A Decision Support System for Generation Planning and Operation in Electricity Markets

Andres Ramos, Santiago Cerisola, and Jesus M. Latorre

Abstract This chapter presents a comprehensive decision support system for addressing the generation planning and operation. It is hierarchically divided into three planning horizons: long, medium, and short term. This functional hierarchy requires that decisions taken by the upper level model will be internalized by the lower level model. With this approach, the position of the company is globally optimized. This set of models presented is specially suited for hydrothermal systems. The models described correspond to long-term stochastic market planning, medium-term stochastic hydrothermal coordination, medium-term stochastic hydro simulation, and short-term unit commitment and bidding. In the chapter it is provided a condensed description of each model formulation and their main characteristics regarding modeling detail of each subsystem. The mathematical methods used by these models are mixed complementarity problem, multistage stochastic linear programming, Monte Carlo simulation, and multistage stochastic mixed integer programming. The algorithms used to solve them are Benders decomposition for mixed complementarity problems, stochastic dual dynamic programming, and Benders decomposition for SMIP problems.

Keywords Electricity competition · Market models · Planning tools · Power generation scheduling

1 Introduction

Since market deregulation was introduced in the electric industry, the generation companies have shifted from a cost minimization decision framework to a new one where the objective is the maximization of their expected profit (revenues minus costs). For this reason, electric companies manage their own generation resources

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and need detailed operation planning tools. Nowadays, planning and operation of generation units rely upon mathematical models whose complexity depends on the detail of the model that needs to be solved.

These operation planning functions and decisions that companies address are complex and are usually split into *very-long-term*, *long-term*, *medium-term*, and *short-term* horizons (Wood and Wollenberg 1996). The very long-term horizon decisions are mainly investment decisions and their description and solution exceed the decision support system (DSS) that we are presenting in this chapter. The long-term horizon deals with risk management decisions, such as electricity contracts and fuel acquisition, and the level of risk that the company is willing to assume. The medium-term horizon decisions comprise those economic decisions such as market share or price targets and budget planning. Also operational planning decisions like fuel, storage hydro, and maintenance scheduling must be determined. In the short term, the final objective is to bid to the different markets, based on energy, power reserve, and other ancillary services, for the various clearing sessions. As a result, and from the system operation point of view, the company determines first the unit commitment (UC) and economic dispatch of its generating units, the water releases, and the storage and pumped-storage hydro system operation.

In hydrothermal systems and in particular in this DSS, special emphasis is paid to the representation of the hydro system operation and to the hydro scheduling for several reasons (Wood and Wollenberg 1996):

- Hydro plants constitute an energy source with very low variable costs and this is the main reason for using them. Operating costs of hydro plants are due to operation and maintenance and, in many models, they are neglected with respect to thermal units' variable costs.
- Hydro plants provide a greater regulation capability than other generating technologies, because they can quickly change their power output. Consequently, they are suitable to guarantee the system stability against contingencies.
- Electricity is difficult to store, even more when considering the amount needed in electric energy systems. However, hydro reservoirs and pumped-storage hydro plants give the possibility of accumulating energy, as a volume of water. Although in some cases the low efficiency of pumped-storage hydro units may be a disadvantage, usually this water storage increases the flexibility of the daily operation and guarantees the long-term electricity supply.

In this chapter we present a proposal for covering these three hierarchical horizons with some planning models, which constitute a DSS for planning and operating a company in an electricity market. The functional hierarchy requires that decisions taken by the long-term level will be internalized by the medium-term level and that decisions taken by the medium-term level will be internalized by the short-term level. With this approach, the position of the company is globally optimized. At an upper level, a stochastic market equilibrium model (Cabero et al. 2005) with monthly periods is run to determine the hydro basin production, as well as fuel and electricity contracts, while satisfying a certain risk level. At an intermediate level, a medium-term hydrothermal coordination problem obtains weekly water release tables for large reservoirs and weekly decisions for thermal units. At a lower level, a stochastic simulation model (Latorre et al. 2007a) with daily periods incorporates those water release tables and details each hydro unit power output. Finally, a detailed strategic UC and bidding model defines the commitment and bids to be offered to the energy market (Baillo et al. 2004; Cerisola et al. 2009). In Fig. 1 the hierarchy of these four models is represented. Different mathematical methods are used for modeling the electric system: mixed complementarity problem (MCP) (Cottle et al. 1992), multistage stochastic programming (Birge and Louveaux 1997), Monte Carlo simulation (Law and Kelton 2000), and stochastic mixed integer programming. With the purpose of solving realistic-sized problems, those models are combined with special purpose algorithms such as Benders decomposition and stochastic dual dynamic programming to achieve the solution of the proposed models.

For using the DSS in real applications, it is important to validate the consistency of the system results. As it can be observed from Fig. 1, several feedback loops are included to check the coherence of the DSS results. As the upper level models pass target productions to lower level models, a check is introduced to adjust the system results to those targets with some tolerance.

Although the DSS conception is general, it has been applied to the Spanish electric system, as can be seen in the references mentioned for each model. In the following Table 1 we present the summary of the demand balance and the installed capacity by technologies of the mainland Spanish system in 2008, taken from Red Electrica de Espana (2008).

