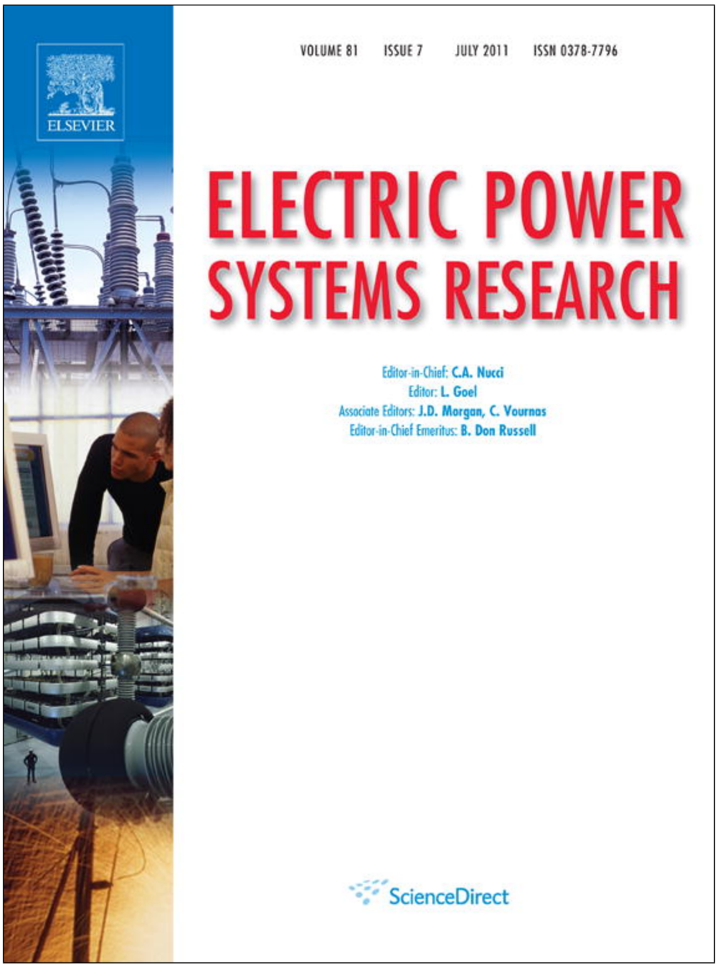
ELSEVIER
VOLUME 81 ISSUE 7 JULY 2011 ISSN 0378-7796
ELECTRIC POWER SYSTEMS RESEARCH
Editor-in-Chief: C.A. Nucci
Editor: L. Goel
Associate Editors: J.D. Morgan, C. Vournas
Editor-in-Chief Emeritus: B. Don Russell
ScienceDirect

Electric Power Systems Research 81 (2011) 1283–1291

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

A Simulated Annealing based approach to solve the generator maintenance scheduling problem

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ARTICLE INFO

Article history:
Received 11 October 2010
Received in revised form
28 December 2010
Accepted 24 January 2011
Available online 25 February 2011

Keywords:
Maintenance
Generators
Scheduling
Simulated Annealing

ABSTRACT

The scheduling of maintenance actions of generators is not a new problem but gained in recent years a new interest with the advent of electricity markets because inadequate schedules can have a significative impact on the revenues of generation companies. In this paper we report the research on this topic developed during the preparation of the MSc Thesis of the second author. The scheduling problem of generator maintenance actions is formulated as a mixed integer optimization problem in which we aim at minimizing the operation cost along the scheduling period plus a penalty on energy not supplied. This objective function is subjected to a number of constraints detailed in the paper and it includes binary variables to indicate that a generator is in maintenance in a given week. This optimisation problem was solved using Simulated Annealing. Simulated Annealing is a very appealing metaheuristic easily implemented and providing good results in numerous optimization problems. The paper includes results obtained for a Case Study based on a realistic generation system that includes 29 generation groups. This research work was proposed and developed with the collaboration of the third and fourth authors, from EDP Produção, Portugal.

1. Introduction

The scheduling of maintenance actions of thermal generators has been subject of study and analysis by many researchers. This implicitly recognizes the importance of this topic in the past in the sense that this was considered a complex problem, whose solution affected the daily unit commitment and the dispatch of generation systems. Preventive maintenance approaches can be broadly grouped in periodic and sequential. In the first group, equipments in general, and power generators in particular, are submitted to maintenance actions that are scheduled at fixed time interval, typically a multiple of some interval taken as the discretization step of the problem, for instance a week. In the second case, the equipments under analysis are recognized as aging systems in the sense that maintenance actions should be scheduled when that is more appropriate considering their actual deterioration. In this sense, the operation conditions of the equipments should be monitored and the adoption of condition-based maintenance policies can lead to more frequent maintenance actions as equipments are aging. This problem is far more complex than periodic maintenance scheduling but it is also more realistic as different equipments can be characterized more accurately regarding their aging stage.

In this paper we address the periodic maintenance problem of generators, in the sense that we aim at scheduling the maintenance actions of the generators in the system along a planning horizon assuming that the time length between maintenance actions of the same generator is fixed. The generator maintenance scheduling problem had a variety of formulations and integrated a number of variables and constraints, reflecting different levels of refinements that were progressively introduced. Nevertheless, a number of features were common to all these formulations: one aimed at scheduling the maintenance actions of a set of generators along a period of typically one or two years discretized in weeks, ensuring that the expected demand was supplied, that the maintenance period of each generator was continuous in time, that the number of maintenance crews available for each generation technology was not exceeded and that at least one maintenance action was scheduled for each generator along the period under analysis. Typically this corresponded to a combinatorial problem formulated using binary variables having the value 1 if a particular generator was scheduled for maintenance in a particular week. The objective of this problem was usually the minimization of the generation cost along the scheduling period.

