NSGA-II ALGORITHM FOR SOLVING COMBINED ENVIRONMENTAL ECONOMIC DISPATCH PROBLEM INCORPORATING ELECTRIC VEHICLES AND WIND ENERGY

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Abstract: *A recent case study conducted at one of the thermal power plants shows that the CO_2 emission which is the main reason for global warming is high compared to maximum limits. Plug-in hybrid electric vehicles (PHEVs) and renewable energy sources, in particular wind energy have recently been getting more interest because of various environmental and economic considerations Hence a solution is proposed to reduce emission level as well as cost of operation by incorporating PHEVs and renewable energy. Combined environmental economic dispatch (CEED) problem proposed in several literatures shows the problem is highly nonlinear. Hence, a powerful optimization tool is required to solve such a problem and because of that NSGA-II algorithm is proposed in this paper. In this paper, the impact of PHEVs and renewable energy integration into the electric grid is investigated. A case study in ten unit system is presented to verify the success of this proposed algorithm.*

Keywords: *Environmental and economic dispatch, Electric vehicle, Modified PSO, NSGA-II, Wind energy.*

1. Introduction

The alarming rate at which the global energy reserves depletion is a major worldwide concern at both economic and environmental levels. The power industry represents a major portion of global emission, which is responsible for 40% of the global CO_2 production, followed by the transportation industry (24%). Climate change is caused by greenhouse gas emissions (GHG) and it is now widely accepted as a real condition that has potentially consequences for human society and industries. This is needed to factor into strategic plans. The fossil fuel sources are rapidly depleting and they are responsible for greenhouse gas emissions. Hence, most of the countries are making their own regulations and policies to minimize the use of fossil fuels in order to reduce the greenhouse gas emissions and to preserve the availability of fossil fuels. Therefore, the use of green and renewable energy sources like wind, solar etc. are promoted by most of the countries. The literature shows that the usage of green and renewable energy sources gets increased year by year. Of course, wind energy is the most representative type of renewable energy today. It will be indubitably important to quantitatively assess the effectiveness of reducing emissions by increasing the penetration of wind power [1].

Similarly, the battery operated vehicles are called as plug-in hybrid electric vehicles (PHEVs) and are integrated with the electrical power network for peak shaving and to minimize the emission from fossil fuel based power stations [2]. PHEV is growing in popularity in most of the countries in an effort to overcome the problems of pollution, depleting natural oil and fossil fuel reserves and rising fuel (petrol, diesel etc.) costs. Also, most of the governments force the automotive industries to reduce the emissions and to adopt cleaner and more sustainable technologies such as PHEVs [3]. Therefore, quite a lot of automobile industries have already begun to expand the PHEV market.The smart grid, which is also called as future grid, involves all the conventional power plants along with renewable energy sources and PHEV. Some literature [4-6] says that the inclusion of PHEV can reduce the emission level in the power network and some other paper claims that instead of reducing emission level, the PHEV increases the emission level. So this has to be discussed further.

In this work, a proposal is given to minimise the emission and cost of both thermal generators and wind electric generators along with PHEV and subjected to several constraints, since only very few papers combines all this category[7]. The impacts of renewable energy and PHEV on combined economic and emission dispatch (CEED) problem are well addressed in this paper. In particular, Weibull wind speed distribution for wind energy analysis is well presented here. The Weibull distribution is a two-parameter function and it is commonly used to fit the wind speed frequency distribution [8]. It provides a convenient representation of the wind speed data for the wind energy cost function calculation purposes, which is not addressed in most of the works.To solve the real time CEED problem, various techniques have been proposed by several researchers [9]. Though, CEED issues have been successfully solved by several existing techniques, the related dispatch programs need to be re-run, when the system changes and thus, it is unsatisfactory for the real time dispatch. Particle swarm optimization (PSO) method is also used [7, 10] to solve CEED problem, since it provides more computational efficiency, less computational effort to reach accurate solutions and best results compared to the other methods, such as the genetic algorithm, evolutionary programming etc. [11].

In this work, modified PSO with time varying acceleration coefficients (MPSO-TVAC) approach, which enhances particle diversity and improves global searching capability is proposed to solve the CEED problem, as an algorithmic level novelty. Also, NSGA-II approach [12-14], which is one of the best optimization techniques, is proposed as novelty to solve the CEED problem incorporating PHEVs and wind energy.

The organization of the paper is as follows. Motivation behind the work is explained in section 2. The section3 illustrates the CEED problem formulation by considering wind farm cost function selection and PHEV modelling. Section 4 explains about the overview of modified PSO and NSGA-II algorithm and the implementation of the same for solving the CEED problem. In section 5, test system and the simulation results are presented and analysed. The conclusions are given in section 6.

2. Motivation for the work

The Southern Regional Load Dispatch Centre (SRLDC), Ministry of Power, Government of India report says that thermal power generation effective installed capacity is increased every year. For example, the thermal power generation installed capacity increased to 5620 MW from 5020 MW in the last 6 months (April 2016 – September 2016) in Tamil Nadu state alone. Similarly, the capacity is increased significantly in other states linked with SRLDC and automatically the level of greenhouse gas emissions is getting increased. Here, we made an attempt to study the emission level in thermal power plants and gas power plants.

Case study 1:A case study conducted at one of the 210 MW thermal power plants in the state of Tamil Nadu, India is given in Table 1 and Table 2. They show the emission level of various gases such as carbon dioxide (CO_2), sulphur dioxide (SO_2), nitrogen oxide (NOX), oxygen (O_2) etc. Table 1 shows average level of emission of CO_2 and O_2 measured at economizer outlet point during a particular day of the month of August 2016. The parameters are measured with the help of ORSAT gas analyzer. It is clearly indicates that emission level is higher than the standard limits. Table 2 gives ambient air emission level measured during the study period.

