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Hydropower Scheduling in Large Scale Power Systems

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1. Introduction

Hydropower is the most important and widely-used renewable source of energy. Nearly one-fifth of the world's energy each year is supplied by hydroelectric power generation, which is more than solar, wind, biomass and all other renewable sources combined.

Brazil is the third largest producer of hydroelectricity in the world, preceded only by China and Canada. (Source: www.eia.gov). In 2009, hydropower accounted for 87 percent of Brazilian electric power generation, with smaller amounts coming from conventional thermal, nuclear, and other renewable sources. But managing a power system with over 110 GW of installed capacity, most of it coming from around 150 hydro plants, is a daunting task.

Hydro plants are located in 8 River Basins with specific hydrologic characteristics. Many of them are capable of storing water on reservoirs that can be used to regulate the river stream flow throughout the year, others are run-of-river plants and are subjected to seasonal river flows. Reservoir operations at a hydro plant affect the whole cascade downstream and the benefits of holding water for future use are not easy to estimate.

To illustrate these characteristics let us observe Itaipu Hydro Plant, with 14 GW of installed capacity, the hydro plant with the greatest generation in the world, located downstream from the Paraná River Basin on the frontier with Paraguay. Fig. 1 shows the average and standard deviation of its monthly inflows.

The seasonal behavior of the stream flow in the Parana River Basin is easily observed in Fig.1. The dry season goes from May to October, with average inflows around 6,000 m^3/s in August. The wet season goes from November to April, with average inflows around 16,000 m^3/s in February. Inflow variability is much higher during the wet season, as indicate the standard deviation values which are near 5,000 m^3/s in February and around 2,000 m^3/s in August.

Seasonal fluctuations are common in stream flow data and being able to smooth it and hedge unexpected events such as droughts and floods is a major concern in reservoir operation problems. Consumption of potable water, water usage for industrial and irrigation purpose, and also river flow control for navigation are some of the issues that constraint reservoir operation for hydropower generation.

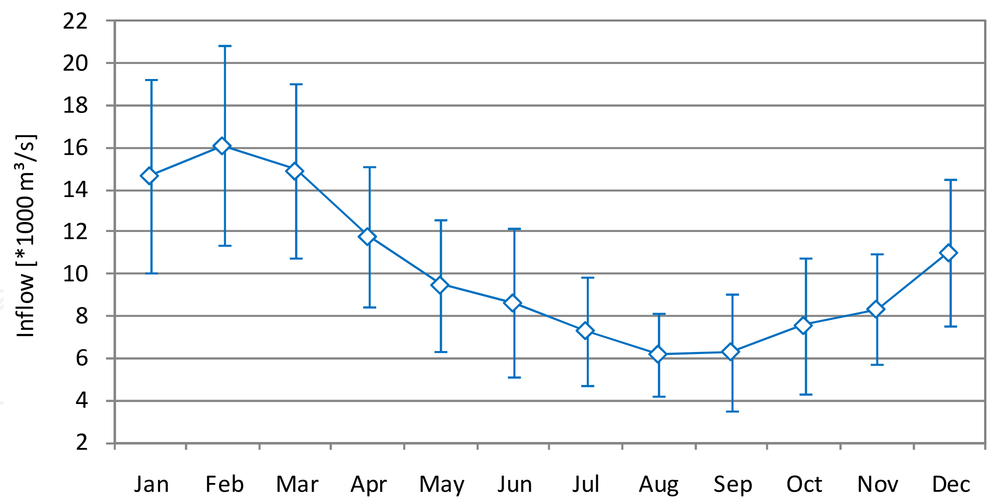

Fig. 1. Average and standard deviation of monthly inflows for the Itaipú hydro plant.

Upstream Itaipú, there are 57 hydro plants located on the several tributaries of the Parana River. The coordination of reservoir operation is extremely important since water is a limited resource and global hydropower generation can be increased if plants are dispatched concerning the whole river basin.

Moreover, stream flow profiles generally differ among River Basins according to the geographic region where they are located. For example, Fig.2 presents the average and standard deviation of monthly inflows for the hydro plants of Santo Antônio, in the Madeira River and Salto Caxias, in the Iguaçu River. The former is located in the northern region (N) of Brazil, flowing across the Amazon rain forest whereas the latter is located in the southern region (S).

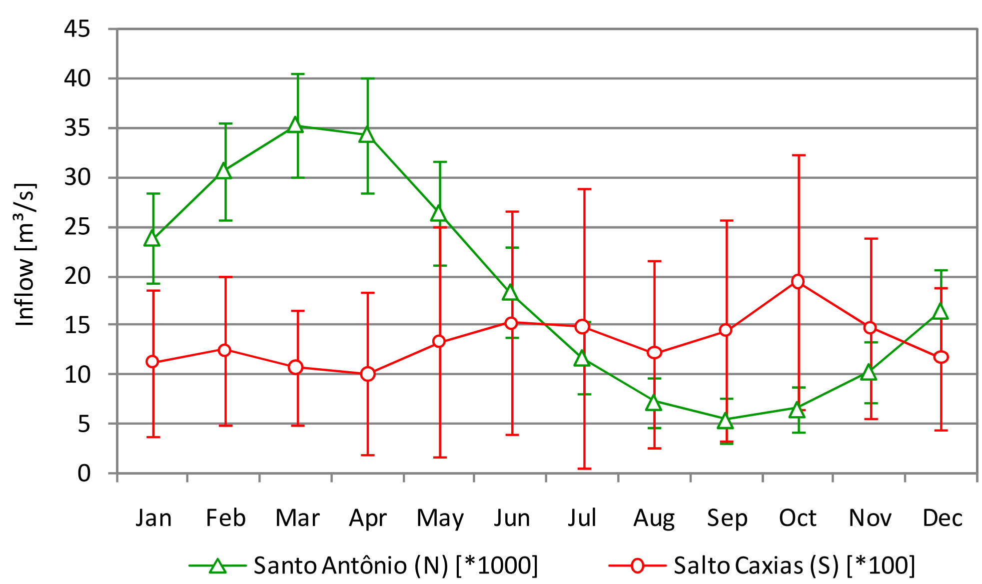

Fig. 2. Monthly inflow profile for two hydro plants located in the Northern (N) and Southern (S) regions of Brazil.

It is possible to observe that the seasonal profile is clearly defined for the northern river with very high inflows (10x greater than that of the southern river) and distinct wet and dry seasons. The minimum average value, in September, is 6.5 times greater than the maximum average inflow, in March. However for Salto Caxias, in the southern region, the inflows do not follow the same pattern. Average values range from 1,010 m^3/s to 1,946 m^3/s and standard deviations are high (over 55% of average) throughout the whole year, reaching 95% of average in the month of July.

Coordinated hydropower scheduling can take advantage from different seasoning so that power generation among regions can be complementary, if the transmission network supports the resulting power flow.

At this level, the basic question is how much water should be used to generate hydropower at the present and how much should be stored for future use. This decision is difficult due to the uncertainty of coming inflows. If the decision is to use increase use at present and the coming inflows are lower than expected, the future costs from thermal generation will be high. Otherwise, if the decision is to store more to the future and the coming inflows are high, there is risk of spillage, which means a waste of power resources. Stream flow forecasting is thus a fundamental issue to support system's operation, increasing benefits and reducing overall costs.

Above all this, one characteristic of hydropower systems deserves special attention: the conversion of water potential energy into electricity is a nonlinear phenomenon, typically expressed as a function of the hydraulic head and the rate of water flow. Nonlinear models should be used to estimate power plants' operation more precisely, especially when the planning horizon is straightened, and real time operation approaches.

Concerning the daily operation, the inflow variation is not an issue whereas meeting the load demand and attending the large set of power systems operating constraints turn it into a very complex scheduling problem. Consumers requirements must be met instant-to-instant because, at this level, the electric system is basically a huge electric circuit with alternating current. Besides the electric circuit laws, the system operation must consider many other aspects, such as forced outage (contingency), stability, voltage collapse, security constraints, multiuse of water and environmental requirements.

The total consumption varies instant-to-instant, but it presents a cyclic pattern as can be seen at Fig.3, which shows a week load, with one hour discretization. Every day there is a maximum load around 19:00h and a minimum load at day-break that reaches about 60% of the peak load.

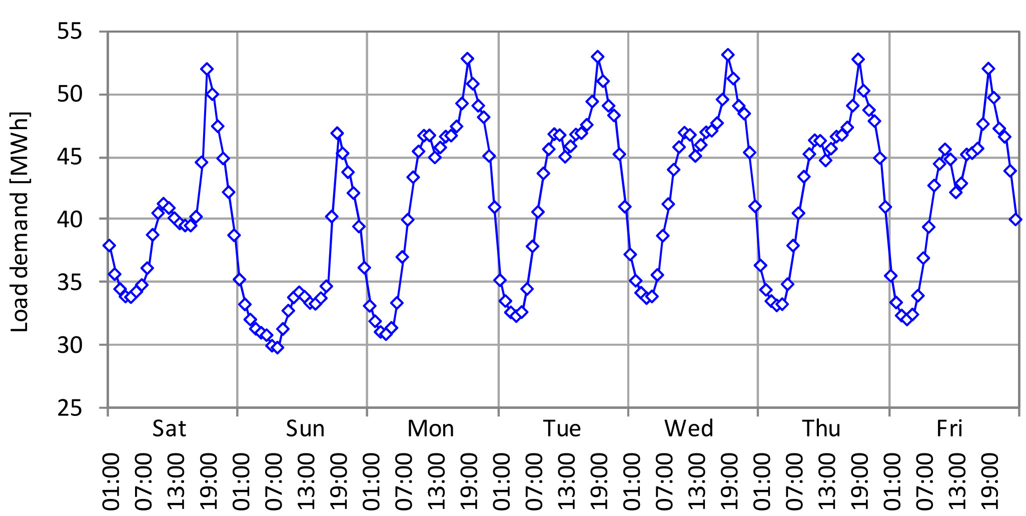

Fig. 3. Load demand curve for the Brazilian power system in a typical week.

In hydro dominant power systems the load tracking should be accomplished by hydro plants, which requires their generating units to be powered on and off along the day. The generating units in operation have great influence on turbine-generator efficiency so that deciding the commitment of hydro generating units constitutes a complex combinatorial optimization problem.