With the introduction of market mechanisms in the electricity sector, this problem started to receive increased attention given

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doi:10.1016/j.epsr.2011.01.013

the implications that the adoption of a good maintenance schedule can have in the revenues of generation agents. In this scope, the generator maintenance scheduling, GMS, problem gained new dimensions given that it is now strongly affected by uncertainties namely determining the behaviour of the demand, by the presence of renewable generation, several of them dependent on volatile primary resources, and also being dependent on electricity prices now determined by market mechanisms.

In this context, this paper describes a GMS model developed in the scope of the MSc thesis concluded in July 2009 by the second author and in close cooperation with a Portuguese generation company. The model aims at minimizing the cost of generating electricity to meet the demand along the period of one year discretized in 52 weeks, considering minimum and maximum limits of generation units, as well as several other constraints directly related with the maintenance problem. The problem includes binary variables to model a generator being scheduled for maintenance in a particular week. In order to solve this combinatorial problem it was used a well known meta-heuristic, Simulated Annealing that proved to be very efficient in several tests that were performed. This paper includes a Case Study considering a generation system integrating 29 thermal generators and expected values both for weekly values of the demand and for the energy coming from other sources and from interconnections with other countries.

According to these ideas this paper is structured as follows. Section 2 summarizes some models and approaches available in the literature addressing the generator maintenance scheduling, GMS, problem together with some general indications on Simulated Annealing. Section 3 describes the GMS optimization problem and Section 4 details the application of Simulated Annealing to this problem. Finally, Section 5 presents the Case Study and Section 6 draws the most relevant conclusions.

2. Literature review

2.1. Generation maintenance scheduling approaches

The definition of schedules to implement maintenance actions on generation units has been addressed in the past as it is recognized by the number of papers on this topic. These formulations can be grouped in two large sets: the first one including approaches using traditional optimisation techniques and the second adopting metaheuristics to address the integer nature of several variables.

Regarding the first group, Ref. [1] formulates the optimization problem to identify the most adequate maintenance schedule using an objective function that aggregates 5 terms – the expected energy generation cost along the period under analysis, the maintenance cost, a reliability driven term, a term related with deviations of the maintenance program regarding the ideal frequency to develop maintenance actions and, finally, a term related with penalties for constraints that are not fully enforced. On the other hand, in [2] the generator maintenance problem is formulated as a large-scale mixed integer non-linear optimization problem and the author discusses the impact on the solution of relaxing several constraints as well as the integer nature of some variables. In this paper the author adopts a combined implicit enumeration and branch-and-bound algorithm. A similar formulation is described in [3] considering the generation cost in the objective function, a reliability index and penalties for violated constraints.

Ref. [4] discusses the benefits of developing optimal maintenance generator schedules given that sub-optimal programs lead to higher generation costs and lower reliability of the generation system and of the entire power system. Apart from that, the maintenance programs affect short and long-term operation and planning actions as unit commitment, pumping and hydro scheduling. In the developed approach the authors use two optimization criteria – generation cost and reliability, and the formulation uses integer variables x_{ik} that if equal to 1 indicate that the maintenance period of unit i starts at week k. The developed approach uses a probabilistic production cost algorithm based on cumulants in order to get the generation cost for the period under analysis.

Ref. [5] proposes a more complex formulation considering a longer planning period and it includes network constraints as well as generator outages. Given the complexity of the resulting problem, the authors use Benders Decomposition to consider network constraints in each planning sub-period.

Regarding the second group, there are several papers using Simulated Annealing, Genetic Algorithms, Tabu Search and fuzzy models to consider different particular aspects of the problem. In this scope, [6] formulates the generator maintenance scheduling problem in a similar way regarding [4] considering an objective function that includes two terms (generation cost and maintenance cost) and constraints related with the continuity of the maintenance actions once started, with the availability of crews to develop maintenance actions for a given generator technology, with specified sequences of maintenance actions for some units, with the generator output limits and with the supply of the demand along the period. This mixed integer problem is solved using Simulated Annealing and the scheduling programs obtained with this approach and with an Integer Programming traditional technique are compared considering a small, a medium and a large generation system. The Simulated Annealing based approach provides faster solutions for the small and medium systems with comparable costs. For the larger generation system the Integer Programming approach is not able to get a solution while the Simulated Annealing provides one.

Refs. [7–9] describe the use of Genetic Algorithms, combined with Simulated Annealing in case of [8,9]. The authors implemented genetic operators to prevent the premature convergence of the simulation together with efficient encoding/decoding techniques concluding that GA's are very effective in dealing with the GMS problem.

The approach described in [10] uses Genetic Algorithms together with fuzzy membership functions to model the two objectives included in this formulation – the reserve margin and the generation cost. Regarding the constraints, this formulation considers limitations on the number of available maintenance crews, limitations on the number of generators in maintenance in the same geographical area in order to limit power transfers between areas and the definition of a window of weeks during which each generator maintenance should be scheduled. Ref. [11] also uses a Genetic Algorithm combined with a fuzzy function to evaluate the solutions. This function combines a crisp penalty function to model the inflexible demand constraint together with fuzzy penalty functions to model the objective and other constraints. In [12] it is described a fuzzy approach that is able to deal with uncertainties affecting the demand and the generation and maintenance costs. This approach uses triangular fuzzy numbers to model the demand and an evolutionary algorithm.

In [13,14] the GMS problem is solved using Tabu Search. In [13] it is used a multi-stage approach to decompose the problem in several sub-problems. The partial results are then combined to produce the global maintenance schedule. In [14] the formulation uses the generation cost and the reserve margin as objectives and the constraints are related with the availability of crews, predefined sequence of maintenance actions for several units and continuity of the maintenance period once a maintenance action starts. The plans provided by the Tabu Search algorithm for two generation systems (one with 4 units and another with 22 units) were compared with the results obtained with an implicit enumeration approach. The results obtained with Tabu Search were very promising given the more reduced computation time and their good quality.

