Schedule of Thermal Units with Emissions in a Spot Electricity Market

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Abstract. A bi-objective optimization approach is presented for solving a generation company short-term thermal schedule problem with a few units, considering the goodness of being schedule, but with emission concern. The startup and shutdown for each unit throughout the time horizon is derived from Pareto-optimal solutions, using a method merging dynamic programming and nonlinear programming to provide schedule of the units. A case study is presented to prove the effectiveness of the approach.

Keywords: Short-term schedule, thermal units, emissions, dynamic programming, Pareto-optimal solution.

1 Introduction

Over the last years, ambitious policy targets and concrete actions have been proposed in order to encourage mitigation of greenhouse anthropogenic gases emissions and ensure environmental sustainability worldwide [1]. A significant share on emission of greenhouse gases into the atmosphere is through the burning fossil fuel on thermal power plants [2]. In 2011, thermal power plants played a dominant role in the mixed power generation, accounting for 54.2 % of total generation in the EU-27 and 57.1 % in Portugal [3]. The expressive share of thermal power plants in a competitive framework forces as a fundamental tackling the schedule problem of thermal units during a short-term horizon in order to conveniently appraise favorable economic conditions for the Generation Companies (GENCO). Within the past 40 years, mathematical programming techniques have been used aiming at the optimization of thermal unit commitment. In early studies, still without the availability of enough computational power to support a full modeling of the problem, the unit commitment was based on priority lists [4]. The development of computational power allowed to model the complexity of the problem, allowing over the years the inclusion of new constraints not only related to operational costs, technical boundaries, but also reserve, minimum up/down time, ramp rate power constraints and supply limits. Furthermore, in nowadays the electricity market framework provides a trading

L.M. Camarinha-Matos, S. Tomic, and P. Graça (Eds.): DoCEIS 2013, IFIP AICT 394, pp. 361–370, 2013.

mechanism based on bilateral contracts suitable for thermal power producers. This kind of mechanism is used in order to allow hedging price volatility. Bilateral contracts are agreements between power producers and consumers to provide a given amount of energy at a predefined price along with a delivering period [5]. Hence, additional modeling must be included in the schedule problem in order to conveniently model electricity market framework influence on the schedule. This paper proposes a bi-objective optimization approach, requiring the use of a method based on Dynamic Programming (DP) and nonlinear programming. A case study is presented for a schedule over a time horizon of 168 hours with hourly periods.

2 Relationship to Internet of Things

Electric power systems are tagged by evolution of computing technologies, allowing the development of powerful optimization approaches able to process decisions under the operational planning. Consequently, every GENCO in the new competitive market paradigm are envisaged in order to ensure convenient management conditions to be a thing in the Internet of Things.

The connection to the Internet of Things conveys adequate decisions for system operators. The interfacing with the internet allows bidirectional communication between the power producers and the remaining decision makers, for instance, regarding real time market information and bilateral contracts. This paper deals with an application contributing to take decision in real time on market information and bilateral contracts.

3 State of the Art

Technical literature presents several optimization methods for solving the unit commitment and the economic dispatch problem: methods have been reported since the old priorities list method [6] to the classical mathematical programming methods until the more recently reported artificial intelligence methods [7]. Although, easy to implement and requiring a small computation time, the priority list method does not ensures an economic convenient solution near a global optimal one, implying a higher operation cost [8]. Within the classical methods are included DP, linear programming, nonlinear programming and Lagrangian relaxation-based techniques [9]. DP methods are flexible but suffer from the "curse of dimensionality", due to the increase in the problem size related with the number of thermal units to be committed and the number of states considered for modeling the thermal behavior of each unit during the time horizon, implying an eventually huge use of computation memory and processing time. Although the Lagrangian relaxation [10] can overcome the previous limitation, does not always lead to a conveniently feasible solution, requiring in order to set a feasible solution the satisfaction of some violated constraints using heuristics, undermining the optimality. Artificial intelligence (AI) methods based on artificial neural networks [11], genetic algorithms [12], evolutionary algorithms [13] and simulating annealing [14] have also been applied. However, the major limitation of the AI methods is the likelihood to obtain a convenient solution near global optimum, especially with a few thermal units. These problems are the ones faced by some GENCO due to the new paradigm, admitting companies with a small number of units to go into business.