The government plays a substantial role in the management of the Brazilian electricity sector (BES). The operation planning of the Brazilian Interconnected System (BIS) is coordinated by an independent system operator (ISO) in accordance to operating rules agreed by the electric sector agents and supervised by a regulatory agency, within a tight pool market arrangement.

These rules aim to establish a coordinated hydrothermal scheduling (HS) for the whole system. The HS problem consists on the determination of a reliable and cost effective power plant dispatching that meets the load demands of the system at every time stage. This involves using the available generation resources optimally to reduce operating costs without compromising the security of the system operation in the future.

In practice, this task is accomplished by a set of optimization and/or simulation models, used to guide the HS of the BIS (Maceira, 2002). The models are connected in a chain that provides operating strategies for each instance of the HS problem, according to the time horizon it covers. These are:

a. Long-Term Hydrothermal Scheduling (LTHS)
b. Short-Term Hydrothermal Scheduling (STHS)

The LTHS problem consists on defining the generation scheduling decisions on a monthly basis for a planning period of several years (five years in the Brazilian case) that supply the load demands at minimum operating costs. The primary concern of this problem relies on uncertainties associated with the long planning horizon, especially regarding inflows. Some simplification in hydropower plants modeling can be acceptable and average values for turbine-generator efficiency can be taken for hydropower generation calculation instead of its nonlinear hill curve function, as it is considered in the Brazilian case.

The LTHS results are used to guide the operation on a short term basis. The monthly power generation decisions are disaggregated into weekly generation and the first week generation is established as a target to the STHS model which will provide a more detailed unit dispatch.

STHS aims to determine the thermal and hydro power outputs and the number of generating units dispatched at each hydro plant to meet the system load demand for each hour of the week ahead. The STHS is designed to optimize some performance criterion but also accomplish the average generation targets established by the LTHS, and respect the operational constraints of the power plants. Hydrologic aspects can be estimated more precisely so that the challenge at this step lies on the representation of systems nonlinearities and the attendance of the operating bounds, such as generation limits, ramp and spinning reserve limits, hydraulic system operation requirements, and transmission system capacities.

This chapter is organized in six sections. Sections 2 and 3 describe the LTHS and the STHS problems respectively, with some discussion on modeling and solution techniques. Section 4 presents the inflow forecasting models applied to the HS. Section 5 illustrates the power systems scheduling concepts in a case study comprising the Brazilian large scale power system. Finally, section 6 states the main conclusions of this chapter.

2. Long term hydrothermal scheduling

Long term hydrothermal scheduling (LTHS) for a multireservoir system consists on a quite complex optimization problem due to issues such as the long planning horizon to be analyzed (several years), the time dependence of decisions, the coupling of hydro plants in the same river basin, and the nonlinear relations involved in the hydro power generation functions and thermal costs. Above all this, the major concern in hydrothermal scheduling is the stochastic nature of inflows. Various approaches have been proposed to solve the LTHS problem and they can all be classified as either stochastic or deterministic according to the modelling of inflows (Labadie, 2004).

Stochastic approaches usually consider the uncertainty of water inflows on the basis of probability distribution functions and most of the applications use stochastic dynamic programming (SDP) as optimization tool (Stedinger et.al., 1984). SDP has been the most commonly used technique for the solution of the LTSH. Among its advantages there is the possibility to explicitly model the uncertainty of inflows and to represent important nonlinear relations inherent to the problem. However, for multireservoir systems, it requires some kind of simplification due to the intense computational requirements (Bellman, 1957).

One way of overcoming this problem is by aggregating multiple reservoirs to form a composite reservoir of energy (Arvanitidis and Rosing, 1970; Turgeon, 1980; Valdes et.al., 1995), and/or by piecewise linear approximation of nonlinear functions (Diniz et.al., 2008) (Dias et.al., 2010). This is the case of the methodology currently used in Brazil which is based on stochastic dual dynamic programming (SDDP) (Pereira and Pinto, 1991), using Benders decomposition (Pereira and Pinto, 1985) with nonlinearities in the power generation and future cost functions modelled as piecewise linear. This approach should be used carefully in large scale systems since it assumes a high correlation between inflows of the hydro plants within the composite reservoir which is not easy to observe in practice.

Deterministic approaches, on the other hand, take into consideration specific hydrological scenarios and provide solutions for individual plants. The stochastic aspects of the problem can thus be implicitly handled by the selection of such inflow scenarios and by the analysis of the optimal deterministic solutions associated with each one of them (Dembo, 1991) (Escudero et.al., 1996). The advantage of this approach, also known as implicit stochastic optimization or Monte Carlo optimization, is that nonlinear models can be directly applied even to large scale hydropower systems. The primary disadvantage is that operational policies are only optimal for the assumed hydrologic time series and deriving a general optimal operation rule may not be straightforward, but a more detailed model describing the operation for individual hydro plants is possible even for very large scale power systems.

Therefore, considering that this chapter is focused on large scale hydropower systems, the LTHS will be defined based on deterministic optimization in a framework of scenarios. The model named Optimal Dispatch for the Interconnected Brazilian National system (ODIN) is based on adaptive model predictive control (MPC) (Camacho and Bordons, 2004), an optimization framework widely applied in real-time control and industrial processes which can provide high quality suboptimal solutions for the LTHS problem with acceptable computational effort.

2.1 Problem formulation

In the LTHS optimization problem the primary goal is to supply the total load demand at minimum expected operating costs for a planning period of several years.

In a hydro dominant power system this source is used primarily for the load attendance but costs associated with hydroelectric power generation are considered to be negligible in relation to those of thermal generation. Therefore the operation can be evaluated by the thermal generation z using the cost function ψ_j which represents generation fuel costs associated to non-hydraulic sources j dispatched additionally to attend the load demand. Costs related to importing electricity from neighboring markets and energy deficits can be modeled in a similar way.

The objective function can thus be written as in Eq.1, and aims to define the hydro plants' releases q that minimize the expected costs of operation with respect to the inflows y, for a planning period with T stages. An interest rate λ_t is applied to calculate the present value of the monthly operating costs. J is the number of thermal plants in the system.

$$\min_{q} \underset{y}{\mathcal{E}} \sum_{t=1}^{T} \left\{ \lambda_t \cdot \sum_{j=1}^{J} \psi_j(z_{j,t}) \right\} \tag{1}$$

The load demand should be attained by the power sources available in the system as stated in Eq.2, where z and p are total thermal and hydro power generation, respectively. G is the power generation of small generation companies not explicitly controlled by the ISO, including hydro plants with less than 30MW of installed capacity and alternative energy sources, such as wind, solar and biomass.

$$z_t + p_t + G_t = D_t \qquad \forall t \quad (2)$$

Total power generation provided by thermal sources in a stage t is given by the sum of individual plants j constrained by their limits for operation, as stated in Eq. 3 and 4.

$$z_t = \sum_{j=1}^{J} z_{j,t} \qquad \forall t \quad (3)$$

$$Z_{j,t}^{\min} \leq z_{j,t} \leq Z_{j,t}^{\max} \qquad \forall j,t \quad (4)$$

In Eq.4 the minimum thermal generation at a stage t is defined by operational limits or imposed by contracts with fuel suppliers. The upper limit is determined by the generation capacity of the plant, which is the installed capacity discounting maintenance and unexpected outage factors.

Total hydro power generation is calculated in Eq.5 as the sum of the energy provided by each individual plant i in a set of I hydro plants during a stage t.

$$p_t = \sum_{i=1}^{I} p_{i,t} \qquad \forall t \ (5)$$

Hydro power generation of a single plant i is a nonlinear function of the water head $h_{i,t}$ and the discharge $q_{i,t}$, as expressed in Eq.6, where k is a constant factor representing the product of water density, gravity acceleration and a conversion factor that gives the energy production in MW. η_i is the turbine/generator efficiency that depends on water head and discharge. Although very important in STHS modelling, for LTHS the average efficiency can be considered for the sake of simplicity.

$$p_{i,t} = k.\eta_i.h_{i,t}.q_{i,t} \qquad \forall i,t \ (6)$$

The water head, in turn, is a nonlinear function of average reservoir storage x^{avg}, water discharged through the turbines q, and total water released from the reservoir u, as expressed in Eq. 7.

$$h_{i,t} = h_{Fi}(x_{i,t}^{avg}) - h_{Ti}(u_{i,t}) - h_{Li}(q_{i,t}) \qquad \forall i,t \ (7)$$

The forebay $h_F(x^{anv})$ and tailrace $h_T(u)$ elevations are calculated by 4th degree polynomial functions and the penstock head loss $h_L(q)$ is determined by a quadratic function of the discharge, but a percentage of the nominal water head or a constant can be used alternatively.

The system dynamics is stated in Eq.8 which describes the water balance in the hydro plants' reservoir.

$$x_{i,t} = x_{i,t-1} + \left(y_{i,t} + \sum_{k \in \Omega_i} u_{k,t} - u_{i,t} - ev_{i,t} - U_C \right).\gamma_t \qquad \forall i,t \ (8)$$

The reservoir storage $x_{i,t}$, of hydro plant i at the end of stage t, is thus given by the sum of the storage at the previous stage plus the total water flow received by the plant during that stage, converted to storage unit by a factor γ_t. The total inflow is determined by the sum of incremental average inflow $y_{i,t}$ plus the total water released from the set of plants Ω_i located immediately above hydro plant i in the same river basin, minus the water released from plant i. Evaporation $ev_{i,t}$ is represented as a nonlinear function of the reservoir storage, and amounts of water taken from the reservoir for alternative purposes U_C are also considered.

The average reservoir storage used in the forebay elevation function (Eq. 7) is thus stated in Eq.9.

$$x_{i,t}^{avg} = \frac{x_{i,t-1} + x_{i,t}}{2} \qquad \forall i,t \ (9)$$

Total water release u is composed by the sum of water discharge q through the turbines plus the water spilled v over the spillways.

$$u_{i,t} = q_{i,t} + v_{i,t} \qquad \forall i,t \ (10)$$

Operating constraints are expressed by Eq. 11 to 14

$$X_{i,t}^{\min} \le x_{i,t} \le X_{i,t}^{\max} \qquad \forall i,t \quad (11)$$

$$u_{i,t} \ge U_{i,t}^{\min} \qquad \forall i,t \quad (12)$$

$$q_{i,t} \le q_{i,t}^{\max}(h_{i,t}) \qquad \forall i,t \quad (13)$$

$$v_{i,t} \ge 0 \qquad \forall i,t \quad (14)$$

Lower and upper bounds on variables are imposed by the physical operational limits of the hydro plants, as well as the limitations associated with multiple uses of water. For example, the lower bound for reservoir and release can vary over time to allow navigation, water supply, irrigation and recreation. The upper bound for reservoir can be imposed for purpose of dam safety and flood control. The upper limit for the discharge in Eq. 13 is also a nonlinear function of water head.

