA algorithm. To apply the SA algorithm for solving the CEED problem; different optimization parameters will take the corresponding physical system parameters as explained by Table 1.

Table 1: Physical system parameters versus optimization problem parameters

Physical System Parameters	Optimization Problem Parameters
temperature	control parameter T
energy of current state	objective cost function
current state of the solid	solution x
ground state	optimal solution $x_{optimal}$
gradual cooling	simulated annealing

The following steps summarize the steps of applying the SA algorithm for solving the CEED problem:

1. Read the CEED problem input data (cost, emission coefficients).
2. Choose a random temperature T; select the parameter α, an initial feasible solution is generated through random process, which is considered as current solution S_i. From [29] the total cost, F is then calculated using equation (8).
$$F = \sum_{i=1}^{N} F_T\ (P_i) + h_i\left|(P_d + \ P_L - \sum_{i=1}^{N}\ P_i)\right| \quad (14)$$
where *PF* is the paper factor and is taken as 1000 [29]
3. A new adjacent solution S_j is created by using the random perturbation and computing the new total cost, F. In the developed SA software, the constrained optimization problem is converted to an unconstrained problem by factor method as shown by (13).
4. The new solution S_j replace the old one S_i based on the value of a random number uniformly distributed Ω and the deviation of cost ΔS ($\Delta S = S_j - S_i$) using the following logic:
$$New\ solution = \begin{cases} acceptable & if\ \ \Omega \le e^{-\Delta s/t} \\ not\ acceptable & otherwise \end{cases} \quad \Omega\ \in\ (0, 1)$$
In case that the new solution is not acceptable; then calculate the deviation of CEED cost ΔS, then generate a random number **Ω** and replace the current solution S_i with the new solution S_j.
5. If the stopping criterion is satisfied then stop the program and print the results
6. In case that the stopping criterion is not satisfied, decrease the control parameter using the following equation and then go to step 3
$$T(t) = \alpha\, T \quad (15)$$
where α is a constant in the range between 0.8, and 0.99.

Figure 4 depicts a flowchart of applying SA algorithm for solving CEED problem.

