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A multi-objective unit commitment problem combining economic and environmental criteria in a metaheuristic approach

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Abstract

The environmental concerns are having a significant impact on the operation of power systems. The traditional Unit Commitment problem (UCP), which minimizes the total production costs is inadequate when environmental emissions need to be considered in the operation of power plants. This paper proposes a metaheuristic approach combined with a non-dominated sorting procedure to find solutions for the multi-objective UCP. The metaheuristic proposed, a Biased Random Key Genetic Algorithm, is a variant of the random-key genetic algorithm, since bias is introduced in the parent selection procedure, as well as in the crossover strategy.

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1. Introduction

The power system generation scheduling is composed of two tasks [1,2]: On the one hand, one must determine the scheduling of the turn-on and turn-off of the thermal generating units; on the other hand, one must also determine the economic dispatch (ED), which assigns the amount of power that should be produced by each on-line

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unit in order to minimize the total operating cost for a specific time generation horizon. The traditional configuration of this problem, known as the Unit Commitment (UC) Problem, was modified to account for environmental concerns, namely due to the goals imposed by the Kyoto protocol and later by the Paris Agreement. The carbon emissions produced by fossil-fueled thermal power plants need also to be minimized. Hence, it is necessary to consider these emissions as another objective. Therefore, we are in the presence of a problem with two, usually, conflicting objectives.

Current research is directed to handle both objectives simultaneously as competing objectives instead of simplifying the multi-objective nature of the problem by converting it into a single objective problem. Several methods have been reported in the literature concerning the environmental/economic dispatch problem such as Genetic Algorithms [3-5], Differential Evolution Algorithms [6,7], Harmony Search Algorithms [8], Gravitational Search Algorithms [9], Particle Swarm Optimization Algorithms [10–12], and Bacterial Foraging Algorithms [13]. These methods fall into the category of metaheuristics, which are optimization methods known to be able to provide good quality solutions within a reasonable computational time (see e.g. [14,15]). Different MOEAs like Niched Pareto Genetic Algorithm (NPGA) [16], Strength Pareto Evolutionary Algorithm (SPEA) [17] and Non-dominated Sorting Genetic Algorithm (NSGA) [18] have been applied to multi-objective problems. Since they use a population of solutions in their search, multiple Pareto-optimal solutions can, in principle, be found in one single run.

In this paper, we propose to address simultaneously the UC and ED problems using multi-objective optimization. A Biased Random Key Genetic Algorithm (BRKGA) combined with a non-dominated sorted procedure and Multi-objective Optimization Evolutionary Algorithm (MOEA) techniques is proposed. The BRKGA developed is based on the framework proposed in [19] and on a previous version developed for the single objective UC problem [20] and [21]. Here, the BRKGA approach includes a ranking selection method, that is used for ordering the non-dominated solutions, and a crowded-comparison procedure as in NSGAII.

The crowded-comparison procedure replaces the sharing function procedure used in original NSGA, which allows for maintain diversity in the population. Furthermore, we compare the algorithm here proposed with the NSGA-II, SPEA2, and NPGA techniques. Our algorithm is tested on the standard 24-hour test system introduced in [22,23]. For this system several cases involving 10 up to 100 generating units are considered.

Nomenclature

Decision Variables:

$y_{t,j}$: Thermal generation of unit j at time period t, in [MW];

$u_{t,j}$: Status of unit j at time t (1 if on; 0 otherwise);

Auxiliary Variables:

$T_j^{on/off}(t)$: Consecutive time periods for which unit j has been on-line/off-line until time period t, in [hours];

Parameters:

T: Time periods (hours) of the scheduling time horizon;

t: Time period index;

N: Number of generation units;

j: Generation unit index;

R_t: System spinning reserve requirements at time t, in [MW];

D_t: Load demand at time period t, in [MW];

Y_{min_j}: Minimum generation limit of unit j, in [MW];

$\boldsymbol{Y_{max_j}}$: Maximum generation limit of unit j, in [MW];

N_b: Number of the base units;

$T_{min_j}^{on/off}$: Minimum uptime/downtime of unit j, in [hours];

$\boldsymbol{T_{c,j}}$: Cold start time of unit j, in [hours];

SD_j: Shut down cost of unit j, in [$];

$Se_{t,j}$: Start-up pollutant emissions of unit j, at time period t in [ton-CO_2] if CO_2 or [mg=Nm^3] if nitrogen oxides;

$\Delta_j^{dn/up}$: Maximum decrease/increase output level in consecutive periods for unit j, in [MW].