2.2 Solution technique: model predictive control

The MPC approach corresponds to an operational policy for LTHS problems based on an open loop feedback control framework. The stochastic aspects of the problem are implicitly handled by the use of expected inflow values and an accurate representation of the generating plants' operational characteristics is possible since optimal dispatch for individualized plants at each stage is obtained from a deterministic nonlinear optimization model.

The decision-making process runs under a simulation model in which the discharge decisions are implemented. This means that for each stage of the simulation procedure, the forecasting and optimization models should be executed over an optimization horizon in order to obtain the discharge decisions to be implemented for the first stage of each optimization.

The feedback control scheme is assured since for each stage the optimization model updates the discharge decisions as a consequence of the new inflow forecasting sequence and of the new initial reservoir storage resulting from the previously simulated water balance.

Previous tests with this approach, focusing specifically on the uncertainty of inflows, evaluated the results for single reservoir systems where dimension is not an issue (Martinez and Soares, 2002; Zambelli et.al. 2009). The approach has shown results equivalent to those of standard methods based on stochastic dynamic programming.

An outline of the MPC operational policy for the LTHS problem is shown in Fig. 4 where, for a given stage t of the simulation horizon, the hydro system is observed and the reservoir storage levels x_{t-1} are taken as the initial condition for the deterministic optimization model that must solve the LTHS problem for a given optimization horizon T^*.

The optimization regards a series of predicted values for the unknown parameters to be considered, in this case, water inflows, determined by the Predictor module, based on past observed values.

The Optimizer module then provides optimal releases for each hydro plant for the optimization horizon but only the discharge decision for the first stage q^*_t is selected and submitted to a simulation model. The latter calculates the consequences of such decision in terms of storage and generation considering the inflow being simulated and makes the necessary corrections, if needed, according to formulation (1)-(14). Corrections are frequently needed due to differences between the predicted inflow series $\bar{y}$ and the simulated inflow series y.

In the following stage *t+1*, the storage level of the reservoirs resulting from simulation is observed, and a new forecasting of inflows is provided based on the latest available information. This procedure of "forecast-optimize-update" is repeated until the end of the planning horizon *T*.

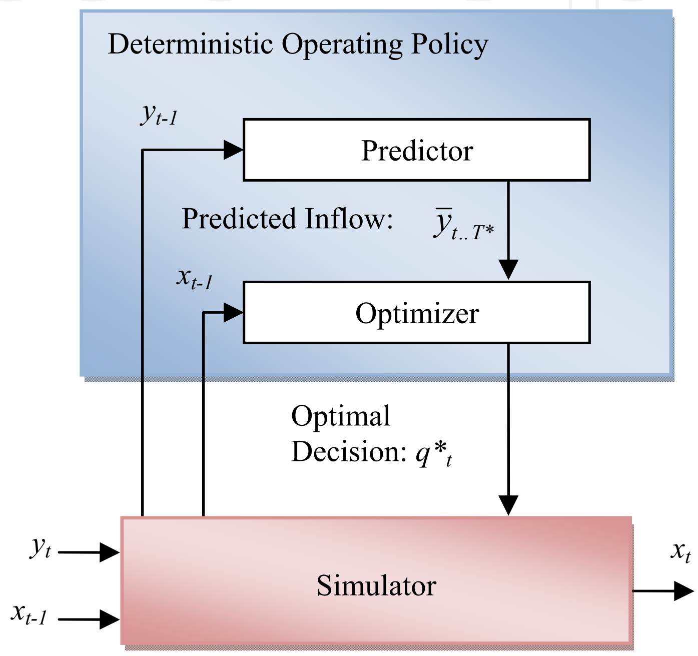

Fig. 4. Model predictive control scheme.

One important aspect affecting the performance of the MPC approach is the boundary conditions of the optimization model in terms of the final storage of the reservoirs and the optimization horizon. Results from the optimization model over the whole period of historical inflow records assuming perfect foresight of inflows indicate that the reservoir storages at the beginning of each dry season are almost always full. With this in mind, the optimization horizon implemented by the MPC approach reported in this paper adopts a rolling horizon of at least 13 months and at most 24 months ahead, depending on the current monthly stage. Full reservoir storage is imposed as a boundary condition at the end of this horizon, adjusted to match the month of April as it is the end of the wet season in almost all the Brazilian river basins. These parameters were estimated based on successive simulation tests with various considerations and have shown to maximize the approach performance.

In the MPC approach the deterministic nonlinear optimization model (1)-(14) can be solved using specialized optimization techniques such as network flow algorithms with capacitated arcs (Oliveira and Soares, 1995) or interior point methods (Azevedo, et. al. 2009). The former was used in the case study presented in section 5. The thermal part of the problem (3)-(4) is determined afterwards by an economic dispatch algorithm (El-Hawary and Christensen, 1979).

3. Short term hydrothermal scheduling

Short-term hydrothermal scheduling (STHS) considers a planning period of one week on an hourly basis. At this step, the two major decisions are the start-up and shutdown of generation units and the generation levels of online units at each time interval. The first decision is called Unit Commitment (UC) and the second is called Generation Schedule (GS). In a hydro-dominant power system, the start-up and shutdown of generating units are concentrated on hydroelectric plants since they should provide the load tracking in order to keep the thermoelectric units operating on a flat dispatch.

The approach presented in this chapter for the STHS is based on optimization models and heuristic procedures and considers some specific characteristics of hydro-dominant systems that make it different from the approaches designed for thermal-dominant power systems, either in terms of performance criterion and problem constraints. In this section the performance criterion adopted is presented as a composition of hydro efficiency loss functions and start-up/shutdown costs of the generating units.

3.1 Performance criterion

3.1.1 Efficiency loss functions for hydroelectric plants

One important characteristic of the operation planning chain for hydro-dominant power systems is that the LTHS establishes the generation target for each hydro plant during the next week. Therefore, an adequate objective function for the STHS should be to generate this target using the lowest possible amount of water. Thus the optimization criterion adopted in this chapter considers the hydro generation efficiency through loss functions expressed in MW (Soares and Salmazo, 1977).

The goal is to represent the generation loss at each hydro plant as a function of its power output. For a given forebay elevation, the increase in generation is accomplished by increasing discharge at each generating unit in operation. This implies on variations of tailrace elevation, penstock head loss and turbine-generator efficiency. The following analysis presents in details the aspects that influence the generation efficiency of a hydro generating unit.

By efficiency of a hydro generating unit it is meant the ratio between power output and discharge input. In mathematical terms, from Eq. 6 and 7, the production function of a hydro plant is given by Eq. 15.

$$p = k.\eta.\{h_F(x) - h_T(u) - h_L(q)\}.q \tag{15}$$

where the indexes were dropped out for the sake of simplicity. The generation efficiency of a hydro plant, given by the ratio between power output and discharge input, also called plant productivity, depends on the turbine-generator efficiency η, the tailrace elevation h_T, and the penstock head loss h_L, and consequently depends on storage x, discharge q and release u.

Fig. 5 shows a typical turbine-generator efficiency curve, also called *hill curve*, of a generating unit. As can be seen, the turbine-generator efficiency depends on net water head and discharge.

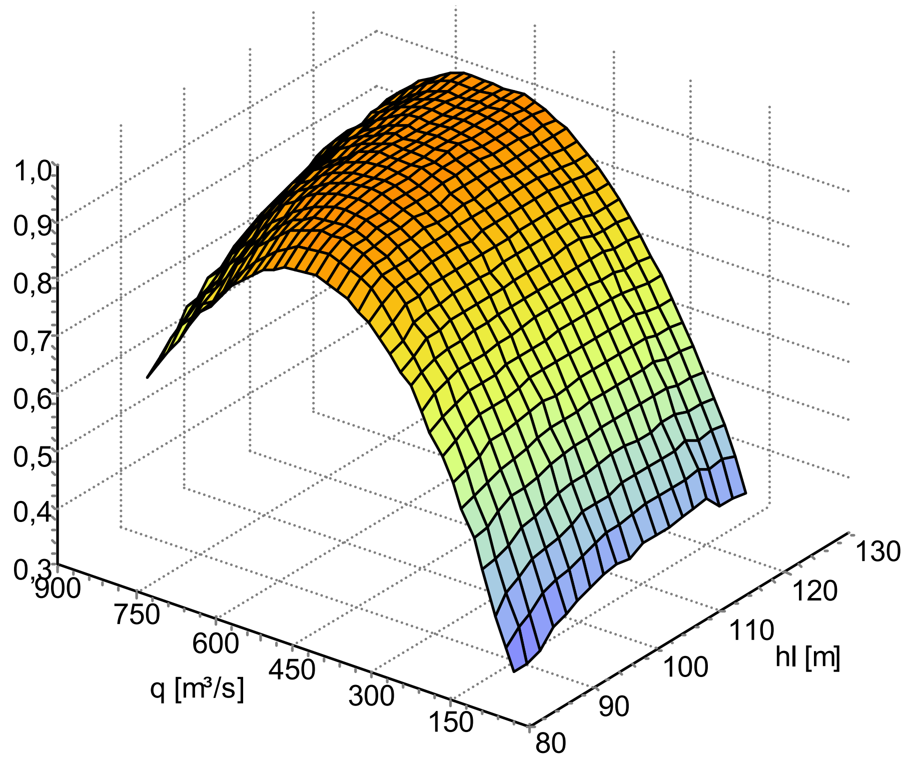

Fig. 5. Turbine efficiency curve (hill curve) of a hydro generating unit.

