SOLVING ENVIRONMENTAL/ECONOMIC DISPATCH PROBLEM USING AN IMPROVED MULTIOBJECTIVE SCATTER SEARCH APPROACH

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Abstract. *The environmental/economic dispatch (EED) problem is a large-scale highly constrained nonlinear multiobjective optimization problem. In recent years, this option has received much attention. Many approaches and methods have been reported to solve the multiobjective EED problem in the literature, such as genetic algorithms, artificial neural networks, particle swarm optimization, and differential evolution. In terms of metaheuristics, recently, scatter search approaches are receiving increasing attention, because of their potential to effectively explore a wide range of complex optimization problems. Scatter search is an evolutionary method that shares with genetic algorithms, the employment of a combination method that combines the features of two parent vectors to form several offspring. It generates a reference set from a population of solutions. Then the solutions in this reference set are combined to get starting solutions to run an improvement procedure, whose result may indicate an updating of the reference set and even an updating of the population of solutions. Furthermore, an important aspect concerning scatter search is the trade-off between the exploration abilities of the combination method and the exploitation capacity of the improvement mechanism. In this paper, we deal with a continuous version of the scatter search algorithm, which works directly with vectors of real components to solve multiobjective EED problems. In the proposed work, we have considered the standard IEEE (Institute of Electrical and Electronics Engineers) 30-bus with six-generators test system and the results obtained by proposed algorithm are compared with the other recently reported results in the literature. Simulation results demonstrate that the proposed improved scatter search algorithm is a capable candidate in solving the multiobjective EED problems. In addition, a quality measure to Pareto-optimal solutions has been implemented where the results corroborate the potential of the proposed improved scatter search technique to solve the multiobjective EED problem and produce high quality nondominated solutions.*

Keywords*: scatter search, environmental/economic dispatch, evolutionary algorithms, six-generators test system.*

1. INTRODUCTION

Environmental/economic dispatch (EED) problem is one of the most important problems in power systems management. It consists of scaling the outputs of generators, in a thermoelectric plant, such that a power demand is supplied while satisfying equality and inequality constraint. Each generation unit has particular aspects in the cost of the fuel spent and the pollutants emitted. There are two objectives to be optimized in this kind of problem: the cost of the generation and the total emission. Both objectives must be minimized, however they are conflicting, i.e. if there is an optimal solution it is impossible to optimize an objective without worsen other objective. Thus, there is not only one solution but a set of solutions that form the Pareto optimal set.

Many researchers have tackled this problem in the past. The first use of multiobjective programming with power systems has been addressed by Cheong and Dillon (1978). However, it is realized that conventional mathematical techniques, such as gradient method, linear programming algorithm, quadratic programming, Lagrange relaxation algorithm, become very complicated when dealing with increasingly complex dispatch problems, and are further limited by their lack of robustness and efficiency in a number of practical applications (Yalcinoz and Köksoy, 2007). However, because of its particularities, an efficient technique must be used to provide good solutions for the EED problems.

Multiobjective EED optimization involves the simultaneous optimization of several incommensurable and often competing objectives. Recently, the research focus has shifted towards handling both the objectives simultaneously. Over the past decade, this option has received much interest due to the development of a number of multiobjective search strategies based on metaheuristics, such as evolutionary and swarm intelligence approaches. Examples are presented in Abido (2003), King et al. (2006), Wang and Singh (2007), Chaturvedi et al. (2008), Cai et al. (2009), and Panigrahi et al. (2011).

In this context, a useful metaheuristic method is the scatter search algorithm. Scatter search (Glover and Laguna, 2000) is a population-based metaheuristic method that uses a set of reference solutions to create new improved solutions. The reference set is formed based on quality and diversity of the solutions. Initially, the best solutions are added to the reference set, and then the most diversified solutions, based on the distance to the already added solutions, are included in the set. The algorithm combines these solutions to create new ones and achieve a desirable result. Nevertheless, the original approach does not consider multiple objectives, so some modifications must be made in order to apply it to solve the EED problem.

