MULTI-OBJECTIVE RISK CONSTRAINED SELF-SCHEDULING OF THE GENCOS FOR THE CORRELATED DEREGULATED MARKETS

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Abstract: This paper addresses a Multi-Objective Particle Swarm Optimization-Dynamic Crowding Distance (MOPSO-DCD) based algorithm to solve the Multi-Objective Risk Constrained Self-Scheduling (MORCSS) problem of the Generator companies (Gencos), in the correlated energy and spinning reserve markets. The proposed MOPSO-DCD method is demonstrated on the single generator system and the standard IEEE 30-bus system and its corresponding results are analyzed. The effectiveness of the proposed approach is demonstrated by comparing the reference Pareto front, generated by using multiple runs of the Cauchy Mutated Mimetic Particle Swarm Optimization (CMMPSO) method. Minimum spacing and the diversity of the Pareto front is taken into account for the performance assessment process

Key words: Cauchy Mutated Mimetic Particle Swarm Optimization, Correlated market, Dynamic Crowding Distance, Multi-Objective Particle Swarm Optimization, Self-Scheduling.

1. Introduction

The objective of the Gencos Self-Scheduling (SS) problem is to effectively schedule the generating units over a given scheduling period, to maximize the expected profit, satisfying various operating constraints of the generators. The modelling of the SS problem for the various entities and for the various market structures without considering the uncertainties is presented in [1-4]. In the past, numerous research works have incorporated risk issues into the Gencos SS problem [5-11]. In General, the only objective of the SS problem is to maximize the expected profit. It is also necessary to consider related societal issues because of the scale of the electric industry and its importance to modern life. One of these issues is the environmental impact of electricity generation. The environmental issues caused by the pollutant emissions produced by fossil-fueled electric power plants, have become a matter of concern. Due to increasing public awareness of environmental protection, and the passing of the clean air act amendments of 1990 [12], modern utilities has been forced to simultaneously optimize both economic and emission objectives.

The formulation of the Multi-Objective Self-Scheduling (MOSS) problem has gathered momentum in recent times. Due to the current scenario, generator owners are forced to limit their emission levels, to escape from the penalties. The optimal strategies of the Gencos in the deregulated environment also depend upon the emission strategies of the Gencos. Jalal Kazempour [13] considered emission as one of the constraints of the SS problem, which is solved for the correlated energy and spinning reserve markets.

The discussions about various multi-objective evolutionary approaches from the analytical weighted aggression to population based approaches, and the Pareto-optimality concepts are discussed in [14]. The recent trend is to handle multi-objectives simultaneously as competing objectives, using modern optimization techniques, such as Genetic Algorithms (GA), Evolutionary Programming (EP) and Particle Swarm Optimization (PSO). Pareto based approaches are most suitable for multi-objective optimization problems, due to the ability to produce multiple solutions in less computation time.

Goldberg [15] introduced Non-Dominated Sorting (NDS) to rank a search population according to Pareto optimality. A ranking based procedure of identifying Non-dominated sets of individuals are proposed to obtain the Pareto frontier. The solution of multi-objective problems by using Non-dominated Sorting Genetic Algorithms (NSGA) was proposed by Srinivas and Deb [16]. However, a large number of Non-dominated solutions may get lost in this approach as the elitism property of Evolutionary Algorithms (EA) has not been included. The Non-dominated Sorting Genetic Algorithm-II (NSGA-II) was proposed in [17] to improve the performance of the NSGA algorithm. The controlled elitism is proposed by Deb and Goel [18] to improve the exploitation-exploration characteristics of NSGA-II.

On the other hand, Particle Swarm Optimization (PSO) based algorithms seem particularly suitable for multi-objective optimization, mainly because of its high speed of convergence. There are several forms of Multi-objective PSO proposed over the years, to solve Multi-objective problems. Carlo Coello et al [19]

proposed a Pareto dominance based PSO approach, to solve multi-objective optimization problems. This algorithm uses the concept of a repository of particles and a mutation operator to improve the solution. Raquel and Prospero Naval [20] proposed a modified solution methodology for the multi-objective optimization problem, by combining the PSO and Crowding Distance (CD) operator for the generation of the hypercube, to locate the edges of the Pareto front. The Dynamic Crowding Distance (DCD) operator was proposed by Luo et al [21] to improve the diversity of the multi-objective evolutionary algorithms.

Considering all these factors, an archive based Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, which includes a DCD operator to solve the Multi-Objective Risk Constrained Self-Scheduling (MORCSS) problem. The MORCSS problem of the price-taking Gencos in the day-ahead energy and spinning reserve markets considering the conflicting objectives of the maximization of profit and the minimization of emission impacts. This proposed algorithm provides multiple solutions to the Gencos to decide their SS in the day-ahead market. The Pareto front obtained using the proposed method, is compared with the reference Pareto front generated by the multiple optimization runs, with the Dynamic Weighted Aggregation (DWA) of individual objectives, using the CMMPSO algorithm. The performance of the proposed multi objective algorithm is compared by measuring the performance measures, such as minimum spacing and diversity with respect to the reference Pareto front.

2. Formulation of the Multi-Objective Risk Constrained Self-Scheduling (MORCSS) Problem

The MORCSS problem of the thermal power generators are formulated as a bi-objective optimization model. The two conflicting objectives are: 1) maximizing the expected profit and 2) minimizing the emission levels, while satisfying all the system operating constraints over the scheduling period. The mathematical formulation of this problem is explained in this section.