The hydro efficiency will be measured by the power loss in generation due to variations on turbine-generator efficiency and net water head. These variations will be calculated in MW in order to be compared on the same basis (Soares and Salmazo, 1997). The hypothesis of identical generating units is assumed, which is true for almost all hydro plants. Thus, for a given number of generating units in operation, the power loss in generation due to variations on tailrace elevation can be calculated as Eq. 16.

$$p_T = k.\eta.\left\{ h_T(u) - h_T^{ref} \right\}.q \tag{16}$$

where h_T^{ref} is the tailrace elevation assumed as a reference. In a similar way, the power loss in generation due to variations on penstock head loss can be computed as Eq. 17.

$$p_L = k.\eta.\left\{ h_L(q) - h_L^{ref} \right\}.q \tag{17}$$

where h_L^{ref} is the penstock head loss assumed as a reference. Finally, the power loss in generation due to variations on turbine-generator efficiency can be calculated as Eq. 18, where η^{ref} is the turbine-generator efficiency assumed as a reference.

$$p_\eta = k.\left\{ \eta(q) - \eta^{ref} \right\}\left\{ h_F(x) - h_T(u) - h_L(q) \right\}.q \tag{18}$$

Fig. 6 shows the loss curves for a given hydro plant with a total of 4 generating units and 1192 MW of installed capacity. Part A details each one of the losses in generation and the total loss with 1 unit on. Part B presents the total loss curves for one up to four generating units.

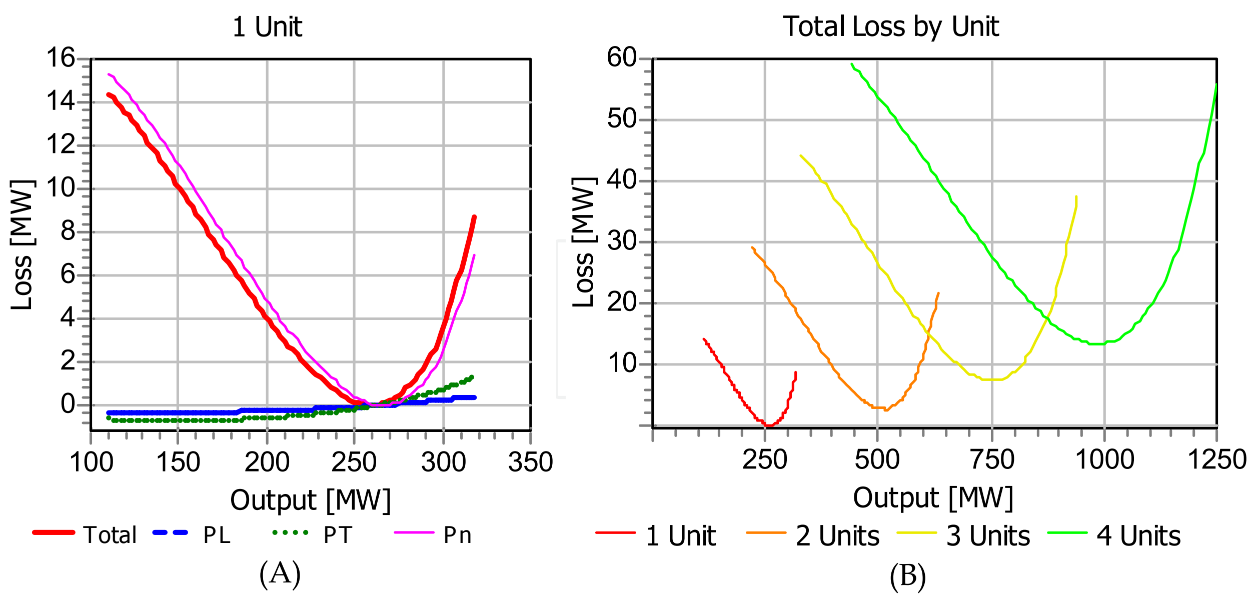

Fig. 6. Loss curves for a hydro plant with A) one and B) several generating units.

In Fig. 6 (A) the three types of generation loss are depicted as well as the total one. It can be noted that the minimum total loss occurs at around 250 MW of output, which is the point adopted as a reference for Eq. (16)-(18). Therefore, at this point the total loss is minimal by construction, and corresponds to the maximal productivity of the hydro plant. It is interesting to observe that the best point in terms of turbine-generator efficiency is around 260 MW whereas the best point in terms of productivity is around 250 MW. This difference is due to the impact of tailrace elevation and penstock head loss over plant's productivity.

In Fig. 6 (B) it is possible to notice that a certain desired output can be provided by multiple unit dispatches, thus the minimum loss criterion helps to define the optimal solution.

3.1.2 Start-up and shutdown costs in hydroelectric plants

Load demand presents significant variations during each day and week. As load increases a larger number of generating units should be committed to power generation and the opposite occurs when the load decreases, once generation should track the load. These frequent start-up and shutdown of generating units should be avoided as much as possible since they represent an increase on tear and wear of the units, reducing their operational life.

For dominant thermal systems the load tracking is most performed by thermal plants and the corresponding start-up and shutdown costs of such units as well as operational constraints such as minimum down and up times of units, rump up and down limits must be considered. For hydro dominant systems, on the other hand, the load tracking can be exclusively performed by hydro plants whose operational constraints and start-up and shutdown costs are less restrictive than for thermal ones. Nilsson e Sjelvgren (1997) estimate that in Sweden the start-up and shutdown costs of hydro generating units are around 3 US$ per MW. This value was adopted in the case study presented in this chapter.

3.2 Problem formulation

The STHS is formulated as a mixed integer nonlinear programming problem whose main goal is to minimize operating costs along a certain planning horizon T on an hourly basis.

The objective function includes the start-up and shutdown costs c_i^s of hydro generation units, the generation loss of hydro plants f_i and the generation costs of thermal plants f_j, as expressed in Eq. 19.

$$Min \quad \sum_{t=1}^{T} \left\{ \sum_{i \in I} \left[c_i^s \left| n_{i,t} - n_{i,t-1} \right| + c^{MW} f_i(n_{i,t}, p_{i,t}) \right] + \sum_{j \in J} f_j(z_{j,t}) \right\} \quad (19)$$

where $n_{i,t}$ is the number of generating units on operation at hydro plant i and stage t; z and p are thermal and hydro power generation, respectively; and c^{MW} is the energy price.

The load demand D should be attained at each stage by the summation of hydro and thermal generation, as in Eq. 20.

$$\sum_{i \in I} p_{i,t} + \sum_{j \in J} z_{j,t} = D_t \qquad \forall t \quad (20)$$

Eq. 21 imposes that each hydro plant should meet the generation targets m_i, provided by the LTHS.

$$\sum_{t=1}^{T} p_{i,t} = m_i \qquad \forall i \quad (21)$$

Spinning reserve requirements are established by eq. 22 where $r_{k,t}$ is the spinning reserve constraint k at stage t for the set of plants $R_{k,t}$, where this constraint applies, and the set of stages T_r, when it holds.

$$\sum_{i \in R_{k,t}} (p_i^{\max} - p_{i,t}) \geq r_{k,t} \qquad t \in T_r ; k = 1..n_{r,t} \quad (22)$$

Eq. 23 defines the ramp limits where $s_{k,t}$ is the maximal ramp at constraint k and stage t for the set of plants $S_{k,t}$, where this constraint applies, and the set of stages T_s, when it holds.

$$\left| \sum_{i \in S_{k,t}} (p_{i,t} - p_{i,t-1}) \right| \leq s_{k,t} \qquad t \in T_s ; k = 1..n_{s,t} \quad (23)$$

Eq. 24 and 25 represent the limits on hydro and thermal generation, respectively. The hydro generation limits vary according to the number of committed generating units.

$$p_i^{\min}(n_{i,t}) \leq p_{i,t} \leq p_i^{\max}(n_{i,t}) \qquad \forall i,t \quad (24)$$

$$Z_j^{\min} \leq z_{j,t} \leq Z_j^{\max} \qquad \forall j,t \quad (25)$$

The limits on the number of generating units associated with a given hydro generation can be defined as in Eq. 26.

$$n_i^{\min}(p_{i,t}) \le n_{i,t} \le n_i^{\max}(p_{i,t}) \qquad \forall i,t \quad (26)$$

The water balance at each reservoir is expressed by Eq.27 where the reservoir storage $x_{i,t}$, of hydro plant i at the end of stage t, is given by the sum of the storage at the previous stage plus the total water flow received by the plant during that stage, converted to storage unit by a factor γ_t. The total inflow is determined by the sum of incremental average inflow $y_{i,t}$ minus the water released from plant i ($u_{i,t}$), plus the total water released from the set of plants Ω_i located immediately above hydro plant i in the same river basin, considering the number of stages $\theta_{m,i}$ for water displacement between plants m and i.

$$x_{i,t} = x_{i,t-1} + \left(y_{i,t} + \sum_{m \in \Omega_i} \left(u_{m,t-\theta_{mi}} \right) - u_{i,t} \right) . \gamma_t \qquad \forall i,t \quad (27)$$

Constraints in Eq. 28 and 29 establish limits for storage and discharge, respectively.

$$X_{i,t}^{\min} \le x_{i,t} \le X_{i,t}^{\max} \qquad \forall i,t \quad (28)$$

$$q_i^{\min} \le q_{i,t} \le q_i^{\max} \qquad \forall i,t \quad (29)$$

Finally, Eq. 30 defines the initial reservoir storages and number of generating units and Eq. 31 imposes that the number of generating units available at the hydro plants is an integer.

$$n_{i,0} ; x_{i,0} \quad given \qquad \forall i \quad (30)$$

$$n_{i,t} \in N \qquad \forall i,t \quad (31)$$

3.3 Solution technique

The detail representation of the generating units in the operation of the hydro plants, which requires the consideration of integer and continuous variables, turns the STHS into a mixed integer nonlinear optimization problem whose solution is quite difficult for large scale systems such as the Brazilian one. In order to overcome this difficulty, a solution technique based on optimization-simulation decomposition is proposed (Kadowaki et. al., 2009). This decomposition is motivated by the fact that most of the hydraulic constraints (28) and (29) are not active at the optimal solution. This suggests a relaxation approach by which the hydraulic constraints (27), (28) and (29) are relaxed during the optimization phase, performed by the optimization model, but are considered during the simulation phase, performed by the simulation model.

