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Solution of Combined Economic Emission Dispatch Problem with Valve-Point Effect Using Hybrid NSGA II-MOPSO

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Additional information is available at the end of the chapter

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Abstract

This chapter formulates a multi-objective optimization problem to simultaneously minimize the objectives of fuel cost and emissions from the power plants to meet the power demand subject to linear and nonlinear system constraints. These conflicting objectives are formulated as a combined economic emission dispatch (CEED) problem. Various meta-heuristic optimization algorithms have been developed and successfully implemented to solve this complex, highly nonlinear, non-convex problem. To overcome the shortcomings of the evolutionary multi-objective algorithms like slow convergence to Pareto-optimal front, premature convergence, local trapping, it is very natural to think of integrating various algorithms to overcome the shortcomings. This chapter proposes a hybrid evolutionary multi-objective optimization framework using Non-Dominated Sorting Genetic Algorithm II and Multi-Objective Particle Swarm Optimization to solve the CEED problem. The hybrid method along with the proposed constraint handling mechanism is able to balance the exploration and exploitation tasks. This hybrid method is tested on IEEE 30 bus system with quadratic cost function considering transmission loss and valve point effect. The Pareto front obtained using hybrid approach demonstrates that the approach converges to the true Pareto front, finds the diverse set of solutions along the Pareto front and confirms its potential to solve the CEED problem.

Keywords: multi-objective optimization, economic emission dispatch, Pareto optimality, NSGAII, MOPSO, B-loss coefficients

1. Introduction

In order to operate the power system economically and also to protect the environment from pollution the power system operator has to carry out optimal scheduling of active power to simultaneously minimize the fuel cost and the emissions from the fossil fuel-fired power plants.

These objectives are desirable to obtain great economic benefit [1] and to reduce the nitrogen oxide (NO_x), sulfur oxide (SO_x) and carbon dioxide (CO_2) pollutants which cause harmful effect on human beings [2]. These conflicting objectives can be formulated as a multi-objective combined economic emission dispatch (CEED) problem. This CEED problem can be solved using traditional mathematical programming techniques such as lambda iteration, gradient search [1] and can also be solved using modern heuristics optimization techniques. The numerous advantages of solving the CEED problem using heuristic optimization methods compared to the traditional mathematical programming techniques are they are population-based, do not require any derivative information, do not use gradient information in search process, use stochastic operators in search process, they are simple to implement and flexible, have inbuilt parallel architecture and they are scalable and are also computationally quick.

A single optimal solution cannot be obtained for a multi-objective CEED problem which simultaneously minimizes the conflicting objectives of fuel cost and emission. Thus the simultaneous minimization of conflicting objectives in a multi-objective optimization problem (MOP) gives rise to a set of tradeoff solution called as Pareto-optimal (PO) solutions [3] which needs further processing to arrive at a single preferred solution. In literature domination based framework using multi-objective evolutionary algorithms (MOEA) which simultaneously minimizes the fuel cost and emission have been employed to solve the CEED problem. These population-based approaches can obtain the multiple non dominated solutions in a single simulation run. These non-dominated solutions portray the tradeoff between fuel cost and emission objectives of CEED problem. Modern meta-heuristic optimization algorithms like Genetic Algorithm [4, 5], Biogeography Based Optimization [6], Particle Swarm Optimization [7], Bacterial Foraging Algorithm [8], Scatter Search [9], Teaching Learning Based Optimization [10], Differential Evolution [11] and Harmony Search Algorithm [12] have been developed and successfully implemented to solve this complex, highly nonlinear, non-convex CEED problem.

The multiple objective CEED problem can also be transformed into a single objective problem using a weighted sum approach and h parameter values. The h parameters are used to overcome the dimensionality problem when combining multi-objectives and the converted single objective problem is then solved using evolutionary algorithms [13–15]. Another technique to solve CEED problem without the h parameter is to normalize the fuel cost and emission components [6] and solve the single objective function using evolutionary algorithms (EA). In these approaches for the chosen value of weights will give one particular PO solution at a time. However, the disadvantage of these methods is that it requires multiple runs to find the set of PO solutions.

Each evolutionary algorithm has its own characteristics and merits; therefore it is natural to think of integrating these different algorithms to handle a complex problem like CEED. In the research field of Evolutionary Algorithms merging of two or more optimization algorithms into a single framework is called hybridization. In [16–21] hybrid multi-objective optimization algorithms have been successfully applied to solve CEED, various complex engineering problems, and standard test functions. The results indicate that the hybrid algorithms are effective, can exchange elite knowledge within the hybrid framework, can do parallel processing, can improve the exploration and exploitation capabilities and can yield more favorable performance than any single algorithm.

In order to obtain a globally optimal solution without being trapped in local optima requires a tradeoff between exploration and exploitation task in the search process. Exploration phase in any algorithm is important to search every part of the solution domain to provide an estimate of the global optimal solution. On the other hand exploitation phase in any algorithm is important to improve the best solutions found so far by searching in their neighborhood. In this chapter, a hybrid framework using Non-Dominated Sorting Genetic Algorithm II (NSGA II) [22] and Multi-objective Particle Swarm Optimization (MOPSO) [23] is used to solve the CEED problem. This hybrid framework integrates the desirable features of the NSGA II and MOPSO while curbing their individual flaws. These population-based approaches use different techniques for exploring the search space and when they are combined will improve the tradeoff between the exploration and exploitation tasks to converge around the best possible solutions. The main purpose of this hybridization technique is to obtain a well-spread and well-diverse PO solution. When the proposed hybrid algorithm is used to solve the highly complex CEED problem the PO solution is obtained in less number of iteration and is also computationally fast when compared to MOPSO.