2.1 Objective Functions

2.1.1 Profit Maximization

Diversification of investments into different types of assets is the main objective of the Gencos in deregulated power market. This will minimize the Gencos exposure to risks, and maximizes the returns on the portfolios. The Gencos profit maximization problem can be formulated as an optimization problem that maximizes the profit and minimizes the risk. The Markowitz portfolio optimization model is used to formulate the profit maximization problem. In the Markowitz mean-variance model, the safety selection of risky portfolio construction is considered as one objective function and the mean profit is defined as one of the constraints. This model is described as:

$$MIN\,(\text{RISK}) = \sum_{i=1}^{T}\sum_{j=1}^{T}P^e(i)V_e^{est}(i,j)P^e(j) +$$

$$\sum_{i=1}^{T}\sum_{j=1}^{T}P^s(i)V_s^{est}(i,j)P^s(j) +$$

$$2\sum_{i=1}^{T}\sum_{j=1}^{T}P^e(i)COV_{e,s}^{est}(i,j)P^s(j) \quad (1)$$

Subject to, $\sum RETURNS\ -\sum COSTS = R^d$ (2)

where i and j are the time indices, P^e and P^s are the scheduled power output in the energy and spinning reserve markets respectively, V_e^{est} and V_s^{est} are the estimated covariance matrix of energy and spinning reserve prices of size ($T \times T$) respectively, $cov_{e,s}^{est}$ is the Covariance of market prices of size ($T \times T$), T is the total scheduling interval and R^d is the desired profit of the portfolio.

Different objective function values are found by varying the desired mean returns. The risk aversion parameter $\beta \in [0,\infty]$ is used for this purpose. The profit maximization objective function with this parameter β can be described as:

F1: $MAX\ \sum RETURNS - \sum COSTS - \beta \sum RISK$ (3)

when, β is zero, the model maximizes the mean return of the portfolio, regardless of the variance (risk). So the sensitivity of the Gencos to the risk increases as β increases from zero to infinity, while it decreases as β approaches zero. The introduction of parameter β makes the problem a single-objective function. The *RETURNS* AND *COSTS* terms are given in equations (4) and (5) respectively. The quadratic cost function with the valve point effect is given in equation (6),

$$\sum RETURNS = \sum_{t=1}^{T}\sum_{k=1}^{N_g}\lambda_e(t)P_k^e(t)U_k(t) +$$

$$\sum_{t=1}^{T}\sum_{k=1}^{N_g}\lambda_s(t)P_k^s(t)U_k(t) \quad (4)$$

where, P_k^e and P_k^s are the scheduled power output of the kth generator in the energy market and spinning reserve market respectively, U_k is the schedule state of

the kth generator (1: unit is on and 0: unit is off), λ_e, λ_s are the prices at the energy and spinning reserve markets respectively and N_g is the number of generating units participates in the SS. The operating cost of the Gencos, participating in the energy and spinning reserve markets is expressed as,

$$\sum COSTS = \sum_{t=1}^{T}\sum_{k=1}^{N_g} C_k(P_k^e(t))U_k(t) + C_k(P_k^s(t))U_k(t) + \\ SUC_k(t)(1-U_k(t))U_k(t) + SDC_k(t)(1-U_k(t))U_k(t-1) \quad (5)$$

where, SUC_k and SDC_k is the start-up and shutdown cost and C_k is the quadratic cost function of the kth generator.

$$C_k(P_k^e) = a_k + b_k P_k^e + c_k P_k^{e2} + \\ \left| d_k \times \sin(e_k \times (P_k^e - P_k^{\min})) \right| \quad (6)$$

where, a_k, b_k, c_k are the cost coefficients and d_k, e_k are the coefficients reflecting the valve point effect of the kth generator. The real power P_k^e will be replaced by P_k^s for the spinning reserve market.

2.1.2 Minimizing Emission Levels

The objective function to minimize the emission levels of the thermal generators are presented below,

$$F2 = MIN\ E_k(P_{k,t}) = \sum_{t=1}^{T}\sum_{k=1}^{N_g} E_k(P_k^e(t))U_{k,t} + \\ E_k(P_k^s(t))U_{k,t} \quad (7)$$

where, E_k is the quadratic emission function of the kth generator (ton/hr) of the atmospheric pollutants caused by the operation of the kth thermal generator. The emission function of the kth generator is given below,

$$E_k(P_k) = f_k + g_k P_k + h_k P_k^2 \quad (8)$$

where, f_k, g_k and h_k are the emission coefficients of the kth generator.

2.2 Generators Operating Constraints

2.2.1 Generator Boundary Limits

The real power boundary limits of the kth generator in the correlated energy and spinning reserve markets is given in equation (9)

$$\left.\begin{array}{l} P_k^{e,\min} \leq P_k^e \leq P_k^{e,\max} \\ P_k^{s,\min} \leq P_k^s \leq P_k^{s,\max} \end{array}\right\} k = 1,...N_g \quad (9)$$

$$P_k^{s,\max} = P_k^{e,\max} - P_k^{e,scheduled} \quad (10)$$

where, $P_k^{e,\min}/P_k^{e,\max}$ and $P_k^{s,\min}/P_k^{s,\max}$ are the minimum and maximum real power boundary limits of the kth generator in the energy and spinning reserve market respectively. The value of $P_k^{s,\min}$ is set to zero and $P_k^{e,scheduled}$ is the scheduled power in the energy market.