2. The multi-objective UCP formulation

In the multi-objective UC problem, one needs to determine an optimal schedule, which minimizes the production cost and emission of atmospheric pollutants over the scheduled time horizon subject to system and operational constraints. Therefore, the multi-objective UC problem should be formulated including both objectives, i.e., the minimization of the operational costs and the minimization of the pollutant emissions.

$$Minimize\ [F(y,u), E(y,u)] \tag{1}$$

Due to its combinatorial nature, multi-period characteristics, and nonlinearities, the UC problem is a hard optimization problem, which involves both integer and continuous variables and a large set of constraints. The first component of the objective is to minimize the system operational costs composed of generation and start-up costs.

$$F(y,u)=\sum_{t=1}^{T}\left(\sum_{j=1}^{N}\left\{F_j\left(y_{t,j}\right).u_{t,j}+SU_{t,j}.\left(1-u_{t-1,j}\right).u_{t,j}+SD_j.\left(1-u_{t,j}\right).u_{t-1,j}\right\}\right), \tag{2}$$

where $SU_{t,j}$ and SD_j are the start-up and shut-down costs of unit j at time period t , respectively. On the other hand, the second objective is to minimize the total quantity of atmospheric pollutant emissions such as NO_x and CO_2.

$$E(y,u)=\sum_{t=1}^{T}\left(\sum_{j=1}^{N}\left\{E_j\left(y_{t,j}\right).u_{t,j}+Se_{t,j}.\left(1-u_{t-1,j}\right).u_{t,j}\right\}\right), \tag{3}$$

where $Se_{t,j}$ is the start-up pollutant emissions of unit j at time period t. The constraints can be divided into two categories: the system constraints and the technical constraints. Regarding the first category of constraints it can be further divided into load requirements and spinning reserve requirements, which can be written as follows:

1) Power Balance Constraints: The sum of unit generation outputs must cover the total power demand, for each time period.

$$\sum_{j=1}^{N} y_{t,j}.u_{t,j} \geq D_t, t\in\{1,2,...,T\} \tag{4}$$

2) Spinning Reserve Constraints: The total amount of real power generation available from on-line units net of their current production level must satisfy a pre-specified percentage of the load demand in order to minimize the probability of load interruption.

$$\sum_{j=1}^{N} Y_{\max_j}.u_{t,j} \geq R_t + D_t, t\in\{1,2,...,T\} \tag{5}$$

The second category of constrains includes unit output range, minimum number of time periods that the unit must be in each status (on-line and off-line), and the maximum output variation allowed for each unit.

3) Unit Output Range Constraints: For each time period t and unit j, the real power output of each generator is restricted by lower and upper limits.

$$Y_{\min_j}.u_{t,j} \leq y_{t,j} \leq Y_{\max_j}.u_{t,j}. \tag{6}$$

4) Ramp rate Constraints: Due to the thermal stress limitations and mechanical characteristics, the output variation levels of each online unit in two consecutive periods are restricted by ramp rate limits.

$$-\Delta_j^{dn} \leq y_{t,j} - y_{t-1,j} \leq \Delta_j^{up}. \tag{7}$$

5) Minimum Uptime/Downtime Constraints: If the unit has already been turned on/off, there will be a minimum uptime/downtime time before it is shut-down/started-up, respectively.

$$T_j^{on}(t) \geq T_{\min,j}^{on} \text{ and } T_j^{off}(t) \geq T_{\min,j}^{off}. \tag{8}$$

3. Multi-objective UCP optimization

3.1. Decoding procedure

The decoding procedure used in all four multi-objective optimization algorithms is the one proposed in [20,21]. For each chromosome, the corresponding solution is obtained in two main stages. Firstly, the output generation level matrix for each unit and time period is computed using the random key values. Each element of the output generation matrix, $y_{t,j}$ is given as the product of the percentage vectors by the periods demand D_t, i.e.,

$$y_{t,j} = D_t \frac{RK_j}{\sum_{i=1}^{N} RK_i}. \tag{9}$$

Here each component of the percentage vectors is given by the corresponding random key entry divided by the sum of all random key values as illustrated in algorithm 1 in [20]. Then, the feasibility of the output levels is checked and whenever a constraint is not satisfied the solution is modified by the repair algorithm presented in [21].