The rest of the chapter is organized as follows. The next section formulates the CEED problem. In Section 3, the transmission loss handling procedure and the constraint handling procedure is explained. In Section 4 the short review of NSGA II and MOPSO is provided. Section 5 is devoted to explaining the hybrid algorithm. In Section 6 the hybrid algorithm is applied on standard IEEE 30 bus systems and it also discusses the simulation results. Finally, the conclusion is drawn in Section 7.

2. Formulation of combined economic emission dispatch (CEED) problem

The combined economic emission dispatch problem has two conflicting objectives. The first objective can be stated as determining the optimal power generation schedule from a set of online generating units to satisfy the load demand subject to several physical and operational constraints to minimize the fuel cost. The second objective can be stated as determining the optimal power generation schedule from a set of online generating units to satisfy the load demand to minimize the pollutant emissions produced by the generating units. Both the conflicting objectives have to be minimized at the same time because operating the system with minimum cost will result in higher emission and considering only the minimum environmental impact is not practical which results in high production cost of the system. This section formulates the objective functions of the CEED problem along with equality and inequality constraints to maintain rigorous standards to meet the practical requirements of the power system. The goal of this chapter is to find the Pareto-optimal solutions of the CEED problem which minimize both these objectives subject to constraints. The mathematical formulation is as follows.

2.1. Objective functions of CEED problem

The general formulation for a multi-objective optimization problem (MOOP) is to minimize the number of objective functions simultaneously. A general mathematical model is represented as follows [21]:

$$\text{Minimize } f(x) = \{f_1(x), f_2(x), \dots, f_m(x)\}, x \in \mathcal{D} \quad (1)$$

where $f(x)$ represents the vector of objectives and $f_i(x), i = 1, 2, \dots, m$ is a scalar decision variable which maps decision variable x into objective space $f_i = \mathfrak{R}^n \rightarrow \mathfrak{R}$. The n -dimensional variable x is restricted to lie in a feasible region \mathcal{D} which is constrained by j in-equality constraint and k equality constraint, i.e.

$$\mathcal{D} = \left\{ x : g_j(x) \leq 0, h_k(x) = 0, j = 1, 2, \dots, J; k = 1, 2, \dots, K \right\} \quad (2)$$

The decision variable x can be written more suitably as

$$x = [x_1, x_2, x_3, \dots, x_n]^T \quad (3)$$

where T is the transposition of the column vector to the row vector. The decision variables are restricted to take a value within a lower $x_i^{(\min)}$ and upper $x_i^{(\max)}$ bounds. These bounds are called the decision space [3].

In MO CEED problem the number of objectives $m = 2$. The mathematical model of CEED is represented as follows:

$$\text{Minimize } f(x) = \{f_1(x), f_2(x)\}, x \in \mathcal{D} \quad (4)$$

subject to power balance equality constraints $h(x)$ and bounds. The function $f_1(x)$ represents the minimization of total fuel cost function and the function $f_2(x)$ represents the minimization of the emissions from the fossil fuel fired plants. The decision variable x consists of the real power generation of the n generating units and can be written as

$$x = [Pg_1, Pg_2, Pg_3, \dots, Pg_n]^T \quad (5)$$

where Pg_i is the real power output of the i^{th} generator.

Power plants commonly have multiple valves that are used to control the power output of the units. In a practical generating unit, when steam admission valves in thermal units are first opened, a sudden increase in losses is registered which results in ripples in the cost function. In order to model these ripples accurately, sinusoidal functions are added to the quadratic cost function [24]. The resulting cost function contains higher order nonlinearity and makes the problem non-differentiable and non-convex. Hence there are two versions of the fuel cost function, the quadratic function represented by $f_1(x)$ and the combination of quadratic and a sinusoidal (valve-point) function represented by $f_{1,v}(x)$. The two versions of the fuel cost functions are given below

$$f_1(Pg) = \sum_{i=1}^n a_i Pg_i^2 + b_i Pg_i + c_i \quad (6)$$

$$f_{1,v}(Pg) = \sum_{i=1}^n a_i Pg_i^2 + b_i Pg_i + c_i + |e_i \sin \{f_i (Pg_i^{\min} - Pg_i)\}| \quad (7)$$

where a_i, b_i, c_i represent the cost coefficients of the generator i . e_i and f_i are coefficients to model the effect of valve point of the generator i .

The second objective function $f_2(x)$ is an emission function which takes into account the major pollutants caused by the fossil fuel fired power plants. The main pollutants from the power plants are the sulfur oxides and nitrogen oxides. The sulfur oxide emissions are proportional to the fuel consumed by the power plants and have the same form as that of the fuel cost function given by (6). The sulfur oxide emission function can be stated as follows [7].

$$f_{2,so}(Pg) = \sum_{i=1}^n S_{i,1} + S_{i,2}Pg_i + S_{i,3}Pg_i^2 \quad (8)$$

The nitrogen oxides emissions are difficult to evaluate as the nitrogen is available in air and also in the fuel. The production of nitrogen gas is related to boiler temperature and air content. The modeling of the nitrogen oxides consists of straight lines and exponential terms. The nitrogen oxides emission function can be stated as follows

$$f_{2,No}(Pg) = \sum_{i=1}^n N_{i,1} + N_{i,2}Pg_i + N_{i,3}e^{N_{i,4}Pg_i} \quad (9)$$

The total emission function is obtained by adding the coefficients of (8) and (9) which gives the combination of the mixture of sulfur oxides and nitrogen oxides pollutants [7]. The total emission function can be stated as follows

$$f_2(Pg) = \sum_{i=1}^n [10^{-2}(\alpha_i + \beta_i Pg_i + \gamma_i Pg_i^2) + \eta_i e^{\delta_i Pg_i}] \quad (10)$$

The total emission function given by (10) has a quadratic term and an exponential term which makes the function highly nonlinear. In (10) $\alpha_i, \beta_i, \gamma_i, \eta_i, \delta_i$ are the emission coefficients of the generator i . The modeling of the emission function is very important because according to the Amendments of the Clean Air Act regulatory agencies might decide to limit power plant emission in the areas where there are high concentrations of harmful contaminants.