Refs. [15,16] compare the performance of several meta-heuristic approaches, namely Tabu Search, Simulated Annealing, Genetic Algorithms, an hybrid Simulated Annealing/Genetic Algorithm approach and an hybrid Tabu Search/Simulated Annealing algorithm. The authors report that the combined use of Simulated Annealing/Genetic Algorithm and of Tabu Search/Simulated Annealing produces better results than the isolated use of a single metaheuristic, although the computational time is sometimes longer. On the other hand, in Ref. [17] the maintenance scheduling problem is formulated as a dynamic non-cooperative game in which the players aim at maximizing their profits coming from selling electricity in the market. The solution corresponds to a Nash equilibrium that is obtained using a backward induction scheme.

Finally, regarding sequential maintenance approaches, Ref. [18] describes a model that combines a profit-based approach more suitable to be used in deregulated systems, rather than a typical cost based model, with a reliability and a market dynamic module. As a result, the authors consider that economics should also drive maintenance policies, namely determining more frequent actions as the equipments and components age. Ref. [19] formulates a reliability driven sequential maintenance scheduling problem for a continuously monitored degrading system that aims at minimizing the global cost of system operation. In this approach the model is continuously updated based on changes in the system state in order to select optimal maintenance schedules. The authors indicate that this model was able to provide optimized maintenance schedules and that it was able to react quickly and in a consistent way to drastic changes in the operation conditions of the equipments.

2.2. Basics about Simulated Annealing

In the last decade, several optimization techniques emerged both in conceptual terms and in current applications. These techniques, often called meta-heuristics, include Tabu Search, Neural Networks, Simulated Annealing, Genetic Algorithms and its development to Genetic Programming. Literature includes nowadays a large number of papers reporting applications of these techniques to several problems showing their success and their special ability to address problems having some particular characteristics.

In particular, Simulated Annealing and Genetic Algorithms are used to address combinatorial problems due to the presence of discrete variables. Traditionally, this type of problems could be tackled in a two-step approach. In a first phase, discrete variables were relaxed into continuous ones, and then the output was rounded to the nearest integer. As it is easily understood, this does not ensure that the selected integer solution corresponds to the optimal one. Other approaches adopted branch-and-bound based techniques, usually leading to a large amount of computation time. Regarding continuous optimization algorithms as gradient techniques, they often converge to local optima and the iterative process would then be trapped in these points where derivatives are zero. Apart from that, the final solution can vary depending on initialization conditions. Finally, in several real life problems, decision makers are not really interested in the global optimum. They are, in fact, interested in a good or adequate solution, for which some quality index is evaluated. The process would end if an improvement, although not impossible to obtain, can lead to a large computational time.

Simulated Annealing was developed by Kirkpatrick et al. [20], followed by Aarts and Korst [21] based on the Metropolis algorithm dated from 1953. It is a search procedure in which it is included the possibility of accepting a solution that is worse than the current one. The simulation starts at an initial solution, x_1, evaluates it using an Evaluation Function, $f(x_1)$, and samples a new solution in the neighborhood of x_1. If this new solution improves $f(x_1)$, then it is accepted. If it is worse than the current one, it can still be accepted depending on a so-called probability of accepting worse solutions. This probability is typically computed using an exponential based expression as it will be detailed in Section 4. This expression depends on the control parameter of the algorithm, the temperature, that should be lowered along the simulation according to a pre-specified cooling scheme. This mechanism will eventually allow escaping from a local optimum avoiding the problems faced by gradient based techniques. Apart from these aspects, there are some issues on this algorithm that deserve clarification:

- the solution of a combinatorial problem, CP, has a clear analogy with the cooling process of a thermodynamic system, TDS. In this analogy, a state of a TDS is equivalent to the solutions or combinations of a CP. The energy of a TDS corresponds to the Evaluation Function, f, of the CP and the temperature of a TDS corresponds to the control parameter of the CP problem;
- a TDS system should be cooled in a slow way. This enables subsystems to reorganize themselves so that a low energy system is built. Similarly, the temperature of the CP must be lowered in a sufficiently slow way in order to identify a good quality solution;
- the temperature T is usually lowered by steps corresponding to a maximum number of iterations. Once this maximum is reached, the current temperature is lowered by a cooling parameter α, in [0.0;1.0]. According to this scheme, at the beginning of the simulation, the probability of accepting worse solutions, $p(n)$, is larger. This turns it more probable to accept worse solutions making the search more chaotic in the sense that larger areas of the solution space are searched. As the process goes on, the temperature is lowered, turning it more difficult to accept worse solutions. This means that the search is eventually being conducted in a promising area from where one does not want to leave;
- the Simulated Annealing algorithm proceeds from one solution x to another one in its neighbourhood. The definition of the neighbourhood of x, $N(x)$, is a strategic aspect of the algorithm in the sense it has an impact on the design of the final solution. The structure of $N(x)$ is quite simple to define in discrete problems. As an example, Simulated Annealing can be used to minimize transmission losses in a network by changing taps of transformers or of capacitor banks. Departing from the nominal positions, one can simply sample a transformer or capacitor, and then sample if the tap goes upwards or downwards by one step. This leads to a neighbour solution regarding the current one;
- finally, the search procedure ends if a stopping rule is achieved. This can correspond to the absence of improvements during a pre-specified number of iterations, to perform a maximum number of iterations or to lower the temperature parameter till a minimum level.