3.2. Repair algorithm

The repair algorithm is composed of several steps. Firstly, the output levels are adjusted in order to satisfy the output range constraints. Next, we have the adjustment of output levels to satisfy ramp rate limits. It follows the repairing of the minimum uptime/downtime constraints violation. Afterwards, the output levels are adjusted in order to satisfy spinning reserve requirements. Finally, the output levels are adjusted for demand requirements satisfaction at each time period. For details on the repairing mechanisms, the reader is referred to [21].

3.3. BRKGA multi-objective UC approach

The BRKGA is adapted using the ranking selection method for ordering the non-dominated solutions according to the Pareto domination concept, while the crowding distance is used to break the ties by choosing the best individuals to be included in new population. Details about the BRKGA approach are given in [19,20]. The initial population, with size N_p, is constructed by generating the random keys. Given a population of chromosomes (random keys) the decoding procedure is applied such that to each chromosome corresponds a feasible UC solution. The fitness function used to evaluate the solutions includes both the total operational cost and CO_2 or NO_x pollutant emissions. We have adopted a fitness procedure similar to that of NSGA-II, given in [24]. Therefore, the population is sorted based on the non-domination concept. Each solution is assigned a fitness (rank) equal to its non-dominated level. The biased selection and biased crossover operators and the introduction of mutants are used to create an offspring population, also of size N_p. On the one hand, the biased selection ensures that one of the parents used for mating comes from a subset containing the best solutions of the current population. On the other hand, the biased crossover chooses with higher probability an allele from the best parent. Mutants are generated in the same way as the initially population and are introduced directly in the next generation. We start by combining the current population with the newly obtained one. The combined population size is the double $(2N_p)$ of the current population and it is sorted by the non-domination criterion (Fast Non-dominated Sorting Approach). The non-domination criteria leads to several levels of non-dominated fronts. The first level includes all non-dominated individuals of the combined population. The second level, contains solutions only dominated by the solutions in the first level. All other levels are defined in a similar way, that is, each level contains only solutions dominated by all previous non-dominated levels. In order to obtain the new population we go through the different levels, in ascending order, and include all its solutions if N_p is not reached; otherwise only some solutions are included, until N_p is reached, using the descending order of crowding distance as a selection criterion.

3.4. *Performance metric*

The solutions of the different MOEAs considered are compared by analysing the approximated Pareto fronts produced. In addition, we also use the set coverage metric [25]. This metric takes into consideration a pair of non-dominated sets comparing the fraction of each set that is covered by the other set. If $Cov(A, B) = 0$; then none of the points in set B are covered by set A. If $Cov(A, B) = 1$; then all points in B are dominated by or equal to points in A. It should be noticed that $Cov(A, B)$ is not necessarily equal to $1 - Cov(A, B)$.

4. Results

The benchmark problem instances include a system with 10 up to 100 generation units for a time horizon of 24 hours. The base case of the 10 generation unit system problem was originally proposed in [22]. For problem details, e.g., see [23] and the reference therein. Subsequentially, the 20, 40, 60, 80 and 100 generators systems were obtained by replicating the base case system (i.e., the 10 generators system) and the load demands are adjusted in proportion to the system size. Here, in all cases, the spinning reserve is kept at 10% of the hourly demand. In Fig. 1, we have plotted the non-dominated solutions for all four methods. As it can be seen, the NPGA is clearly dominated by the other three methods. Regarding the remaining methods, from Fig. 1 it can be seen that the non-dominated solutions of the NSGA are almost always dominated by the ones obtained by the BRKGA and SPEA2.