2.2. Active power balance equality constraint and bounds

In order ensure that the total real power generation exactly match with the total load demand Pd and transmission loss Pl in the system a power balance equality constraint given in (11) should be satisfied.

$$h(x) = \sum_{i=1}^n Pg_i - Pd - Pl = 0 \quad (11)$$

The transmission losses in the power network are function of Pg and can be represented using B-matrix coefficients (Kron's loss formula [1]) as follows

$$Pl(Pg) = \sum_{i=1}^n \sum_{j=1}^n Pg_i B_{ij} Pg_j + \sum_{i=1}^n B_{0i} Pg_i + B_{00} \quad (12)$$

where B_{ij} , B_{0i} , B_{00} are transmission loss coefficients. There are instances in literature where the power losses in the system is neglected and the power balance equation given by (11) is curtailed as follows

$$h(x) = \sum_{i=1}^n Pg_i - Pd = 0 \quad (13)$$

The above equations given by (11) and (13) are most common form of power balance equation found in the literature.

The power output of each generator i should lie within its minimum limit (Pg_i^{min}) and maximum limit (Pg_i^{max}) given by

$$Pg_i^{min} \leq Pg_i \leq Pg_i^{max}; i = 1, 2, 3, \dots, n \quad (14)$$

2.3. Combined economic emission dispatch

The purpose of the CEED problem is to determine the Pareto-optimal real power generation vector $x^* = [Pg_1^*, Pg_2^*, Pg_3^*, \dots, Pg_n^*]^T$ that minimize the two conflicting objective given by (7) and (10) while satisfying the real power equality constraint given by (11) and the bounds given by (14). The bi-objective CEED problem can be formulated as

$$\text{Minimize } f = [f_{1,v}(Pg), f_2(Pg)] \quad (15)$$

In MO CEED problem, the economic and emission objectives will conflict with each other and is not possible to satisfy them simultaneously. There is no way of improving these objectives without degrading at least one of these objectives and the resulting set of non-dominated solutions thus obtained are called Pareto-optimal set. The objective function values of all elements in the PO set in the objective space constitute the Pareto front. When the sufficient number of PO solutions is available for the CEED problem then it is possible to find a convex curve containing these solutions to produce the Pareto front. The two main goals of MO CEED problem:

1. Find a set of non-dominated solutions which lie on the Pareto-optimal front
2. Find a wide spread of non-dominated solutions to represent the entire range of the Pareto-optimal front.

3. Constraint handling mechanism

At any stage of the algorithm whenever a new population is being generated it is very important to make sure that the population lies within the decision space. While solving the CEED problem this implies that the population should satisfy the equality constraints and bounds. If the transmission losses are neglected than the k^{th} variable of the candidate solution Pg_k can be calculated by subtracting the sum of the power generations (excluding the

k^{th} variable) $\sum_{i=1}^{n-1} Pg_i$ from the power demand Pd . If the power transmission losses are considered, to determine Pg_k and to maintain the equality constraint becomes hard. It is done using the following steps.

Step 1. Update the variables belonging to the set α_n by normal optimization process of an evolutionary algorithm.

$$Pg_i = Pg_i^{min} - rand * (Pg_i^{min} - Pg_i^{max}); i \in \alpha_n \quad (16)$$

Here *rand* is a uniformly distributed random number in the range of $[0, 1]$. The set α_n contains all the integers in the range $[1, n]$ except k , where k is a randomly generated integer which lies in the range of $[1, n]$

Step 2. If updating of the variables is carried out using any other technique then regulate the updated variables which violate the lower bounds as $Pg_i = Pg_i^{min}; i \in \alpha_n$. Regulate the updated variables which violate the upper bounds as $Pg_i = Pg_i^{max}; i \in \alpha_n$.

Step 3. Obtain the value of the k^{th} variable of the candidate solution Pg_k by solving the following quadratic equation (17) whose coefficients are associated with the variables belonging to the set α_n and the transmission loss coefficients [7]. To improve the potential candidate solution and also to improve the flexibility and diversity of the optimization algorithm the value of k is randomly generated integer between 1 and n .

$$B_{kk}Pg_k^2 + \left(2 \sum_{i \in \alpha_n} B_{ki}Pg_i + B_{0k} - 1 \right)Pg_k + \left(Pd + \sum_{i \in \alpha_n} \sum_{j \in \alpha_n} Pg_i B_{ij}Pg_j + \sum_{i \in \alpha_n} B_{0i}Pg_i - \sum_{i \in \alpha_n} Pg_i + B_{00} \right) = 0 \quad (17)$$

Out of the two roots of the quadratic equation (17), one root will be selected as the value of the variable Pg_k using the following procedure. If both the roots of the quadratic equation lie within the bounds then the root which has the minimum value is selected. If only one root lies within the bounds, this root is selected as the value of Pg_k and the other root which lies outside the bounds is neglected. If both the roots lay outside the bounds the value of Pg_k is set equal to Pg_k^{min} .