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Table 1

Emission level at economizer outlet

Parameter	CO_2 (%)		O_2 (%)	
	Measured level	Limits	Measured level	Limits
Level	21.56	14.99	3.49	4.26

Table 2

Ambient air emission

Parameter	SO_2 (µg/Nm^3)	NOX (µg/Nm^3)	SPM (µg/Nm^3)
Measured level	34.08	0.23	Not tested
Limits	80	80	100

Case study 2: Similarly, a case study is conducted at one of the gas turbine power station in Tamilnadu state during August 2016. The emission level is listed in Table 3. It indicates clear violation of standards.

Table3

Emission level at gas turbine power plant

Parameter	NOX (ppm)	CO (ppm)	SO_2 (ppm)
Measured level	28	9.1	Not tested
Limits	20	2-4	0-2

Another side, it is well known that wind energy is one of the promising energy sources in the world.

The wind generator installed capacity and power generation level in Tamilnadu state during the last 6 months is given in Table 4. It is seem to be the wind energy installed capacity is increased nearly 400kW in the last 6 months. The power generation level is only 30% when it is compared with installed capacity. If the percentage of wind power generation capacity is increased, the thermal power plant share can be reduced significantly. Similarly, plug-in electric vehicles (PHEV) are identified as another alternative energy source. Also, it is well known that combining thermal energy with green energy like wind energy can reduce the emission (CO_2 etc.) as well as cost of operation of thermal plants.

Table 4

Wind power generation during April-September 2016

Month	April	May	June	July	August	Septem-ber
P_G(kW)	302.8	1018.6	1882.4	2041.2	2525.7	2277.3
I_C (kW)	7251.9	7525.3	7525.3	7525.3	7525.3	7616.2

Source: http://www.srldc.org/var/ftp/reports/pdf

Therefore an environmental/economic dispatch problem is designed in this work to determine the optimum loading of all committed units to minimize the emission as well as cost of the thermal plants by integrating green energy like wind energy and electric vehicles.

3. Mathematical problem formulation

The environmental/economic dispatch problem [7] is designed to determine the optimum loading of all committed units to minimize the cost and emission functions subject to the system constraints.

3.1 Objective function

The proposed problem is designed to determine the optimum loading of all the committed units to minimize the cost function and emission subject to the system constraints. Therefore the objective function is given by the equation (1). For a specified power plant, both cost and emission can be expressed as a quadratic function, as described in equations (2) and (3), respectively.

$$\text{Objective function} = w_c TC + w_e TE \quad (1)$$

Where, TC is total (Generation) cost function, TE is total emission function, w_c is cost coefficient and w_e is emission coefficient.

The total fuel cost TC (\$/hr) of N generating units can be represented as follows.

$$TC = \sum_{i=1}^{N} a_i + b_i P_i(t) + c_i P_i^2(t) \quad (2)$$

Where, $P_i(t)$ is generated power of i^{th} unit at hour t.a_i, b_i, c_i is fuel cost coefficients of i^{th} unit and N is number of generator units.

The total GHG emission, TE (tons/hour) of N generating units can be represented as,

$$TE = \sum_{i=1}^{N} (A * \left(\gamma_i P_i^2(t) + \beta_i P_i(t) + \alpha_i\right) + \xi_i * \exp Pit*\lambda i) \quad (3)$$

Where, $\gamma_i, \beta_i, \alpha_i, \xi_i and \lambda_i$ are greenhouse gas (GHG) emission coefficients of thei^{th}unit and A is emission curve coefficient.

3.2 Constraints

The objective function represented by equation (1) is subjected to physical and operating constraints as given in equations (4) and (5) and presented as follows.

Load balance: $\sum_{i=1}^{N} P_i(t) = D(t) + P_{loss}(t) \quad (4)$

Where, $D(t)$is demand of network at hour t and $P_{loss}(t)$ active power loss at hour t.

Generating unit capacity limit:

$$P_{imin} \leq P_i(t) \leq P_{imax} \quad (5)$$

Where,P_{imin} is minimum generating power of thei^{th} unit and P_{imax} is maximum generating power of the i^{th} unit.

3.3 Modeling of wind farm

The characterization of wind farm model in the CEED problem is a challenging task. The average wind power is considered for the calculation in most of the cases. Although, this approach seems intuitionally fine and can be easily implemented, it has so many drawbacks. Hence, it is necessary to model the wind farm in a more accurate and detailed manner. Therefore, the wind farm is modeled based on the detailed cost function as given in equation (6).

$$C = \sum_{i=1}^{N_{wf}} C_d(w_i) + \sum_{i=1}^{N_{wf}} C_p(W_{iav} - w_i) + i=1NwfCr(wi-Wiav) \quad (6)$$

Where, N_{wf} is number of wind farms, $C_d(w_i)$is direst cost function for the i^{th}wind farm, $C_p(W_{iav} - wi$ is penalty cost of ith wind farm due to under-estimation of expected wind power and $C_r(w_i - W_{iav})$ is reserve requirement cost of i^{th} wind farm due to over estimation of expected wind power.

3.3.1 Direct cost function for wind farm

In this work, all wind turbines in wind farm are represented by a single wind turbine. This factor will typically take the form of a payment to the wind farm operator for the wind generated power actually used.

A linear cost function (first term) for power output of i^{th} wind farm is formulated as given in equation (7).

$$C_d(w_i) = d_i w_i \quad (7)$$

Where, d_i is direct cost coefficient for the i^{th} wind farm and w_i is scheduled wind power output of the i^{th} wind farm.