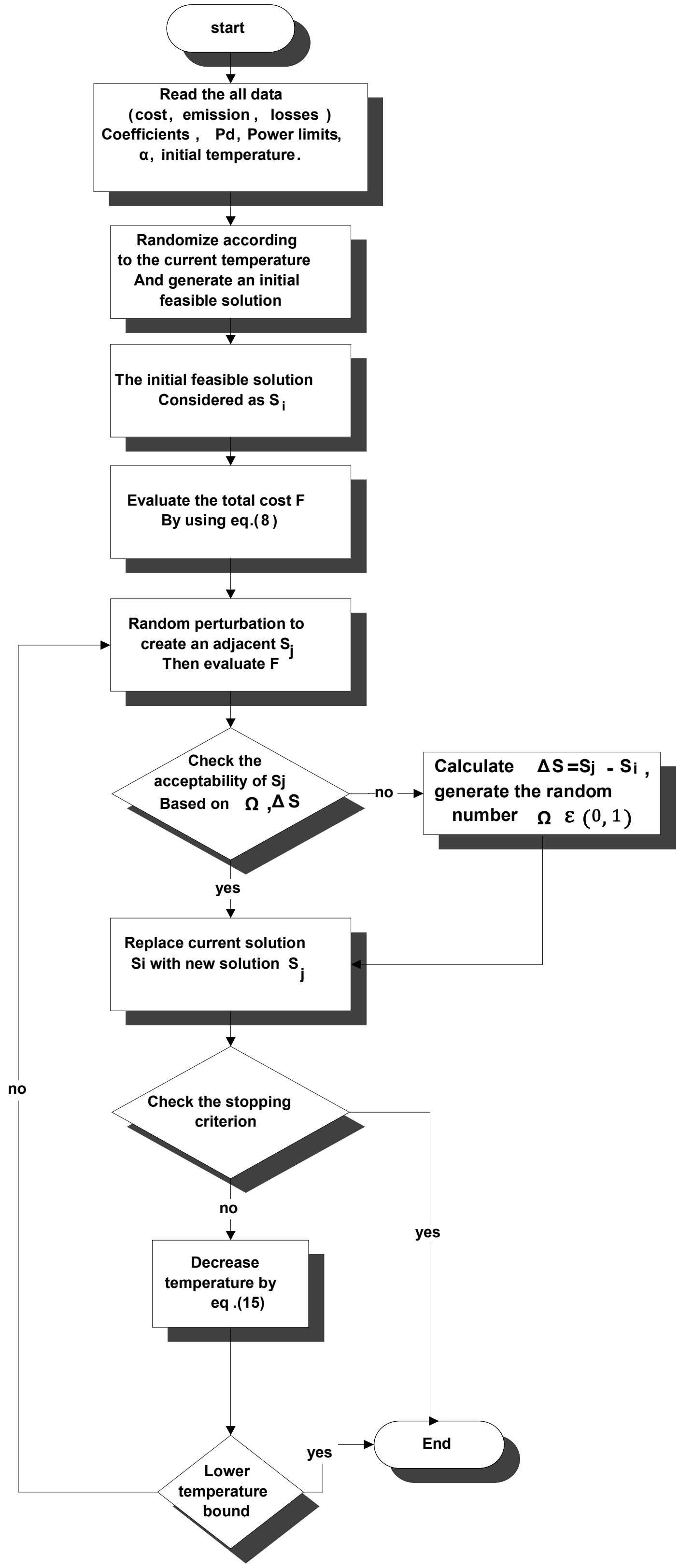

Fig.4. Flowchart of SA algorithm for CEED problem

C. Particle Swarm optimization algorithm

PSO algorithm is one of the evolutionary techniques, able to find the optimal solutions in a shortest time for non-linear optimization problems [17], [30]. The original PSO algorithm simulates of social behavior to the movement of organisms in a bird flock or fish school [26]. PSO is initialized with a population (called a swarm) of random particles and then searches for optima by updating generations. Each particle (agent) in PSO represents a feasible solution to the optimization problem in multi-dimensional search space. In the end the swarm will converge to optimal positions. Contrary to the other evolutionary computation techniques each particle in PSO is also associated with a velocity. Each particle is updated by two "best" values: the best solution it has achieved so far (p_{best}), and the global best value, obtained so far by any particle in the population (g_{best}). The particle position is computed by the following equation:

$$X_i(k+1) = X_i(k) + V_i(k) \tag{16}$$

The particle velocity is computed by the following equation [31]:

$$V_i(k+1) = \omega\, V_i(k) + c_1.\mathrm{rand}().\big(P_i(k) - X_i(k)\big) + c_2.\mathrm{rand}().\big(g(k) - X_i(k)\big) \tag{17}$$

The CEED problem is a nonlinear complex multi objective optimization problem with feasible operating zones constraints, to reach optimal solution, PSO algorithm is proposed to optimal schedule of units under different operating conditions. The PSO algorithm is simple in concept, easy to implement and computational efficient. The proposed PSO method steps as follow:

The following steps summarize the steps of applying the PSO algorithm for solving the CEED problem:

1. Define cost coefficients, valve point effect coefficients, emission coefficients, and loss coefficients.
2. Initialize a swarm of N_P x N_G agents with random positions and velocities on D dimensions in the problem space, by using maximum and minimum operating limits of the generators.
3. P_i= [P_1, P_2,..... P_N]. Where NP is the number of individuals and NG is the number of generators, and Pi is the real power outputs of NG thermal generators.
4. Randomly generate particle velocities.
5. Evaluate the objective (fitness) function values of the particles by using equation (7), these values are set as the p_{best} value of the particles. Penalties are given for violations of demand constraint.
6. Identify the best value, g_{best} between all the values.
7. Update the particle velocities for each particle using (17).
8. Update the positions for each particle using (16).
9. Calculate the new objective function value using the new positions of the particles. If the new value is better than the previous p_{best}, the new value is set to p_{best}. If the stopping criterion is met, the positions of particles represent the optimal solution. Otherwise the procedure is repeated from step 4.

Figure 5 depicts a flowchart of applying PSO algorithm for solving CEED problem.

