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# Long-Term Hydropower Scheduling Based on Deterministic Nonlinear Optimization and Annual Inflow Forecasting Models

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***Abstract*— This paper proposes an operational policy for long-term hydropower scheduling based on deterministic nonlinear optimization and annual inflow forecasting models using an open-loop feedback control framework. The optimization model precisely represents hydropower generation by taking into consideration water head as a nonlinear function of storage, discharge and spillage. The inflow is made available by a forecasting model based on a fuzzy inference system that captures the nonlinear correlation of consecutive inflows on an annual basis, then disaggregating it on a monthly basis. In order to focus on the ability of the approach to handle the stochastic nature of the problem, a case study with a single-reservoir system is considered. The performance of the proposed approach is evaluated by simulation over the historical inflow records and compared to that of the stochastic dynamic programming approach. The results show that the proposed approach leads to a better operational performance of the plant, providing lower spillages and higher average hydropower efficiency and generation.**

***Index Terms*— fuzzy inference systems, inflow forecasting, long-term hydro-thermal scheduling, nonlinear optimization, stochastic dynamic programming.**

## I. Introduction

ONE main concern in Long-Term Hydropower Scheduling (LTHS) is the stochastic nature of water inflows. One common approach is to consider the randomness of inflows by their probability distribution functions and apply Stochastic Dynamic Programming (SDP) models [1].

SDP has been widely suggested for dealing with reservoir operational problems due to its ability to handle the nonlinear relations between variables and the stochastic nature of inflows. The main drawback is that the computational burden grows exponentially with the size of the system, the so-called "curse of dimensionality" [2], and some sort of simplification is required in the case of multiple-reservoir systems.

One very common simplification consists of using aggregated composite models to represent multiple-reservoir systems as if they had a single reservoir [3], [4]. Although proving only a rough simplification of the hydropower system operation, this approach has been applied in many hydropower systems around the world since it allows the straightforward application of SDP based methods.

Some approaches try to overcome the drawback of dimensionality by using Bender's cuts in a stochastic, multistage decomposition framework, approximating the expected costs as piecewise linear functions [5], or using linear programming tools [6], in all cases some linearization is assumed [7], [8].

One widely used alternative for the LTHS problem is based on a deterministic model within the framework of scenario techniques. In this approach, the operational policy is based on the solutions of a deterministic optimization model for a set of different scenarios used to represent the stochastic nature of inflows [9], [10], [11].

Another effective approach, also based on deterministic optimization models, is the open-loop feedback control (OLFC) policy, where the operating decision is obtained for the most probable inflow scenario provided by a forecasting model adjusted on a monthly basis. Tests with single-reservoir systems indicate a performance similar to that using SDP methodology [12].

This paper proposes an operational policy for LTHS, called Predictive Control (PC), based on deterministic nonlinear optimization and annual inflow forecasting models, using an OLFC framework. The deterministic optimization model precisely represents hydropower generation by taking into consideration water head as a nonlinear function of storage, discharge and spillage. The improvement with respect to previous work [12] is that inflow is now provided by a forecasting model based on a Fuzzy Inference System (FIS) that captures the nonlinear correlation between consecutive inflows on an annual basis. The annual inflow forecasting is then disaggregated on a monthly basis. Design aspects of the optimization model, such as planning horizon and final reservoir storage conditions, are discussed.

In order to evaluate the ability of the PC approach to handle the stochastic nature of the problem, a case study with a single-reservoir hydropower system is considered. Data from a real Brazilian hydro plant was used. The performance of the PC approach was evaluated by simulation over the period represented by historical inflow records and compared with the results of the SDP approach.

The paper is organized as follows: Section II describes the deterministic nonlinear optimization model. Section III

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presents the proposed PC approach and some implementation details. Section IV describes the stochastic dynamic programming approach. Section V describes the FIS model implemented for inflow forecasting. Section VI presents the study performed and Section VII states the conclusions of the paper.