Emissions concerns in the literature are mostly addressed for the economic dispatch problem [15], stating only the power output level of each unit but not the on/off status and availability for generation at each hour. The short-term thermal unit schedule problem has to take into account two assessments, i) the thermal units online at each hour and ii) the power output level for each online unit at each hour, so as to suit economic and/or environmental targets on time horizon of one day to one week [9]. The effects of the short-term thermal unit schedule are significant, in sense that a better operation achieves not only a reduction in the fuel consumption [16], but meets environmental concerns: once electric power generation is obtained from fuel-fossil power plants, the anthropogenic emission cannot be overlooked in nowadays. The emission modeling in the short-term schedule problem [17] has not been deeply tackled as in the case of the economic dispatch problem. Hence, in this paper the goodness of being schedule and the emission concern are included in the short-term schedule of thermal units.

4 Problem Formulation

The short-term thermal unit schedule problem can be stated as to find the schedule on status and the power generated for each thermal unit i at each time period t that optimizes performance criterions involving costs, emissions and market trading subject to a set of constraints on the operation of the units.

4.1 Objective Function

The proposed framework considers two different objectives in which the first one expresses the total fuel cost of thermal units and the second one expresses the total emissions of pollutants into the atmosphere. Mathematically, the bi-objective vector to be minimized is given by:

$$\{\sum_{t=1}^{T}\sum_{i=1}^{I} C_{it}(u_{it}, p_{it}), \sum_{t=1}^{T}\sum_{i=1}^{I} \omega E_{it}(u_{it}, p_{it})\}. \quad (1)$$

I is the number of thermal units; T is number of periods in the time horizon; for unit i in t period, $C_{it}(u_{it}, p_{it})$, u_{it}, p_{it}, $E_i(u_{it}, p_i)$ are respectively the fuel cost function, the commitment state (on/off) , the power generated and is the emission function. Since the total fuel cost and total emissions are expected to be conflicting objectives, implying the impossibility to find out a single optimal solution that simultaneously satisfies both objectives. Thus, the set of best compromise solution, known as the Pareto front, can be determine using the weight-sum method, converting the bi-objective vector (1) into a family of single objective function given by a convex combination of the objectives, i.e., given by:

$$(1-\lambda)\sum_{t=1}^{T}\sum_{i=1}^{I}C_{it}(u_{it},p_{it})+\lambda\sum_{t=1}^{T}\sum_{i=1}^{I}\omega E_{it}(u_{it},p_{it}). \quad (2)$$

ω is a unit price penalty factor associated with the emission and λ is a weighting factor, which should obey $0 \le \lambda \le 1$. If $\lambda = 0$, the solution correspond to minimum cost, the usual unit commitment, and if $\lambda = 1$, the solution is minimum emissions commitment. The fuel cost and emissions functions for the operation of each thermal unit depend on the power generated by that unit and can be modeled as a second order quadratic functions respectively given by:

$$C_{itop}(u_{it},p_{it})=(a_{it}+b_{it}p_{it}+\frac{1}{2}c_{it}p_{it}^{2})u_{it}. \quad (3)$$

$$E_{itop}(u_{it},p_{it})=(\alpha_{it}+\beta_{it}p_{it}+\frac{1}{2}\gamma_{it}p_{it}^{2})u_{it}. \quad (4)$$

a_i, b_i, c_i and α_i, β_i, γ_i are respectively the cost coefficients and the emission coefficients for thermal unit i. A GENCO can trade energy via bilateral agreements. Hence, an augmenting term must be included into (2). The augmented objective function is given by:

$$(1-\lambda)\sum_{t=1}^{T}\sum_{i=1}^{I}C_{it}(u_{it},p_{it})+\lambda\sum_{t=1}^{T}\sum_{i=1}^{I}\omega E_{it}(u_{it},p_{it})-\sum_{t=1}^{T}\sum_{i=1}^{I}\pi_{t}(p_{it}-d_{t}). \quad (5)$$