The optimization model determines the number of generating units in operation at each hydro plant and stage and their respective generation schedule, as well as the generation at each thermal plant and stage that attains the load demand, the generation targets of the power plants and the limits on ramp, spinning reserve, generation and number of available generation units. After solving the optimization model, the solution obtained ($p_{i,t}$*, $n_{i,t}$*) is simulated at the simulation model in order to identify violations on the relaxed constraints. If violations are identified new constraints are included in the optimization model optimization in order to eliminate them, and this procedure is repeated until all the hydraulic constraints are satisfied.

Figure 7 shows the iterative procedure that implements the optimization-simulation decomposition approach.

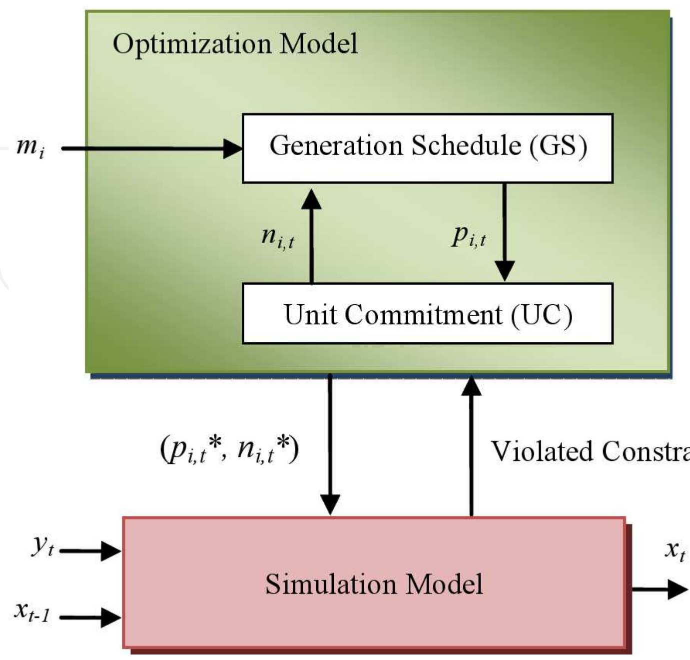

Fig. 7. Relaxation approach for solving the STHS problem.

The optimization model, by its turn, is also decomposed into two sub-problems: the UC sub-problem, that determines the number of generating units in operation at each hydro plant and stage for a given power generation, and the GS sub-problem, that determines the generation at each hydro plant and stage for a given number of generating units in operation. These sub-problems are solved iteratively until convergence is achieved when no more changes occur in the solution. The UC sub-problem is an integer nonlinear optimization problem for each hydro plant and can be efficiently solved by dynamic programming. The GS sub-problem, by its turn, is a continuous nonlinear programming problem that can be efficiently solved by Newton method, on a relaxation framework with respect to the inequality constraints.

4. Inflow forecasting

Forecasting of river inflows is an important input for planning and scheduling of hydroelectric power system, converting the cleaner energy stored in water reservations into electric energy and planning and managing water resources as effectively as possible (Al-Zùbi, et. al., 2010).

In spite of the economic and environmental aspects involved the fact that most of the electricity in Brazil comes from hydroelectric power plants makes the development of accurate inflow forecasting models essential.

These models need to be able of dealing with the dynamics, uncertainty and nonlinearities inherent to natural phenomena. The necessity of models with the capability of processing uncertainties is reinforced by the presence of missing data and the production of wrong values due to technical or human error.

In that sense, several researches have been devoted to the formulation and development of accurate inflow forecasting models. In general, the river flow models are assigned to one out of three broad categories: deterministic, conceptual or parametric.

Deterministic models describe the rainfall-runoff process using physical laws of mass and energy transfer. Conceptual models provide simplified representations of key hydrological process using a perceived system. Parametric models use mathematical transfer functions to relate meteorological variables to runoff (Dawson & Wilby, 2001).

Deterministic and conceptual models require a large amount of high-quality data associated with hydrological, meteorological and natural geographical characteristics as well as human activities. In general, all the information required by deterministic and conceptual models – such as soil moisture and evapotranspiration- are not available for all the basins under consideration, especially when we are dealing with a large scale system such as the Brazilian one.

On the other hand, parametric models do not foreshadow a detailed understanding of the basin's physical characteristics, nor does it require extensive data pre-processing (Zhang, et. al., 2009).

Following this line of modelling, different approaches for inflow forecasting based on computational intelligence have emerged as an alternative for building inflow time series forecasting models. They are particularly powerful in situations where it is difficult to determine the physical process or when it is not possible to obtain a physical interpretation of the mathematical model representation (Price, 2008).

The main attribute associated to neural networks are the ability of modelling non-linear mapping between variables involved in several areas, including hydrology, where the most common structures are neural networks (Maier & Dandy, 2000; Bowden, et. al., 2005; Othman & Naseri, 2011) and radial basis functions (Jayawardena, et. al., 2006; Lin & Wu, 2011).

During the last decades, several proposals based on fuzzy systems and hybrid models have also found increasing applications in hydrology (Nayak, et. al., 2004; Luna, et. al., 2009), possible (Al-Zùbi, et.al., 2010). Fuzzy systems are useful to model uncertainties presented in hydrological variables, increasing flexibility for modelling the nonlinear relationships; and when combined with nonlinear optimization techniques, they appear as a very promising approach, obtaining structures that can be interpreted on the basis of IF-THEN rules.

Zambelli et. al. (2009) used an offline Fuzzy Inference System (FIS) for predicting annual inflows that are disaggregated into monthly samples used for long-term hydropower scheduling. Luna et. al. (2009) used an adaptive version of the FIS for the daily inflow forecasting of several basins and hydroelectric plants, considering precipitation information and the last inflows registered as input variables. The results of the adaptive FIS outperformed the ones achieved by a conceptual model for a short term forecast horizon, whereas the combination of both results outperformed the independent ones for longer lead times.

Therefore, this work makes use of Takagi-Sugeno FIS (Takagi & Sugeno, 1985), for monthly, weekly and daily inflow forecasting. The learning algorithm is based on the unsupervised clustering algorithm Subtractive Clustering (SC) (Chiu, 1994) and the offline version of the Expectation Maximization (EM) algorithm (Jacobs, et. al., 1991). The model structure and optimization algorithm is fully detailed in (Luna, et. al., 2010).

4.1 Monthly inflow forecasting

Two approaches were considered for obtaining the monthly inflow forecast sequences necessary for the PC approach.

4.1.1 Monthly models (FIS-M)

The seasonality of the monthly flows under study suggests the use of twelve independent models, as the technique traditionally used for the BES based on periodic autoregressive models (Maceira and Bezerra, 2007).

Therefore, the first approach adopted in this work consists of adjusting twelve different FIS models, one for each month of the year. Generally, these models are optimized by considering a one-step-ahead forecast error, which results in the degradation of performance when applied to a long-term forecasting task, although their performance is relatively good for one-step-ahead inflow forecasting.

Besides, the model complexity is in part limited by the size of the historical records available, due to the large amount of data necessary for the adjustment of all the model parameters.

In order to determine adequate models considering both accuracy and complexity, models were selected by the evaluation of the Bayes Information Criterion (BIC), which considers not only the reduction of the Root Mean Square Error (RMSE) but also the model complexity represented by the number of parameters to adjust.

Inflow data is normalized to the unit interval. Input variables were selected from a set of possible inputs composed by the last six lags of the time series. Input-output data set was split up into two subsets, the training set used for model optimization and the testing set used for validation and testing. Validation and testing sets were kept the same because of the limited duration of the historic inflow time series available.

Hence, monthly models were obtained through the following procedure

1. Build the input-output patterns considering a subset of possible inputs;
2. Define the initial set of fuzzy rules via the SC algorithm and the input-output patterns built previously;
3. Optimize the model parameters by the EM algorithm and
4. Evaluate the BIC penalization function.

The model with the lowest BIC was the chosen one. For a multi-step ahead forecasting task, these models were fed back with previous forecast results.

4.1.2 Annual models (FIS-A)

The second approach is based on the reduction of the long-term forecasting error by using a top-down forecast strategy (FIS-A). Top-down forecasting (TD) is extremely useful for improving the accuracy of detailed forecasts, since errors are compensated and variations can cancel each other out (Lapide, 2006).

The FIS-A approach predicts the aggregation of the twelve future monthly inflow samples (the aggregate inflow for the next year from the current month) by adjusting a unique model on an annual basis.

Input and model selection was also performed considering the BIC penalization function, following the procedure adopted by the FIS-M approach.

Consequently, the forecast results were disaggregated into the respective monthly estimates. This disaggregation was performed using the historical contribution factors of each month of the year, based on long-term average values.

4.2 Weekly inflow forecasting

Weekly inflow forecasting is essential for an adequate dispatch of generation of hydropower plants in the SIN. Weekly inflow time series for every hydropower plant in the SIN is composed by fifty two weeks a year. Figure 8 shows historical mean and standard deviation of weekly inflow time series for Furnas UHE, where we can observe a high variability during humid periods (at the beginning and at the end of the year).

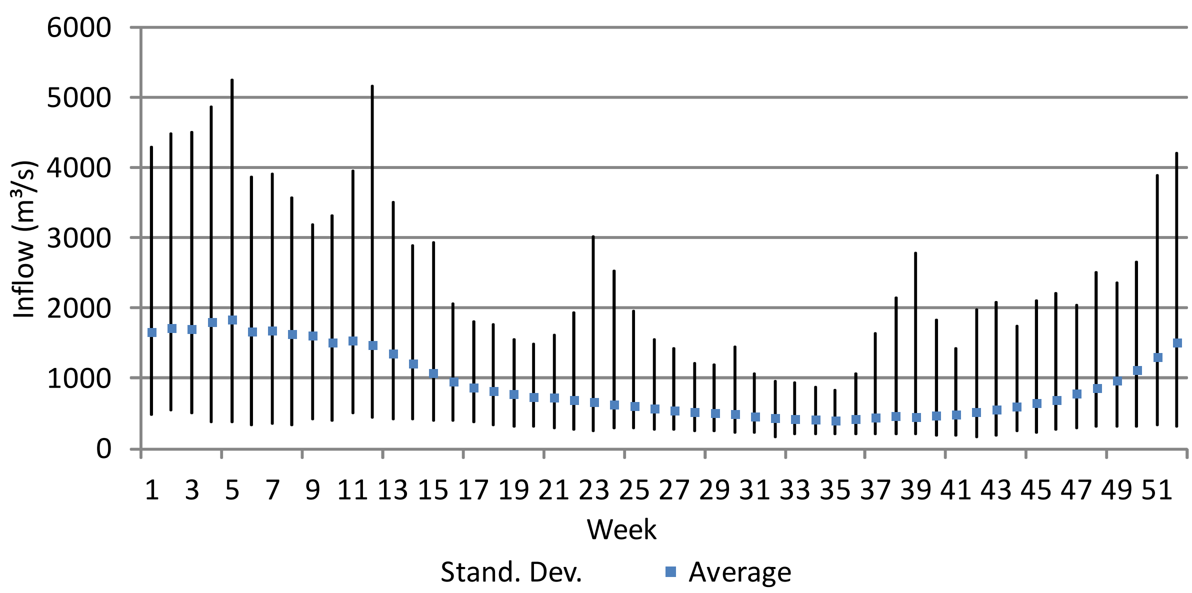

Fig. 8. Weekly historical average and standard deviation for Furnas UHE.