2 Long-term Stochastic Market Planning Model

In a liberalized framework, market risk management is a relevant function for generating companies (GENCOs). In the long term they have to determine a risk management strategy in an oligopolistic environment. Risk is defined as the probability of a certain event times the impact of the event in the company's objective of an expected return. Some of the risks that the GENCOs face are operational risk, market risk, credit risk, liquidity risk, and regulatory risk. Market risk accounts for the risk that the value of an investment will decrease due to market factors' movements. It can be further divided into equity risk, interest rate risk, currency risk, and commodity risk. For a GENCO the commodity risk is mainly due to the volatility in electricity and fuel prices, in unregulated hydro inflows and in the demand level.

The purpose of the long-term model of the DSS is to represent the generation operation by a market equilibrium model based on a conjectural variation approach, which represents the implicit elasticity of the residual demand function. The model decides the total production for the considered periods (months) and the position in futures so as to achieve the acceptable risk for its profit distribution function. Stochasticity of random variables are represented by a scenario tree that is computed by clustering techniques (Latorre et al. 2007b). Traditionally, models that represent

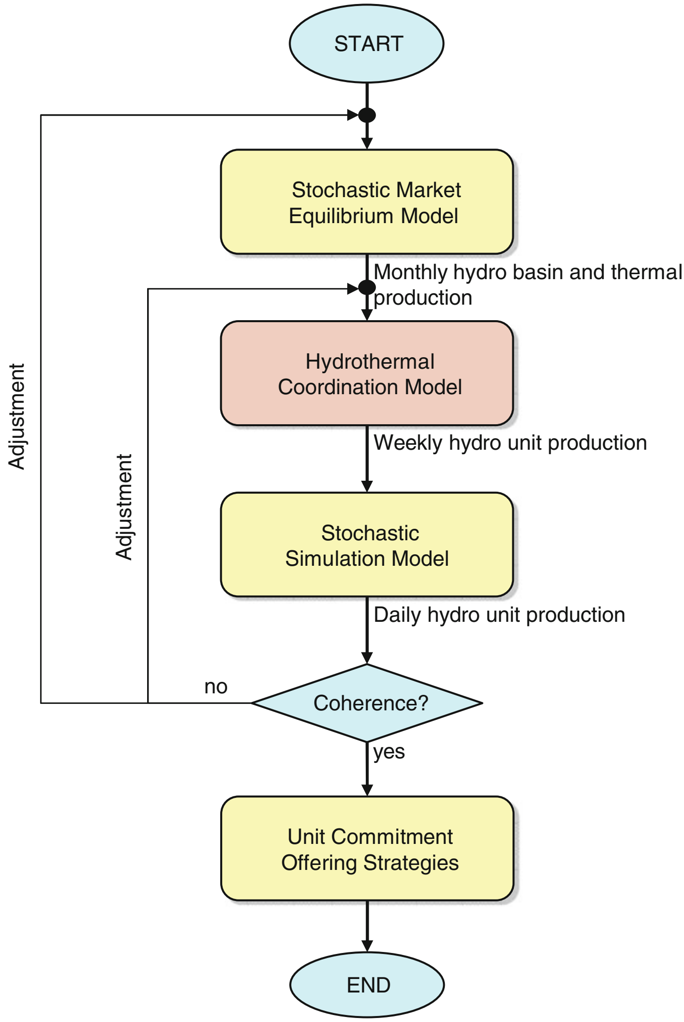

Fig. 1 Hierarchy of operation planning models

market equilibrium problems are based on linear or mixed complementarity problem (Hobbs et al. 2001a; Rivier et al. 2001), equivalent quadratic problem (Barquin et al. 2004), variational inequalities (Hobbs and Pang 2007), and equilibrium problem with equilibrium constraints (EPEC) (Yao et al. 2007). The formulation of this problem is based on mixed complementarity problem (MCP), that is, the combination of Karush–Kuhn–Tucker (KKT) optimality conditions and complementary slackness conditions, and extends those techniques that traditionally are used to represent the market equilibrium problem to a combined situation that simultaneously

Table 1 Demand balance and installed capacity of mainland Spanish electric system

	GWh	MW
Nuclear	58,756	7,716
Coal	46,346	11,359
Combined cycle	91,821	21,667
Oil/Gas	2,454	4,418
Hydro	21,175	16,657
Wind	31,102	15,576
Other renewable generation	35,434	12,552
Pumped storage hydro consumption	3,494	
International export	11,221	
Demand	263,961	

considers the market equilibrium and the risk management decisions, in a so-called integrated risk management approach.

2.1 Model Description

The market equilibrium model is stated as the profit maximization problem of each GENCO subject to the constraint that determines the electricity price as a function of the demand, which is the sum of all the power produced by the companies. Each company profit maximization problem includes all the operational constraints that the generating units must satisfy. The objective function is schematically represented by (Fig. 2).