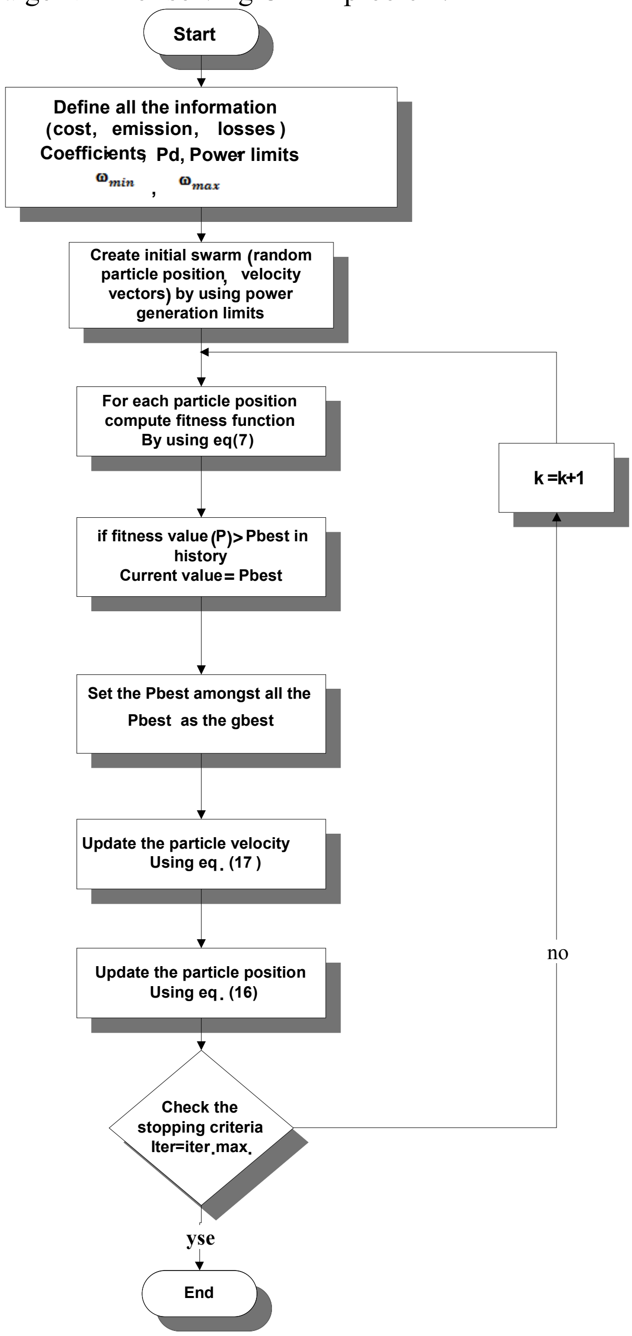

Fig.5. Flowchart of PSO algorithm for solving CEED problem

7. Simulation and Results

Both the SA and PSO are applied to IEEE-30 bus system with 6 generating units and 41 transmission lines with four tap changing transformers. The results are compared with that obtained by the classical Lagrange method. The single-line diagram of this system is shown in Figure 6. The values of fuel cost and emission coefficients and the loss coefficient matrix of the six generating units are shown in the appendix. The simulation is carried out using Matlab program.

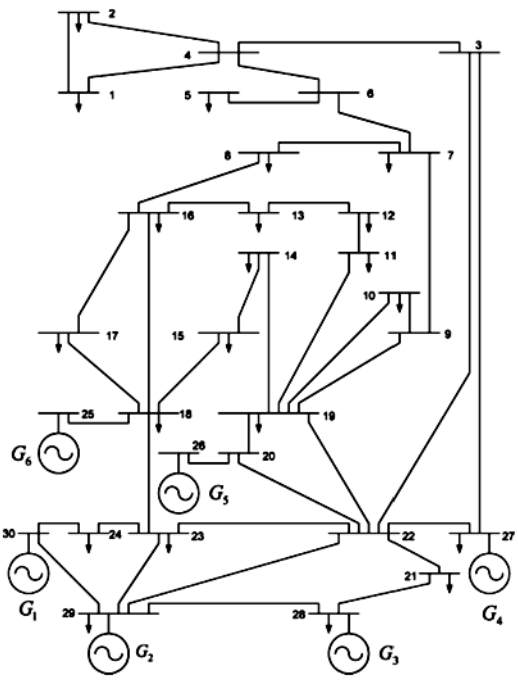

Fig.6. Single-line diagram of IEEE30-bus system

The problem is solved for different types of PPF and different load values (light =125 MW, medium=200 MW, and heavy =250 MW). Tables 3-5 give the simulation results obtained by applying the three proposed methods for different case studies. Theses tables illustrate the total cost, total fuel cost, total emission, losses power, and solution time for LR, SA, and PSO methods at different PPF types and three values of the demand. The minimum value of each parameter is clarified in bold.

These tables show that; the type of price penalty factor has a major effect on all the studied parameters. In most cases the min/max PPF is better than other PPF types.