Step 4. Calculate the residue P_{RD} by subtracting the total system demand Pd and the total system transmission loss Pl from the sum of the total power generation $\sum_{i=1}^n Pg_i$.

If $|P_{RD}| < tol$, then go to step 7; otherwise go to step 5. Here, *tol* is the demand tolerance usually set as $0.001 p.u.$

Step 5. Recalculate Pg_i using Eq. (16).

Step 6. Repeat step 3, step 4 and step 5 until $|P_{RD}| < tol$. This step will ensure that the candidate solution will always lie within the decision space.

Step 7. Stop the constraint handling procedure.

The main purpose of this constraint handling mechanism is to increase the flexibility and diversity of the algorithm and to make sure that the candidate solution generated at any point of the algorithm always lies within the decision space.

4. NSGA II and MOPSO algorithms for solving CEED problem

Several Evolutionary Multi-objective (EMO) algorithms like NSGAI, MOPSO, SPEA 2 (Strength Pareto Evolutionary Algorithm), GDE 3 (Generalized Differential Equation) have been designed and used in solving numerous complex real world problems involving two or more objectives. All these algorithms can find the multiple Pareto-optimal solutions in a single run. Out of all these available algorithms, two of the widely used reliable methods for solving bi-objective optimization problems are the NSGA II and MOPSO. This section provides the review of these two EMO algorithms.

NSGA II was proposed in [22] as an improvement of the NSGA proposed in [25]. This NSGA II algorithm was the revised version of NSGA to overcome the following criticisms:

- Computational complexity associated with non-dominated sorting.
- Lack of elite-preserving strategy.
- Lack of maintaining diversity among obtained solutions.

The NSGA II algorithm is very efficient for solving multi-objective optimization problems since it incorporates an efficient elitism preserving technique using non-domination sorting. The population is ranked based on non-domination sorting before the selection is performed. All non-dominated individuals are classified into one category. Another layer of non-dominated individuals are considered after the group of classified individuals are ignored. This process is continued until all individuals in the population are classified. NSGA II also uses a mechanism for preserving the diversity and spread of the solutions without specifying any additional parameters (NSGA uses fitness sharing). This crowding distance operator guides the selection process towards a uniformly spread out Pareto-optimal front. *The NSGA II algorithm for solving the CEED problem is stated below:*

- **Specify the parameters for the CEED problem**
 - The total demand of the power system P_d
 - Fuel cost and emission coefficients for each generating unit
 - B matrix coefficients for transmission loss calculations
 - Number of decision variables $nVar$
 - Lower bounds of the decision variables $VarMin$
 - Upper bounds of the decision variables $VarMax$
- **Specify the parameters for NSGA II Algorithm**
 - Population Size $nPop$

- Maximum number of iteration MaxIt
- Crossover Percentage pCrossover
- Mutation Percentage pMutation
- Mutation rate mu
- Mutation step size sigma
- **Initialize Population**
 - Generate a random nPop size population
 - Once the random population is initialized the Constraint Handling Mechanism proposed in Section 3 is carried out.
- **Evaluate the objective functions**
 - Evaluate the fuel cost objective function E and emission objective function F
- **Perform Non Domination Sorting**
- **Calculate Crowding Distance and rank the population based on Non Dominated fronts**
- **For each generation do**
 - Create offspring population
 - Selection, Crossover and Mutation
 - Apply Constraint Handling Mechanism
 - Evaluate the fuel cost objective function E and emission objective function F
 - Merge the parent and offspring population
 - Perform non domination sorting
 - Calculate crowding distance and rank based on non-domination fronts
 - Select solutions
 - Each front is filled in ascending order
 - Last front-descending order of crowding distance
 - Store the non-dominated solutions in list F_1
 - Plot the non-dominated solutions in list F_1
 - Increment generation count
- **End for**

In order to handle multiple objectives Pareto dominance is incorporated into PSO algorithm and the MOPSO algorithm is proposed in [23]. The algorithm proposed in [23] uses an external repository of particles to keep a record of the non-dominated vectors found along the search

process. At each generation, for each particle in the swarm, by using Roulette wheel selection, a leader is selected from the external repository. This leader then guides other particles towards better regions of the search space by modifying the flight of the particles. A special mutation operator is applied to the particles of the swarm and also to the range of each design variable of the problem to be solved to improve the explorative behavior of the algorithm. The value of the mutation operator is decreased during the iteration. To produce well spread Pareto fronts the MOPSO algorithm in [23] uses an adaptive grid. *The MOPSO algorithm for solving the CEED problem is stated below:*

- **Specify the parameters for the CEED problem**
 - The total demand of the power system P_d
 - Fuel cost and emission coefficients for each generating unit
 - B matrix coefficients for transmission loss calculations
 - Number of decision variables n_{Var}
 - Lower bounds of the decision variables Var_{Min}
 - Upper bounds of the decision variables Var_{Max}
- **Specify the parameters for MOPSO Algorithm**
 - Maximum number of iteration $MaxIt$
 - Population Size n_{Pop}
 - Repository size n_{Rep}
 - Inertia Weight w and Inertia Weight damping rate w_{damp}
 - Personal learning coefficient c_1 and Global learning coefficient c_2
 - Number of grids per dimension n_{Grid}
 - Inflation Rate α , leader selection pressure β , Deletion selection pressure γ
 - Mutation rate μ
- **Initialize Swarm Population**
 - Generate a random swarm particles
 - Once the random particles are initialized the Constraint Handling Mechanism (Section 3) is carried out.
 - Store the values of the particles as their personal best p_{Best}
- **Determine Domination**
 - Initialize external repository rep
 - Create grid and find grid index