3. Mathematical formulation of the problem

3.1. Overview

The developed model was designed to build maintenance schedules of a set of thermal generators. In case the system has an hydro component and/or renewable and dispersed generation not submitted to dispatch and paid according to feed-in schemes and/or interconnections with other countries, it should be estimated the demand to be supplied by the thermal sub-system subtracting the hydro and dispersed generation components and interconnection injections from the total demand for each period. The model considers that thermal stations are either available or completely unavailable for operation for reasons apart from maintenance. This unavailability can be specified on a weekly basis or for some periods along each week. As an example, this allows incorporating information regarding periods during which some stations are not typically used. Regarding maintenance, the units are either completely in maintenance or not in maintenance. When available, the maximum available output of each unit is constant. Regarding the constraints, the formulation considers the following ones:

- the maintenance action is performed continuously. This means that when started, an unit is unavailable due to maintenance for a number of weeks corresponding to the duration of the action;
- each unit should be submitted to one maintenance action per year;
- the demand should always be satisfied and some reserve margin should be provided by the set of available generators;
- there is a limited number of crews to implement maintenance actions for each generation technology.

Considering these general ideas, the formulation aims at minimizing the generation cost along a planning period T, discretized in 52 weeks. The week demand is represented by a diagram organized in 5 steps as follows:

- Step 1 – 5% of the week, corresponding to 8.4 h;
- Step 2 – 30% of the week, corresponding to 50.4 h;
- Step 3 – 18% of the week, corresponding to 30.24 h;
- Step 4 – 20% of the week, corresponding to 33.6 h;
- Step 5 – 27% of the week, corresponding to 45.36 h.

3.2. Formulation of the optimization problem

Given the above general aspects, we used the following notation to formulate the optimisation problem:

- C_{kj} – variable generation cost of unit k, in step j, in €/GWh;
- P_{kjt} – generation of unit k, in step j, in week t, in MW. This value is assumed constant during step j of week t;
- ΔT_j – duration in hours of step j;
- D_{jt} – demand in step j, in week t, in MW. This value is assumed constant during step j of week t;
- H_{jt} – hydro generation in step j, in week t, in MW. This value is assumed constant during step j of week t;
- W_{jt} – wind generation in step j, in week t, in MW. This value is assumed constant during step j of week t;
- OG_{jt} – other generation available in step j, in week t, in MW. This value is assumed constant during step j of week t;
- INT_{jt} – power from interconnections with other countries in step j, in week t, in MW. This value is assumed constant during step j of week t;
- Res_{jt} – reserve required to be available in step j, in week t, in MW. This requirement is assumed constant during step j of week t;
- $P_k^{\max}$ and $P_k^{\min}$ – rated and minimum powers of unit k, in MW;
- P_{kjt}^{+} and P_{kjt}^{-} – maximum and minimum available powers for unit k, in step j, in week t, in MW. These values are assumed constant during step j of week t;
- m_{kt} – state of unit k in week t regarding maintenance. If $m_{kt}=1$ unit k is in maintenance in week t. If $m_{kt}=0$ then it is not in maintenance;
- i_{kt} – availability of unit k, in week t. If specified as 1 in week t for unit k, then this unit can be scheduled to run in that period;
- a_{kj} – availability of unit k in step j. If specified as 1 for unit k in step j, then this unit can be scheduled to run in every step j, along the whole year;
- S_k – duration in weeks of the maintenance action of unit k;
- t_k – week in which the maintenance action of unit k will start;
- t_k^- to t_k^+ – initial and final weeks, inclusive, of the scheduling period during which the maintenance action of unit k should be located. The values specified for t_k^- and t_k^+ should be according to $t_k^+ - t_k^- + 1 \geq S_k$. This means that from week t_k^- to week t_k^+ there is a number of weeks enough to do the maintenance action of unit k, that is, this number of weeks is not less than S_k;
- V_r^+ – maximum number of units of the same technology r that can be in maintenance simultaneously;
- V_r – set of units of the same technology r;
- K – number of units;
- J – number of steps used to model the demand;
- T – total number of weeks;
- R – number of different thermal generator technologies.

According to this notation the generator maintenance scheduling problem is formulated by (1)–(13).

$$\min Z = \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{k=1}^{K} C_{kj}(P_{kjt}) \cdot \Delta T_j \tag{1}$$

$$\text{subj.} \quad \sum_{k=1}^{K} P_{kjt} = D_{jt} - H_{jt} - W_{jt} - OG_{jt} - INT_{jt} \quad \text{for} \quad j = 1 \ldots J; \quad t = 1 \ldots T \tag{2}$$

$$\sum_{k=1}^{K} P_{kjt}^{+} \geq D_{jt} - H_{jt} - W_{jt} - OG_{jt} - INT_{jt} + Res_{jt} \quad \text{for} \quad j = 1 \ldots J; \quad t = 1 \ldots T \tag{3}$$

$$P_{kjt}^{-} \leq P_{kjt} \leq P_{kjt}^{+} \quad \text{for} \quad k = 1 \ldots K; \quad j = 1 \ldots J; \quad t = 1 \ldots T \tag{4}$$

$$P_{kjt}^{+} = (1 - m_{kt}) \cdot i_{kt} \cdot a_{kj} \cdot P_k^{\max} \quad \text{for} \quad k = 1 \ldots K; \quad j = 1 \ldots J; \quad t = 1 \ldots T \tag{5}$$

$$P_{kjt}^{-} = (1 - m_{kt}) \cdot i_{kt} \cdot a_{kj} \cdot P_k^{\min} \quad \text{for} \quad k = 1 \ldots K; \quad j = 1 \ldots J; \quad t = 1 \ldots T \tag{6}$$

$$\sum_{t=1}^{T} m_{kt} = S_k \quad \text{for} \quad k = 1 \ldots K \tag{7}$$

$$\sum_{t=t_k}^{t_k+S_k-1} m_{kt} = S_k \quad \text{for} \quad k = 1 \ldots K \tag{8}$$

$$t_k^- \leq t_k \leq t_k^+ \quad \text{for} \quad k = 1 \ldots K \tag{9}$$

$$t_k + S_k - 1 \leq t_k^+ \quad \text{for} \quad k = 1 \ldots K \tag{10}$$

$$\sum_{k \in Vr} m_{kt} \leq V_r^+ \quad \text{for} \quad r = 1 \ldots R, \quad t = 1 \ldots T \tag{11}$$

$$m_{kt} \in \{0, 1\} \quad \text{for} \quad k = 1 \ldots K; \quad t = 1 \ldots T \tag{12}$$

$$t_k \in \{1, 2, 3, \ldots, 52\} \quad \text{for} \quad k = 1 \ldots K \tag{13}$$