Table 3: Comparison between the proposed methods for different PPF types at 125 MW

PPF type	Method	Total Cost $/hr	Total emission kg/hr	Total Fuel Cost $/hr	P_L MW	Solution time sec
max/max	**LR**	636.614	144.530	**329.932**	1.249	0.40158
min/min		628.459	149.416	333.303	1.124	0.36895
min/max		**383.600**	**144.530**	329.932	1.249	1.29748
max/min		1803.4	148.186	341.693	**1.020**	0.67917
average		872.109	148.202	337.636	1.057	0.40921
common		404.532	150.067	332.086	1.164	**0.34752**
max/max	**SA**	680.868	161.158	**330.227**	1.364	37.987
min/min		652.687	163.567	337.789	1.214	34.2488
min/max		**410.182**	**161.158**	330.227	1.364	30.0495
max/min		1833.3	163.355	340.058	**1.199**	**28.4158**
average		902.960	163.187	340.875	1.204	38.9590
common		427.512	164.899	332.425	1.279	29.2855
max/max	**PSO**	766.023	160.883	397.409	1.178	0.3246
min/min		683.578	**154.934**	**357.435**	1.223	0.1610
min/max		**502.052**	169.481	412.897	1.435	0.1729
max/min		2037.8	172.1	432.8	1.2	**0.2**
average		947.556	155.588	371.322	**1.146**	0.2189
common		486.461	158.670	389.301	1.172	0.1576

Table 4: Comparison between the proposed methods for different PPF types at 250 MW

PPF type	Method	Total Cost $/hr	Total emission kg/hr	Total Fuel Cost $/hr	P_L MW	Solution time sec
max/max	**LR**	1329.2	**288.368**	741.955	5.404	0.51527
min/min		1395.6	327.298	849.865	3.037	0.39006
min/max		**841.070**	329.423	**720.233**	7.163	**0.21236**
max/min		3524.8	326.542	866.991	2.881	0.90044
average		1874.2	326.492	853.556	**3.010**	0.53733
common		997.506	333.075	840.098	3.256	0.29655
max/max	**SA**	1379.5	**321.350**	741.254	5.821	16.1415
min/min		1414.6	343.370	844.128	**4.073**	2.43088
min/max		**867.817**	367.882	**719.973**	7.421	16.3763
max/min		3537.1	346.423	860.205	4.073	1.97352
average		1895.9	340.672	846.397	4.087	**1.78708**
common		1001.3	324.975	805.986	4.256	2.28230
max/max	**PSO**	1356.4	**296**	**737.3**	5.8	0.9
min/min		**929.069**	327.968	843.326	3.605	0.1567
min/max		1003.3	327.2	843.4	**3.1**	**0.01**
max/min		3689.8	340.1	852.9	3.4	0.1
average		1547.3	340.6	862.0	3.7	0.2
common		987.050	336.398	867.845	3.433	0.1762

Table 5 gives a comparison between minimum values of CEED results obtained by applying the proposed methods for different PPF types and different load values.

Table 5: Comparison between minimum values of CEED results obtained by applying the proposed methods for different PPF types and load values

Load	Method	F_T, $/hr	E_T, kg/hr	F_C, $/hr	P_L, MW	**Time,** sec
125 MW	**LR**	**383.6002** min/max PPF	**144.5308** min/max PPF	**329.9326** min/max PPF	**1.0204** max/min PPF	0.347521
	SA	410.1822	161.1585	330.2277	1.1998	28.415891
	PSO	502.0529	154.9344	357.4358	1.1466	**0.2** min/max PPF
200 MW	**LR**	**634.7168** min/max PPF	**217.1880** max/max PPF	**550.0272** min/max PPF	**1.9211** max/max PPF	0.196003
	SA	662.3026	244.2022	550.2772	2.5966	3.493122
	PSO	991.8227	219.7	565.3	3.1	**0.2** max/min
250 MW	**LR**	**841.0701** min/max PPF	**288.3688** max/max PPF	720.2330	**3.0105** average PPF	0.212367
	SA	867.8171	321.3507	**719.9732** min/max PPF	4.0731	1.787088
	PSO	929.0697	296.00	737.3	3.1	**0.01** min/max PPF

From Table 5 it can observe that:

1. For all the studied load conditions, the minimum total costs are obtained by applying LR method with min/max PPF
2. The minimum total emission values are obtained by applying LR method. It is obtained using min/max PPF for a load of 125MW, and by using max/max PPF for 200, and 250 MW loads.
3. Minimum power losses are obtained by applying LR method with different PPF types for the different load values.
4. PSO algorithm is the fastest method among the studied ones.