- **For each generation do**
- **For each particle do**
 - Select leader from external repository
 - Update particle position and velocity
 - Apply Constraint Handling Mechanism
 - Evaluate the fuel cost objective function E and emission objective function F
 - Apply Mutation and calculate new solutions
 - Apply Constraint Handling Mechanism
 - Determine Domination
 - Update pBest
- **End for**
 - Add non dominated particles to the repository
 - Determine domination of new repository members
 - Keep only the non-dominated members in the repository
 - Update grid and grid index
 - If repository is full delete members
 - Plot the members in the external repository
 - Modify inertia weight
- **End for**

5. Hybrid NSGA II and MOPSO algorithm for solving CEED problem

The mechanism of the proposed hybrid approach for solving the CEED problem is to integrate the desirable features of NSGA II (retaining the elitism feature) and MOPSO (exploitation capability) while curbing the individual flaws (NSGAI—does not have an efficient feedback mechanism, PSO overutilization of resources). The mechanism to explore the search space differs in both the algorithms. GA uses mutation and crossover operators which will enhance the exploration task of the hybrid algorithm. The particles in PSO are influenced by their own knowledge and information shared among swarm members. PSO enhances the exploitation task of the hybrid algorithm by finding better solutions from the good ones by searching the neighborhood of good solutions. In this hybrid algorithm at every generation, the Pareto dominance of the population is computed and based on these values non dominated sorting is performed [19]. In order to avoid premature convergence, the elite upper half of the population are enhanced by NSGA II algorithm while the lower

half of the population are considered as swarm particles and are optimized by MOPSO to make them converge around the best possible solutions. *The hybrid NSGA II-MOPSO algorithm for solving the CEED problem is stated below:*

- **Specify the parameters for the CEED problem**
- **Specify the parameters for NSGA II Algorithm**
 - Population Size $nPop$
 - Maximum number of iteration $MaxIt$
 - Crossover Percentage $pCrossover$
 - Mutation Percentage $pMutation$
 - Mutation rate mu
 - Mutation step size $sigma$
- **Specify the parameters for MOPSO Algorithm**
 - Repository size $nRep$
 - Inertia Weight w and Inertia Weight damping rate $wdamp$
 - Personal learning coefficient $c1$ and Global learning coefficient $c2$
 - Number of grids per dimension $nGrid$
 - Inflation Rate $alpha$, leader selection pressure $beta$, Deletion selection pressure $gamma$
 - Mutation rate mu
- **Initialize Population**
 - Generate a random $nPop$ size population
 - Once the random population is initialized the Constraint Handling Mechanism proposed in Section 3 is carried out.
- **Evaluate the objective functions**
 - Evaluate the fuel cost objective function E and emission objective function F
- **For each generation do**
 - Perform Non Domination Sorting
 - Calculate Crowding Distance and rank the population based on Non Dominated fronts
 - Truncate and divide the population into two halves.
 - Using the upper half of the population create offspring population
 - Selection, Crossover and Mutation

- Perform Constraint Handling Mechanism
- Evaluate the fuel cost objective function E and emission objective function F
- Merge the parent and offspring population
- Perform non domination sorting
- Calculate crowding distance and rank based on non-domination fronts
- Select solutions
 - Each front is filled in ascending order
 - Last front- descending order of crowding distance
- Store the non-dominated solutions in list F_1
- Plot the non-dominated solutions in list F_1
- Position and cost of the particle are initialized from the lower half of the population
- Store the values of the particles as their personal best $pBest$
- Determine Domination
 - Initialize external repository rep
 - Create grid and find grid index
- For each particle do
 - Select leader from external repository
 - Update particle position and velocity
 - Constraint Handling Mechanism
 - Evaluate the fuel cost objective function E and emission objective function F
 - Apply Mutation and calculate new solutions
 - Apply Constraint Handling Mechanism
 - Determine Domination $pBest$
- End for
- Add non dominated particles to the repository
- Determine domination of new repository members
- Keep only the non-dominated members in the repository
- Update grid and grid index
- Modify inertia weight

- Create a new set of particles half the size $nPop$ and fill it with the non-dominated solutions in the repository followed by the $pBest$
- Combine the populations of NSGA II and the new set of particles of the MOPSO
- Increment generation count
- **End for**

6. Numerical tests

In order to validate the proposed hybrid algorithm, the CEED problem was solved for IEEE 30-bus system and the results are presented in this section. The fuel cost coefficients with valve-point loading, emission coefficients, and generator limits are adapted from [26] and is given in **Table 1**. The transmission loss B-matrix coefficients are obtained by running a load flow program and is in [26] is adapted here and given in **Table 2**. The total power demand in the system is 2.834 p.u. to the base of 100 MVA. Program in MATLAB was developed for the Hybrid Algorithm to perform CEED and executed on 1.60 GHz, Intel T2050 processor, 1.5 GB RAM HP Pavilion Laptop with WINDOWS 7 operating system. Various test cases are considered to compute the Pareto front of the multi-objective CEED problem. The Pareto-optimal front is obtained using the NSGA II algorithm and also using the MOPSO algorithm given in Section 4. The Pareto front obtained from the hybrid approach given in Section 5 is then compared with the Pareto front obtained using NSGAI and MOPSO algorithm.