3.3.2 Cost due to underestimation of wind power

The second and third terms in equation (6) are related to the uncertain nature of the WF power output given in equation (8) and (9), respectively [8]. The second term, which gives penalty cost due to underestimation for i^{th} wind farm is given in equation (8).

$$C_p(W_{iav} - w_i) = k_{pi} \int_{w_i}^{w_r} (w - w_i) f_w(w) dw \quad (8)$$

Where, k_{pi} is penalty cost coefficient because of the underestimation of wind Power for i^{th} Wind farm, w_r is rated wind farm capacity and $f_w(w)$ is probability density functions of wind power output.

3.3.3 Cost due to over estimation of wind power

The third term in the equation (6) is the reserve requirement cost that is similar to penalty cost except that in this case, it is a cost due to the available wind power being less than the scheduled wind power. Thus, the cost due to provision of reserve i.e. due to overestimation situation for i^{th} wind farm is given as,

$$C_r(w_i - W_{iav}) = k_{ri} \int_0^{w_i} (w_i - w) f_w(w) dw \quad (9)$$

Where, k_{ri} is reserve cost (over estimation) coefficient for the i^{th} wind farm.

The direct cost coefficient and penalty cost may be zero, if the wind power plant is not owned by the system operator. The probability density function of the wind energy conversion system output power is obtained by the well-known two-parameter weibull function.

3.3.4 Wind power model and weibull function

The weibull distribution is a two-parameter function and is commonly used to fit the wind speed frequency distribution. This family of curves has been shown to give a good fit to measured wind speed data. The weibull function provides a convenient representation of the wind speed data for wind energy calculation purposes. The wind speed variations for a given site can be well defined by the weibull probability density function (PDF) with two parameters namely, the scale parameter (c) and the shape parameter (k). The PDF of weibull distribution is given in equation (10).

$$f_v(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} e^{-(v/c)^k}, \ 0<v<\infty \quad (10)$$

Where, k *is* *w*eibull shape parameter at a given location, c is *w*eibull scale parameter at a given location and v is wind speed.

The cumulative distribution function (CDF) is represented by equation (11).

$$F_v(v) = 1 - e^{-(v/c)^k} \quad (11)$$

The power (W) generated by the wind generators can be represented as given in equation (12).

$$W = \frac{1}{2} \rho A V^3 C_p \quad (12)$$

Where, ρ is density of air (kg/m^3), A is area swept by the wind turbine blade (m^2) and C_p is co-efficient performance.

The power generated by the wind turbine at different wind velocities is stated as given in equation (13).

$$\left.\begin{array}{ll} w = 0\,, & v < v_i and v > V_o \\ w = w_r \frac{(v - v_i)}{(v_r - v_i)}\,, & v_i \le v \le v_o \\ w = w_r\,, & v_r \le v \le v_o \end{array}\right\} \quad (13)$$

Where, v_i is cut-in wind velocity, v_r is rated wind velocity and v_o is cut-out wind velocity. The probability of wind power between these two extreme velocities is given by a weibull function PDF. Thus, the PDF of the wind energy conversion system output power is indicated by $f_w(w)$ in equation (14) and is obtained by the well-known two-parameter weibull function.

$$f_w(w) = \frac{k l v_i}{w_r c}\left(\frac{(1+pl)v_i}{c}\right)^{k-1} \exp\left(-\left(\frac{(1+pl)v_i}{c}\right)^k\right) \quad (14)$$

Where, $\rho = \frac{w}{w_r}$ is the ratio of wind power output to rated wind power and $v = \frac{(v_r - v_i)}{v_i}$ is the ratio of linear range of wind speed to cut-in wind speed which are intermediate variables.

The penalty cost due to underestimation for the i^{th} wind farm is computed as given in equation (15).

$$C_p(W_{iav} - w_i) = k_{pi}\{\int_{w_i}^{w_r} (w - w_i) f_w(w) dw + w_i\{\exp(-\left(\frac{v_r}{c}\right)^k - \exp(-\left(\frac{v_o}{c}\right)^k)\}\} \quad (15)$$

Similarly, the analysis for overestimation condition is computed as given in (16).

$$C_r(w_i - W_{iav}) = k_{ri}\{\int_0^{w_i} (w_i - w) f_w(w) dw + w_i\{1 - \exp(-\left(\frac{v_i}{c}\right)^k + \exp(-\left(\frac{v_o}{c}\right)^k)\}\} \quad (16)$$

3.4 Modeling of PHEV

The V2G is relatively a new concept, where the electric energy is stored in the EV battery and can also be fed back to the power grid. The V2G structure has a bidirectional energy flow. That is, the energy flows from electric vehicles to grid and grid to electric vehicles. Utility grid operators can communicate with the plugged-in vehicles via the established communication link. Utility can buy energy from the vehicle owners, when it is required during peak hours and sell it back, when demand is low during off peak hours. Therefore, PHEV can be modeled either as load or energy source based on the operating mode [15-16]. Now, the load balance constraint in equation (4) is modified as equation (17), when PHEVs are considered as source along with wind power.

$$\sum_{i=1}^{N} P_i(t) + \sum_{i=1}^{N_{PEV}(t)} \eta P_j^{PEV}(t)\left(\Psi_{pre} - \Psi_{dep}\right) + Pwindt{=}Dt{+}Ploss(t) \quad (17)$$

Similarly, the equation (4) is modified, when PHEVs are considered as load as given in equation (18).

$$\sum_{i=1}^{N} P_i(t) + P_{wind}(t) = D(t) + P_{loss}(t) + i{=}1NPEV(t)\eta PjPEVt\Psi pre{-}\Psi dep \quad (18)$$

Where, $P_{wind}(t)$ is wind farm output power and $P_j^{PEV}(t)$ is power of j^{th} PHEV and $N_{PEV}(t)$ is number of PHEVs at time t. η is efficiency of the PHEV system and Ψ_{pre}, Ψ_{dep} is present and departure state of PHEV's battery charges respectively.