In this formulation, we aim at minimizing the generation cost to supply the demand along the period T. As mentioned before, this period T is organized in weeks and the demand is specified by a load diagram organized in J steps. These steps remain constant along the whole scheduling period. This objective function is subjected to the following constraints:

- constraints (2) enforce that the demand D_{jt} is supplied in each step j and in every week t. This supply is obtained using the K generation units and also by hydro generation, H_{jt}, by wind parks, W_{jt}, by other generation sources, OG_{jt}, and by interconnections with other countries, INT_{jt}. The energy from the hydro subsystem, from wind parks, other generation sources and from the interconnections with other countries should be specified based on estimates taking into account historical values;
- on the other hand, constraints (3) indicate that in each week t and in each step j, the sum of the maximum powers of the available thermal units should exceed the demand to be supplied by the thermal subsystem at least by the specified reserve level, Res_{jt};
- constraints (4) bound the output of the K units to minimum and maximum values, in each step j and in each week t. These minimum and maximum values depend on the availability of each unit and on its rated and minimum powers;
- constraints (5) and (6) determine the maximum and the minimum possible output of unit k, in each step j and week t. This maximum output depends on the rated power of the unit, P^{max}, on its availability regarding maintenance modeled by the variable m_{kt} and on its availability regarding other aspects apart from maintenance. This is modeled by i_{kt} for each unit k in each week t and by a_{kj} for each unit k in each time step j. As mentioned before the values of i_{kt} and of a_{kj} can be used to give indications regarding, for instance, periods (time steps or periods of the year) during which some thermal units are not typically running. If the input values of both i_{kt} and a_{kj} are specified as 1 for a given unit k for every t and j, this means the unit can be running all along the year except during the maintenance period;
- constraints (7) enforce that each unit k has to be subjected to a maintenance action per year with a duration of S_k weeks;
- constraints (8) enforce that the period of S_k weeks during which unit k is in maintenance is continuous;
- constraints (9) indicate that the maintenance action of unit k has be to conducted between t_k^- and t_k^+;
- constraints (10) enforce that the maintenance action of unit k has to be finished at most at week t_k^+;
- constraints (11) limit the number of simultaneous maintenance actions of units of the same technology r, given the available number of crews for technology r, V_r^+. For each type of generator technology it is established a constraint of this type. In this sense, r represents the technology index and V_r is the set of generators of the same technology r. For each technology, this constraint indicates there is a maximum number of m_{kt} binary variables assuming the value 1 for each week t and this maximum number corresponds to V_r^+ for technology r. This limitation means that there is a maximum number of similar generators that can be in maintenance in each week t, and this limit can be associated with the capacity the generation company has to run simultaneous maintenance actions over similar generators, assuming that there are crews more specialized on a given technology and some others dedicated to other technologies;
- finally, (12) indicates that variables m_{kt} are binary ones and (13) specifies the possible values that the t_k variables can assume.

To solve this problem it is necessary to input the generation costs, the generation from other sources and the injections from interconnections, the required reserve margin in each week and in each time step, the duration of each time step and the corresponding demand, the minimum and rated powers of each thermal unit, the duration of the maintenance period of each unit and the availability parameters of each unit in each week and in each time step. After solving this problem, one obtains the dispatch of each unit k in each week and time step, P_{kjt}, the value 1 or 0 of the binary variables m_{kt} indicating the state of each unit in each week t regarding maintenance and the value of the t_k indicating the starting week of the maintenance action of unit k.

It is also important to mention that this formulation can include a fictitious generator apart from the ones that really integrate the generation park in order to model the energy not supplied. This generator will have a large generation cost and so whenever used it will cause an increase of the objective function of the problem since we are in fact penalizing solutions with non-zero energy not supplied. This indicates that this resource, although fictitious, should only be used as a last strategy to balance the generation with the demand, as it would imply demand curtailment. It is then clear that the solution algorithm to be used will tend to distribute maintenance actions along the planning period in order not to turn the generation of this fictitious generator different from zero. The solution algorithm to detail in the next section is based on Simulated Annealing and it characterizes each identified solution by the value of an Evaluation Function defined as the addition of the generation cost given by (1) plus penalties over the constraints that are violated by the solution under analysis. This aspect will be further developed in the next section.

4. Solution algorithm

The discrete nature of the GMS problem justified the adoption of Simulated Annealing given its natural adaptation to incorporate discrete variables and parameters, its implementation easiness and the good results it has been providing in several engineering applications. Regarding the characteristics of Simulated Annealing that turns this metaheuristic so appealing, Ref. [22] discusses its performance considering the convergence and also its speed of convergence. The authors consider that the convergence proof detailed in [22] is a reassuring property, namely if the temperature reduces at a sufficiently slow rate and the cooling scheme is adequate. Extensive experiments on the application of Simulated Annealing on several classes of problems described by the authors lead to the conclusion that "overall, Simulated Annealing is a generally applicable and easy-to-implement probabilistic approximation algorithm that is able to produce good solutions for an optimization problem, even if we do not understand the structure of the problem well."