π_t is electricity price at period t and d_t is the power contracted with bilateral agreements associated with energy that have to be delivered at period t. This objective function admits the possibility of buying energy in the market if production is not enough to satisfy agreements. The objective function (5) can be seen as the application of the weighted-sum method for a bi-objective optimization problem with the objective vector given by:

$$\{\sum_{t=1}^{T}\sum_{i=1}^{I}C_{it}(u_{it},p_{it})-\pi_{t}(p_{it}-d_{t}),\sum_{t=1}^{T}\sum_{i=1}^{I}\omega E_{it}(u_{it},p_{it})-\pi_{t}(p_{it}-d_{t})\}. \quad (6)$$

In other words (5) can be seen as an objective vector with coordinates respectively given by the objective function associated with the minimum emission and minimum cost commitment both with bilateral contract agreements. The start-up cost of thermal units is a term to be added the fuel operation cost in (3) and depends upon the number of periods x_t the unit has been offline prior to startup. The start-up cost is given by:

$$SU_{it}=uccool_{i0}(1-e^{-\frac{5x_{t}}{utcool_{i}}}). \quad (7)$$

$uccool_{i0}$ is the cold start-up cost and $utcool_i$ is the cooling time constant. Also, the start-up emission can be included into (4) in the same way as given by (7).

4.2 Constraints

The optimization problem is subject to a set of constraints due to operation conditions that can include the following:

a) Availability of thermal units: The sum of online units cannot exceed the maximum number of thermal units allowed online in period t.

$$\sum_{i\in I} u_{it} \le NMV_t \ . \tag{8}$$

b) Power balance constraint: The power generated by the thermal units must meet at least a demand D_t in each period t, ignoring transmission losses in the system.

$$\sum_{i\in I} p_{it} \ge D_t \ . \tag{9}$$

c) Spinning reserve constraint: The spinning reserves R_t in period t are necessary in order to ensure reliability.

$$\sum_{i\in J\subset I} \overline{p}_{it} \ge D_t + R_t \ . \tag{10}$$

d) Operating ramp rate constraints: The power generated over any two consecutive online periods is restricted by the ramp-down DR_i and ramp-up UR_i limits.

$$DR_i \le p_{it+1} - p_{it} \le UR_i \ . \tag{11}$$

e) Generator Capacity Constraints: Each thermal unit is restricted by its minimum and maximum limits on power generation.

$$u_{it}\underline{p}_{it} \le p_{it} \le u_{it}\overline{p}_{it} \ . \tag{12}$$

f) Minimum up time constraint: The minimum up time UD_i imposes that unit i have to be on by at least the minimum up time before shutdown.

$$u_{it}(1-u_{it+1}) = 1 \text{, if equal to 1, the shutdown occurs at period } t+1 \ . \tag{13}$$

g) Minimum down time constraint: The minimum down time DD_i imposes that unit i have to be down by at least the minimum down time before startup.

$$u_{it+1}(1-u_{it}) = 1 \text{, if equal to 1, the start-up occurs at period } t+1 \ . \tag{14}$$

h) Bilateral agreement constraint: If necessary in order to ensure that a bilateral agreement is fulfilled the difference between generated power and contracted power with bilateral agreements can be imposed as a non-negative constraint.

$$\sum_{i\in I} p_{it} - d_t \ge 0 \qquad \text{for} \qquad t = 1, 2, \ldots, T \ . \tag{15}$$

The minimum up/down time constraints are used to avoid thermal stress, implying future augmenting maintenance. More constraints are possible to into the problem, but the complexity will be augmented, implying an augmented processing time. Particularly, instead of (15) is possible to have bilateral agreement only strong fulfilled at particularly periods, leaving to other periods the possibility of buying energy in the market to fulfill agreements.

5 Case Study

The proposed bi-objective optimization approach is tested on GENCO with three thermal units in a competitive electricity market with bilateral contracts. Simulation studies are carried out on hourly basis over a scheduling time horizon of 168 hours. The fuel cost and emission coefficients are given in Table 1.