In the long term the demand is represented by a load duration curve divided into peak, shoulder, and off-peak levels by period, the period being a month. For each load level the price p is a linear function of the demand d,

$$p = p_0 - p_0' \sum_c q_c \tag{1}$$

$$d = \sum_c q_c = q_c + q_c^- \tag{2}$$

p_0, p_0' being the intercept and slope of the inverse demand function, q_c the production of company c, and q_c^- the production of the remaining companies different from c. Then, the profit of each company becomes quadratic with respect to the quantities offered by companies. It accounts for those revenues that depend on the spot price and those that depend on long-term electricity contracts or take-or-pay fuel contracts. Schematically it can be stated as

$$\max \sum_\omega pr^\omega \sum_{t \in c} \left[p^\omega q_t^\omega - c^\omega(q_t^\omega) \right] \tag{3}$$

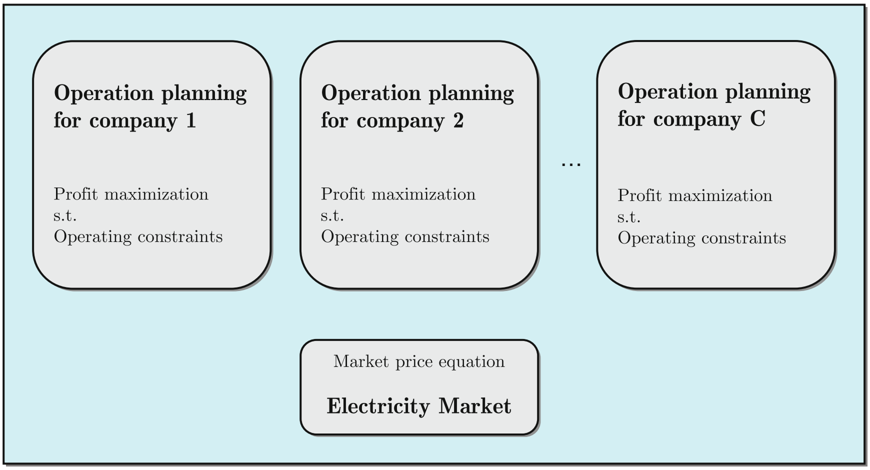

Fig. 2 Market equilibrium problem

ω being any scenario of the random variates, pr^{ω} the corresponding probability, p^{ω} the price, q_t^{ω} the energy produced by thermal unit t belonging to company c in scenario ω, and $c^{\omega}(q_t^{\omega})$ the thermal variable costs depending quadratically on the output of thermal units.

When considering the Cournot's approach, the decision variable for each company is its total output, while the output from competitors is considered constant. In the conjectural variation approach the reaction from competitors is included into the model by a function that defines the sensitivity of the electricity price with respect to the output of the company. This function may be different for each company:

$$\frac{\partial p}{\partial q_c} = -p_0'\left(1 + \frac{\partial q_c^-}{\partial q_c}\right). \tag{4}$$

Operating constraints include fuel scheduling of the power plants, hydro reservoir management for storage and pumped-storage hydro plants, run-of-the-river hydro plants, and operation limits of all the generating units.

We incorporate in the model several sources of uncertainty that are relevant in the long term, such as water inflows, fuel prices, demand, electricity prices, and output of each company sold to the market. We do this by classifying historical data into a multivariate scenario tree. The introduction of uncertainty extends the model to a stochastic equilibrium problem and gives the company the possibility of finding a hedging strategy to manage its market risk. With this intention, we force currently future prices to coincide with the expected value of future spot prices that the equilibrium returns for each node of the scenario tree. Future's revenues are calculated as gain and losses of future contracts that are canceled at the difference between future and spot price at maturity. Transition costs are associated to contracts and computed when signed.

The risk measure used is the *Conditional Value at Risk* (CVaR), which computes the expected value of losses for all the scenarios in which the loss exceeds the *Value at Risk* (VaR) with a certain probability α, see (5).

$$CVaR_X(\alpha) = \mathbb{E}\left[X|X \geq VaR_X(\alpha)\right], \tag{5}$$

where X are the losses, $CVaR_X(\alpha)$ and $VaR_X(\alpha)$ are the CVaR and VaR of α quantile.

All these components set up the mathematical programming problem for each company, which maximizes the expected revenues from the spot and the futures market minus the expected thermal variable costs and minus the expected contract transaction costs. The operating constraints deal with fuel scheduling, hydro reservoir management, operating limits of the units for each scenario, while the financial constraints compute the CVaR for the company for the set of scenarios. Linking constraints for the optimization problems of the companies are the spot price equation and the relation of future price as the expectation of future spot prices.

The KKT optimality conditions of the profit maximization problem of each company together with the linear function for the price define a *mixed linear complementarity problem*. Thus the market equilibrium problem is created with the set of KKT conditions of each GENCO plus the price equation of the system, see Rivier et al. (2001). The problem is linear if the terms of the original profit maximization problem are quadratic and, therefore, the derivatives of the KKT conditions become linear.

The results of this model are the output of each production technology for each period and each scenario, the market share of each company, and the resulting electricity spot price for each load level in each period and each scenario. Monthly hydro system and thermal plant production are the magnitudes passed to the medium-term hydrothermal coordination model, explained below.

3 Medium-term Stochastic Hydrothermal Coordination Model

By nature, the medium-term stochastic hydrothermal coordination models are high-dimensional, dynamic, nonlinear, stochastic, and multiobjective. Solving these models is still a challenging task for large-scale systems (Labadie 2004). One key question for them is to obtain a feasible operation for each hydro plant, which is very difficult because models require a huge amount of data, due to complexity of hydro systems and by the need to evaluate multiple hydrological scenarios. A recent review of the state of the art of hydro scheduling models is done in Labadie (2004).

According to the treatment of stochasticity hydrothermal coordination models are classified into deterministic and stochastic ones.

- *Deterministic models* are based on network flows, linear programming (LP), nonlinear programming (NLP), or mixed integer linear programming (MILP), where binary variables come from commitment decisions of thermal or hydro units or from piecewise linear approximation of nonlinear and nonconvex water head effects. For taking into account these nonlinear effects, successive LP solutions are often used. This process does not converge necessarily to the optimal solution, see Bazaraa et al. (1993).