4. Solving CEED problem

In this work, the powerful optimization algorithms like PSO, modified PSO & NSGA-II algorithms are used to solve the highly nonlinear CEED problem.

4.1 Conventional PSO algorithm

PSO algorithm is a population based stochastic optimization technique introduced by Kennedy and Eberhart. It is motivated by the behavior of organisms such as, fish schooling and bird flocking. In the recent years, PSO algorithm has been successfully employed to solve many real world optimization problems. In the PSO algorithm, each particle can be represented by its position and velocity. The particles change their positions by flying around in a multidimensional search space, until a relatively unchanged position has been encountered. In the search space, particle best is the best position corresponding to the best fitness encountered so far, by a particle and is denoted as Pbest, whereas, global best is the best position encountered so far, among the whole population and is denoted as Gbest. The velocity and position of each particle are updated using Eqs. (19) and (20), respectively.

$$V_{j,d}^{(k+1)} = wV_{j,d}^{k} + c_1 rand_1\left(Pbest_{j,d}^{k} - X_{j,d}^{k}\right) + c_2 rand_2\left(Gbest_{j,d}^{k} - X_{j,d}^{k}\right) \quad (19)$$

$$X_{j,d}^{(k+1)} = X_{j,d}^{k} + CV_{j,d}^{(k+1)} \quad (20)$$

Where, k is the current iteration; $V_{j,d}^{k}$ is the velocity of the jth particle in the dth dimension at iteration k; $Pbest_{j,d}^{k}$ is the own best position of particle j in the dth dimension until iteration k; $Gbest_{j,d}^{k}$ is the best particle in the swarm in the dth dimension at iteration k; c1 and c2 are the cognitive and social component acceleration coefficients, respectively; rand1 and rand2 are the uniformly distributed random numbers between 0 and 1; $X_{j,d}^{k}$ is the position of particle j in the d^{th} dimension at iteration k; C is the constriction factor calculated using Eq. (21); w is the inertia weight, which is linearly decreasing as the generations proceed and is updated using Eq. (22).

$$C = \frac{2}{\left(2-\phi-\sqrt{\phi^2-4\phi}\right)} \quad (21)$$

$$w = W_{max} - \frac{(W_{max} - W_{min})}{G_{max}} * G \quad (22)$$

Where, ϕ = 4.1; Wmax and Wmin are the initial and final values of inertia weights, respectively; Gmax is the maximum number of generations; G is the current generation.

To control excessive roaming of particles, the velocity of each particle obtained using Eq. (19) is restricted by their upper and lower limits and is given by Eq. (23).

$$V_d^{min} \le V_d \le V_d^{max} \quad (23)$$

Where, V_d^{max} is the velocity maximum and V_d^{min} is the velocity minimum in the dth dimension and is given by Eqs. (24) and (25), respectively.

$$V_d^{max} = \frac{\left(x_d^{max} - x_d^{min}\right)}{K} \quad (24)$$

$$V_d^{min} = -V_d^{max} \quad (25)$$

Where, K=5 is the parameter to control the number of intervals in the dth dimension. Even though, PSO algorithm can determine a better solution in a fast convergence rate, its ability to fine tune the optimal solution is lacking because of lack of diversity at the end of the search.

4.2 Modified PSO

In order to prevent premature convergence, the proposed modified particle swarm optimization-Time variant acceleration coefficient (MPSO-TVAC) algorithm is employed. The crossover operator and time varying acceleration coefficients are used to enhance particle diversity and improve global searching capability. The position of particle j, is obtained in Eq. (19) and is mixed with $Pbest_j$ to generate the new position as shown in Eq. (26).

$$x_{j,d}^{k+1} = \begin{cases} x_{j,d}^{k+1} if rand \leq C_r \\ Pbest_{j,d}^{k} otherwise \end{cases} \quad (26)$$

Where, Cr is the crossover probability. In the conventional PSO algorithm, c_1 and c_2 are fixed as 2.0. Relatively, high value of the social component c_2 in comparison with cognitive component $c_1$and leads to particles being trapped into local optimum and relatively high value of cognitive component results to wander the particles around the search space. In order to obtain solution quality, the acceleration coefficients are updated using the following equations:

$$c_1 = \left(c_{1f} - c_{1i}\right) + \left(\frac{G}{G_{max}}\right) * c_{1i} \quad (27)$$

$$c_2 = \left(c_{2f} - c_{2i}\right) + \left(\frac{G}{G_{max}}\right) * c_{2i} \quad (28)$$

Where, c_{1i} and c_{2i} are the initial values of c_1 and c_2, respectively; c_{1f} and c_{2f} are the final values of c_1 and c_2, respectively. Local search space is reduced as c_1 decreases and c_2 increases to accelerate the solution towards the global convergence.

4.3 Parameters selection

The performance of PSO greatly depends on three parameters such as cognitive parameter (c_1), social parameter (c_2) and the weight factors W_{min} and W_{max}. The balance among these factors determines the balance between local and global searching capability. The objective function used in this PSO based optimization problem is the minimization of total fuel cost as given in equation (1) and it is subjected to the constraints as listed in equations (4) and (5).