Simulated Annealing metaheuristic starts at an initial maintenance schedule and evolves to a new schedule by sampling new maintenance periods for some units. Each schedule is evaluated considering the generation costs along the whole period T given by (1), plus penalties on the constraints (2)–(13) that are violated by the schedule under analysis. This means that for a new sampled schedule the algorithm goes through the constraints of the problem, identifies the constraints that are violated and adds the associated generation cost to a penalty term for each violated constraint. For instance for an equality constraint, this term is obtained multiplying a penalty factor by the absolute value of the difference of the right hand side and the left hand side of the constraint under analysis. A new solution is then identified in the neighborhood of the current one and after evaluating this new solution (that is, computing the generation cost and the penalty terms over the violated constraints), a decision is taken to accept it or not. The following paragraphs detail the application of Simulated Annealing to this particular problem.

(i) Consider an initial maintenance schedule, denoted by x^o;
(ii) Analyze the current solution:
  a. compute the generation cost along the period T. To do this the generation cost is minimized along the T weeks and the J time steps using a merit order dispatch, considering the variable generation costs of the generators. For each week and time

Table 1
Data for the thermal generation system.

Type	P^{min} (MW)	P^{max} (MW)	C_k (€/GWh)	S_k (week)	Type	P^{min} (MW)	P^{max} (MW)	C_k (€/GWh)	S_k (week)
Coal_1	98	292	62367.42	3	CCGT_8	198	330	57497.17	4
Coal_2	98	292	62367.42	3	Fuel_1	142	236	107092.89	6
Coal_3	98	292	62367.42	3	Fuel_2	142	236	107092.89	6
Coal_4	98	292	62367.42	3	Fuel_3	142	236	107092.89	6
Coal_5	109	298	64335.81	3	Fuel_4	142	236	107092.89	6
Coal_6	109	298	64335.81	3	Fuel_5	71.2	118	112411.98	5
Coal_7	109	298	64335.81	3	Fuel_6	71.2	118	112411.98	5
Coal_8	109	298	64335.81	3	Fuel_7	71.2	118	112411.98	5
CCGT_1	210	420	54156.98	3	Fuel_8	71.2	118	112411.98	5
CCGT_2	210	420	54156.98	3	Fuel_9	71.2	118	119288.15	5
CCGT_3	235.2	392	55166.61	3	Fuel_10	71.2	118	119288.15	5
CCGT_4	235.2	392	55166.61	3	Fuel_11	33.6	56	123347.52	5
CCGT_5	235.2	392	55166.61	3	Diesel_1	49.5	82.5	285632.60	2
CCGT_6	198	330	57497.17	4	Diesel_2	49.5	82.5	285632.60	2
CCGT_7	198	330	57497.17	4	ENS	–	1000	–	–

Table 2
Demand to be supplied by thermal generators in some weeks and in the 5 periods (GWh).

Step	Duration (% of the week)	Week 1	Week 10	Week 20	Week 30	Week 40	Week 52
1	5	34.20828	26.45884	25.68045	36.29361	28.16563	22.63457
2	30	205.29750	148.96730	146.83110	201.82260	160.12520	120.20270
3	18	123.15130	89.17773	84.69330	108.74640	89.31160	72.16986
4	20	99.40688	78.86910	74.19964	88.68652	89.12970	80.30825
5	27	90.63492	90.79465	83.60142	106.20510	119.49480	94.59578

step it is obtained the dispatch using the available generators and taking into account the demand to be supplied and the generations from other sources and from the interconnections;

b. check if any constraints (2)–(13) are violated. If some of them are violated, then compute the corresponding penalty terms as detailed in the beginning of this section;
c. the value of the Evaluation Function EV^o is the sum of the generation cost plus penalties on the identified violated constraints;
d. assign EV^o to EV^{opt} and to $EV^{current}$;
e. assign x^o to x^{opt} and to $x^{current}$;
f. set the iteration counter, IC, to 1;
g. set the worse solution counter, WSC, at 0;

(iii) Identify a new schedule. Sample an unit k and sample a week between t_k^- and $t_k^+ - S_k + 1$ to start its maintenance. Conditioning this sampling in this way means that constraints (9) and (10) will not be violated for this unit. The new schedule is then denoted as x^{new};

Table 3
Final maintenance schedule obtained for Simulation 2 (Part 1 – weeks 1–26).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
Coal_1																										
Coal_2																										
Coal_3																										
Coal_4														■	■	■										
Coal_5																					■	■	■			
Coal_6															■	■	■									
Coal_7																										
Coal_8																						■	■	■		
CCGT_1																										
CCGT_2																										
CCGT_3														■	■	■										
CCGT_4																	■	■	■							
CCGT_5																					■	■	■			
CCGT_6														■	■	■	■									
CCGT_7															■	■	■	■								
CCGT_8											■	■	■	■												
Fuel_1																										
Fuel_2							■	■	■	■	■	■														
Fuel_3																■	■	■	■	■	■					
Fuel_4						■	■	■	■	■	■															
Fuel_5			■	■	■	■	■																			
Fuel_6															■	■	■	■	■							
Fuel_7																										
Fuel_8								■	■	■	■	■														
Fuel_9																										
Fuel_10																										
Fuel_11																				■	■	■	■	■		
Diesel_1																							■	■		
Diesel_2																		■	■							

Table 4
Final maintenance schedule obtained for Simulation 2 (Part 2 – weeks 27–52).