Even though each week has its own characteristics, it is not possible to adjust a model for each week, mainly because of the short historical series and the large scale of the problem addressed in this work. Therefore, we chose the setting of a single model for each UHE. The model adjusted following the procedure adopted by the FIS-M approach was used for a multi-step ahead forecasting task, considering a lead-time varying from one up to five weeks ahead.

5. Case study

In order to illustrate the application of the concepts described in the previous sections a case study simulating the monthly operation schedule from June, 2011 to December, 2015 for the whole Brazilian power system was considered. It comprises 147 hydro plants (95.6 GW of power capacity) and 144 thermal plants (32.4 GW of power capacity) with real operative constraints and the expansion plans for a planning horizon of 55 months ahead.

The MPC approach is usually implemented and simulated on a monthly basis in a framework of scenarios. Inflow series are taken from historical database, extending from

1936 to 2010, comprising 75 scenarios of 55 months each. In this paper, however, due to limitations in space, only two scenarios were considered: a favourable one (A) corresponding to the scenario beginning on June, 2005 and an unfavourable one (B) corresponding to a scenario beginning on June, 1952.

All constraints presented in the formulation of the optimization problem (1)-(14) have been considered in the simulation. The forebay h_F and tailrace h_T elevations were represented by 4th degree polynomial functions and the penstock head loss h_L by a linear function.

System data used for the case study were taken from official data source, accessible online (www.ons.org.br), and reflect the system configuration by June/2011.

The expected values of inflows used by the optimization model within the MPC framework were given by the FIS forecasting model described on section 4.1 and considered two strategies: monthly forecast (FIS-M) and annual forecast (FIS-A). In the latter the monthly values are derived from the relative contribution of long-term average values of historical inflows for each month to its annual value.

5.1 LTHS results

The simulation results for both inflow scenarios and considering the two inflow forecasting approaches presented on section 4.1 are summarized in table 1.

Favorable scenario (A)

	Cost [Million US$]	Hydro Gen. [MW]	Termal Gen. [MW]	Final Storage [MW-month]
FIS-M	7.307,22	53894,30	647,70	217347,00
FIS-A	7.526,52	53778,10	764,00	228997,00

Unfavorable scenario (B)

	Cost [Million US$]	Hydro Gen. [MW]	Termal Gen. [MW]	Final Storage [MW-month]
FIS-M	65.610,75	43837,5	10704,5	50478,8
FIS-A	48.459,70	44022,0	10519,8	45783,3

Table 1. Simulation results from MPC approach.

As can be seen, there are no significant differences on the favourable scenario with respect to the forecasting inflow approach considered. While the cost is slightly lower (3%) for the FIS-M approach, the final storage is also slightly lower (5%), resulting on quite similar performances. For the unfavourable scenario, however, the expressive higher performance of the FIS-A approach in terms of cost (26%) is not compensated by its slightly lower final storage (9%). This is an interesting feature of the proposed approach since it is on the most critical inflow situations, where the operational costs are higher, that the annual inflow approach provides better performances.

The evolution of the system's stored energy with both approaches and inflow scenarios is presented in Fig. 9. The stored energy is calculated by the sum of the useable water on the reservoir of each hydro plant pounded by the average cumulative productivity of this plant, which in turn is the summation of the efficiencies of all hydro plants located downstream.

It is possible to notice that the FIS-A approach yields to higher stored energy in both inflow scenarios. In general, the system's reservoirs go down in the dry season as a consequence of using the water to regulate river's flow. During the wet season the reservoirs recover to near full levels. This behavior is observed for the favorable scenario (A) as the stored energy presents peaks and valleys around the months of April and November, respectively, which constitutes the beginning and ending of the wet season in the majority of Brazilian's River Basins.

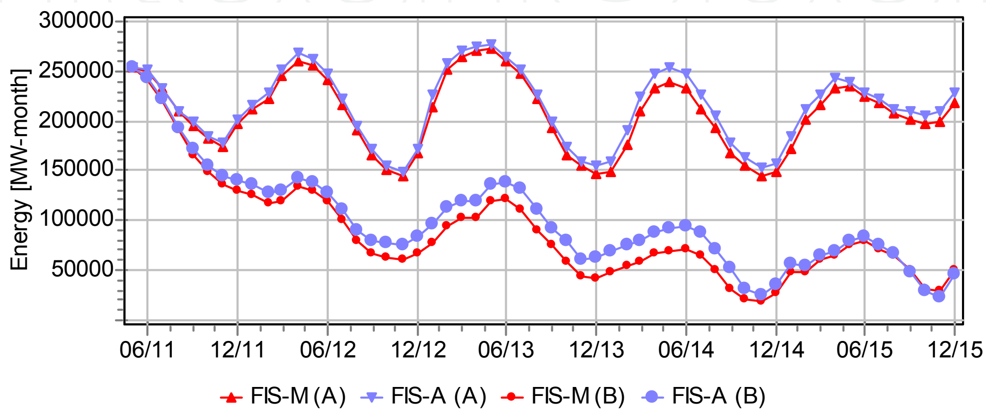

Fig. 9. Stored Energy evolution.

However, in the unfavorable scenario (B), the reservoirs are unable to recover and the stored energy is reduced year by year. Differences between the monthly and annual approaches are more expressive and reach 24.2 GW-month of stored energy in May, 2014. This is a consequence of the better inflow forecast with FIS-A since optimal decision intend to preserve the water reserves but inflow errors are compensated in simulation by increasing the plant's releases.

In Fig. 10 the operating costs are presented with both approaches and inflow scenarios. A cut was done in December, 2013 to allow rescaling in the remaining period.

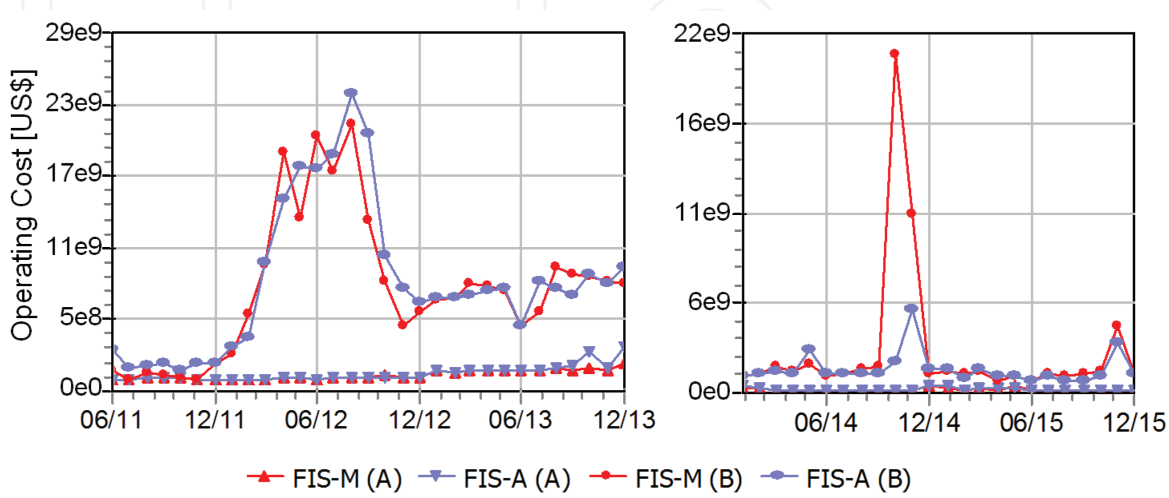

Fig. 10. Operating costs evolution.

In the favorable scenario (A) the operating costs are very close and in the first two years they suggest that thermal dispatch is near minimal. Nevertheless in the unfavorable scenario (B) the costs are higher and the FIS-M approach presented a maximum of 22 billion dollars in October, 2014 related to the lack of power supply to meet the demand. FIS-A approach not only avoids this deep energy shortage but also presents smoother cost variations which indicates less volatile energy prices.

The higher costs incurred by this approach in the first year are a consequence of the anticipation of thermal dispatch to save water and gain efficiency in the hydro plants. This phenomena known as *head effect* is related to the fact that operating with higher water heads the plants can deliver more power with the same (limited) water supply, a feature which is only possible to reproduce with nonlinear optimization models.

Three cascaded hydro plants were selected to present further detail of the individual operation with FIS-A for the favorable inflow scenario. Plants 1 and 2 have accumulation reservoirs whereas Plant 3 is a run-off-river plant. Plant 1 is the most upstream and plant 3 the most downstream in this river. Fig. 11 shows the reservoir storage trajectory for the three cascaded hydro plants.