Table 1. Fuel cost and emission coefficients for thermal units

	U1	U2	U3
a_i	277	300	320
b_i	26.500	26.300	26.100
c_i	0.045	0.051	0.031
α_i	40	43	38
β_i	-1.6×10^{-3}	-1.3×10^{-3}	-1.9×10^{-3}
γ_i	0.008	0.009	0.006
$\underline{p}_i$ (MW)	40	120	240
$\overline{p}_i$ (MW)	120	400	700
UR_i (MW)	40	120	240
DR_i (MW)	20	80	160
UD_i (h)	4	5	7
DD_i (h)	3	3	5
$utcool_i$ (h)	4	5	7
$uccool_{i0}$ (Eur)	2200	2400	3000

Based on [18], the price penalty factor used for emissions is $\omega = 12.3$ Eur/Mg. The numerical computing testing has been performed on a 1.9-GHz-based processor with 2 GB of RAM using as a computing language the VBA for Microsoft Excel platform. Nonlinear and DP methods was used in order to solve the proposed short-term thermal unit schedule problem, being the first step to determine the feasible solutions taking into account the minimum up/down time constraints and total cooling time of each unit. The generated power was computed for each thermal unit schedule. The total number of states is 1120 to be processed at each hour. The energy price profile and the energy contracted at each hour are shown in Fig. 1.

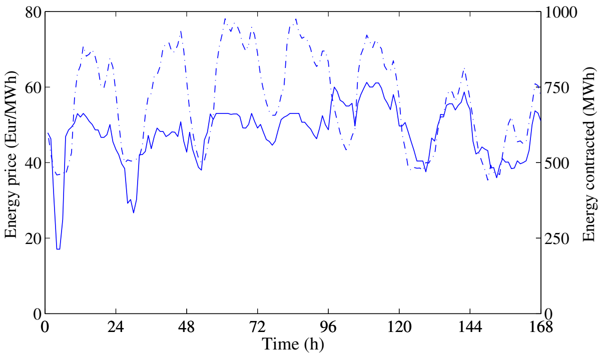

Fig. 1. Price profile *(solid line)* and energy contracted *(dashed–dotted line)*

The computed energy over the time horizon as function of λ is given in Table 2.

Table 2. Energy contracted and supplied, as function of the weighting factor λ

λ	Total costs (Eur)	Energy contracted (MWh)	Energy supplied (MWh)
0.0	4117780	119096	138084
0.2	4092690	119096	120329
0.4	3923691	119096	119135
0.6	3729017	119096	119096
0.8	3568313	119096	119096
1.0	3408946	119096	119096

The major surplus between the supplied and contracted energy happens for with $\lambda = 0$. The power contracted, the power supplied and the hourly units committed are respectively shown for $\lambda = 0$ in Fig. 2 and Fig. 3.

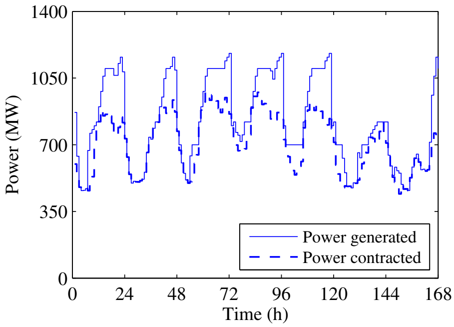

Fig. 2. Power generated and contracted, $\lambda = 0$

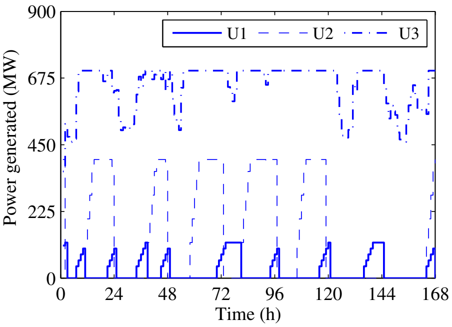

Fig. 3. Unit power generated, $\lambda = 0$

Fig. 2 shows that the power generated is greater than the contracted power at some hours. This is due to higher values of energy prices at these hours. The values of power contracted are closer to the ones obtain for lower energy prices, because is not profitable to generate more energy than the necessary to comply with bilateral agreement. Fig. 4 shows different behaviours for each thermal unit due to differences in startup costs. Both thermal units U1 and U2 are off when the energy price is lower, while U3 is on in order to avoid incur if shutdown occurred on the higher startup cost.