- *Stochastic models* are represented by stochastic dynamic programming (SDP), stochastic linear programming (SLP) (Seifi and Hipel 2001), and stochastic nonlinear programming (SNLP). For SLP problems decomposition techniques like Benders (Jacobs et al. 1995), Lagrangian relaxation, or stochastic dual dynamic programming (SDDP) (Pereira and Pinto 1991) can be used.

In this medium-term model, the aggregation of all the hydro plants of the same basin in an equivalent hydro unit (as done for the long-term model) is no longer kept. We deal with hydro plants and reservoir represented individually, as well as we include a cascade representation of their physical connections. Besides, thermal power units are considered individually. Thus, rich marginal cost information is used for guiding hydro scheduling.

The hydrothermal model determines the optimal yearly operation of all the thermal and hydro power plants for a complete year divided into decision periods of 1 week. The objective function is usually based on cost minimization because the main goal is the medium-term hydro operation, and the hydro releases have been determined by the upper level market equilibrium model. Nevertheless, the objective function can be easily modified to consider profit maximization if marginal prices are known (Stein-Erik and Trine Krogh 2008), which is a common assumption for fringe companies.

This model has a 1 year long scope beginning in October and ending in September, which models a hydraulic year, with special emphasis in large reservoirs (usually with annual or even hyperannual management capability). Final reserve levels for large reservoirs are given to the model to avoid the initial and terminal effects on the planning horizon. Uncertainty is introduced in natural inflows and the model is used for obtaining optimal and "feasible" water release tables for different stochastic inflows and reservoir volumes (Fig. 3).

The demand is modeled in a weekly basis with constant load levels (peak and off-peak hours, e.g.). Thermal units are treated individually and commitment decisions are considered as continuous variables, given that the model is used for medium-term analysis. For hydro reservoirs a different modeling approach is followed depending on the following:

- *Owner company*: Own reservoirs are modeled in water units (volume in hm^3 and inflow in $m^3\ s^{-1}$) while reservoirs belonging to other companies are modeled in energy units as equivalent and independent power plants with one reservoir each, given that the reservoir characteristics of the competitors are generally ignored.
- *Relevance of the reservoir*: Important large reservoirs are modeled with nonlinear water head effects while smaller reservoirs are represented with a linear dependency; therefore, the model does not become complex unnecessarily.

Unregulated hydro inflows are assumed to be the dominant source of uncertainty in a hydrothermal electric system. Temporal changes in reservoir reserves

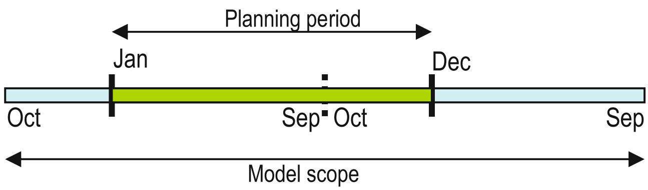

Fig. 3 Model scope for yearly operation planning

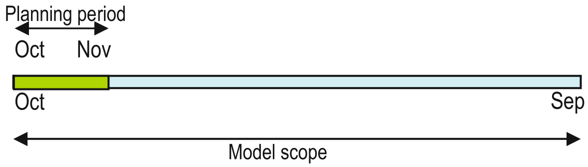

Fig. 4 Model scope for next future decisions under uncertain inflows

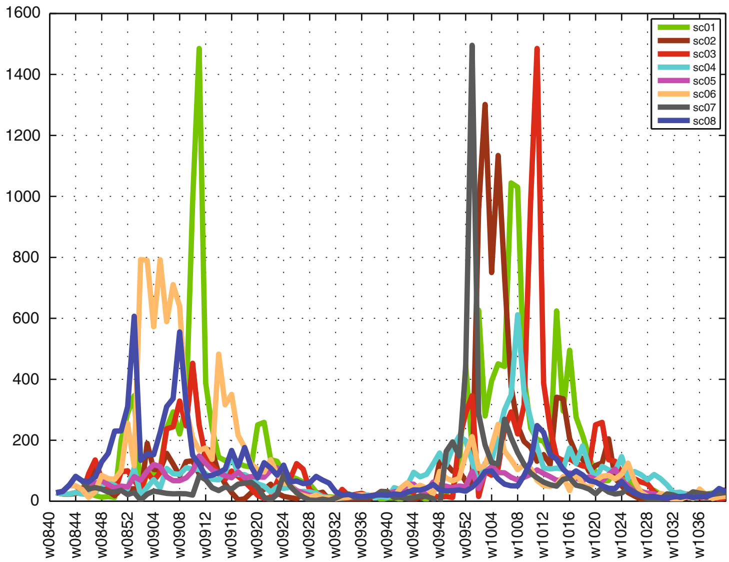

Fig. 5 Scenario tree with eight hydro inflows' scenarios from week 40 of year 2008 to week 39 of year 2010 expressed in ($m^3\ s^{-1}$)

are significant because of stochasticity in hydro inflows, highly seasonal pattern of inflows, and capacity of each reservoir with respect to its own inflow (Fig. 4).