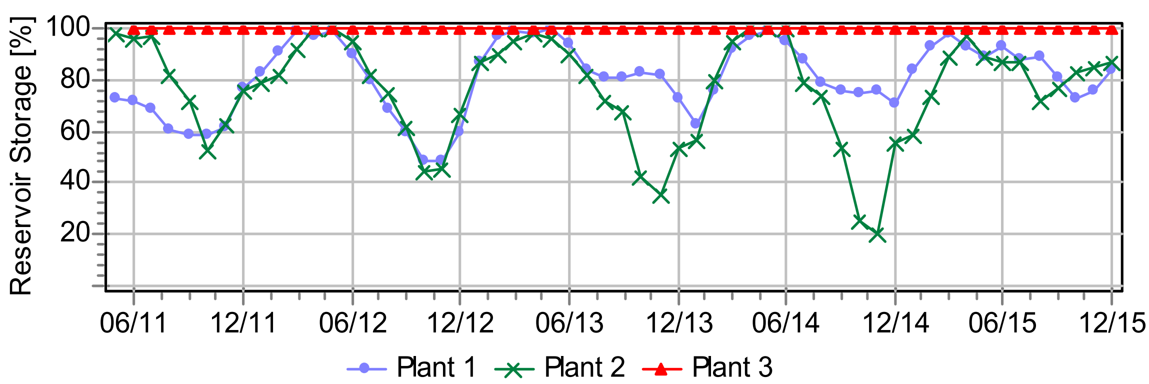

Fig. 11. Reservoir storage trajectory for three cascaded hydro plants.

The forecasted inflow series for Plant 1 is presented in Fig. 12 along with the simulated one. It can be seen that the forecasted series is quite acceptable, although there are peaks at the beginning of years 2012 and 2013 that were not identified by the forecasting model.

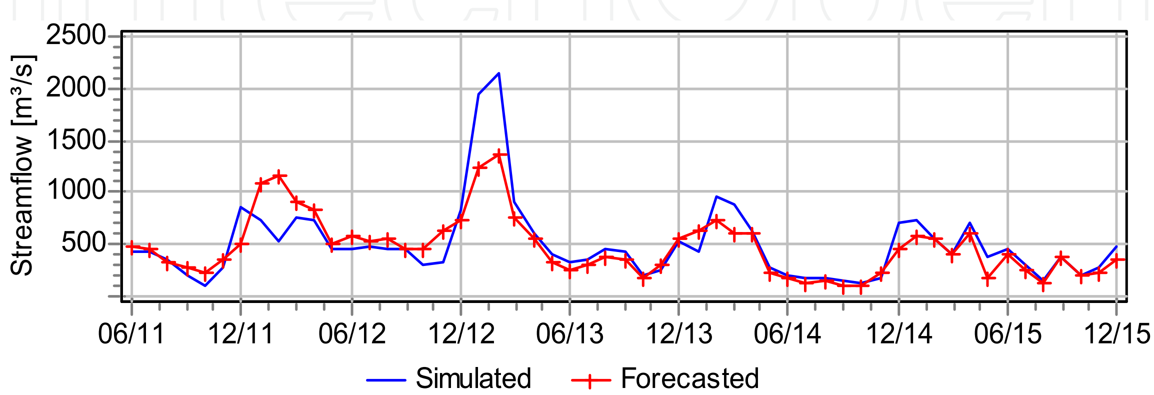

Fig. 12. Simulated and Forecasted stream flows for Plant 1 with FIS-A in favorable scenario.

Still it is important to notice that in the LTHS with MPC approach the forecasting model tries to hit the annual trend, which is more relevant than the specific monthly inflows. This is due to the fact that the discharge decisions of the optimization model are much more sensitive to the total annual inflow than to the specific values of each month (Zambelli et al. 2009).

5.2 STHS results

Next step on the operation planning chain, STHS is fed with the power generation of the first week ahead, disaggregated from the monthly generation determined by the LTHS model for each individual plant. The results of the STHS model will be presented for the same three cascaded hydro plants. Their generation targets in this case study were 493.60; 930.10; and 373.00 MW, respectively.

As shown in the LTHS problem, Plants 1 and 2 have accumulation reservoirs for annual flow regulation and therefore, in a week time period do not vary significantly. Plant 3, in turn, is a run-of-river plant in a long term planning horizon but presents reservoir head variations in short term planning.

In the first iteration of the relaxation procedure, the simulation model identifies violations of reservoir's maximum level in the optimal solution for Plant 3 from the third day until the end of the week. A new constraint was then added and the optimization model solution was updated. Reservoir storage of Plant 3 before and after the additional constraint is presented in Fig. 13 where the violation is eliminated. It is important to note that the generation targets remained satisfied.

STHS inputs and outputs for the selected plants are presented in Table 2.

	Generation Target [MW]	Initial Forebay Elevation [m]	Final Forebay Elevation [m]
Plant 1	493.6	652.62	652.45
Plant 2	930.1	517.71	519.67
Plant 3	373.0	430.67	431.30

Table 2. STHS simulation results.

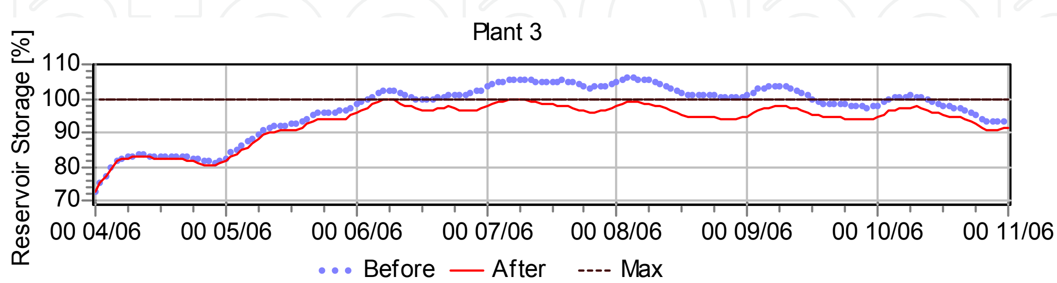

Fig. 13. Reservoir storage for Plant 3 with constraint violation.

The UC and GS solutions solutions change to fulfill the operating constraints, not only for the referred plant, but all cascaded plants can be affected. UC and GS solutions before and after the additional constraint are presented in Figs. 14 and 15, respectively for the three selected hydro plants.

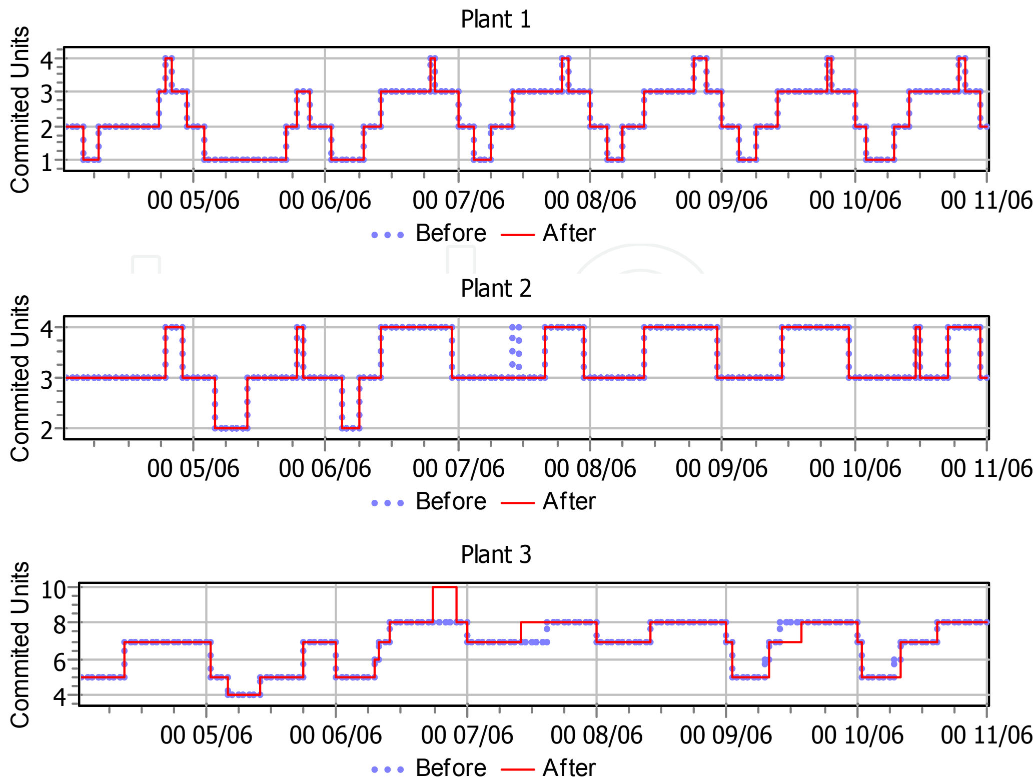

Fig. 14. Unit Commitment solution before and after the new constraint.

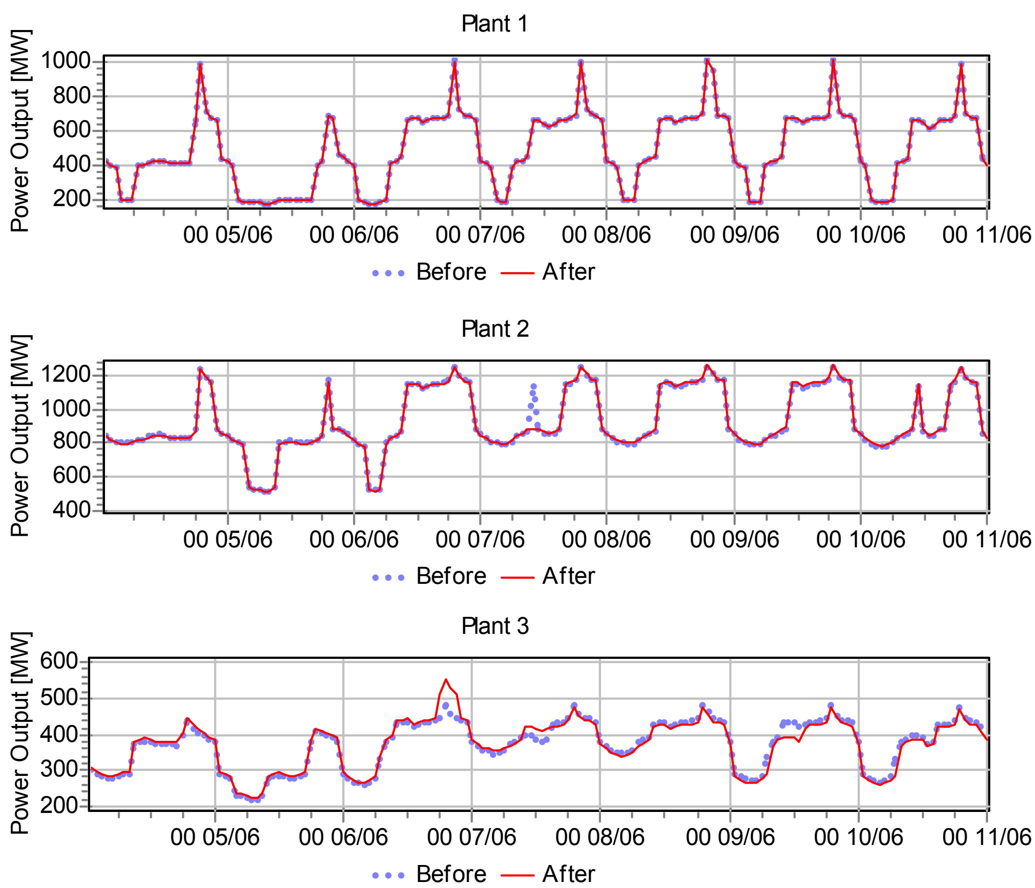

Fig. 15. Generation Schedule before and after the new constraint.