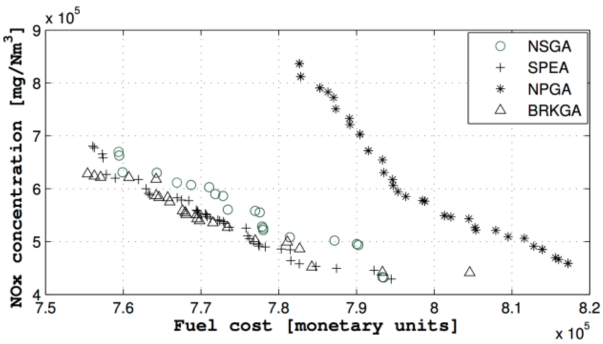

Fig. 1. Pareto-optimal fronts obtained from different algorithms in a single run for 10 units.

From the results reported in Table 1 it can be concluded that the non-dominated solutions of SPEA2 cover relatively higher percentages of the other solutions. In addition, BRKGA is the second best algorithm, in terms of coverage performance. Although the BRKGA front often dominates higher percentages of the corresponding NPGA and NSGA-II fronts, BRKGA non-dominated solutions rarely cover SPEA2 solutions. Nevertheless, this is not always the case since, for example, considering the problem with 100 thermal units, we can observe in Table 1 that, on average, the BRKGA front dominates on average 35.5 % of the corresponding SPEA2 front, while the non-dominated set produced by SPEA2 dominates only 16.3% of the non-dominated BRKGA solutions.

Table 1. Percentage of non-dominated solutions coverages of set B covered by those in set A.

10 units set A/set B	BRKGA	NSGA II	NPGA	SPEA2
BRKGA	---	75.5	69.5	31.5
NSGA II	12.7	---	44.5	0
NPGA	23.8	38.5	---	2
SPEA2	54.4	97	90	---
20 units				
BRKGA	---	46.3	50.5	46.5
NSGA II	34.6	---	56.8	53.5
NPGA	28.6	33.3	---	35.5
SPEA2	48.1	29.5	42.3	---
40 units				
BRKGA	---	75.8	62.5	64.8
NSGA II	3.9	---	38.1	16.3
NPGA	4.8	56.1	---	27.4
SPEA2	13.6	76.6	56.1	---
60 units				
BRKGA	---	75.2	55.6	24.3
NSGA II	0.6	---	54.6	0
NPGA	0.15	37.8	---	5.7
SPEA2	35.7	100	92.6	---
80 units				
BRKGA	---	80.3	77	0
NSGA II	0	---	64.6	0
NPGA	0	28.1	---	0
SPEA2	99.4	100	100	---
100 units				
BRKGA	---	82.6	57.9	35.5
NSGA II	0.4	---	50.2	0
NPGA	0	36.8	---	0
SPEA2	16.3	98.2	99.7	---

Moreover, the non-dominated set obtained by BRKGA dominates 82.6% of the non-dominated solutions found by NSGA II, while the front obtained by NSGA II dominates less than 0.4 % of the non-dominated solutions produced by BRKGA. Finally, the BRKGA front dominates on average 57.9% of the corresponding NPGA front while the non-dominated set produced by NPGA do not cover any solutions produced by BRKGA.

5. Conclusions

A compromise between the unit operating costs and the level of pollutants emission implies the consideration of a multi-objective problem. In this paper, a new multi-objective Biased Random Key Genetic Algorithm approach (BRKGA) is used to provide Pareto optimal solutions for the environmental/economic unit commitment problem. The proposed algorithm is combined with the non-dominated sorting procedure and crowded comparison operator used in NSGA II technique. The algorithm maintains a finite-sized archive of non-dominated solutions, which is continuously updated in the presence of new solutions based on the concept of Pareto dominance. The proposed approach has been assessed through a comparative study, for the case study problem, with the other multi-objective optimization techniques by resorting to benchmark problem instances. The best results are obtained for BRKGA and SPEA2 approaches. Comparatively to the SPEA2, the BRKGA algorithm has best diversity performance. The results show that the BRKGA can be an effective method for producing tradeoff curves with a small CPU-time requirement. Tradeoff curves such as those presented here may give decision makers the ability of making environmentally friendly decisions.

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