## II. Deterministic Nonlinear Optimization Model

The LTHS problem, in its deterministic version and for single-reservoir hydropower systems, can be formulated as the following nonlinear programming problem:

$$\alpha(x_0) = \min \sum_{t=1}^{T-1} \psi(D_t - P_t) \tag{1}$$

Subject to:

$$P_t = k.h_t.q_t \tag{2}$$

$$h_t = \phi(x_t^{avg}) - \theta(u_t) - \xi(q_t) \tag{3}$$

$$x_t = x_{t-1} + (y_t - u_t)\gamma_t \tag{4}$$

$$x_t^{avg} = \left(x_{t-1} + x_t\right)/2 \tag{5}$$

$$u_t = q_t + v_t \tag{6}$$

$$X_t^{\min} \le x_t \le X_t^{\max} \tag{7}$$

$$u_t \ge U_t^{\min} \tag{8}$$

$$Q_t^{\min} \le q_t \le q_t^{\max}(h_t) \tag{9}$$

$$v_t \ge 0 \tag{10}$$

where:

| | |
|---|---|
| $t$ | time stage index (months) |
| $T$ | number of time stages in planning period |
| $\psi$ | thermal generation cost (in \$) |
| $D$ | load demand (in *MW*) |
| $P$ | hydropower generation (in *MW*) |
| $x$ | reservoir storage at end of stage (in $hm^3$) |
| $X^{\min}$ | minimum reservoir storage (in $hm^3$) |
| $X^{\max}$ | maximum reservoir storage (in $hm^3$) |
| $u$ | release from reservoir (in $m^3/s$) |
| $U^{\min}$ | minimum release (in $m^3/s$) |
| $q$ | discharge through turbines (in $m^3/s$) |
| $Q^{\min}$ | minimum discharge (in $m^3/s$) |
| $q^{\max}$ | maximum discharge function (in $m^3/s$) |
| $v$ | spillage from reservoir (in $m^3/s$) |
| $k$ | constant factor (in $MW/(m^3/s).m$) |
| $\phi$ | forebay elevation function (in *m*) |
| $\theta$ | tailrace elevation function (in *m*) |
| $\xi$ | penstock head loss function (in *m*) |
| $y$ | inflow into reservoir (in $m^3/s$) |
| $\gamma$ | number of seconds in stage by $10^6$; |

The objective function of an LTHS problem depends on the specific power system where the hydropower system is located. In deregulated power markets, for instance, the objective might be to maximize revenues from selling energy on the market, whereas in vertical hydrothermal power systems, it might be to minimize the cost of thermal generation. In relation to inflow uncertainty, which is the focus of this paper, the specific objective does not matter.

This paper adopts the thermal generation fuel cost $\psi$ as the objective function in (1). Imports from neighboring systems and load shortage could also be considered as dummy thermal plants. The cost function $\psi$ is calculated by the economic dispatch of thermal plants and, as a consequence, is a convex decreasing function of hydropower generation $P_t$, for a given load demand $D_t$.

Hydropower generation at stage *t*, represented by (2), is a nonlinear function of water head and discharge. Water head, in turn, is a nonlinear function of average reservoir storage, water discharge through the turbines, and also water spillage from the reservoir, given by (3). The upper limit of the discharge, given in (9), is also a nonlinear function of water head. The constant $k$ represents the product of water density, gravity acceleration, and average turbine/generator efficiency.

Equality constraints in (4) represent the water balance in the reservoir, where terms such as evaporation have not been considered for the sake of simplicity. Lower and upper bounds on variables, expressed by constraints (7)-(10) are imposed by the physical operational constraints of hydro plants, as well as the constraints associated with multiple uses of water. Since spillage *v* does not produce energy, and therefore does not reduce thermal costs, it can be handled as a slack variable. It will only be different from zero if the release is greater than discharge's maximum value ($u > q^{\max}$) and the reservoir can not accommodate more water ($x = X^{\max}$).

The solution of the deterministic nonlinear optimization model (1)-(10) for a given initial reservoir storage $x_0$ is obtained by a network flow algorithm specially developed to take advantage of the problem structure [13]. Network flow algorithms are known to be approximately 100 times more efficient than are classical linear programming algorithms based on the Simplex Method, and they have been widely applied to hydropower scheduling. This is because they allow an efficient representation of the base matrix as a tree in the network. The network flow algorithm implemented to solve problem (1)-(10) simplifies the representation of bases (trees) and the procedure for their change by exploring a network which has only three arcs (storage, discharge and spillage variables) leaving each node, with the nodes representing hydro plants between time stages.

## III. Predictive Control Approach

The PC approach corresponds to an operational policy for LTHS problems based on an OLFC framework. The discharge decisions at each stage are obtained from a deterministic nonlinear optimization model for a given inflow sequence provided by a forecasting model.

In OLFC, the forecasting model provides an inflow sequence for a given optimization horizon, and the optimization model provides the optimal discharge solutions during that time horizon based on the forecasted inflow sequence. Hence, the optimal discharge for the first stage of the optimization model will be the PC discharge decision for the current stage.