2.2.2 Generator Ramp Up/Down Limits

The ramp up and ramp down limits of the kth generator in the correlated energy and spinning reserve markets is given in equation (11)

$$\left.\begin{array}{l} [P_k^e(t-1) - DR_k(1+U_k(t))U_k(t-1)] \leq P_k^e(t) \\ [P_{k,}^s(t-1) - DR_k(1+U_k(t))U_k(t-1)] \leq P_k^s(t) \\ [P_k^e(t-1) - UR_k(1+U_k(t-1))U_k(t+1)] \leq P_k^e(t) \\ [P_k^s(t-1) - UR_k(1+U_k(t-1))U_k(t+1)] \leq P_k^s(t) \end{array}\right\} \quad (11)$$

where, UR_k / DR_k are the up/down ramp rate limits of the kth generating unit.

2.2.3 Minimum Up / Down Time Limit

The minimum up and down time limits of the kth generating unit for the correlated market is given in equations (12) and (13).

$$\left.\begin{array}{l} (U_k(t) - U_k(t-1)(T_{on}(t-1) - MUT_k)) \leq 0 \\ (U_k(t) - U_k(t-1)(T_{off}(t-1) - MDT_k)) \geq 0 \end{array}\right\} \quad 12)$$

where T_{on}/T_{off} is the time counter for which a unit has been on/off at hour t and can be expressed as:

$$\left.\begin{array}{l} T_{on}(t) = (1+T_{on}(t-1))U_k(t) \\ T_{off}(t) = (1+T_{off}(t-1))(1-U_k(t)) \end{array}\right\} \quad (13)$$

where MUT_k / MDT_k are the minimum up/down time limits of the kth generator.

2.3 Multi-Objective Formulation

Multi-objective optimization problem have two or more objectives to be optimized simultaneously. The Pareto front concept describes the optimal trade-off

possibilities between the objectives. The MORCSS problem has two conflicting objectives; the main objective is to maximize the profit of the Gencos, and at the same time, the emission levels of the generators have to be minimized. This problem can be mathematically formulated as a Multi-objective optimization problem as follows:

$$MIN\ F_T = [\ 1/F1(P_k^e, P_k^s, U_k),\ F2(P_k^e, P_k^s, U_k)\ ]\ (14)$$

Subject to, $\quad h(P_k^e, P_k^s) \qquad\qquad (15)$

where, h is the inequality constraint representing the generator boundary limits, ramp rate limits and minimum up/down time constraints.

3. Multi-Objective Particle Swarm Optimization Algorithm

The similarity of the PSO with Evolutionary Algorithms (EA) makes evident the notion that using a Pareto ranking scheme [15] could be a straightforward way to extend the approach to handle multi-objective optimization problems. The best solutions found by the individual particle in the past run could be used to store the generated Non-dominated solutions. This would be similar to the elitism used in evolutionary multi-objective optimization.

The performance of MOPSO can be attributed to its use of an external archive of non-dominated solutions found in previous iterations. The Cauchy Mutation (CM) operator improves the exploratory capabilities of the algorithm, and prevents premature convergence. However, it should be noted that the use of CD of each solution, as a diversity operator by NSGA-II was able to produce a better distribution of the generated Non-dominated solutions, compared to the results generated by MOPSO that uses an adaptive grid [19] in maintaining the diversity of the generated solutions. The computation time of the PSO algorithm is less compared to that of the EA. This fact suggests that the PSO has been extended to solving multi-objective optimization problems, by incorporating the mechanism of DCD computation in the global best selection, and the deletion method of the external archive of non-dominated solutions, whenever the archive is full.

The DCD operator, together with a CM operator, maintains the diversity of Non-dominated solutions in the external archive. The algorithmic steps of the proposed method are as follows,

Step1: For i =1 to M (M is the population size)

- Randomly initialize the particle $P[i]$
- Randomly initialize the velocity of the particles $v[i] = 0$

- Evaluate the fitness function of each of the particles

- Store the personal best $\left(p_{best}[i]\right)$ value of the particles

- Store the global best $\left(g_{best}\right)$ value among all the particles

End

Step2: Initialize the iteration counter $iter = 0$

Step3: Store the position of the non-dominated vectors found in P into the external archive A.

Step4: Repeat

- Compute the DCD values of each of the non-dominated solutions in the archive A.

- Sort the non-dominated solutions in A in descending DCD values

For i=1 to M

- Randomly select the global best guide for $P[i]$ from a specified top portion of the sorted archive A and its position to g_{best}.

- Compute the new velocity:

$$v[i] = \chi \begin{bmatrix} \omega \times v[i] + C_1 \times rand_1(p_{best} - P[i]) + \\ C_2 \times rand_2(A[g_{best}] - P[i]) \end{bmatrix} \quad (16)$$

where $p_{best}[i]$ is the best position that the particle i has reached and $A[g_{best}]$ is the global best guide for each non-dominated solution.

- Compute the new position of the particle $P[i]$:

$$P[i] = P[i] + v[i] \qquad (17)$$

if $P[i]$ violates the boundary limits, then the decision variable takes the value of its corresponding lower and upper boundary limits, and its velocity is multiplied by -1, so that it searches in the opposite direction.