In case 1 the fuel cost function is modeled as a quadratic function with sine term to incorporate the valve-point effect. The transmission losses are also considered in this case. The Pareto front obtained using NSGA II, MOPSO, and Hybrid NSGAI-MOPSO is shown in **Figures 1, 2 and 3** respectively. In all these figures there is a discontinuity in the Pareto front due to modeling of the valve point loading effect of generators.

The parameter settings for NSGA II are obtained using trial and error is as follows: $M = 2$; Population Size $nPop = 100$; Maximum number of iteration $MaxIt = 100$; Crossover Percentage

| Unit i | Generation Limits | | Fuel Cost Coefficients with valve point loading | | | | | Emission Coefficients | | | | |
|----------|-------------------|--------------|---|-------|-------|-------|--------|-----------------------|-----------|------------|-----------|------------|
| | Pg_i^{min} | Pg_i^{max} | a_i | b_i | c_i | e_i | f_i | α_i | β_i | γ_i | η_i | δ_i |
| 1 | 0.05 | 0.5 | 10 | 200 | 100 | 15 | 6.283 | 4.091 | -5.554 | 6.490 | $2e^{-4}$ | 2.857 |
| 2 | 0.05 | 0.60 | 10 | 150 | 120 | 10 | 8.976 | 2.543 | -6.047 | 5.638 | $5e^{-4}$ | 3.333 |
| 3 | 0.05 | 1.00 | 20 | 180 | 40 | 10 | 14.784 | 4.258 | -5.094 | 4.586 | $1e^{-6}$ | 8.000 |
| 4 | 0.05 | 1.20 | 10 | 100 | 60 | 5 | 20.944 | 5.326 | -3.550 | 3.380 | $2e^{-3}$ | 2.000 |
| 5 | 0.05 | 1.00 | 20 | 180 | 40 | 5 | 25.133 | 4.258 | -5.094 | 4.586 | $1e^{-6}$ | 8.000 |
| 6 | 0.05 | 0.60 | 10 | 150 | 100 | 5 | 18.480 | 6.131 | -5.555 | 5.151 | $1e^{-5}$ | 6.667 |

Table 1. Fuel costs Coefficients with valve point loading, Emission Coefficients, Generator limits of IEEE 30 bus system.

| | | | | | | |
|----------|--------------|-----------|------------|-----------|-----------|-----------|
| B | 0.02180 | 0.01070 | -0.00036 | -0.00110 | 0.00055 | 0.00330 |
| | 0.01070 | 0.01704 | -0.00010 | -0.00179 | 0.00026 | 0.00280 |
| | -0.00040 | -0.00020 | 0.02459 | -0.01328 | -0.01180 | -0.00790 |
| | -0.00110 | -0.00179 | -0.01328 | 0.02650 | 0.00980 | 0.00450 |
| | 0.00055 | 0.00026 | -0.01180 | 0.00980 | 0.02160 | -0.00010 |
| | 0.00330 | 0.00280 | -0.00792 | 0.00450 | -0.00012 | 0.02978 |
| B_0 | $1.0731e-05$ | 0.0017704 | -0.0040645 | 0.0038453 | 0.0013832 | 0.0055503 |
| B_{00} | 0.0014 | | | | | |

Table 2. B-Loss Coefficients for IEEE 30 bus test system.

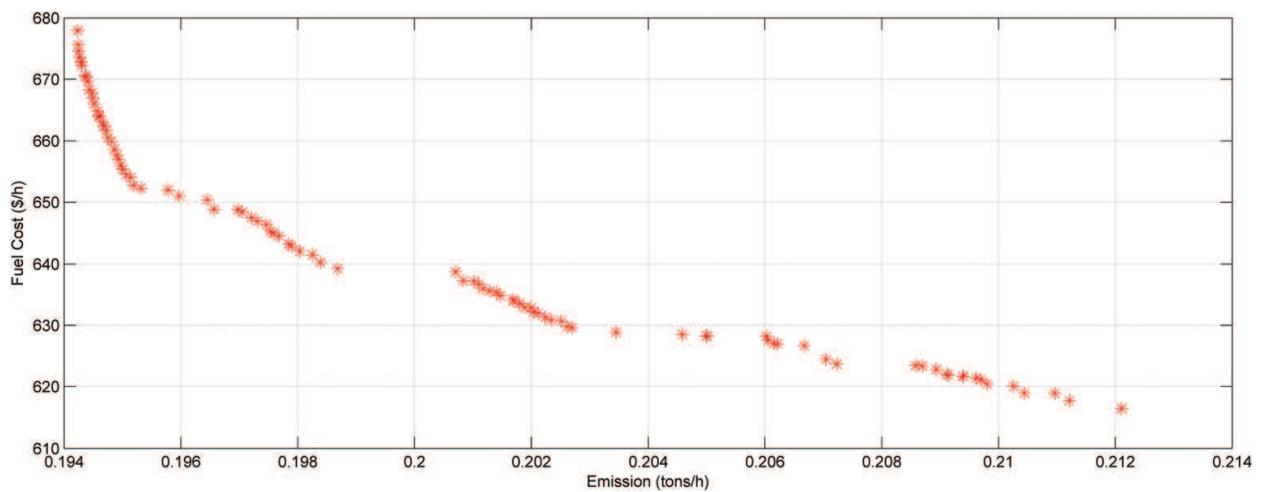


Figure 1. Pareto-optimal curve for IEEE 30 bus system obtained using NSGA II.