Stochasticity in hydro inflows is represented for the optimization problem by means of a multivariate scenario tree, see Fig. 5 as a real case corresponding to a specific location. This tree is generated by a neural gas clustering technique (Latorre et al. 2007b) that simultaneously takes into account the main stochastic inflow series and their spatial and temporal dependencies. The algorithm can take historical or synthetic series of hydro inflows as input data. Very extreme scenarios can be artificially introduced with a very low probability. The number of scenarios generated is enough for medium-term hydrothermal operation planning.

3.1 Model Description

The *constraints* introduced into the model are the following:

- Balance between generation and demand including pumping: Generation of thermal and storage hydro units minus consumption of pumped-storage hydro units is equal to the demand for each scenario, period (week), and subperiod (load level).
- Minimum and maximum yearly operating hours for each thermal unit for each scenario: These constraints are relaxed by introducing slack and surplus variables that are penalized in the objective function. Those variables can be strictly necessary in the case of many scenarios of stochasticity. This type of constraints is introduced to account for some aspects that are not explicitly modeled into this model like unavailability of thermal units, domestic coal subsidies, CO_2 emission allowances, capacity payments, etc.
- Minimum and maximum yearly operating hours for each thermal unit for the set of scenarios.
- Monthly production by thermal technology and hydro basin: These constraints establish the long-term objectives to achieve by this medium-term model.
- Water inventory balance for large reservoirs modeled in water units: Reservoir volume at the beginning of the period plus unregulated inflows plus spillage from upstream reservoirs minus spillage from this reservoir plus turbined water from upstream storage hydro plants plus pumped water from downstream pumped-storage hydro plants minus turbined and pumped water from this reservoir is equal to reservoir volume at the end of the period. An artificial inflow is allowed and penalized in the objective function. Hydro plant takes water from a reservoir and releases it to another reservoir. The initial value of reservoir volume is assumed known. No lags are considered in water releases because 1 week is the time period unit.
- Energy inventory balance for reservoirs modeled in energy: Reservoir volume at the beginning of the period plus unregulated inflows minus spillage from this reservoir minus turbined water from this reservoir is equal to reservoir volume at the end of the period. An artificial inflow is allowed and penalized in the objective function. The initial value of reservoir volume is assumed known.
- Hydro plant generation is the product of the water release and the production function variable (also called efficiency): This is a nonlinear nonconvex constraint that considers the long-term effects of reservoir management.
- Total reservoir release is equal to the sum of reservoir releases from each downstream hydro plant.

- Pumping from a reservoir: Pumped water is equal to the pumped-storage hydro plant consumption divided by the production function.
- Achievement of a given final reservoir volume with slack and surplus variables: This final reserve is determined by the upper level long-term stochastic market equilibrium model of the DSS. The reserve levels at the end of each month of the problem are also forced to coincide with those levels proposed by the stochastic market equilibrium model.
- Minimum and maximum reservoir volume per period with slack and surplus variables: Those bounds are included to consider flood control curve, dead storage, and other plan operation concerns. The slack variables will be strictly necessary in the case of many scenarios.
- Computation of the plant water head and the production function variable as a linear function: Production function variable is a linear function of the water head of the plant that is determined as the forebay height of the reservoir minus the tailrace height of the plant. Tailrace height of the plant is the maximum of the forebay height of downstream reservoir and the tailrace height of the plant.
- Computation of the reservoir water head and the reservoir volume as a nonlinear function: Reservoir water head is determined as the forebay height minus the reference height. Reserve volume is a quadratic function of the reservoir water head.
- Variable bounds, that is, reservoir volumes between limits for each hydro reservoir and power operation between limits for each unit.

The *multiobjective function* minimizes:

- Thermal variable costs plus

$$\min \sum_{t\omega} pr^{\omega} c_t q_t^{\omega} \tag{6}$$

  q_t^{ω} the energy produced by thermal unit t in scenario ω and c_t the variable cost of the unit.
- Penalty terms for deviations from the proposed equilibrium model reservoir levels, that is, slack or surplus of final reservoir volumes, exceeding minimum and maximum operational rule curves, artificial inflows, etc.
- Penalty terms for relaxing constraints like minimum and maximum yearly operation hours of thermal units.

It is important for this model to obtain not only optimal solutions but also feasible solutions that can be implemented. Different solutions and trade-offs can be obtained by changing these penalties.

The main results for each load level of each period and scenario are storage hydro, pumped-storage hydro and thermal plant operation, reservoir management, basin and river production, and marginal costs. As a byproduct the optimal water release tables for different stochastic inflows and reservoir volumes are obtained. They are computed by stochastic nested Benders' decomposition technique (Birge and Louveaux 1997) of a linear approximation of the stochastic nonlinear optimization problem. These release tables are also used by the lower level daily stochastic simulation model, as explained in the next section.

4 Medium-term Stochastic Simulation Model

Simulation is the most suitable technique when the main objective is to analyze complex management strategies of hydro plants and reservoirs and their stochastic behavior. Simulation of hydrothermal systems has been used in the past for two main purposes:

- *Reliability analysis of electric power systems.* An example of this is given in Roman and Allan (1994), where a complete hydrothermal system is simulated. The merit order among all the reservoirs to supply the demand is determined as a function of their reserve level. Simulated natural hydro inflows and transmission network are considered. The goal is to determine the service reliability in thermal, hydro, or hydrothermal systems.
- *Hydrothermal operation.* In De Cuadra (1998) a simulation scheme for hydrothermal systems is proposed, where medium and long-term goals (maintenance, yearly hydro scheduling) are established. The system is simulated with stochastic demand and hydro inflows. For each day an optimization problem is solved to achieve the goals obtained from long-term models.