The power contracted, the power supplied and the hourly units committed are respectively shown for $\lambda = 1$ in Fig. 4 and Fig. 5.

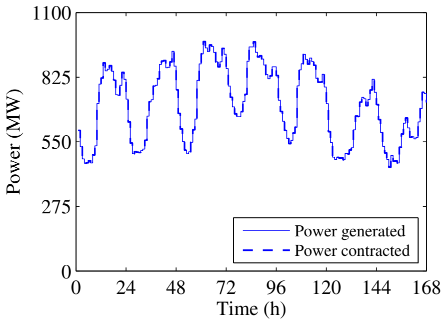

Fig. 4. Power generated and contracted, $\lambda = 1$

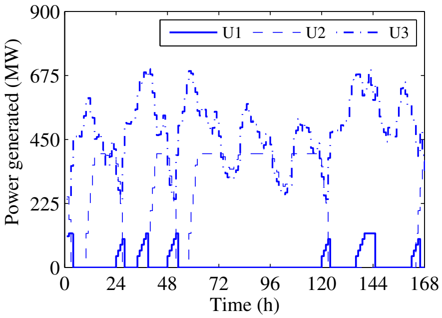

Fig. 5. Unit power generated, $\lambda = 1$

Fig. 4 shows that the power generated trajectory equals the power contracted, comparing Fig. 3 with Fig. 5 the power generated by each thermal unit is different: the schedule of the thermal units U2 and U3 are different due to the coefficients of the fuel cost and emission cost functions. Unit U1 comes into operation for the lower levels of the power contracted either with $\lambda = 0$ or $\lambda = 1$.

The computed trade-off curve between the total fuel cost and emission cost, the Pareto front, drown with the Pareto optimal solutions in shown Fig. 6.

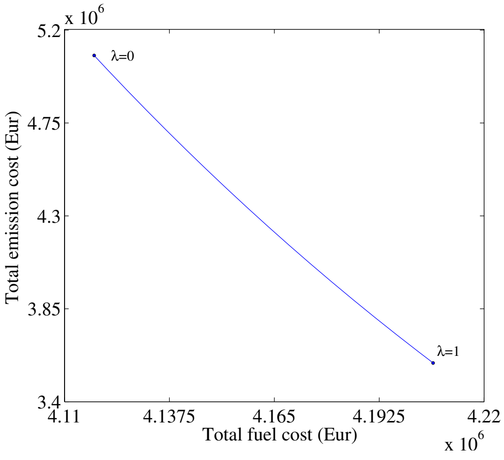

Fig. 6. Pareto optimal solutions

Fig. 6. shows that the objective function are conflicting ones due to the need to compromise between units with significant less cost, but with significant levels of emission, and others with greater cost but lesser emission. The first are committed regarding small costs, the second regarding small emissions.

6 Conclusions

A short-term generation scheduling approach for thermal units in small GENCO's is proposed. The approach considers the goodness of being schedule with the emission concern. Operation constraints of thermal units like ramp rate constraints and minimum up/down time constraints are taken into account, using DP and nonlinear programming. Numerical results allow concluding that the proposed approach is suitable to obtain the trade-off curve to assist on the generation scheduling decisions: according to the trade-off curve, a significant reduction on emissions can be achieved by rescheduling the thermal units, but implying an increase in operational cost. Although, DP suffers from the "curse of dimensionality", therefore impracticable to be used on large-scale systems, on small GENCO's the use of the DP is reasonable. Further work will be carried out including mixed integer programming in order to improve the computation performance and introduce new model considerations.

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