	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52
Coal_1																			■	■	■					
Coal_2														■	■	■										
Coal_3																								■	■	■
Coal_4																										
Coal_5																										
Coal_6																										
Coal_7																	■	■	■							
Coal_8																										
CCGT_1								■	■	■																
CCGT_2																■	■	■								
CCGT_3																										
CCGT_4																										
CCGT_5																										
CCGT_6																										
CCGT_7																										
CCGT_8																										
Fuel_1																	■	■	■	■	■	■				
Fuel_2																										
Fuel_3																										
Fuel_4																										
Fuel_5																										
Fuel_6																										
Fuel_7	■	■	■	■	■																					
Fuel_8																										
Fuel_9								■	■	■	■	■														
Fuel_10	■	■	■	■	■																					
Fuel_11																										
Diesel_1																										
Diesel_2																										

(iv) Analyze the new schedule computing the generation cost, identifying the associated violated constraints and computing the respective penalty terms. Obtain EV^{new};

(v) If $EV^{new} < EV^{opt}$ then assign EF^{new} to EF^{opt} and to $EF^{current}$; assign x^{new} to x^{opt} and to $x^{current}$; set the worse solution counter, *WSC*, at 0;

(vi) If $EF^{new} \geq EF^{opt}$ then

a. get a random number $p \in [0.0; 1.0]$;

b. compute the probability of accepting worse solutions $p(x^{new})$ by (14). In this expression K_{Boltz} represents the Boltzman constant and T is the temperature parameter;

$$p(x^{new}) = e^{(EF^{current} - EF^{new})/(K_{Boltz} \cdot T)} \tag{14}$$

c. if $p \leq p(x^{new})$ then assign x^{new} to $x^{current}$ and EF^{new} to $EF^{current}$;

d. if the solution x^{new} is worse than the best solution identified so far, then increase the worse solution counter, *WSC*, by 1;

(vii) If *WSC* is larger than a specified maximum number of iterations without improvements than go to (ix);

(viii) If the iteration counter *IC* is larger than the maximum number of iterations per temperature level then:

a. decrease the temperature level T by a rate α smaller then 1.0;

b. if the new temperature level is smaller then the minimum allowed temperature then go to (ix);

c. set the iteration counter *IC* to 1;

Else, increase the iteration counter *IC* by 1;

Go back to (iii);

(ix) End.

When going to step (vi) of this algorithm, the new solution is worse than the optimal one so far identified. This means that x^{new} will not replace x^{opt}. It can however replace $x^{current}$. If $x^{current}$ is better than x^{new}, that is, if $EF^{current} < EF^{new}$, then the exponent of (14) becomes negative and so the value computed for $p(x^{new})$ is less than 1.0. The acceptation of x^{new} will then depend on the sampled p number as indicated in the step (vi.c). If $x^{current}$ is worse than x^{new}, that is, if $EF^{current} > EF^{new}$, then the exponent of (14) becomes positive and so the value computed for $p(x^{new})$ is larger than 1.0. This means that the sampled p number will always be less than $p(x^{new})$ and so in this case x^{new} will replace $x^{current}$, although it is nor better than $x^{current}$.

5. Case Study

5.1. System data

The Case Study used to illustrate the described approach is based on a realistic thermal generation system that includes 29 units as follows:

- coal fire plants – 2360 MW in 8 generation units;
- CCGT – 3006 MW in 8 generation units;
- fuel oil – 1708 MW in 11 generation units;
- diesel – 165 MW in 2 generation units.

Apart from these units, the generation system also has inputs from hydro stations, wind parks, other generation sources (as cogeneration and small hydro stations dispersed along the network) and interconnections with other countries. In order to incorporate a reliability index in the model, we also considered a fictitious unit to model energy not supplied, as detailed at the end of Section 3.2. This unit has a very large generation cost when compared with the costs of the other thermal stations. This means that, in a given week t and demand step j, this fictitious unit will only be dispatched if the other available cheaper stations are already in the limit. As mentioned in Section 3.2, this implicitly means that the corresponding maintenance schedule should not have a large concentration of units simultaneously in maintenance in the same weeks to prevent the demand from being larger than the available capacity leading to energy not supplied. Since the cost of the mentioned fictitious generator is very large, we are in fact penalizing maintenance schedules leading to non-zero values of the energy not supplied.

For each of the mentioned 29 thermal stations we specified the minimum and rated powers, the variable generation cost and the duration in weeks of the corresponding maintenance action. These elements are indicated in Table 1. We assumed that the minimum and rated powers and the variable cost are constant along the whole year and do not change when going from one demand step to another one.

Apart from these elements, we also specified the number of crews available for each technology, the demand for step j in each week t, the duration of each step as indicated in Section 3.1 and the energy obtained from the hydro subsystem, from the wind parks, from other generation sources and from the interconnections for each step j and week t. This means that for each step j and week t it is possible to obtain the energy to be supplied by the thermal system. As an example and for illustration purposes, Table 2 includes the values of the energy to be supplied by thermal generators in weeks 1, 10, 20, 30, 40 and 52 in each of the 5 steps that were considered. These energy values can be readily converted in power admitting that the demand is constant in each time step. As an example, in week 1 in step 1 the demand to be supplied by thermal generators is 34.20828 GWh. Assuming that this time step corresponds to 5% of the 168 h of the week, that is, to 8.4 h, the average power in this step is 4072.41 MW. In week 1 in step 5 this value reduces to 1998.12 MW. According to these values and the generation variable costs it is then possible to obtain a merit order dispatch of the available generators and so to estimate the generation cost of that step. The global generation cost corresponds to the addition of the costs obtained for each time step j in each week t.

5.2. Results for Simulation 1

In the first simulation we admitted that all units were available in all weeks during the year, that is $i_{kt} = 1$ for every k and t and $a_{kj} = 1$ for every step j. On the other hand, in this Simulation we specified no preference on particular weeks to locate the maintenance actions of the generators. This means that in this first simulation we admitted that $t_k^- = 1$ and that $t_k^+ = 52$. In order to run the Simulated Annealing algorithm we specified that the number of iterations to run at the same temperature level was 200, that the number of worse solutions before convergence was 1000 and the temperature cooling coefficient α was set at 0.95.