In this paper, we propose a scatter search methodology to deal with multiobjective problems based on Deb's approach (Deb, 2000). Thus, an improvement in the combination method is proposed. The results of the original and proposed approaches are compared to other techniques presented in literature of EED. These algorithms have been implemented on standard IEEE (Institute of Electrical and Electronics Engineers) 30-bus six-generators system in order to obtain the trade-off between the cost and emission. Results show that the modifications proposed increased the capability of scatter search algorithm

The remainder of the paper is organized as follows: section 2 presents the concepts of scatter search, section 3 presents the algorithm of scatter search and the proposed approach, in section 4 describes the formulation of the optimization problem and sections 5 and 6 present the results and conclusions, respectively.

2. SCATTER SEARCH

Scatter search is a metaheuristic algorithm that can be considered an evolutionary algorithm in the sense that it incorporates the concept of population. However, scatter search usually avoids using many random components and typical evolutionary operators such as mutation or crossover operators do not fit, theoretically, with the philosophy of this algorithm.

The original Scatter Search (SS) algorithm has 5 procedures: a diversification generation method to randomly generate diversified trial solutions; an improvement method to improve current solutions toward the optimum solution; a reference set update method to update the set of reference solutions with the best solutions; a subset generation method to create subsets for the combination method; and a combination method to combine the reference solutions and generate new offspring. Next subsections describe each procedure.

2.1. Diversification generation method

This method generates solutions so that they are uniformly distributed in the search space. Each dimension of the search space is divided in 4 regions of equal size and the number of times each region is used should be almost the same to guarantee diversity in the population. Table 1 shows an example of a diversified population generated with this procedure. We have randomly generated 100 solutions x=[x_1 x_2 x_3 x_4] with each dimension using uniform distribution between 0 and 1. The values are the number of times that each variable appeared in each range.

Table 1. Example of a diversified population.

Range	x_1	x_2	x_3	x_4
0.00 – 0.25	23	23	27	23
0.25 – 0.50	24	26	24	22
0.50 – 0.75	28	22	22	24
0.75 – 1.00	25	29	27	31

This procedure do not consider the objective function values, it is focused on the distribution of the population in the search space.

2.2. Improvement method

In order to increase the exploitation capability of scatter search an improvement method is used and its goal is to transform a solution in a better one in terms of objective function or feasibility. Typically this method is a local search procedure which is carried out until no improvement is detected in the solution. However, since each solution is improved using this procedure, it needs to be a very fast and effective method in order to not increase the computational demand.

2.3. Reference set update method

The reference set contains high quality solutions, in terms of objective function, and diverse solutions. Its size is equal to b=b_1+b_2, where b_1 is the number of high quality solutions and b_2 is the number of diversified solutions. Initially, we remove the best b_1 solutions from the population and add them to the reference set. Then, the b_2 diverse solutions must be added to the reference set and removed from the population. To evaluate which solution is more diversified, is calculated the minimum of the Euclidian distance between each solution and the reference solutions, i.e. given a solution in the population, the distances between the solution and each reference solution is calculated and the minimum value found is assigned to that solution. So, the solution of the population with the maximum distance value is the most diversified solution.

These two steps for adding solutions to the reference set increase the exploration capability of the algorithm and help to avoid being trapped in local minima.

2.4. Subset generation method

This procedure creates subsets of the reference set to use in the combination method. In this paper are used subsets of size equal to 2. All possible subsets are generated; however, a subset already used is discarded because it will recreate solutions already used in the algorithm.

2.5. Combination method

The combination method is one of the most important steps of the algorithm. It uses the subsets created in the subset generation method to combine solutions and create new ones. Consider two reference solutions x_1 and x_2, three new solutions are created using the following:

$$\begin{aligned} C_1 &= x_1 - d \\ C_2 &= x_1 + d \\ C_3 &= x_2 + d \end{aligned} \tag{1}$$

$$d = r\frac{(x_1 - x_2)}{2} \tag{2}$$

where r is a random number generated in the range between 0 and 1.