The selected parameters of PSO for this problem are tabulated in Table 5. One of the most important issues to find the optimum solution effectively and efficiently, while designing the PSO algorithm is its parameters. The necessary conditions for selecting cognitive and social parameters are the value of c_1 equals to c_2 and they ranges between 0 and 4. The cognitive component (c_1) encourages the particles to move toward their own best positions found so far, whereas the social component (c_2) are useful in finding the global optimal solution. The social component always pulls the particles towards the global best particle found so far. Hence, other combinations for these parameters have also tried, but the optimal solution is arrived, when the values of c_1 and c_2 are selected as 2. The values of minimum and maximum inertia weights are selected as 0.4 and 0.9, respectively. Initially, the inertia weight is kept as 0.4 in order to support for exploration i.e., global search. Then, the value of inertia weight is kept as 0.9 in order to support exploitation i.e., local search. This kind of decaying inertia weight approach is proposed to do favor for global search at the start of the algorithm and the local search later. Other combinations for all the above values are also tried in trial and error basis, but the optimal solution is arrived with this selected parameters only.

Table 5

The parameter selection for PSO

Cognitive Factor c_1	Social Factor c_2	Minimum Inertia Weight Factor W_{min}	Maximum Inertia Weight Factor W_{max}	Number of Particles
2	2	0.4	0.9	50

The MPSO algorithm is applied to solve the combined environmental/economic dispatch (CEED) non-linear problem. The steps involved to find the optimal value of the control variables for the CEED problems are as follows:

1. Initialization: Set the time counter *k=0* and generate randomly n particles within feasible range.
2. Counter updating: Update the time counter *k=k+1*.
3. Weight updating: Update the inertia weight using the Eq. (29).

$$W = W_{max} - \frac{(W_{max} - W_{min})}{iter_{max}} * iter \quad (29)$$

4. Velocity updating: Using the global best and individual best, the i^{th} particle velocity is updated using Eq. (30).

$$V_j^{(k+1)} = wV_j^k + c_1 rand_1 x\left(Pbest_j^k - X_j^k\right) + c_2 rand_2 x\left(Gbest_j^k - X_j^k\right) \quad (30)$$

5. Position updating: Based on the updated velocities, each particle changes its position according to the following Eq. (31).

$$X_j^{(k+1)} = X_j^k + CV_j^{(k+1)} \quad (31)$$

Where, C is the constriction factor calculated using Eq. (32).

$$C = \frac{2}{\left(2-\emptyset-\sqrt{\emptyset^2-4\emptyset}\right)} \quad (32)$$

6. In order to prevent premature convergence to fine tune the optimal solution to enhance particle diversity and to improve global searching capability crossover operator and time varying acceleration coefficients been used.

7. The position j, is obtained just in equation (31) is mixed with $Pbest_j$ to generate the new position as shown in Eq. (26).

8. The acceleration coefficients are updated using the following equation to improve the solution quality and to avoid from particle being trapped and wander around the search space.

$$C_1 = \left(C_{1f} - C_{1i}\right) + \left(\frac{G}{G_{max}}\right) * C_{1i} \quad (33)$$

$$C_2 = \left(C_{2f} - C_{2i}\right) + \left(\frac{G}{G_{max}}\right) * C_{2i} \quad (34)$$

Where, C_{1i} and C_{2i} are the initial values of C_1 and C_2; C_{1f} and C_{2f} are the final values of C_1 and C_2.

9. Compute the objective function f.

10. Individual best updating: If $f_j < f_j^*$, for i=1...n, then update individual best as $X_j^*(k) = X_j(k)$ and $f_j^* = f_j$ and go to step 11; else go to step 4.

11. Global best updating: If $f_j^* < f^{**}$, then update global best as $X^{**}(k) = X_j^*(k)$ and $f^{**} = f_j^*$ and go to step 12; else go to step 5.

12. Stopping criteria: If the number of iterations reaches the maximum allowable number, then stop; otherwise go to step 2.

4.4 NSGA-II

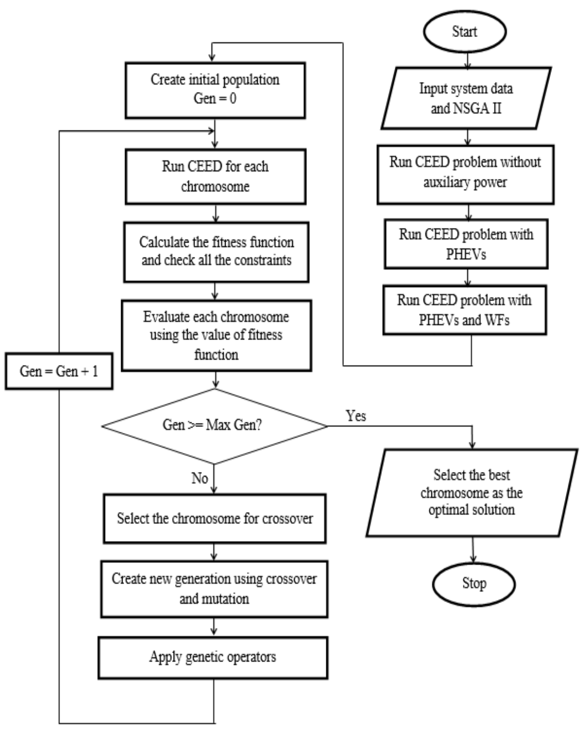

Fig.1 Flow chart of proposed NSGA-II Algorithm

The NSGA-II algorithm [12-14] is applied to solve the combined environmental/economic dispatch (CEED) non-linear problem. The algorithm is selected since the two objectives, environmental dispatch and economic dispatch are contradictory to each other. The steps involved to find the optimal value of the control variables for the CEED problem are as follows. The flow chart is shown in Figure 1

Step 1: Initialize a population with the set of random variables. Input system data and initialize the algorithm parameters. The number of decision variables is the number of generators. Initialize a population such that it satisfies the boundary conditions of the generators.