- Generate a uniformly distributed random number ($rand_i$) between 0 and 1 and compare each generated random number ($rand_i$) with P_m. If $P_m > rand_i$ then mutate the particle by the following equation,

$$x_{i,k}^{\text{iter}+1} = x_{i,k}^{\text{iter}} + f(x_{i,k}^{iter})v_{i,k}^{\text{iter}}\delta_k \qquad (18)$$

where δ_k is a Cauchy random number.

- Evaluate the fitness function of each of the particles in P

End

- Insert all the new non-dominated solutions in P into A, if they are not dominated by any of the stored solutions. All dominated solutions in the archive by the new solution are removed from the archive. If the archive is full, the solution to be replaced is determined by the following steps:

  i) Compute the DCD values of each non-dominated solution in the archive A.

  ii) Sort the Non-dominated solutions in A in descending DCD values.

  iii) Randomly select a particle from a specified bottom portion which compromises the most crowded particles in the archive; then replace it with the new solution.

  iv) Update the personal solution of each particle in P. If the current p_{best} dominates the position in memory, the particles position is updated using $p_{best}[i] = P[i]$

- Increment iteration count t.

Step 5: Until the maximum number of iterations is reached repeat the previous steps.

3.1 Dynamic Crowding Distance Computation

In Multi-objective optimization algorithms, the horizontal diversity of the Pareto front is very important. The horizontal diversity is often realized by removing excess individuals in the Non-Dominated Set (NDS), when the number of non-dominated solutions exceeds the population size. The MOPSO uses the CD measure as given in equation (19) to remove excess individuals. The individuals having the lower value of CD are preferred over individuals with a higher value of CD in the removal process.

$$CD_i = \frac{1}{m}\sum_{k=1}^{m}\left|f_{i+1}^k - f_{i-1}^k\right| \qquad (19)$$

where m is the number of objectives, f_{i+1}^k is the kth objective of the $i+1^{th}$ individual and f_{i-1}^k is the kth objective of the $i-1^{th}$ individual after sorting the population according to the CD. The major drawback of the CD is the lack of uniformity, in obtaining non-dominated solutions as illustrated in Figure 1.
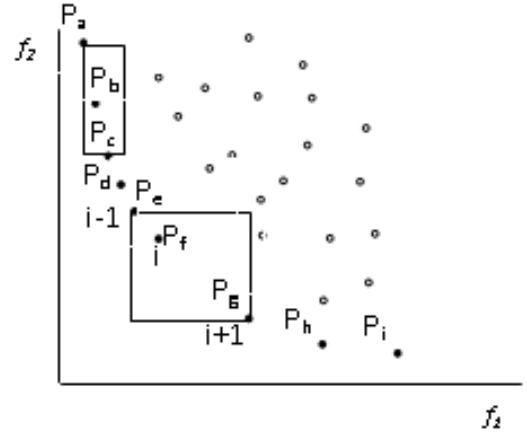

Figure 1. Crowding Distances of Individuals

In Figure 1, if the normal CD method is adopted, then the individuals P_c, P_d, and P_e are deleted from the NDS, since they have small CD values. Because of that, some parts of the Pareto front are too crowded and some parts are sparse. Also, the CD of P_b is small, because one side of the rectangle is short, while the other side is long. However, the CD of P_f is large because the length of one side is almost equal to that of the other side. If one individual must be removed between the individuals P_b and P_f, because of small CD value, individual P_b will be removed and P_f will be retained in the NDS. But, in order to get good horizontal diversity, the individual P_b should be

maintained, because the individual P_b helps to maintain a uniform spread. To overcome this problem, the Dynamic Crowding Distance (DCD) [21] method is suggested.

In this approach, one individual with the lowest DCD value is removed every time and the DCD is recalculated for the remaining individuals. The individuals DCD is calculated as follows:

$$DCD_i = \frac{CD_i}{\log\left[\dfrac{1}{z_i}\right]} \tag{20}$$

where CD_i is calculated using equation (19) and z_i using equation (21),

$$z_i = \frac{1}{m}\sum_{k=1}^{m}\left(\left|f_{i+1}^k - f_{i-1}^k\right| - CD_i\right)^2 \tag{21}$$

where z_i is the variance of the CDs of individuals, which are neighbors of the ith individual. z_i can give information about the variations of CD of different objectives. In Figure 1, the individual P_b has a larger value of z_i than the individual P_f, and the DCD of P_b is larger than that of P_f. Therefore, the individuals similar to P_b in the NDS will have more chance to be retained.

Assume that the population size is N, the NDS at the jth generation is Q(j) and its size is M. If M > N, the DCD based strategy is used to remove M-N individuals from the NDS. The algorithmic steps of the DCD algorithm are given below:

Step 1 : If $\left|Q(j)\right| \leq N$ then go to step 5, else go to step 2.

Step 2 : Calculate the individuals' DCD in the Q(j) by using equation (20).

Step 3 : Sort the non-dominated set Q(j) based on DCD.

Step 4 : Remove the individual which has the lowest DCD value in the Q (j).

Step 5 : If $\left|Q(j)\right| \leq N$, stop the population maintenance; otherwise go to step 2 and continue.

3.2 Constraint Handling

The proposed MOPSO-DCD algorithm adopted the constraint handling mechanism used in NSGA-II, due to its simplicity in using the feasibility and non-dominance of solutions when comparing solutions. A solution x_1 is said to constrained-dominate a solution x_2 if any of the following conditions is true:

• Solution x_1 is feasible and solution x_2 is not.