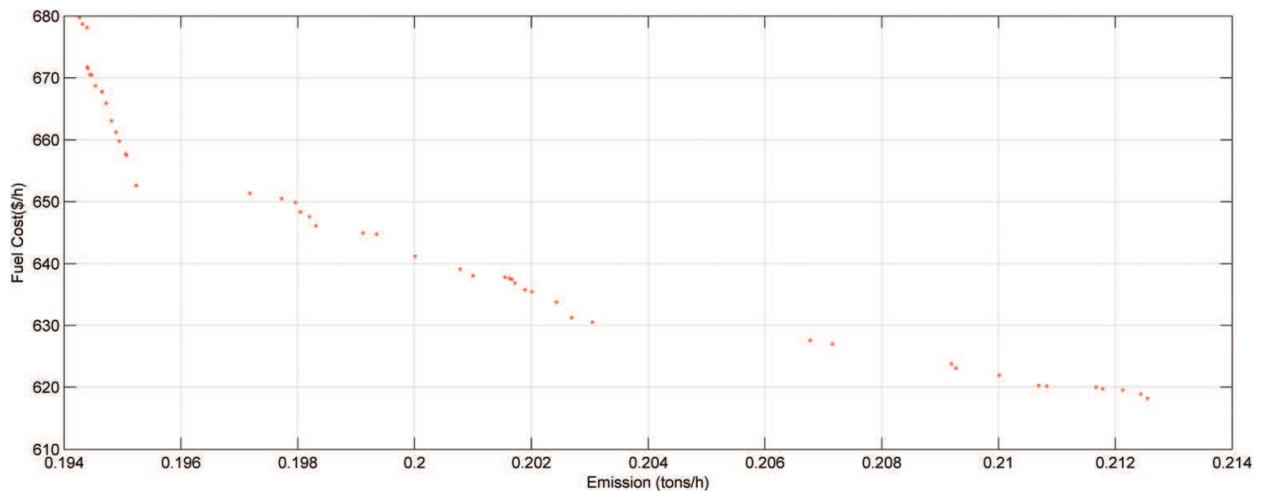


Figure 2. Pareto-optimal curve for IEEE 30 bus system obtained using MOPSO.

$p_{Crossover} = 0.7$; Mutation Percentage $p_{Mutation} = 0.4$; Mutation rate $\mu = 0.02$. The extreme points of the Pareto front and time for execution of NSGAI algorithm are provided in **Table 3**.

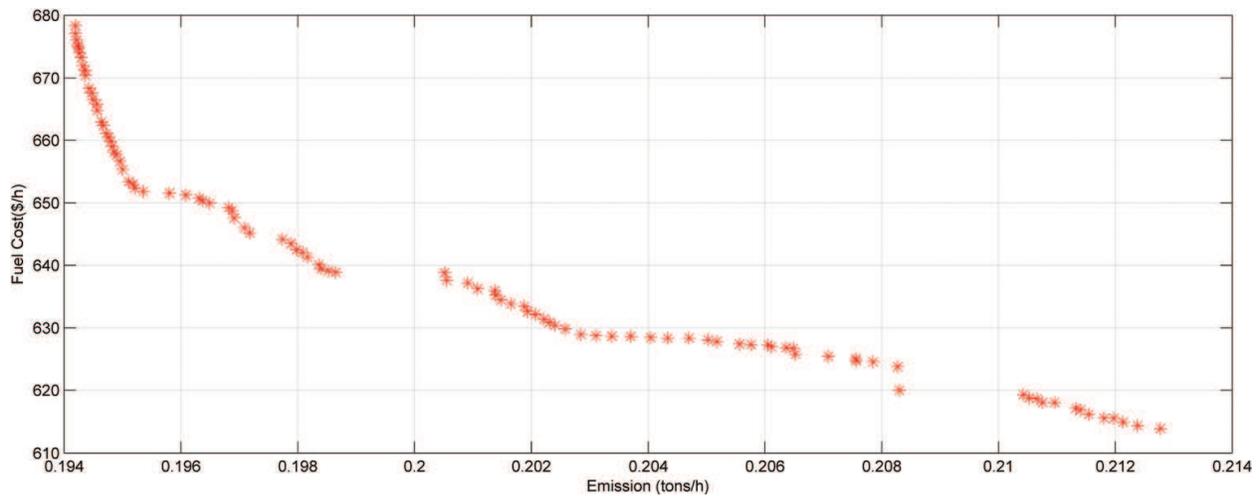


Figure 3. Pareto-optimal curve for IEEE 30 bus system obtained using Hybrid NSGAI and MOPSO Algorithm.

The parameter settings for MOPSO is obtained using trial and error is as follows: $M = 2$; Maximum number of iteration $MaxIt = 500$; Population Size $nPop = 250$; Repository size $nRep = 100$; Inertia Weight $w = 0.5$; Inertia Weight damping rate $wdamp = 0.99$; Personal learning coefficient $c1 = 1$; Global learning coefficient $c2 = 2$; Number of grids per dimension $nGrid = 10$; Inflation Rate $alpha = 0.1$, leader selection pressure $beta = 2$, Deletion selection pressure $gamma = 2$; Mutation rate $mu = 0.1$. The extreme points of the Pareto front and time for execution of MOPSO algorithm are provided in Table 3. We can observe from Figure 2 and Table 3 that there are difficulties in MOPSO algorithm in obtaining well spread Pareto front and also very slow convergence to the Pareto front when compared to NSGA II. This can be improved if the proposed hybrid approach is used to solve the CEED problem.