3. ALGORITHM OF THE SCATTER SEARCH AND THE PROPOSED IMPROVED VERSION

The algorithm just uses the methods described above in the same sequence. An initial random population is created and each element is improved using the improvement method. Then, is constructed the reference set with the best solutions and the most diversified solutions. The reference set is used to create new solutions using the combination method and it is updated with the best and the most diverse solutions of the population. If there are no new solutions, the reference set is rebuilt using the diversification generation method. The algorithm is carried out until a number of iterations is achieved. Figure 1 shows the main steps of SS algorithm.

```
Create a population of solutions using
       Diversification Generation Method
Improve each solution
Create the reference set with the bests and the most diverse solutions

While i < Number of Iterations
   Combine reference solutions
   Improve created solutions
   if New solutions
      Update reference set
      i =i + 1;
   else
      Rebuild reference set
   end
end
Present the best solution found
```

Figure 1. Pseudo code of SS.

The variable called “New solutions” is a flag to notify whether new solutions were created or not. After the application of the Combination method, all solutions are evaluated and if there is at least one solution better than any reference solution (according to the objective function value or the distance value) then the flag "New solutions" is set to true, otherwise is set to false. Thus, the reference set is updated or rebuilt according to the flag's value.

In this paper we propose a new scheme for the combination method. Instead of use equations (1) and (2), we create four new solutions using the following:

$$\begin{cases} C_1 = a_1 x_1 + (1-a_1)x_2 \\ C_2 = a_2 x_1 + (1-a_2)x_2 \\ C_3 = a_3 x_1 + (1-a_3)x_2 \\ C_4 = a_4 x_1 + (1-a_4)x_2 \end{cases} \tag{3}$$

where a_i is a random number with uniform distribution generated in the range [-1,1]. This scheme creates solutions more diversified because it uses different random numbers for each solution created. Also, it creates four new solutions instead of three as the original method. This increases the capability of explore the search space of the algorithm, which is very important in problems such as the environmental/economic dispatch that has a big search space.

A change in the improvement method is also necessary because the original method do not deal with multiple objectives. In this paper we suggest a simple but efficient modification which is described by the following equations.

$$X_{1,I} = Y_I + \delta Y_I \tag{4}$$

$$X_{2,\neg I} = Y_{\neg I} + \delta Y_{\neg I} \tag{5}$$

$$\begin{cases} X_{3,I} = Y_I + \delta Y_I \\ X_{3,\neg I} = Y_{\neg I} - \delta Y_{\neg I} \end{cases} \tag{6}$$

$$\begin{cases} X_{4,\neg I} = Y_{\neg I} + \delta Y_{\neg I} \\ X_{4,I} = Y_I - \delta Y \end{cases} \tag{7}$$

where Y is the solution to be improved, δ is a constant number, I is a random logical vector which indicates the dimension to be modified, $\neg I$ is the negation of I and X_i is the i-th solution constructed. The algorithm creates these 4 solutions from Y and the best between them (according to all objectives) substitutes Y. This improvement method is used in both approaches the original and the proposed.

In this paper, to deal with multiple objectives, is used the concepts of Pareto dominance and crowding distance (Deb, 2000). Given two vectors $\vec{u} = (u_1, \ldots, u_k)$ and $\vec{v} = (v_1, \ldots, v_k)$, u dominates v if and only if $\forall i \in \{1, \ldots, k\}, \vec{u} \le \vec{v} \wedge \exists i \in \{1, \ldots, k\} : \vec{u} < \vec{v}$. In other words, in at least one dimension u is less than v and in no other dimension v is less than u. The objective vectors are evaluated using this concept and a solution that dominates another is preferred. The solutions that are not dominated by any other are the Pareto optimal solutions and constitute the Pareto set of non-dominated solutions. In multiobjective optimization this set is the desired set of solutions. The population of solutions is analysed on this aspect and the first front is constructed with the non-dominated solutions of the population, then these solutions are stored and removed from the population, the second front is then constructed with the remaining non-dominated solutions and so on until all solutions are stored in a front. The first front is the set of best solutions in the population and its solutions are in the same level, so, to decide the best solution between two of the same front, the concept of crowding distance is used. To calculate the crowding distance of a solution i is used:

$$D_i = \sum_{k=1}^{m} \frac{f_k(i+1) - f_k(i-1)}{f_k^{\max} - f_k^{\min}} \tag{8}$$

where D is the distance, f_k is the k-th objective function's value of the i-th solution. The solutions of the boundaries of the front have their distance set to infinite. And the solution with the great crowding distance is preferred. These two concepts are used to construct the reference set; the solutions are sorted by the fronts and by the crowding distances.

4. FORMULATION OF THE OPTIMIZATION PROBLEM

The EED problem is formulated as a multiobjective optimization one, where one objective is the total emission of pollutants and the cost of generation related to the fuel used. These two objectives should be optimized while satisfying equality and inequality constraints. The problem evaluated in this paper is the standard IEEE 30-bus with six-generators test system. The IEEE 30-bus test case represents a portion of the American Electric Power System (in the Midwestern US) as of December, 1961 (see Figure 2) with 41 transmission lines. Details and data of IEEE 30-bus are presented in Gong (2010), Vahidinasab and Jadid (2010), Abido (2003) and Farag (1995). The data for the optimization problem are given by Tables 2 to 4. The system base is 100 MVA.

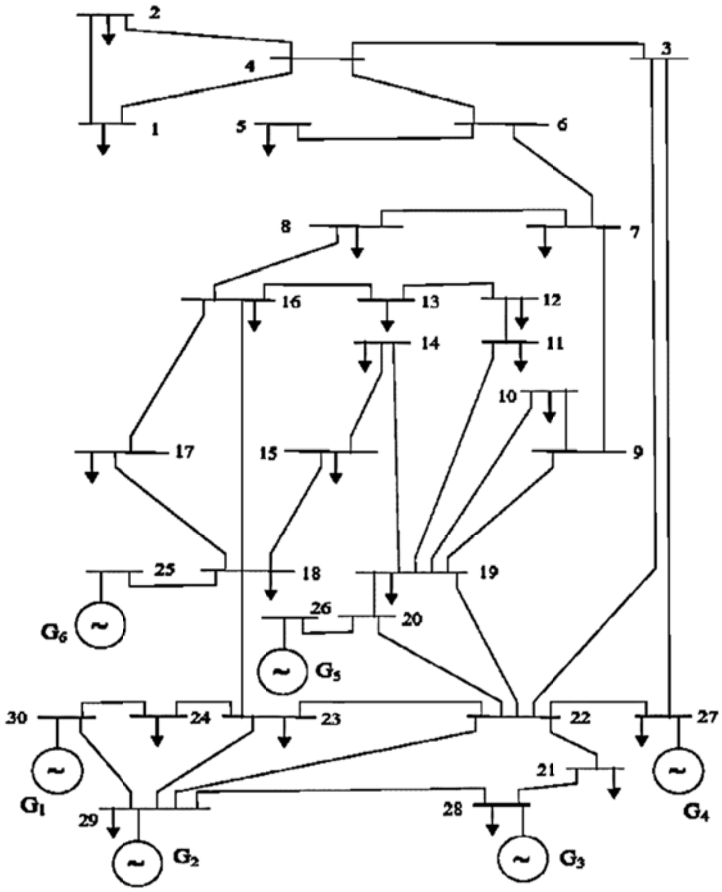

Figure 2. IEEE 30-bus six-generators system.

Table 2. Lower and upper boundaries of each generator.

Power (p.u.)	G_1	G_2	G_3	G_4	G_5	G_6
P_{min}	0.05	0.05	0.05	0.05	0.05	0.05
P_{max}	0.5	0.6	1.0	1.2	1.0	0.6

Table 3. Data for the objective functions.