The power generated by the generators is the decision variable. Based on randomly created generation, the constraints and objective function values are calculated. Here the constraint considered is load balance and the objective function values of cost and emission levels are calculated individually. Here penalty less constraint handling method is used.

Step 2: The initialized population is sorted based on non- domination of both the objective function values.

Step 3: Once the non-dominated sort is complete the crowding distance is assigned. Since the individuals are selected based on rank and crowding distance, all the individuals in the population are assigned a crowding distance value.

Step 4: Once the individuals are sorted based on non-domination and with crowding distance assigned, the selection is carried out using a crowded-comparison-operator. The individuals are selected by using a binary tournament selection with crowed-comparison-operator.

The crossover and mutation operations are carried out in the selected parents and offspring are created.

The objective function values for the offspring are calculated.

Step 5: The offspring population is combined with the current generation population to form 2X population size.

Step 6: Since, all the previous and current best individuals are added in the population, elitism is ensured. The entire offspring and parent Population is now sorted based on non-domination and all the individuals in the population are assigned a rand and crowding distance value. The new generation is filled by each front subsequently until the population size exceeds the current population size by using the rank value and crowding distance value. Hence, the process repeats to generate the subsequent generations. The process is stopped with the stopping criteria of 'number of generations'.

5. Results and discussion

In this study, a ten generating unit system along with 40 MW of wind farm and 50 thousand PHEVs is analyzed. The parameters of the generators and its cost and emission coefficients for the ten unit system are given in Annexure I. Three scenarios are considered to investigate the effects of integrating PHEVs and wind energy sources on the electricity as follows: Without auxiliary power, With PHEVs in grid-to-vehicle mode and With PHEVs and wind farm. Thus, to assess the effects of PHEVs and wind power, these three cases have been applied to the CEED problem by using PSO, modified PSO and NSGA-II algorithms. All the calculations and simulations are performed in MATLAB 2010b software. The ten unit system is simulated and the demand of the system is divided into 24 hours (intervals) for a whole day.

5.1 Without auxiliary power

First, the proposed algorithms are applied one by one to the ten-unit system without considering the auxiliary power (that is, PHEVs and wind power) for solving the objective function given in equation (1). The results are given in Table 6 for each hour. For simplicity, results obtained with NSGA-II algorithm are only presented here.

The total emission for the first case is 16916.6 tons per day and the total electricity production cost is $614540 per day. In the Table 6, column 1 shows the time of the day in hours and column 2 is the distribution system load demand for that time interval. The optimal control values of the ten unit generator's active power output are given from column 3 to column 12. The fuel cost and emission value of the given CEED problem for the first case is shown in column 13 and column 14, respectively.

Table 6

Cost and emission level without auxiliary power

Time	Demand (MW)	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)	P7 (MW)	P8 (MW)	P9 (MW)	P10 (MW)	Cost ($)	Emission (Ton)
1	700	207.24	150	120.32	122.43	25	20	25	10	10	10	20870	400
2	750	213.88	162.31	130	130	38.8	20	25	10	10	10	21870	435
3	850	250.84	199.92	130	130	64.23	20	25	10	10	10	24010	510
4	950	287.79	237.53	130	130	89.67	20	25	10	10	10	25900	790
5	1000	306.28	256.34	130	130	102.38	20	25	10	10	10	27100	791
6	1100	343.24	293.94	130	130	127.81	20	25	10	10	10	27900	792
7	1150	361.17	312.75	130	130	140.53	20	25	10	10	10	28700	795
8	1200	380.19	331.55	130	130	153.25	20	25	10	10	10	30030	799
9	1300	425.42	377.57	130	130	162	20	25	10	10	10	24200	800.2
10	1400	402.91	455	130	130	162	65.08	25	10	10	10	24300	801
11	1450	438	455	130	130	162	80	25	10	10	10	23600	802
12	1500	455	455	130	130	162	80	25	43	10	10	24400	802.5
13	1400	402.91	455	130	130	162	65.08	25	10	10	10	24300	801
14	1300	425.42	377.57	130	130	162	20	25	10	10	10	24200	800.2
15	1200	380.19	331.55	130	130	153.25	20	25	10	10	10	30030	799
16	1050	324.75	275.14	130	130	115.1	20	25	10	10	10	26900	791.5
17	1000	306.28	256.34	130	130	102.38	20	25	10	10	10	27100	791
18	1100	343.24	293.94	130	130	127.81	20	25	10	10	10	27900	792
19	1200	380.19	331.55	130	130	153.25	20	25	10	10	10	30030	799
20	1400	402.91	455	130	130	162	65.08	25	10	10	10	23900	811
21	1300	425.42	377.57	130	130	162	20	25	10	10	10	24200	810.2
22	1100	343.24	293.94	130	130	127.81	20	25	10	10	10	27900	792
23	900	295.06	244.93	130	130	25	20	25	10	10	10	23500	610
24	800	232.36	181.12	130	130	51.52	20	25	10	10	10	21700	590
												614540	**16916.6**

5.2 PHEVs in grid-to-vehicle (G2V) mode for load leveling

In this case, PHEVs are operated in G2V mode for load leveling purpose. That is, the PHEVs are integrated with the grid for charging during off-peak hours for load leveling. 50000 PHEVs are taken for analysis and the details are given in Table 7. According to the data, the additional load of 418.5 MWh (50000×10 kWh×0.93×0.9) = 418.5 MWh) is added to the total demand. Hence, the demand is increased by 34.87 MW during the off-peak hours as given in Table 8. The CEED problem is solved and the results are obtained as given in Table 6.Since, the additional loads (418.5 MWh) are added, the net cost and emission are get increased in this case as given in the Table 8 as compared to Table 6.