The Parameter setting for the hybrid algorithm is same as those given above expect for the settings provided here Population Size $nPop = 200$; Maximum number of iteration $MaxIt = 50$; Repository size $nRep = 20$. The extreme points of the Pareto front and time for execution of the proposed NSGAI-MOPSO hybrid algorithm are provided in Table 3. From Table 3 it is clear that the extreme points found by the hybrid algorithm are better than NSGA II and MOPSO

| Method | Pg_1 | Pg_2 | Pg_3 | Pg_4 | Pg_5 | Pg_6 | Pl | Fuel Cost (\$/h) | Emission (Tons/h) | Time Taken (s) |
|--------------------|--------|--------|--------|--------|--------|--------|---------|------------------|-------------------|----------------|
| NSGA II | 0.0649 | 0.3866 | 0.6851 | 0.7999 | 0.5399 | 0.3886 | 0.03126 | 616.426 | 0.2121 | 367 |
| | 0.4070 | 0.4528 | 0.5416 | 0.4198 | 0.5365 | 0.5087 | 0.03279 | 677.941 | 0.1942 | |
| MOPSO | 0.0626 | 0.4106 | 0.6885 | 0.7994 | 0.5472 | 0.3564 | 0.03090 | 618.211 | 0.2125 | 1507 |
| | 0.4412 | 0.4574 | 0.5501 | 0.3821 | 0.5523 | 0.4832 | 0.03242 | 678.702 | 0.1943 | |
| Hybrid NSGAI-MOPSO | 0.0500 | 0.3893 | 0.6861 | 0.8001 | 0.5490 | 0.3911 | 0.03178 | 613.85 | 0.2127 | 662 |
| | 0.4109 | 0.4563 | 0.5429 | 0.4002 | 0.5435 | 0.5128 | 0.03279 | 678.30 | 0.1942 | |

Table 3. Comparison of extreme points (shown in bold) and time taken for convergence using NSGAI, MOPSO and Hybrid NSGA II-MOPSO for IEEE30 bus system with valve point loading.

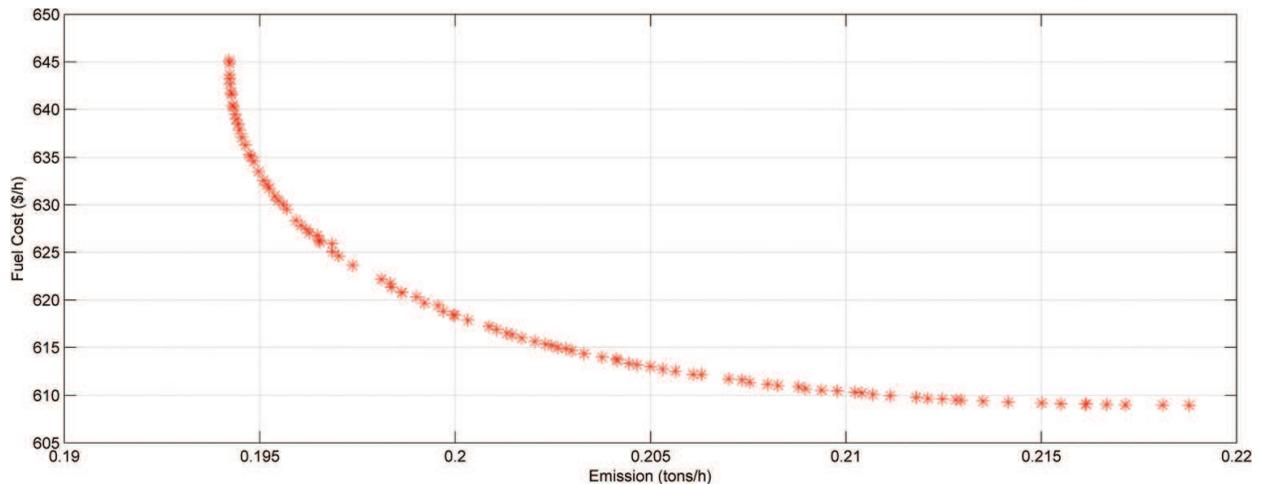


Figure 4. Pareto-optimal curve for IEEE 30 bus system without valve point effect obtained using hybrid NSGAI and MOPSO algorithm.

algorithm. Even though the time of execution of the Hybrid algorithm is slower than NSGA II it is able to find well spread Pareto front compared to NSGA II. The hybrid algorithm is far superior to MOPSO in terms of converge speed and also in finding well spread Pareto-optimal front.

In case II the valve point effect is neglected from the fuel cost curve and is solved using the proposed hybrid approach using the same parameters. The Pareto front obtained is shown in **Figure 4** and is a continuous curve when compared to the Pareto front shown in **Figure 3**. In **Figure 3** the Pareto front is discontinuous due to the effect of the Valve point loading in the cost curve. Both these case studies indicate that the hybrid approach is effective to solve the CEED problem.

7. Conclusion

In this chapter, a hybrid multi-objective optimization algorithm based on NSGA II and MOPSO have been proposed to solve the highly nonlinear, highly constrained combined economic emission dispatch problem. At any stage of the algorithm, only feasible solution is created because of the incorporation of the proposed constraint handling mechanism. During every iteration of the hybrid algorithm new population is created and NSGA II is applied on best performing individuals whereas MOPSO is applied on the lower ranked individuals to strengthen the exploration and exploitation capability of the algorithm. This hybrid approach is tested on an IEEE 30 bus system. The results obtained shows that the hybrid approach is efficient for solving CEED problem and is also able to quickly converge to a better Pareto-optimal front when compared to MOPSO algorithm. The result obtained by the hybrid approach also demonstrates it is able to yield a wide spread of solutions and convergence to true Pareto-optimal fronts.

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