• Both solutions x_1 and x_2 are infeasible, but solution x_1 has a smaller overall constraint violation.

• Both solutions x_1 and x_2 are feasible and solution m dominates solution n.

When comparing two feasible particles, the particle which dominates the other particle is considered a better solution. On the other hand, if both particles are infeasible, the particle with a lesser number of constraint violations is a better solution.

3.3 Global Best Selection

The selection of the global is a crucial step in a MOPSO algorithm. It affects both the convergence capability of the algorithm, as well as the maintenance of a good spread of the Non-dominated solutions. In the MOPSO-DCD, a bounded external archive stores the Non-dominated solutions found in the previous iteration. It is to be noted that any of the Non-dominated solutions in the archive can be used as the global best guide of the particles in the swarm. But we want to ensure that the particles in the population move towards the sparse regions of the search space.

In the MOPSO-DCD, the global best guide of the particles is selected from among those non-dominated solutions with the highest DCD values. Selecting different guides for each particle in a specified top part of the sorted archive, based on a decreasing DCD, allows the particles in the primary population to move towards those non-dominated solutions in the external archive, which are in the least crowded area in objective space.

Also, whenever the archive is full, the DCD is again used in selecting which solution to replace in the archive. This promotes diversity among the stored solutions in the archive since those solutions which are in the most crowded areas, are most likely to be replaced by a new solution.

4. Implementation Of MORCSS model

The implementation of MORCSS problem is discussed in this section. The self-scheduling of the generators in day-ahead market is based on the forecasted LMP values. The variance and covariance matrices up to 'N-1' days are estimated from the available LMP data. The Pareto front with a set of non-dominated solution is obtained using the MOPSO-DCD algorithm depends upon the risk strategies of the Gencos. Multiple Criteria Decision Making (MCDM)

techniques are generally employed in an evaluation of Pareto-optimal solutions, to choose the best amongst them. A modified Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) [22] based on Shannon entropy function [23] is used for this purpose which is similar to the one proposed in [26]. The unit commitment status and the scheduled real power outputs of generators in the correlated energy and spinning reserve markets owned by the Gencos for the 24 hour time period is obtained using the same procedure mentioned above, subject to the minimization of the emission levels and maximization of the expected profit from the selected portfolio.

5. Numerical Results and Discussions

A power producer owning a single generating machine in the PJM market and an IEEE 30-bus system with six generating machines in the day-ahead energy and reserve markets are used to test the multi-objective MORCSS model. The cost, emission coefficients and the technical data, the forecasted LMP values of the energy and spinning reserve markets and the estimated covariance matrices for the single generator system, are presented in Appendix.

First, the profit and the emission optimization of the MORCSS problem are solved individually using the CMMPSO [24] algorithm, to obtain the reference Pareto front. The reference front is generated in multiple runs of the Dynamic Weighted Aggregation (DWA) of objectives. The CMMPSO based algorithm is used as an optimization algorithm. For a two-objective problem, weights can be modified during the optimization. The combined objectives of the MORCSS model are given below,

$$\text{Fcombined} = w_1(t)F_1(P_k^e, P_k^s, U_k) + \\ w_2(t)F_2(P_k^e, P_k^s, U_k) \quad (22)$$

$$w_1(t) = \left|\sin(2\pi t / F)\right| \text{ and} \\ w_2(t) = 1 - w_1(t) \quad (23)$$

where t is the iteration index, 'F' is the weights' change frequency and 'w' is a weighting factor indicating the relative importance of its associated objective during the optimization. If the Pareto front is concave in the nature, then the solution obtained by the DWA is better than the fixed weight method.

By varying 't' and 'F', a reference Pareto front with 40 non dominated points is obtained. This reference

Pareto front also includes two extreme points corresponding to $w = 0$ and $w = 1$. The comparisons of the scheduled real power, total profit and total emission values, using the CMMPSO algorithm for the two risk levels, are tabulated in Table 1.

Table 1. Optimal Solution of Single Generator System using the CMMPSO

Hour	β = 0.0		β = 0.05	
	P^e (MW)	P^s (MW)	P^e (MW)	P^s (MW)
1	206.5174	27.8193	117.3575	42.5089
2	33.3783	27.2062	221.7253	25.3638
3	237.5062	19.6957	274.6201	20.3705
4	207.5018	41.9043	242.5523	20.5504
5	194.2703	33.1284	290.8746	34.7893
6	34.3412	26.2061	269.8908	6.4635
7	61.8539	42.9825	162.9515	17.1860
8	31.0760	19.9036	188.7858	33.5446
9.	265.2294	25.2948	279.7858	23.9063
10	98.1602	41.6720	258.5291	31.1578
11	230.6436	28.2174	177.5739	27.1805
12	77.4144	38.3518	231.2073	35.1533
13	217.8192	28.0329	156.3114	53.6977
14	226.0698	42.2667	231.5532	1.4799
15	243.3177	31.1036	139.4325	41.2006
16	251.5151	19.1071	291.3936	13.2746
17	50.5443	22.2994	112.4157	13.1879
18	64.5210	22.3591	251.1599	40.0999
19	227.1968	16.3831	275.3588	53.9290
20	57.5594	23.0649	267.5486	13.4552
21	242.4722	25.9063	218.3404	34.1975
22	168.5870	41.3339	283.8619	28.8470
23	263.3438	27.1628	271.5379	43.1436
24	48.5398	44.9286	225.8333	2.7588
Total Expected Profit (TEP) in ($)	18,959		16,177	
Total Emission (TE) in (ton)	1962		627	

Then, the MORCSS problem is solved by using the proposed MOPSO-DCD algorithm. The population size is fixed at 150 and the archival size is fixed at 100 particles. The global best from the top 10% sorted archival replaces one of the non-dominated solutions in the bottom 10% of the archival. The DCD parameters are calculated based on the Crowding Distance (CD) and the variance of the CD. For the MORCSS model, 10 independent trails are conducted using the proposed algorithm for the different initial populations.