Further, this increase in the GHG emission level is explained as follows. When, PHEVs are operated in G2V mode, an additional load (418.5 MWh) is imposed on the grid, so that it makes the units to operate in a new operating point. Because, the emission curves of the units are incremental and non-linear, the additional emission will not increase linearly. Even a small increase from the nominal operating point leads to a great rise in emission. This inference is mentioned in very few literatures including [7]. Therefore, it is shown that the shifted emission from the transportation industry to the electric industry is due to the presence of PHEVs, which increases the net emission.

Table 7

PHEVs data

Number of PHEVs	50000
Battery capacity	10 kWh
System efficiency	0.93
Depth of discharge of battery	10%

Table 8

Cost and emission level with PHEVs in G2V mode

Time	Demand (MW)	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)	P7 (MW)	P8 (MW)	P9 (MW)	P10 (MW)	Cost ($)	Emission (Ton)
1	734.87	224.87	150	130	130	25	20	25	10	10	10	21500	431
2	784.87	274.87	150	130	130	25	20	25	10	10	10	22660	560
3	884.87	263.73	213.08	130	130	73.1	20	25	10	10	10	24500	590
4	984.87	300.69	250.65	130	130	98.54	20	25	10	10	10	26500	788.9
5	1034.87	319.17	269.45	130	130	111.25	20	25	10	10	10	27600	798.5
6	1134.87	356.12	307.06	130	130	136.68	20	25	10	10	10	29500	800
7	1184.87	368.36	319.51	130	130	162	20	25	10	10	10	30200	800.1
8	1234.87	393.14	344.73	130	130	162	20	25	10	10	10	31100	800.78
9	1334.87	382.87	455	130	130	162	20	25	10	10	10	24300	802.5
10	1400	448	455	130	130	162	20	25	10	10	10	24200	801.5
11	1450	438	455	130	130	162	80	25	10	10	10	24500	801
12	1500	455	455	130	130	162	80	25	43	10	10	24400	802
13	1400	448	455	130	130	162	20	25	10	10	10	24600	801
15	1200	380.19	331.55	130	130	153.25	20	25	10	10	10	30200	798.5
16	1050	324.75	275.14	130	130	115.1	20	25	10	10	10	25000	798.25
17	1000	306.28	256.34	130	130	102.38	20	25	10	10	10	27010	798
18	1100	343.24	293.94	130	130	127.81	20	25	10	10	10	28700	798.4
19	1200	380.19	331.55	130	130	153.25	20	25	10	10	10	28900	798.5
20	1400	448	455	130	130	162	20	25	10	10	10	24500	801.5
21	1300	425.42	377.57	130	130	162	20	25	10	10	10	24400	800.5
22	1134.87	356.12	307.06	130	130	136.68	20	25	10	10	10	27200	791
23	934.87	282.21	231.84	130	130	85.82	20	25	10	10	10	25700	790
24	834.87	245.25	194.23	130	130	60.39	20	25	10	10	10	23400	566.6
												628770	**18117.0**

5.3 With PHEVs and wind farm

Here, the wind farm of 40 MW capacities along with PHEVs is added to the network to generate the electricity. The wind speed data for 24 hours is given in Table 9.

Table 9

Wind speed data

Hour	Velocity (m/s)	Hour	Velocity (m/s)	Hour	Velocity (m/s)
1	9	9	10	17	10.5
2	12.5	10	10	18	10
3	13	11	8.2	19	12.4
4	11.5	12	15	20	6.2
5	5.4	13	12	21	3.4
6	8.3	14	16.2	22	7
7	9.5	15	13.8	23	5.6
8	14.5	16	12.4	24	3

The shape parameter (k) and scale parameter (c) of the Weibull distribution are calculated by using maximum likelihood approach. The obtained values are converged after ten iterations. The converged values are K = 5.8138 and C = 11.9967. The CEED problem is solved and cost and emission level are attained as $589660 and 14457.19 tons/day, respectively as given in Table 10.

Compared to previous case, the reduction in both total cost and CO_2 emission are greatly achieved. Particularly, the reduction of cost achieved is $23660/day and annual saving is $8635900/year, when PHEV and wind power is added with the conventional power unit. Similarly, the difference in emission level is 2333 tons/day and the annual reduction is 851545 tons/year. The results confirm the significance of renewable energy participation in the power market.