The impact of including valve point loading effect into economic dispatch problem can be explained by Tables 6-8. In these tables the valve point loading effect is illustrated for different dispatch types. The tables demonstrate that both total cost and total losses are increased when considering that effect. This means that for accurate calculations it is not wise to ignore valve effect because of the physical nature of thermal generation units.

Table 6: Impact of including valve point loading effect into economic dispatch problem at 250 MW load by applying LR method

		Max/Max PPF		**Min/Max PPF**	
		Without VPE	**With VPE**	**Without VPE**	**With VPE**
CEED	F_T	1279.1	1329.2	815.1893	841.0701
	F_C	699.5508	741.9553	687.0771	720.2330
	E_T	285.3664	288.3688	310.2859	329.4232
	P_L	5.2153	5.4046	6.4337	7.1639
Economic Dispatch	$F_T = F_C$	699.5508	741.9553	687.0771	720.2330
	E_T	285.3664	288.3688	310.2859	329.4232
	P_L	5.2153	5.4046	6.4337	7.1639
Emission Dispatch	F_T	579.5927	466.5172	128.1122	106.6689
	F_C	699.5508	561.0609	687.0771	550.0272
	E_T	285.3664	217.188	310.2859	231.3501
	P_L	5.2153	3.7386	6.4337	4.4681

Table 7: Impact of including valve point loading effect into economic dispatch problem at 250 MW load by applying SA method

		Max/Max PPF		Min/Max PPF	
		Without VPE	**With VPE**	**Without VPE**	**With VPE**
CEED	F_T	1348.7	1379.5	850.2232	867.8171
	F_C	726.6261	741.2545	717.0747	719.9732
	E_T	351.7755	321.3507	375.9530	367.8820
	P_L	5.7005	5.8215	6.6381	7.4217
Economic Dispatch	$F_T = F_C$	714.6426	714.8320	714.6426	714.8320
	E_T	403.2274	405.6175	403.2144	405.6098
	P_L	7.4388	8.4137	7.4383	8.4135
Emission Dispatch	F_T	641.9882	631.3212	149.0717	137.5053
	F_C	738.2497	756.9824	765.7769	760.5434
	E_T	339.9148	309.2626	348.1142	319.4270
	P_L	5.0717	5.2629	4.8598	5.6136

Table 8: Impact of including valve point loading effect into economic dispatch problem at 250 MW load by applying PSO method

		Max/Max PPF		Min/Max PPF	
		Without VPE	**With VPE**	**Without VPE**	**With VPE**
CEED	F_T	1282.6	1356.4	937.7458	1003.3
	F_C	698.3	737.3	796.0058	843.4
	E_T	289.6	296	328.3123	327.2
	P_L	5.3	5.8	3.3931	3.1
Economic Dispatch	$F_T = F_C$	688.282	858.7515	806.196	862.2819
	E_T	304.6267	324.0004	328.0258	341.4979
	P_L	6.1504	3.4009	3.4646	3.645
Emission Dispatch	F_T	577.3889	756.6333	143.7566	159.5732
	F_C	717.7704	867.4259	793.6019	840.9037
	E_T	278.088	345.5714	332.2175	331.4121
	P_L	4.4892	3.3869	3.3806	3.1938

It is evident from tables 6-8, that the total cost, total fuel cost, total emission, and power losses, are increased when taking the valve point effect into consideration.

The optimal values of the power generated from each unit when applying the three studied method with max/max and min/max PPF are depicted in Figures 7-9 for a load of 250 MW.