A set of extreme non-dominated solutions for the two risk levels of the MORCSS problem is obtained. The optimal solution is obtained from the set of non-dominated solutions, as given in Table 2.

Table 2. Optimal Solution of a Single Generator System using the MOPSO-DCD

Hour	β = 0.0		β = 0.05	
	P^e (MW)	P^s (MW)	P^e (MW)	P^s (MW)
1	204.4522	27.2629	115.5971	41.6587
2	31.0445	26.6621	18.3994	24.8565
3	235.1311	19.3018	270.5008	19.9631
4	205.4268	41.0662	238.9140	20.1394
5	192.3276	32.4658	286.5115	34.0935
6	231.9978	25.6820	265.8424	6.3342
7	160.2354	42.1229	160.5072	16.8423
8	228.7652	19.5055	185.9540	32.8737
9.	262.5771	24.7889	275.5890	23.4282
10	196.1786	40.8386	254.6512	30.5346
11	228.3372	27.6531	174.9103	26.6369
12	175.6403	37.5848	227.7392	34.4502
13	215.6410	27.4722	153.9667	52.6237
14	223.8091	41.4214	228.0799	1.4503
15	240.8845	30.4815	137.3410	40.3766
16	248.9999	18.7250	287.0227	13.0091
17	149.0389	21.8534	110.7295	12.9241
18	261.8758	21.9119	247.3925	39.2979
19	224.9248	16.0554	271.2284	52.8504
20	254.9838	22.6036	263.5354	13.1861
21	240.0475	25.3882	215.0653	33.5135
22	166.9011	40.5072	279.6040	28.2701
23	260.7104	26.6195	267.4648	42.2807
24	147.0544	44.0300	222.4458	2.7036
TEP in ($)	18,989		16,237	
TE in (ton)	1,942		611	

The comparison of the Pareto front obtained by using the CMMPSO and MOPSO-DCD for the two risk levels is shown in Figure 2 and Figure 3 respectively. From Figures 2 and Figure 3, it is clear that the Pareto front obtained by the MOPSO-DCD is closer to the reference Pareto front. The execution time of the CMMPSO algorithm to produce 10 non-dominated solutions is approximately 35 minutes, while that of the MOPSO-DCD algorithm is 15 minutes. The multiple solutions provided by the proposed approach can be effectively used by the generator owners, to SS their generators in the energy and spinning reserve markets
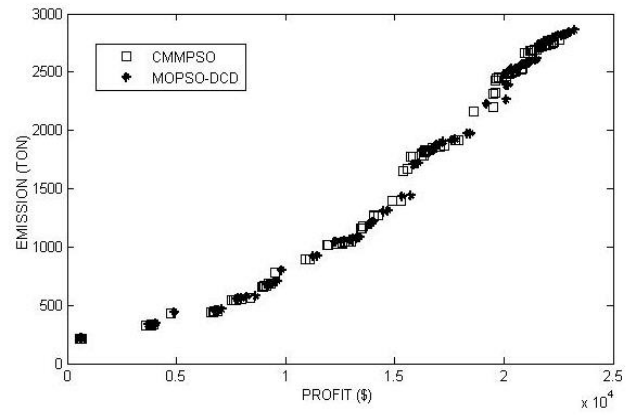

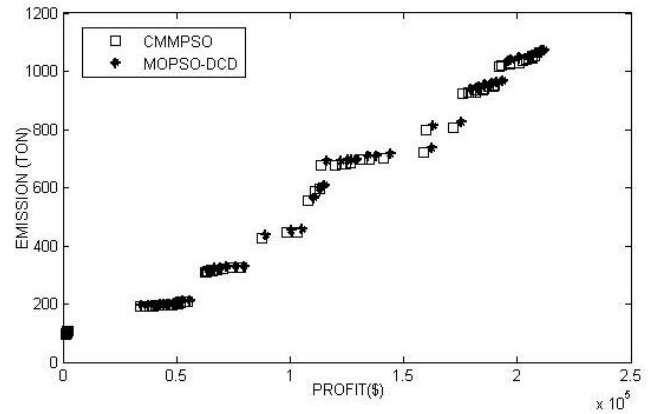Figure 2. Comparison of the Pareto Front of the Single Generator System (β = 0.0)

Figure 3. Comparison of the Pareto Front of the Single Generator System (β = 0.05)

For further validation, the proposed MOPSO-DCD algorithm is applied to the six generator IEEE 30-bus system. The forecasted energy and spinning reserve prices, the technical data and the estimated covariance matrixes are tabulated in Appendix.

The population size and the archival size are fixed as 400 and 300 respectively. Ten independent trials are simulated, by using the MOPSO-DCD algorithm and the extreme non-dominated solutions for the two risk penalty parameters are obtained. The optimal solution obtained for the two risk levels by using TOPSIS, is tabulated in Tables 3 and 4 respectively. The optimal expected profit and the emission obtained without risk, by using the CMMPSO algorithm, are 8582.14 and 5512.89 respectively. For the value of risk penalty parameter β = 0.05, the profit and the emission values are 6014.29 and 3752.65 respectively.