This procedure constitutes the decision-making process of the OLFC approach, which runs under a simulation model where the decision is 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 decision to be implemented.

The feedback control scheme is assured since for each stage the forecasting model updates the inflow forecasting sequence, taking into account the last inflow that occurred during the simulation. Furthermore, for each stage, the optimization model updates the discharge decision as a consequence of the new inflow forecasting sequence and of the new initial reservoir storage resulting from the previously simulated water balance.

An outline of the PC operational policy for the LTHS problem is shown in Fig. 1 where, for a given stage $t$ of the simulation horizon $T$, the hydro system is observed and the reservoir storage levels $x_{i,t-1}$ are taken as the initial condition for the deterministic optimization model that must solve the LTHS problem for an optimization horizon $T^*$. This optimization is accomplished by considering the inflow sequence $y^*_{i,t..T^*}$ supplied by the inflow forecast model, being the discharge $q^*_{i,t}$ of the first stage selected as the decision of the PC operational policy implemented in the simulation. In the next stage $t$+1, the resulting state of the system $x_{i,t}$ is observed, and the inflow forecasting is updated on the basis of the past information $y_{i,1..t-1}$, including the last inflow which occurred. This forecasting-optimization procedure is repeated until the end of the simulation horizon.

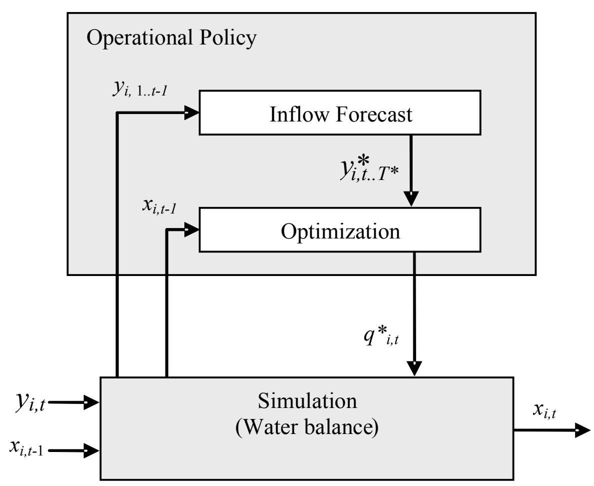


Fig. 1. Open-loop feedback control framework scheme.

One important aspect affecting the performance of the PC approach is the boundary conditions of the optimization model in terms of the final storage of the reservoir and the optimization horizon. Results with perfect foresight over the whole period of historical inflow records indicate that the reservoir storage at the beginning of each dry season is almost always the maximum. With this in mind, the optimization horizon implemented by the PC approach reported in this paper adopts a rolling horizon that terminates at the beginning of the first dry season at least a year in the future with the final storage as full.

## IV. Stochastic Dynamic Programming Approach

Closed-loop feedback control (CLFC) optimization is the central characteristic of the SDP technique. The goal of the SDP policy is to determine a rule for decision making for each stage of the planning period which will provide the optimal decision for each possible state of the system. Mathematically, the SDP technique determines a sequence of decision functions mapping the states onto decisions so as to minimize expected costs.

In some applications, the system state can be constituted by only the storage variable, such as when the inflow is considered to be a stochastic variable independent on time. In other situations, however, when the stochastic variable of inflow is modeled by autoregressive models, the system state must be increased to include the inflow from previous stages in order to represent the time dependence of inflows, a procedure which makes the “curse of dimensionality” even more crucial.

It is assumed here that the stochastic variable representing inflow during each stage depends on the inflow of the previous stage. This means that inflows are represented by a first-order periodic autoregressive model PAR(1) which describes the stochastic process as a Markov chain [2]. For reservoir operation, the state variables are the water stored in the reservoir at the beginning of each stage and the water inflow during the previous stage, to establish a hydrological trend. The control variable is the discharge from the reservoir during the time stage. The LTHS problem, in its stochastic version, can be formulated as:

$$\alpha(x_0) = \min \, E_{y_t/y_{t-1}} \left\{ \sum_{t=1}^{T-1} \psi_t\,(D_t - P_t) \right\} \tag{11}$$

subject to constraints (2)–(10), where $E_{y_t/y_{t-1}}(.)$ is the expected value with respect to the inflow during stage $t$, conditioned by the inflow during stage $t$-1. For each stage, decisions are ranked based on the minimization of the sum of the present cost plus that of the expected future cost, assuming optimal decision-making for all subsequent stages. According to Bellman’s Optimality Principle [2], the optimal decision is obtained by solving the following recursive equation:

$$\alpha_t(x_t, y_{t-1}) = \min_{\Omega_t} \left\{ \psi_t(D_t - P_t) + \int_{-\infty}^{+\infty} \alpha_{t+1}(x_{t+1}, y_t). \right.$$
$$\left. .f(y_t / y_{t-1}).dy_t \right\} \tag{12}$$

where: $\Omega_t = \{q_t \,/\, subject\ to\ (2)-(10)\}$, $\alpha_t(x_t, y_{t-1})$ represents the minimum expected operational cost from stage $t$ until the end of the planning period $T$, assuming the system at state