Variable	G_1	G_2	G_3	G_4	G_5	G_6
Cost (*$/h*)						
a	10	10	20	10	20	10
b	200	150	180	100	180	150
c	100	120	40	60	40	100
Emission (*ton/h*)						
α	4.091	2.543	4.258	5.326	4.258	6.131
β	-5.554	-6.047	-5.094	-3.550	-5.094	-5.555
γ	6.490	5.638	4.586	3.380	4.586	5.151
ζ	2.0e-4	5.0e-4	1.0e-6	2.0e-3	1.0e-6	1.0e-5
λ	2.857	3.333	8.000	2.000	8.000	6.667

Table 4. *B*-loss coefficients matrix.

B	Values					
	0.1382	-0.0299	0.0044	-0.0022	-0.0010	-0.0008
	-0.0299	0.0487	-0.0025	0.0004	0.0016	0.0041
	0.0044	-0.0025	0.0182	-0.0070	-0.0066	-0.0066
	-0.0022	0.0004	-0.0070	0.0137	0.0050	0.0033
	-0.0010	0.0016	-0.0066	0.0050	0.0109	0.0005
	-0.0008	0.0041	-0.0066	0.0033	0.0005	0.0244
B_0	-0.0535	0.0030	-0.0085	0.0004	0.0001	0.0015
B_{00}	9.8573e-4					

4.1. Objective function

Considering a plant with n generation units, the total fuel cost is defined as:

$$F_{fuel} = \sum_{i=1}^{n} \left(a_i + b_i P_i + c_i P_i^2 \right) \tag{9}$$

where P_i is the output of the i-th generator and a_i, b_i and c_i are the cost coefficients of the i-th generator.

The emission function is described by (4), and

$$F_{emission} = \sum_{i=1}^{n} \left(10^{-2} \left(\alpha_i + \beta_i P_i + \gamma_i P_i^2 \right) + \zeta_i \exp(\lambda_i P_i) \right) \tag{10}$$

where α, β, γ, ζ and λ are the emission coefficients.

4.2. Constraints

There are two types of constraints in the environmental/economic dispatch problem: the power balance and the generation capacity of the units. The first one is an equality constraint which relates to the demand and the transmission losses, that is, the power generated must cover the demand P_D and the real power loss P_L as follows.

$$\sum_{i=1}^{n} P_i = P_D + P_L \tag{11}$$

The power losses are modelled as a function of the outputs of generators, as in (6). In this case,

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00} \tag{12}$$

where B_{ij}, B_{0i} and B_{00} are the loss coefficients.

5. SIMULATION RESULTS

Simulations were made using MatLab environment (MathWorks). In order to eliminate stochastic discrepancies, 20 independent runs were carried out using different initial populations. The number of initial solutions in the population is 20 and the number of reference solutions 10, being the first 5 the bests and the last 5 the more diversified. The parameter $\delta = 0.02$ was used for both approaches. Results presented here are compared to a hybrid algorithm based on particle swarm optimization and differential evolution (MO-DE/PSO) presented in Gong et al. (2010) and a multiobjective differential evolution (MODE) presented in Wu et al. (2010). The best values found are bolded.

Table 5 presents the best results for the cost of generation, while in Table 6 are presented the best results for the emission. The best result for the cost was found by our Improved Scatter Search (ISS) and the best result for the emission was found by MO-DE/PSO, however all results are very near. Table 7 presents a statistical comparison between the proposed and the original SS approaches. Figure 3 shows the best fronts found by both SS and ISS algorithms.

Table 5. Best results for the cost.

Technique	Reference	Cost	Emission	G_1	G_2	G_3	G_4	G_5	G_6
SS	this paper	604.1014	0.2127	0.1695	0.2915	0.5839	0.8891	0.5316	0.3794
ISS	this paper	**603.5125**	0.2191	0.1717	0.2877	0.5821	0.9831	0.5031	0.3179
MO-DE/PSO	Gong et al. (2010)	606.0073	0.2209	0.1220	0.2843	0.5857	0.9962	0.5149	0.3566
MODE	Wu et al. (2010)	606.1260	0.2195	0.1332	0.2727	0.6018	0.9747	0.5146	0.3617

Table 6. Best results for the emission.