The Pareto fronts obtained for the two risk levels by using the CMMPSO and MOPSO-DCD are compared and shown in Figures 4 and 5 respectively.
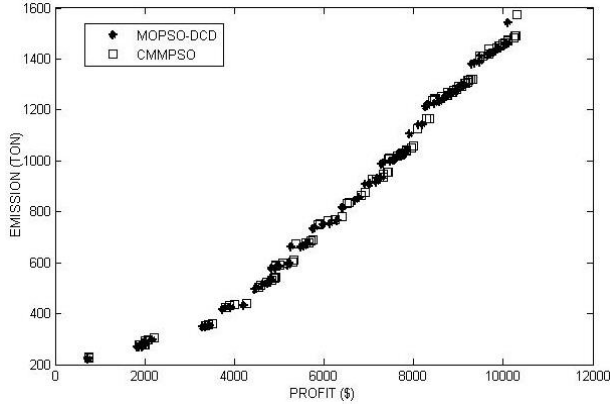
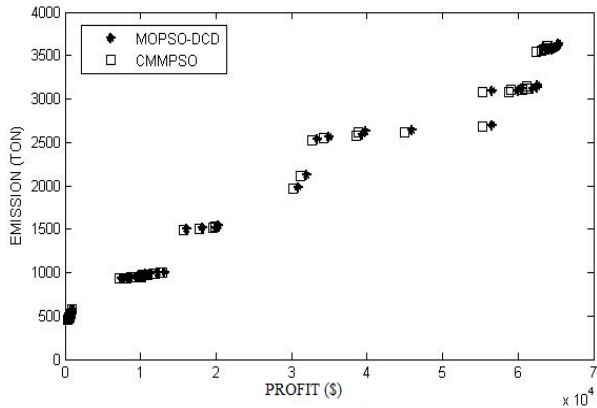Figure 4. Comparison of the Pareto front of the IEEE 30-Bus System (β = 0.0)

Figure 5. Comparison of the Pareto front of the IEEE 30-Bus System (β = 0.05)

5.1 Performance Evaluation of MOPSO-DCD Algorithm

In order to conduct a quantitative assessment of the performance of the MOPSO-DCD algorithm, two factors are taken into consideration.
1) Minimize the spacing of the Pareto front produced by the proposed algorithm, with respect to the reference Pareto front, obtained using the CMMPSO algorithm.   2) Maximize the diversity of the solutions found, to have a distribution of vectors as smooth and uniform as possible.

The minimum spacing and divergence measures [25] are obtained for the single generator system and IEEE 30-Bus system, by comparing the reference Pareto front with Pareto fronts obtained in 5 independent runs, by using the MOPSO-DCD algorithm. The best, worst and mean value for the single generator system and IEEE 30-Bus system are given in Table 5.

Table 5. Statistical Measures Comparison of the Test Systems

Single Generator System ($\beta = 0.05$)			
Performance measures	Best	Worst	Mean
Minimum spacing	0.0212	0.0321	0.0278
Diversity	0.575	0.422	0.511
IEEE 30-Bus System ($\beta = 0.05$)			
Performance measures	Best	Worst	Mean
Minimum spacing	0.0332	0.0399	0.0312
Diversity	0.495	0.411	0.431

6.   Conclusion

This paper proposed a MOPSO–DCD based solution methodology for the MORCSS problem of the Gencos, in the correlated energy and spinning reserve markets. This problem is formulated as a multi-objective optimization problem with conflicting objectives of the maximization of profit and the minimization of the emission impacts. Two test systems are considered for the validation. The reference Pareto front is generated using multiple runs of the CMMPSO algorithm and is compared with the Pareto front generated using the proposed algorithm for validation. The results obtained by using the proposed MOPSO-DCD method shows that the algorithm is fast and efficient in solving MORCSS problem. The multiple Pareto optimal solutions are obtained in one simulation run. The set of non-dominated solutions provide many options for the price taking Gencos for the self- scheduling problem. The results indicate that the obtained solutions are distributed and have good diversity characteristics.

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Table 3. Optimal Solution of the IEEE 30-Bus System using the MOPSO-DCD without Risk