The first solution was obtained by a random procedure and the corresponding value of the Evaluation Function was larger than 31.4×10^9 €. This large value is very much determined by penalties on violated constraints associated with this initial random solution. However, this does not mean that we accept that some constraints have a hard nature (in the sense they have to be enforced) and some others are soft (in the sense that some violations could be acceptable). This large initial value of the Evaluation Function only reflects the way the initial schedule was obtained, that is adding the generation cost with the penalties over the violated constraints. The graph in Fig. 1 illustrating the evolution of the Evaluation Function for the current solution and for the so far best identified solution shows that the value of this function decreases along the simulation. After the first thousand iterations the Evaluation Function decreased to about 1.4×10^9 €, that is decreased by about 30×10^9 €. This indicates that it was possible to identify solutions not violating any constraint and also completely supplying the demand without using the fictitious generator representing energy not supplied. So, the penalties over the violated constraints are progressively eliminated and the energy not supplied also gets cancelled, if it was not zero in the first schedule. This means that the adoption of penalties over the violated constraints just corresponds to an operational technique that is used to enforce feasibility and does mean that some constraints have a hard nature and some others have a soft one, as mentioned above.

In this case, the simulation ends after 14.130 iterations and the temperature is lowered till 0.243. The final schedule displays a relatively large concentration of maintenance actions in the period from week 14 to 20. This is due to fact that in these weeks the energy demand to be supplied by thermal stations is more reduced because there are larger inputs from hydro stations and wind parks. This enables locating more maintenance actions in these weeks.

5.3. Results for Simulation 2

In the second simulation we admitted that some units were not available in some weeks. For instance, one of the CCGT units was not available from week 45 to 52, one coal station was not available from week 45 to 52, one fuel station was not available from week 16 to 22 and another fuel station was not available from week 30 to 37. This means that i_{kt} was set at 0 for these units in these weeks. Apart from that, for some stations we specified values for t_k^- and for t_k^+ different from 1 and from 52, respectively. This means that we specified preferences for the scheduling of their maintenance actions. For instance, for one CCGT we specified $t_k^+ = 20$, for another CCGT unit we specified $t_k^+ = 30$, for one fuel unit we specified $t_k^- = 30$ and $t_k^+ = 50$ and for another fuel station we specified $t_k^- = 20$ and $t_k^+ = 40$. As a result, for this last fuel station the maintenance period should be located between week 20 and week 40 (inclusive) and regarding the first mentioned CCGT the maintenance period should be between week 1 and week 20 (inclusive). The graph in Fig. 2 shows the evolution of the Evaluation Function after the first two thousand iterations. As in Simulation 1, in the beginning the value of the Evaluation Function is very large due to penalties on violated constraints and also due to the fact that there is Energy Not Supplied but, as mentioned in Section 5.2 all constraints are considered as hard in the sense that a feasible maintenance schedule will have all the constraints enforced. As the process goes on, constraint violations are eliminated and Energy Not Supplied comes to zero. The iterative process ends after 23.997 iterations and the temperature is lowered to 0.110. Finally, Tables 3 and 4 show the final maintenance schedule along the 52 weeks of the year. As for Simulation 1, this schedule also shows a large concentration of maintenance actions from week 14 to 25. The demand values and the inputs from

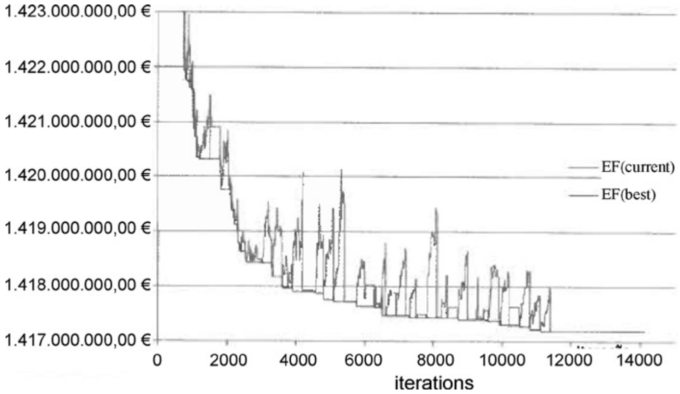

Fig. 1. Evolution of the Evaluation Function along the iterative process.

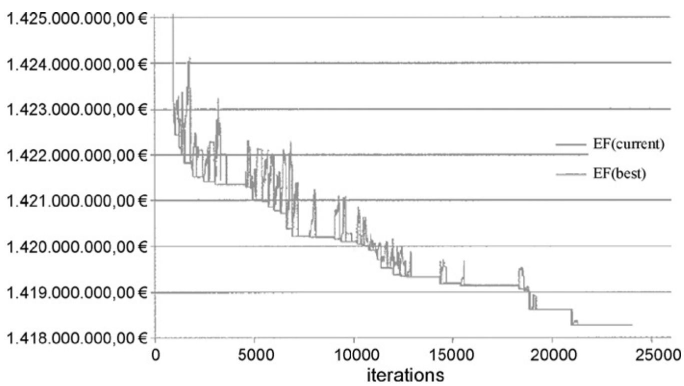

Fig. 2. Evolution of the Evaluation Function along the iterative process.

hydro and wind parks are the same ones that were used in the first simulation and so the amount of energy to be supplied by the thermal generators is more reduced in this period creating more room to locate more maintenance actions in these weeks. As a final indication, this simulation took less than 15 min in a laptop with an Intel Pentium Dual Processor.

6. Conclusions

In this paper we addressed the problem of building good quality generator maintenance schedules given the relevance of this topic in the context of the advent of competition in the electricity sector. This is a complex optimization problem formulated as a mixed-integer problem for which we applied Simulated Annealing, given its abilities to address combinatorial problems and its easiness of implementation. The formulation minimizes the generation cost along the maintenance planning horizon and it implicitly includes a reliability measure when penalizing non zero values of energy not supplied. The problem integrates constraints related with the continuity of the maintenance actions, with the limited number of crews for some generation technologies and with the preferences of the Decision Maker to locate some maintenance actions along the year. The Simulated Annealing application shows good performance and it is able to produce good maintenance schedules with short computation times.

Acknowledgement

The second author thanks EDP Produção SA for having provided guidance and data to conduct this research.

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