The hydro simulation model presented in this section takes into account the detailed topology of each basin and the stochasticity in hydro inflows, see Latorre et al. (2007a). It is directly related to the previous medium-term hydrothermal model, based on optimization. The stochastic optimization model guides the simulation model through a collection of hydro weekly production objectives that should be attained in different weeks for the largest hydro reservoirs. Once these guidelines are provided, the simulation model checks the feasibility of these goals, may test the simplifications made by the optimization model, and determines the energy output of hydro plants, the reserve evolution of the reservoirs and, therefore, a much more detailed daily operation. This double hierarchical relation among different planning models to determine the detailed hydro plants operation has also been found in Turgeon and Charbonneau (1998). It is a dynamic model, whose input data are series of historical inflows in certain basins' spots. Historical or synthetic series (obtained by forecasting methods) can be used for simulation. For this reason, it is also a stochastic model. Finally, system state changes take place once a day. These events can be changes of inflows, scheduled outages, etc. Consequently, the model is discrete with 1 day as time step. This is a reasonable time step because the usual model scope is 1 year and no hourly information is needed. The simulation model deals with plausible inflow scenarios and generates statistics of the hydro operation. Its main applications are the following:

- Comparison of several different reservoir management strategies
- Anticipation of the impact of hydro plant unavailabilities for preventing and diminishing the influence of floods
- Increment of hydro production by reducing the spillage

The model is based on the object-oriented paradigm and defines five classes that are able to represent any element of a hydro basin. The object oriented programming (OOP) paradigm (Wirfs-Brock et al. 1990) becomes very attractive for simulation because it allows to encapsulate the basic behavior of the elements and permits the independent simulation of each system element, which simply needs to gather information from incoming water flows from the closest elements to it. The model incorporates a simulation algorithm in three phases that decides the production of the hydro plants following several strategies about reservoir management. These management strategies and a description of the five classes are presented next.

4.1 Data Representation

A natural way to represent the hydro basin topology is by means of a graph of nodes, each one symbolizing a basin element. Those nodes represent reservoirs, plants, inflow spots, and river junctions. Nodes are connected among them by arcs representing water streams (rivers, channels, etc). Each node is independently managed, although it may require information about the state of other upstream basin elements. As a result of this data structure, object-oriented programming is a suitable approach to solve the problem of the simulation of a hydro basin (Fig. 6).

Analyzing real hydro basin patterns, we have concluded that five classes are enough to represent adequately every possible case. These object types are described in the next section. Additionally, different reserve management strategies can be pursued in a reservoir element. These nodes represent reservoirs, channels, plants, inflows, and river junctions, which are now described.

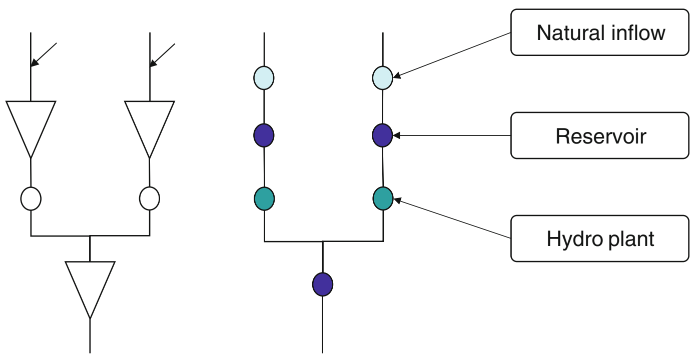

Fig. 6 Basin topology represented by a graph of nodes

4.1.1 Reservoirs

The objects representing reservoirs have one or more incoming water streams and only one outgoing. Apart from other technical limitations, they may have a minimum outflow release, regarding irrigation needs, sporting activities, or other environmental issues. Besides, they may have rule volume curves guiding their management. Examples are minimum and maximum rule curves, which avoid running out of water for irrigation or spillways risk.

Reservoirs are the key elements where water management is done. The chosen strategy decides its outflow, taking into account minimum and maximum guiding curves, absolute minimum and maximum volume levels, and water release tables. The different management strategies are described in Sect. 4.2.

4.1.2 Channels

These elements carry water between other basin elements, like real water streams do. They do not perform any water management: they just transport water from their origin to their end. However, they impose an upper limit to the transported water flow, which is the reason to consider them.

4.1.3 Plants

Kinetic energy from the water flow that goes through the turbine is transformed into electricity in the plant. In electric energy systems, hydro plants are important elements to consider due to their flexibility and low production costs. However, in this simulation model water management is decided by the reservoir located upstream. Hence, from this point of view they are managed in the same fashion as channels: they impose an upper limit to the transported flow.

As a simulation result, electric output is a function of the water flow through the plant. This conversion is done by a production function depending on the water head, which is approximated linearly. Water head is the height between the reservoir level and the maximum between the drain level and the level of the downstream element. In hydro plants, once the water flow has been decided, daily production is divided between peak and off-peak hours, trying to allocate as much energy as possible in peak hours where expensive thermal units are producing.

In addition, some plants may have pumped-storage hydro units, which may take water from downstream elements and store it in upstream elements (generally, both elements will be reservoirs). It is important to emphasize that, in this simulation model, pumping is not carried out with an economic criterion, as it does not consider the thermal units, but with the purpose of avoiding spillage.