$(x_t, y_{t-1})$, and $f(y_t / y_{t-1})$ is the probability density function of the inflow during stage $t$ conditioned by the inflow in stage $t$-1.

The backward resolution of the recursive equation (12) requires the discretization of the state and control variables, as well as of the conditioned probability density function of the inflows, which reinforces the "curse of dimensionality" already mentioned.

The optimization problem is divided into stages and, for each stage, the optimal control variable is chosen in order to minimize the cost function for each possible state of the system. The state variable is represented by the reservoir storage combined with the inflow of the previous stage. The control variable is the water discharge. Indexes $i$ and $j$ are associated with the discrete inflow variables $y_t$ and $y_{t-1}$, respectively. An outline of this procedure can be seen in Fig. 2.

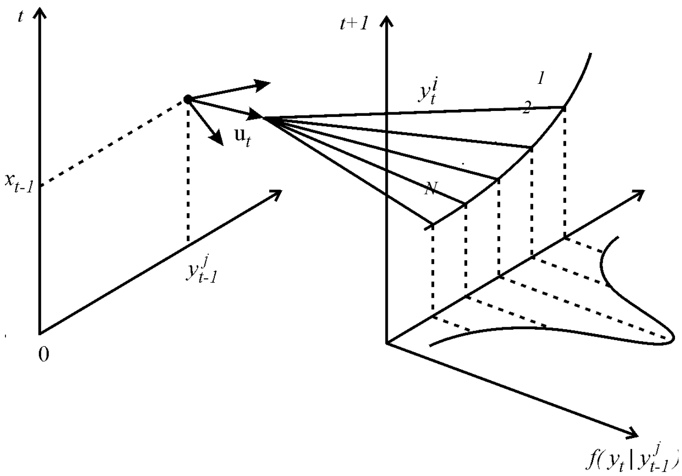


Fig. 2. SDP schematic representation.

For the SDP model, not only the time correlation of the inflow series, but also its probability distribution must be modeled and these choices may affect the SDP performance for LTHS. A periodically stationary Gaussian distribution is generally considered for practical applications, although periodically stationary distributions do not properly represent characteristics such as asymmetry and the non-steady behavior of the variance due to climate changes (dry periods involve less variance, whereas humid periods involve greater variance).

In the SDP approach used here, the inflows are approximated by the normal density distribution, using lognormal transformation and conditioned periodically stationary distribution [16].

## V. Inflow Forecasting Modeling

### A. Fuzzy Inference Model

Various approaches exploiting the fuzzy logic artificial intelligence have emerged in the past years as an alternative to the construction of effective predictors for their ability of efficiently mapping the non-linear nature of relations between independent and dependent variables [17]. Indeed, a great variety of strategies using neural networks and fuzzy systems have proved their efficiency for time series prediction, especially for river streamflow forecasting [18], [19].

In this work inflow is forecasted using a nonlinear model based on a Fuzzy Inference System (FIS), which is based on the first order Takagi-Sugeno (TS) fuzzy system [20]. The general structure adopted for the FIS is depicted in Fig. 3, where $x^t = [x_1{}^t, x_2{}^t, ..., x_p{}^t] \in R^p$ is the input vector at instant $t$ and $\hat{y}^t \in R$ is the output model for input $x^t$.

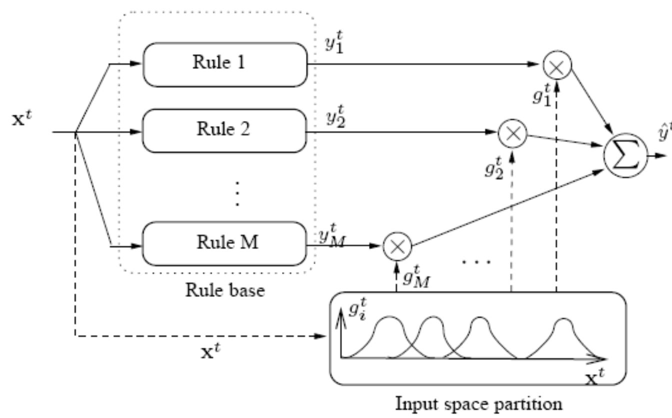


Fig. 3. FIS general representation.