As can be seen, the differences in the scheduling of the selected plants are quite small. Plant 1 was not affected by the new constraint whereas in Plant 2 the fourth unit was not committed at 10h, day 07/06 which consequently reduced the generation at this time. On the other hand, in Plant 3 where the violation occurred the scheduling has slightly changed by increasing the generation on the first three days and reducing it on the last four days so that its generation target remains satisfied.

The results for the whole Brazilian system show that most of the hydraulic constraints relaxed are not active in the optimal solution, justifying the adoption of the relaxation procedure proposed for the STHS. A case study without the start-up and shutdown costs has also been performed. The results show that in this case the number of start-up and shutdown increase from 1,610 to 2,346 whereas the generation loss reduces from 311,667.7 to 309,178.8 MWh. Thus, the proposed approach allows the decision maker to choose the desirable trade-off between these two objectives by fixing the appropriate start-up and shutdown cost.

6. Conclusion

This chapter has presented an approach for hydropower scheduling in large-scale hydro-dominant power systems. An operation planning chain composed of two steps have been suggested. The first step corresponds to the long term hydrothermal scheduling (LTHS) that determines the generation at each plant and month over a planning horizon of up to 5 years ahead. The first month decision is then disaggregated into weekly intervals, and constitutes the generation targets for the next planning step. The second step corresponds to the short term hydrothermal scheduling (STHS) that determines the generation at each plant and hour over a planning horizon of 168 hours ahead.

To solve the LTHS problem a Model Predictive Control approach has been proposed by which a deterministic nonlinear optimization model is executed at each month to provide the generation decisions and then disaggregated into weekly intervals. To feed the optimization model with forecasted inflows, a Fuzzy Inference System (FIS) approach has been implemented in two different ways: one on a monthly basis (FIS-M) as it is usually adopted in the literature, and one on an annual basis (FIS-A), further disaggregated on a monthly basis proportional to the historical average values.

To solve the STHS problem an optimization- simulation decomposition approach based on relaxation has been suggested. According to this approach, the hydraulic balance constraints and limits are relaxed resulting on a mixed integer nonlinear optimization problem that minimizes the generation loss and start-up/shutdown costs at hydro plants while attaining the generation targets established by the LTHS. Then, the generation scheduling and the number of hydro generating units dispatched are provided to a simulator model that calculates the corresponding hydraulic variables and identifies possible violations. This violations yield new constraints to be added to the optimization model and the procedure is repeated until all hydraulic violations are eliminated.

A case study with the Brazilian power system composed of 147 hydro plants comprising 95.6 GW of power capacity and 144 thermal plants comprising 32.4 GW of power capacity illustrates the proposed approach. Two inflow scenarios were considered in the LTHS, one favorable and one unfavorable. In both scenarios the FIS-A approach has presented better results, especially in the unfavorable case when 26% of cost savings have been obtained.

This result reflects two facts: that inflow forecasting errors are lower on an annual basis than on a monthly basis, and that the generation decisions are more dependent on the total future inflows than any particular month value.

With respect to the STHS problem, the case study reported shows that the relaxation procedure concerning the hydraulic constraints is quite efficient since most of these constraints are not active in the optimal solution. Furthermore, the few violated constraints can be easily eliminated by the addition of appropriate linear constraints in the optimization model.

Further research is going on to improve the proposed methodologies. In particular other optimization techniques are being developed to substitute or to validate the heuristic approach used to solve the mixed integer nonlinear programming problem in the STHS.

7. Acknowledgment

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8. References

Al-Zùbi, Y., Sheta, A. and Al-Zùbi, J. (2010). Nile River Flow Forecasting Based Takagi-Sugeno Fuzzy Model, Journal of Applied Sciences, 10: 284-290.

Bowden, G. J., Maier, H. R. andDandy, G. C. (2005). Input determination for neural network models in water resources applications. Part 2. Case Study: forecasting salinity in a river," Journal of Hydrology, no. 301, pp. 93–107.

Camacho, E.F. and Bordons, C. (2004). Model Predictive Control. Springer, Berlin.

Chiu, S. (1994). A cluster estimation method with extension to fuzzy model identification, Procs of The IEEE International Conference on Fuzzy Systems, vol. 2, pp. 1240–1245.

Dawson, C. and Wilby, R. (2001). Hydrological modelling using artificial neural networks, Progress in Physical Geography, vol. 25, no. 1, pp. 80–108.

El-Hawary, M. E. and Christensen, G. S. (1979). Optimal Economic Operation of Electric Power System. Academic Press.

Gwo-Fong Lin & Ming-Chang Wu (2011). An RBF network with a two-step learning algorithm for developing a reservoir inflow forecasting model, Journal of Hydrology, In Press, Corrected Proof, Available online.

Jacobs, R. Jordan, M., Nowlan, S. and Hinton, G. (1991). Adaptive mixture of local experts. Neural Computation, vol. 3, no. 1, pp. 79–87.

Jayawardena, A.W., Xu, P.C., Tsang, F.L. and Li, W.K. (2006). Determining the structure of a radial basis function network for prediction of nonlinear hydrological time series, Hydrological Sciences Journal 51 (1), pp. 21–44.

Jun Zhang; Chun-tian Cheng, Sheng-li Liao, Xin-yu Wu & Jian-jian Shen (2009). Daily reservoir inflow forecasting combining QPF into ANNs model. Hydrol. Earth Syst. Sci. Discuss., 6, 121-150.

Kadowaki, M. Ohishi, T., Martins, L.S.A. and Soares, S. (2009) Short-term hydropower scheduling via an optimization-simulation decomposition approach. 2009 IEEE Power Tech Conference.

Lapide, L. (2006). Top-down & bottom-up forecasting in S&OP. Journal of Business Forecasting 25(2). pp. 14-16.

Luna I., Maciel, L., Lanna, R. da Silveira, F. and Ballini, R. (2010). Estimating the Brazilian central bank's reaction function by fuzzy inference system. Communications in Computer and Information Science, vol. 81, pages 324--333. Springer.

Luna, I.; Soares, S., Lopes, J.E.G. and Ballini, R. (2009). Verifying the use of evolving fuzzy systems for multi-step ahead daily inflow forecasting. Procs.of the 15th International Conference on Intelligent System Applications to Power Systems, pp. 1–6.

Maceira, M.E.P and Bezerra, C.V. (1997) Stochastic Streamflow Model for Hydroelectric Systems, 5th International Conference on Probabilistic Methods Applied to Power Systems – PMAPS, Vancouer, Canada.

Maceira, M.E.P., Terry, L.A., Costa, F.S., Damázio, J.M. and Melo, A.C.G. (2002). Chain of optimization models for setting the energy dispatch and spot price in the Brazilian system. Proceedings of the Power System Computation Conference - PSCC'02, Sevilla, Spain.

Maier, H. R. & Dandy, G. C. (2000). Neural networks for prediction and forecasting of water resources variables: Review of modelling issues and applications. Envir. Modelling and Software, 15, 101–124.

Nayak, P., Sudheer, K. Rangan, D. and Ramasastri, K. (2004). A neuro-fuzzy computing technique for modeling hydrological time series, Journal of Hydrology, vol. 291, pp. 52–66.

Nilsson, O. and Sjelvgren, D. (1997) Hydro unit start-up costs and their impact on the short term scheduling strategies of Swedish power producers. IEEE Transactions on Power Systems, vol. 12, no. 1, pp. 38–44.

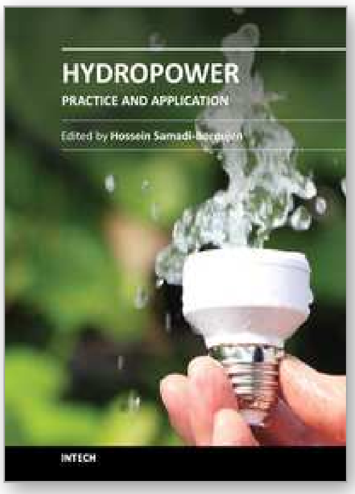
Othman, F. and Naseri, M. (2011). Reservoir inflow forecasting using artificial neural Network, International Journal of the Physical Sciences Vol. 6(3), pp. 434-440.

Price, R. (2008). Lecture on knowing the context between hydroinformatics and flood modelling, UNESCO-IHE Institute for Water Edutation, Tech. Rep.

Soares, S. and Salmazo, C. T. (1997) Minimum loss predispatch model for hydroelectric power systems," IEEE Transactions on Power Systems, vol. 12, no. 3, pp. 1220–1228.

Takagi, T. and Sugeno, M. (1985). Fuzzy identification of systems and its applications to modeling and control, IEEE Transactions on Systems, Man and Cybernetics, no. 1, pp. 116–132.

Zambelli, M.; Luna, I. and Soares, S. (2009). Long-Term hydropower scheduling based on deterministic nonlinear optimization and annual inflow forecasting models. Procs. of the PowerTech Conference, pp. 1–8.



Hydropower - Practice and Application

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Hydroelectric energy is the most widely used form of renewable energy, accounting for 16 percent of global electricity consumption. This book is primarily based on theoretical and applied results obtained by the authors during a long time of practice devoted to problems in the design and operation of a significant number of hydroelectric power plants in different countries. It was preferred to edit this book with the intention that it may partly serve as a supplementary textbook for students on hydropower plants. The subjects being mentioned comprise all the main components of a hydro power plant, from the upstream end, with the basin for water intake, to the downstream end of the water flow outlet.