Table 10

Cost and emission level with PHEVs and wind farm

Time	Demand (MW)	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)	P7 (MW)	P8 (MW)	P9 (MW)	P10 (MW)	V2G (MW)	P_W (MW)	Cost ($)	Emission (Ton)
1	700	211.12	150	122.5	124.6	36.9	20	25	10	10	10	-32.19	12	27500	798.5
2	750	225.52	174.16	130	130	25	20	25	10	10	10	-32.19	22.5	22100	479
3	850	253.87	203	130	130	66.3	20	25	10	10	10	-32.19	24	24500	650
4	950	292.3	242.12	130	130	92.7	20	25	10	10	10	-32.19	19.5	26400	689.53
5	1000	267.73	217.99	130	130	110.2	20	25	10	10	10	-32.19	1.2	21500	476.37
6	1100	287.34	237.94	130	130	162	20	25	10	10	10	-32.19	9.9	24500	675
7	1150	301.99	252.85	130	130	133.8	20	25	10	55	10	-32.19	13.5	24610	610.01
8	1200	305.6	256.53	130	130	136.3	20	25	10	10	10	38.04	28.5	23600	568.73
9	1300	326.83	272.13	130	130	162	20	25	10	55	10	38.04	15	26000	648.7
10	1400	319.01	405	130	130	162	45.9	25	10	10	10	38.04	15	25500	780.25
11	1450	340.36	405	130	130	162	80	25	55	10	10	38.04	9.6	29700	785.70
12	1500	369.96	405	130	130	162	80	25	10	10	10	38.04	30	26500	650.51
13	1400	395.72	348.23	130	130	162	20	25	10	10	10	38.04	21	27390	780.23
14	1300	311.96	262.99	130	130	162	20	25	10	10	10	38.04	30	22780	487.35
15	1200	293.92	244.64	130	130	162	20	25	10	10	10	38.04	26.4	23610	575.10
16	1050	256.27	206.33	130	130	102.3	80	25	10	10	10	-32.19	22.2	22110	453.20
17	1000	234.5	184.18	130	130	162	20	25	10	10	10	-32.19	16.5	21600	400.01
18	1100	289.59	250.41	130	130	132.1	20	25	10	10	10	-32.19	15	23310	500.07
19	1200	301.9	242.77	130	130	133.7	36.3	25	10	10	10	38.04	22.2	23400	527.17
20	1400	346.36	405	130	130	162	20	25	10	10	10	38.04	3.6	27100	779.01
21	1300	324.26	285.69	130	130	162	20	25	55	10	10	38.04	0	28200	780.23
22	1100	279.37	240.01	130	130	162	20	25	10	10	10	-32.19	6	21500	549.25
23	900	220.55	180.16	130	130	84.6	20	25	10	10	10	-32.19	1.8	21720	410.72
24	800	194.26	143.22	130	130	59.7	20	25	10	10	10	-32.19	0	21532	409.35
														589660	**14457.19**

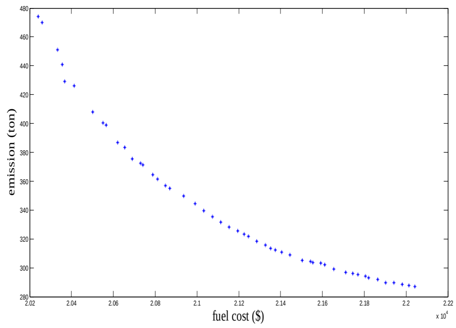

Fig. 2Pareto Front of NSGAII algorithm

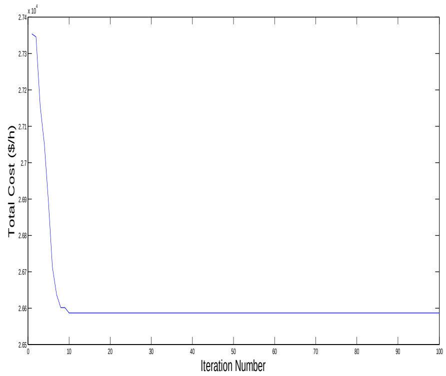

Fig. 3 Converge characteristics of modified PSO

Table 11

Comparison of results

Configur -ation	Cost ($)			Emission (Ton)		
	PSO [7]	MPSO-TVAC	NSGA-II	PSO [7]	MPSO -TVAC	NSGA -II
Without auxiliary power	645825	642464	614540	20922	20407	16917
With PHEVs in G2V mode	653148	650677	628770	21686	20904	18117
With PHEVs in V2G mode	647975	640487	613320	19967	19499	16790
With PHEVs and WF	640115	614316	589660	20309	18842	14457
Reduction	7860	26171	23660	1377	657	2333
Reduction in %	1.22	4.26	4.01	6.78	3.49	16.14

The Pareto front of NSGA-II algorithm of the ten unit system by considering PHEVs and wind farm for a particular demand is shown in Figure 2. Similarly, the modified PSO algorithm is applied to solve the CEED problem and final results are tabulated in Table 11. The convergence characteristic of the ten unit system with considering PHEVs and wind farm is shown in Figure 3. It illustrates the comparison of the proposed scenarios with respect to total cost and emission. Based on the results given in Table 11, the fourth case (with PHEVs and wind power) is preferable, because of less cost and emission. It is evident from the results that the proposed NSGA-II algorithm provides best results compared to other methods proposed and existing works available in the literature.

6. Conclusion

The integration of PHEVs and wind energy into conventional thermal generation systems and their impact on the environmental/economic dispatch are investigated in this work to minimize CO_2 emission as well as operating cost of thermal power. Three different optimization algorithms are tested to solve the nonlinear problem. A ten unit thermal power generation system is considered and tested with four different scenarios in order to analyze the effectiveness of the proposed approach. It is identified that NSGA-II algorithm is giving better results compared to PSO and MPSO algorithms for the particular problem. The test results have confirmed the effectiveness and robustness of these proposed algorithms.

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Annexure I

Ten unit generation system data

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
P_{max}(MW)	455	455	130	130	162	80	85	55	55	55
P_{min}(MW)	150	150	20	20	25	20	25	10	10	10
a($/h)	1000	970	700	680	450	370	480	660	665	670
b($/MWh)	16.19	17.26	16.6	16.5	19.7	22.26	27.74	25.92	27.27	27.79
c($/MWh^2)	0.00048	0.00031	0.002	0.00211	0.00398	0.00712	0.0079	0.00413	0.00222	0.00173
α(ton/h)	10.33	10.33	30.03	30.03	32	32	33	33	35	36
β(T/MWh)	-.2444	-0.2444	-0.4069	-0.4069	-0.3813	-0.3813	-0.3902	-0.3902	-0.3952	-0.3986
γ(T/MWh^2)	0.00312	0.00312	0.00509	0.00509	0.00344	0.00344	0.00465	0.00465	0.00465	0.0047