4.1.4 Natural Inflows

These objects introduce water into the system. They represent streamflow records where water flow is measured, coming from precipitation, snowmelt, or tributaries. These elements have no other upstream elements. The outflow corresponds to the day been simulated in the series. These series may come from historic measures or from synthetic series obtained from forecasting models based on time series analysis.

4.1.5 River Junctions

This object groups other basin elements where several rivers meet. An upper bound limits the simultaneous flow of all the junction elements. An example of this object appears when two reservoirs drain to the same hydro plant. As both reservoirs share the penstock, this element has to coordinate both reservoirs' behavior.

4.2 Reservoir Management Strategies

Reservoir management is the main purpose of the simulation; the rest of the process is an automatic consequence of this. Different strategies represent all possible real alternatives to manage reservoirs with diverse characteristics. These strategies combine the implicit optimization of the upper level models with operational rules imposed by the river regulatory bodies to the electric companies. They are discussed in the following paragraphs.

4.2.1 Water Release Table

This strategy is used for large reservoirs that control the overall basin operation. Typically, those reservoirs are located at the basin head. The water release table is determined by the long-term optimization model and gives the optimal reservoir outflow as a multidimensional function of the week of the year of the simulated day, the inflows of the reservoir, the volume of the reservoir being simulated, and the volume of another reservoir of the same basin, if that exists, that may serve as a reference of the basin hydrological situation. The reservoir outflow is computed by performing a multidimensional interpolation among the corner values read from the table.

4.2.2 Production of the Incoming Inflow

This strategy is specially indicated for small reservoirs. Given that they do not have much manageable volume, they must behave as run-of-the-river plants and drain the incoming inflow.

4.2.3 Minimum Operational Level

In this strategy, the objective is to produce as much flow as possible. Of course, when the reservoir level is below this operational level no production is done. When the volume is above this minimum operational level, the maximum available flow must be turbined to produce electricity. This strategy can be suitable for medium-sized reservoirs when little energy is available in the basin.

4.2.4 Maximum Operational Level

With this strategy, the volume is guided to the maximum operational level curve. This is a curve that prevents flooding or spillage at the reservoirs. The reason behind this operation is that when the water head is larger, the production will be higher. However, in case of extreme heavy rain it can be dangerous to keep the reservoir at this level. This strategy can be suitable for medium-sized reservoirs when enough energy is available in the basin.

4.3 Simulation Method

Simulating a hydro basin allows to observe its evolution for different possible hydro inflows. Operation of hydro units follows the management goals of the reservoirs and the limitations of the other river basin objects. However, other factors can force changes in previous decisions, for example, avoiding superfluous spillage and assurance of minimum outflows. To achieve this purpose we propose a three-phase simulation method consisting in these phases:

1. Decide an initial reservoir management, considering each reservoir independently. It also computes the ability of each reservoir to modify its outflow without reaching too low or high water volumes.
2. Modify the previous management to avoid spillage or to supply irrigation and ecological needs. This uses the modification limits computed in the previous step.
3. Determine the hydro units' output with the final outflows decided in the previous step.

Results are obtained for each series, both in the form of detailed daily series and mean values, and mean and quantiles of the weekly values are also calculated. This permits general inspection of the results for each reservoir as well as a more thorough analysis of the daily evolution of each element of the river basin.

5 Short-term Unit Commitment and Bidding Strategies

The last step in the decision process is faced once the weekly production decisions for the thermal units and the daily hydro production are obtained with the medium-term stochastic optimization and simulation models, respectively. The optimal unit commitment schedule for the next day will comply with those decisions taken by upper level models of the DSS.

We assume an electricity market where agents have to indicate, by means of an offering curve, the amount of energy they are willing to sell for different prices for each of the 24 h of the next day. In the same manner, agents willing to purchase electricity may indicate the quantities they are willing to buy for different prices. An independent system operator (ISO) intersects both curves and sets the hourly price for the very next day. Those prices are denoted as market clearing prices. We focus our attention on a marginal pricing scheme where those offers with prices less than the market clearing price are accepted, while those whose price is higher than the market clearing price are rejected.

In this framework, companies are responsible of their offer and suffer the uncertainty of the disclosure of the market price, which is mainly induced by the uncertain behavior of the agents. Even more, if they have a large market share, their own offer may affect the final price. We model this uncertainty of the market clearing price by means of the residual demand function. The residual demand function is created for each company eliminating from the purchase offer curve the sell offer curves of the remaining agents. By doing this we obtain a function that relates the final price to the total amount of energy that the company may sell. Once this relation is available, the company may optimize its benefit determining the amount of energy that maximizes their profit, defined as the difference between the revenues earned in the market and the production costs.

The residual demand function so far commented is clearly unavailable before the market clearing process is done, and thus the company has to estimate it based on historical data (e.g., from the market operator). Nevertheless to say, for a relative small company that can be considered as a price taker, it is just enough to estimate the market prices for the next day.

With the purpose of deciding the committed units for the next day and with the intention of including the weekly thermal and hydro production decision taken by the DSS, we consider the problem of operating a diversified portfolio of generation units with a 1 week time horizon. This problem decides the hourly power output of each generation unit during the week of study, which implies choosing the generating units that must be operating at each hour. We introduce uncertainty by means of a weekly scenario tree of residual demand curves. The scenario tree branches at the beginning of each day and serial correlation is considered for the residual demand curves of the same day. This residual demand curves considered are neither convex nor concave, and we model them as well as the profit function by introducing binary variables.