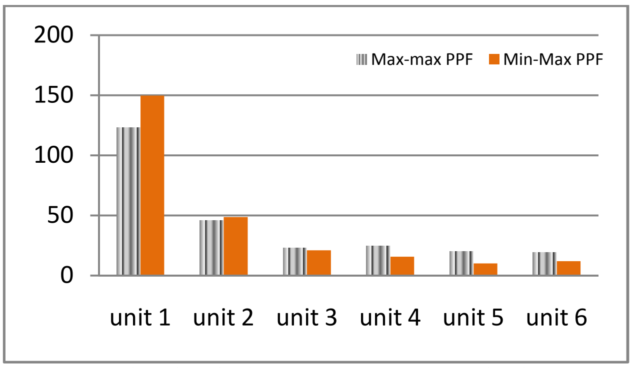

Fig. 7. Optimal solution at 250 MW for the best PPF using LR

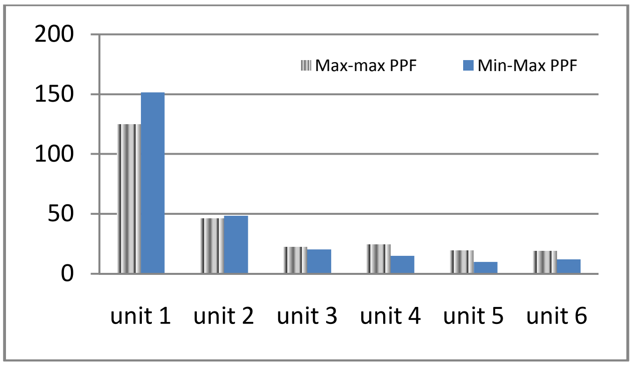

Fig. 8. Optimal solution at 250 MW for the best PPF using SA

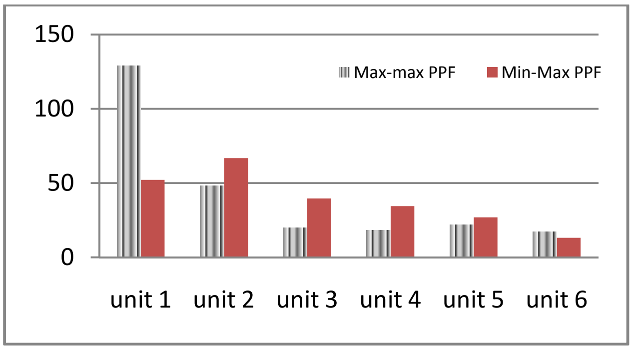

Fig. 8. Optimal solution at 250 MW for the best PPF using PSO

8. Conclusions

This paper applies the concept of smart economic dispatch to solve the combined economic and emission dispatch problem considering valve point effect. In modern smart grids the wireless communication is used to transfer the data between the thermal power plants and SCADA system. Main control center uses the predicted load curve to determine a hourly required demand load value then transfer this value to the SCADA system. The solution method model searching between the different types of PPF and three proposed solution methods (Lagrangian method or SA or PSO), to give optimal results (minimum emission, minimum cost) for the CEED problem considering valve point loading effect. The proposed algorithms are tested on the IEEE 30-bus system with six generating units. Several cases are investigated to test and validate the consistency of detecting optimal or near optimal solution for each objective. According to the selected solution method the optimal solution is obtained then the generators set point adjustment controller (GSAC) give order to the thermal power plants according to the value of total measured emission. The simulation is performed in Matlab environment. A comparison between the three methods is presented. The comparison proves that the type of price penalty factor has a major effect on both the total cost, and system power losses. The min/max PPF is better than other PPF types for most cases. The comparison also proves that PSO algorithm is the fastest method among the studied ones. For different dispatch types, both total cost and total losses are increased when considering valve point loading effect. This means that for accurate calculations it is not wise to ignore valve effect.

9. Appendix

Table A1: Generator limits, costs and emission coefficients

Unit No.	Power limits		Fuel cost coefficients			Valve point effect coeff.		Emission coefficients		
	P^{min} MW	P^{max} MW	a $/hr	b $/MW.hr	c $/MW².h	d $/h	e rad/MW	α kg/MW^{2}hr	B kg/MW.hr	γ kg/hr
1	50	200	0	2	0.00375	15	0.063	0.0126	-0.9	22.983
2	20	80	0	1.7	0.0175	14	0.084	0.02	-0.1	25.313
3	15	50	0	1	0.0625	12	0.15	0.027	-0.01	25.505
4	10	35	0	3.25	0.00834	10	0.20	0.0291	-0.005	24.9
5	10	30	0	3	0.025	10	0.25	0.029	-0.004	24.7
6	12	40	0	3	0.025	12	0.18	0.0271	-0.0055	25.3

Table A2: loss coefficient matrix of the 6 generating units

B					
0.000218	0.000103	0.000009	-0.000010	0.000002	0.000027
0.000103	0.000181	0.000004	-0.000015	0.000002	0.000030
0.000009	0.000004	0.000417	-0.000131	-0.000153	-0.000107
-0.000010	-0.000015	-0.000131	0.000221	0.000094	0.000050
0.000002	0.000002	-0.000153	0.000094	0.000243	-0.000001
0.000027	0.000030	-0.000107	0.000050	-0.000001	0.000358
B0					
-0.000003	0.000021	-0.000056	0.000034	0.000015	0.000078
B00					
0.000014					

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