P_1^e	P_2^e	P_3^e	P_4^e	P_5^e	P_6^e	P_1^s	P_2^s	P_3^s	P_4^s	P_5^s	P_6^s
200.00	80.00	46.18	22.19	27.25	30.30	18.12	16.41	13.44	6.53	3.92	2.83
89.33	52.42	19.72	29.68	27.55	25.86	2.909	5.545	3.226	6.48	3.220	8.80
156.44	66.91	29.24	28.53	23.01	31.92	6.183	4.041	2.378	1.41	2.41	10.7
181.77	68.74	29.30	34.96	22.92	28.67	18.833	8.322	0	0.58	4.05	6.72
177.73	52.14	26.31	20.67	10.81	26.88	18.89	14.18	8.015	5.23	0.705	5.81
200.00	36.85	25.05	17.82	19.72	19.11	3.607	18.00	6.974	5.85	2.10	2.55
188.64	77.28	28.07	23.21	24.65	12.00	32.48	10.80	11.61	4.29	2.80	5.60
136.65	63.79	15.69	16.21	12.09	15.50	29.92	6.172	5.672	4.01	4.73	5.89
119.32	80.00	31.75	12.50	22.08	28.60	23.19	6.326	2.907	3.21	0.98	2.57
176.75	44.52	17.26	28.79	21.37	28.64	11.76	16.89	11.55	4.57	2.60	3.66
182.50	72.96	21.68	26.22	11.26	24.49	10.75	10.93	1.763	7.03	2.77	6.79
177.03	44.348	17.47	35.00	26.02	26.53	19.21	5.089	9.302	3.73	3.85	3.66
194.36	39.53	37.14	25.61	26.60	25.09	29.65	16.84	6.161	6.18	3.05	11.0
79.037	26.52	20.36	19.67	25.51	35.84	7.188	5.196	9.166	2.06	3.83	4.75
108.81	42.06	19.84	12.71	18.97	35.137	11.06	15.96	4.556	2.07	0.73	2.31
89.436	45.18	26.52	25.78	20.61	27.99	23.70	15.38	7.555	6.71	1.49	10.6
180.90	51.56	25.89	22.63	23.22	16.50	23.35	3.975	2.019	0.92	4.48	9.37
137.09	77.13	25.64	15.21	18.32	28.60	15.85	0	13.97	1.68	3.69	8.23
172.62	46.35	31.18	18.03	27.48	12.00	14.62	15.18	2.898	2.51	0.84	8.80
158.57	50.61	48.66	28.81	20.11	37.96	19.35	13.33	8.085	6.57	2.66	9.27
200.00	54.53	45.61	13.19	19.44	18.80	34.20	6.128	10.26	3.85	1.34	6.92
167.98	27.93	43.73	23.59	14.37	36.54	38.05	12.40	1.911	3.01	1.98	3.04
200.00	70.07	33.39	28.08	15.33	27.69	13.83	7.095	11.62	6.96	4.02	1.46
67.106	54.92	47.93	30.36	16.38	32.66	31.75	2.884	9.083	3.31	3.99	7.39
Total Expected Profit in ($) = 8586.22											
Total Emission in (ton) = 5522.41											

Table 4. Optimal Solution of the IEEE 30-Bus System using the MOPSO-DCD with Risk Factor (β) of 0.05

P_1^e	P_2^e	P_3^e	P_4^e	P_5^e	P_6^e	P_1^s	P_2^s	P_3^s	P_4^s	P_5^s	P_6^s
182.6	49.82	22.98	24.3	27.39	30.43	25.31	9.84	3.89	7.22	4.35	5.05
183.1	56.66	15.43	26.7	20.54	17.40	33.53	4.62	13.64	5.39	3.64	8.87
151.6	31.70	22.01	12.2	19.96	33.00	6.633	8.93	2.386	6.45	1.47	6.23
175.1	46.62	46.71	32.95	29.54	32.75	11.19	14.0	1.100	2.99	4.67	8.22
189.5	69.24	30.43	20.2	18.68	29.88	12.44	13.61	9.343	6.48	3.94	7.76
147.5	57.81	36.26	14.3	22.76	16.34	19.63	6.586	5.269	4.84	0.76	10.8
181.7	42.73	44.54	29.8	27.09	30.00	25.49	4.040	2.981	5.05	3.56	2.99
83.72	66.57	46.70	16.8	21.47	36.59	27.36	14.69	13.50	1.64	1.03	5.98
186.3	53.25	18.68	24.8	20.14	35.62	3.344	4.668	7.543	5.94	0.67	1.99
135.6	35.65	31.22	29.9	18.86	37.02	9.965	1.586	14.38	0.36	3.12	4.57
144.2	64.63	29.52	20.8	29.01	22.66	23.31	15.00	12.79	6.89	3.10	1.33
161.9	31.76	43.89	30.8	26.99	12.00	27.14	5.271	5.653	7.43	1.72	0.85
151.6	46.53	41.71	29.7	13.81	29.99	14.25	16.72	4.460	7.54	2.35	8.11
127.6	63.27	19.86	22.7	11.49	12.16	6.262	3.314	12.18	2.55	5.00	1.13
92.09	21.42	38.30	21.3	23.99	22.17	5.142	11.55	0.451	2.84	0.74	2.66
81.11	64.58	25.00	25.7	14.80	22.06	23.63	17.35	0.574	1.39	3.72	6.81
189.1	33.17	43.92	13.3	22.85	32.35	1.003	7.794	5.929	6.85	3.92	2.64
176.8	74.00	19.25	25.2	23.79	19.30	0.511	10.90	6.104	0.89	2.28	10.4

185.2	44.87	38.32	11.2	26.85	35.96	32.52	19.76	3.841	3.58	0.58	10.6
170.8	23.43	30.25	29.5	17.77	17.78	35.16	16.90	1.759	2.34	4.14	10.3
162.4	25.58	24.51	22.19	18.90	34.60	14.86	8.908	8.505	2.59	1.13	6.18
160.8	44.80	16.57	23.5	24.13	25.19	19.65	6.905	8.125	1.66	3.38	4.33
162.6	70.19	35.80	21.5	12.42	40.00	28.53	9.980	5.432	1.84	2.80	7.35
84.74	65.19	33.45	29.1	15.68	14.34	13.45	14.08	14.24	6.98	1.96	9.83
Total Expected Profit in ($) = 6013.7											
Total Emission in (ton) = 3753.1											