Technique	Reference	Cost	Emission	G_1	G_2	G_3	G_4	G_5	G_6
SS	this paper	633.1502	0.194600	0.3999	0.4378	0.5153	0.4652	0.5376	0.4891
ISS	this paper	632.5669	0.194600	0.3601	0.4417	0.5591	0.4353	0.5730	0.4741
MO-DE/PSO	Gong et al. (2010)	646.0243	**0.194179**	0.4118	0.4616	0.5435	0.3922	0.5454	0.5148
MODE	Wu et al. (2010)	642.8490	0.194200	0.39266	0.46256	0.56311	0.40309	0.5676	0.47826

Table 7. Comparison of SS and ISS approaches.

Technique	Spacing	Average distance to origin	Quantity of optimal solutions
SS	0.2861	615.3772	103
ISS	0.3564	613.6338	105

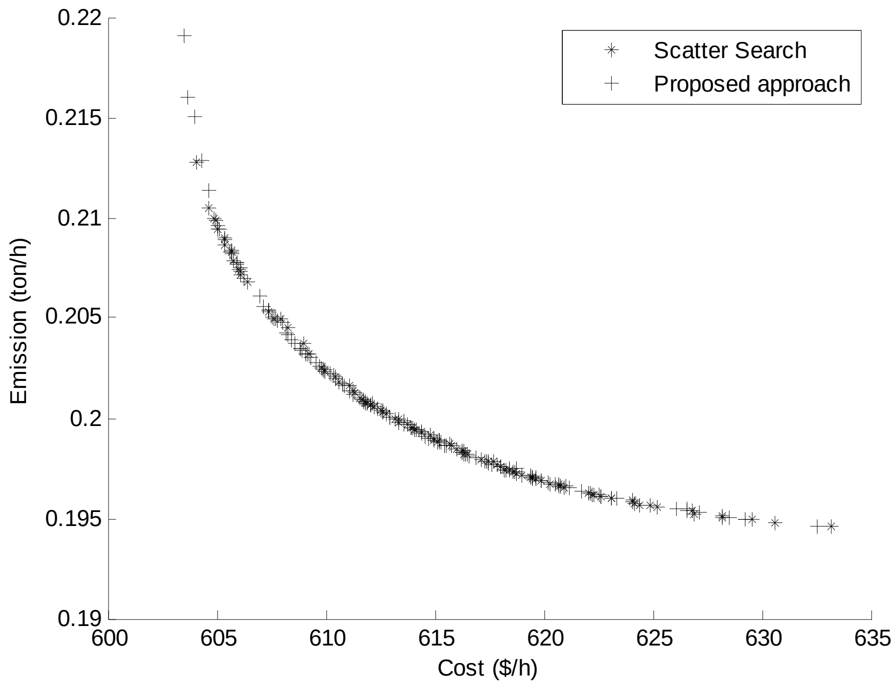

Figure 3. Fronts found by the SS and ISS algorithms.

6. CONCLUDING REMARKS

EED is a multiobjective problem having conflicting objectives, as the minimization of emission is contrary to the maintenance of cost economy. This paper evaluated the performance of a SS method and an ISS approach when dealing with an EED multiobjective problem. In this context, some changes were necessary for the study, and a modification of the original combination method was introduced. The proposed approach performed better than the original and showed promising results for a standard IEEE 30-bus with six-generators test system. However the results are very near and some bigger modifications need to be tested to further increase the SS capability of deal with multiobjective problems.

In order to make a comparison against competing solution methods, other results for the IEEE 30-bus with six-generators test system presented in the recent literature were showed in Tables 4 and 5. In this context, the results using the proposed ISS based on some comparison metrics are competitive.

In order to explore the abilities of the proposed methodology, our future research will test the ISS approach in other multiobjective EED problems. We will also need to carry out more formal performance measurements on the ISS algorithm, for example using the Mann-Whitney rank-sum test.

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