So, the weekly unit commitment of the DSS is formulated as a large scale stochastic mixed integer programming problem. The problem decides the commitment schedule for the 7 days of the upcoming week, although just the solution of the very first day is typically the accepted solution. For the next day a new weekly unit commitment problem ought to be solved. For realistic large-scale problems a decomposition procedure may be used. The reader is referenced to Cerisola et al.

(2009), where a Benders-type algorithm for integer programming is applied for the resolution of a large-scale weekly unit commitment problem.

The objective function of the unit commitment problem maximizes the revenues of the company for the time scope:

$$\max \sum_h \Pi_h(q_h) = \sum_h p_h q_h = \sum_h R_h^{-1}(q_h) q_h, \tag{7}$$

where $\Pi_h(q_h)$ is the revenue of company in hour h, q_h the company output, p_h the spot price, $R_h(p_h)$ the residual demand faced by the company, and $R_h^{-1}(q_h)$ the inverse residual demand function.

In general, this revenue function is not concave but can be expressed as a piecewise-linear function by using auxiliary binary variables Cerisola et al. (2009).

We complete this section with a brief description of the *constraints* that constitute the mathematical problem of the unit commitment model:

- Market price is a function of total output and revenue is also a function of total output; both are modeled as piecewise linear equations using the δ-form as in Williams (1999).
- The production cost of each thermal unit is a linear function of its power output and its commitment state, which is modeled with a binary variable.
- The company profit is defined as the difference between the market revenue and the total operating cost.
- Maximum capacity and minimum output of thermal units are modeled together with the commitment state variable as usual. If the commitment state is off, the unit output will be zero.
- Ramp limits between hours are modeled linearly.
- Start-up and shut-down decisions are modeled as continuous variables, and their values decided by a dynamic relation between commitment states of consecutive hours.
- The power output for each hydro unit is decided by the higher level model of the DSS.
- The model forces the weekly thermal production of each plant to be equal to the decision of the medium-term hydrothermal coordination problem.

6 Conclusions

In this chapter we have presented a complete DSS that optimizes the decisions of a generation company by a hierarchy of models covering the long-term, medium-term, and short-term planning functions, see Fig. 7. The decisions taken from the highest model are passed to the lower level model and so on. These models are specially suited for representing a hydrothermal system with the complexities derived from

Table 2 Summary of characteristics of the models

	Long-term stochastic market planning	Medium-term stochastic hydrothermal coordination	Medium-term stochastic hydro simulation	Short-term unit commitment and bidding strategies
Scope	1 year	1 year	1 year	1 week
Time step	1 month	1 week	1 day	1 h
Stochastic variables	Fuel prices Hydro inflows aggregated monthly Demand	Hydro inflows aggregated weekly	Daily inflows	Residual demand curves
Stochastic representation	Monthly scenario tree	Weekly scenario tree	Series with given initial point	Daily scenario tree
Aggregation level	Hydro system aggregated by basins Thermal system aggregated by technologies	Hydro and thermal systems represented by units	Hydro units represented separately	Hydro units aggregated by offering unit Thermal units represented separately
Input data from higher level model	Risk management level (CVaR)	Hydro production for each month and basin Thermal production for each month and technology	Weekly water release tables for large reservoirs	Weekly production for thermal units Daily production for hydro units
Economic and operational decisions	Long-term fuel and electricity contracts Hydro production for each month and basin Thermal production for each month and technology	Budget planning Weekly water release tables for large reservoirs Weekly production for thermal plants	Daily production for hydro units	Bidding strategy for the next 24 h
Mathematical method	Mixed complementarity problem	Multistage stochastic linear programming	Monte Carlo simulation	Multistage stochastic mixed integer programming
Algorithm	Benders decomposition for mixed complementarity problems	Stochastic dual dynamic programming		Benders decomposition for MIP problems

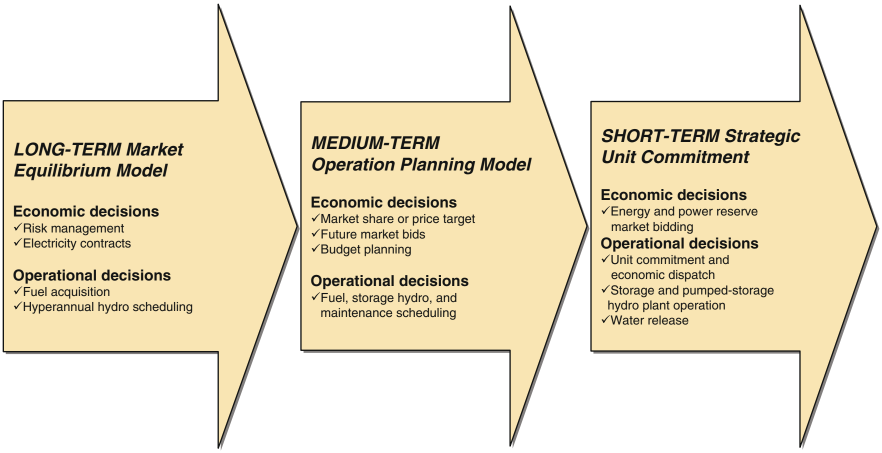

Fig. 7 Hierarchy of operation planning functions

hydro topology and stochastic hydro inflows that are conveniently incorporated into the models.

Table 2 summarizes the main characteristics of the models that are solved hierarchically passing the operation decisions to achieve the optimality of the planning process.

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