Input space is partitioned in $M$ sub-regions, with each one of these represented by a fuzzy rule $R_i$, $i=1,..,M$. Each input pattern will have a certain degree of membership in relation to each region of the partitioned input space, calculated with Gaussian membership functions $g_i(x^t) = g_i{}^t$ that strongly depend on centers and covariance matrices related to the fuzzy partitioning and membership functions. Therefore, the model output $\hat{y}^t$, representing the predicted value for a future time stage, is calculated by means of the non-linear weighted averaging between local output $y_i{}^t$ and their respective degree of membership $g_i{}^t$, according to the following equation:

$$\hat{y}^t = \sum_{i=1}^{M} g_i{}^t \times y_i{}^t \tag{13}$$

The number of fuzzy rules codified in the model structure is defined using an unsupervised clustering algorithm called the *Subtractive Clustering* algorithm, proposed in [21]. In this case, consequents of the fuzzy rule were defined as linear models, so that $y_i{}^t = \theta_i \times x^t$.

Model parameters (spreads and coefficients for local models) were adjusted in an offline fashion using the Expectation Maximization algorithm [22].

### B. Forecast Approaches

Two approaches were evaluated for obtaining the inflow forecast sequences necessary for the PC approach. The first (FIS-M) 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.

The second approach, which is the contribution of this paper, deals with LTHS through 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 [23], since errors are compensated and variations can cancel each other out.

The FIS-A approach predicts the aggregation of the twelve future monthly inflow samples (the aggregate inflow for the next year) by adjusting twelve different models on an annual basis, the *m*-th FIS model thus provides the aggregate of the sample for the next twelve months. Let the annual aggregate forecast given by the annual *m*-th FIS model be represented by $\hat{y}^{t,m}{}_{FIS-A}$, where *m* also represents the actual month of stage *t*. The estimates for the inflows for the next *k* months are represented by $\hat{y}_k$, with $k=t+1,..,t+h$. Thus, $\hat{y}^{t,m}{}_{FIS-A}$ is defined as:

$$\hat{y}^{t,m}{}_{FIS-A} = \sum_{k=t+1}^{t+h} \hat{y}_k \qquad (14)$$

where *h* represents the forecast horizon (lead time) adopted during the PC approach; in this case, it is set to *h=12*. Then, instead of adjusting twelve FIS models for monthly streamflow forecasting in a direct way, the TD approach (FIS-A) adjusts twelve models on an annual basis. Consequently, the forecast results will then need to be disaggregated into the respective monthly estimates.

The disaggregation of the annual inflow forecasting into twelve monthly samples is performed using the historical contribution factors of each month in the year, based on long-term average values.

The results presented in the following sections will show the importance of working with accurate models considering the aggregate of future monthly samples over the entire optimization horizon, leading to better results in PC approach when compared to that of the other forecast strategy analyzed.

## VI. Case Study

The PC and SDP approaches were implemented and tested in a case study comprising a single-reservoir hydropower system. The Emborcação hydro plant, at the top of the Paranaíba River in Southeastern part of Brazil was selected. With an installed capacity of 1.2 GW and usable storage capacity over 13 km$^3$, it is one of the most important plants in the region. In order to get a balanced hydro-thermal system, the thermal plant capacity, in GW, was considered to be equal to the installed capacity of the hydro plant, and the load demand was assumed constant and equal to half the installed capacity of the system.

For the SDP operational policy, a time correlation of lag-one was assumed between inflows, leading to a stochastic Markov chain process. In this case, the discretization adopted for the state variable (storage) was 100, and for the control variable (discharge) a local search technique based on the golden section method avoided discretization. The stochastic variable (inflow) was modeled using a lognormal conditioned probability density function with 10 discrete values.

The operational cost $\psi$, representing the minimum fuel cost for thermal generation, is given by the quadratic function in (15) which is a good fit for the cost of thermal generation in the Brazilian power system.

$$\psi = 0.02(D_t - P_t)^2 \qquad (15)$$

The PC and SDP approaches were implemented and simulated on a monthly basis for the entire historical inflow sequence, extending from 1931 to 2008. All constraints presented in the formulation of the optimization problem (1)-(10) have been considered in the simulation. The forebay $\phi$ and tailrace $\theta$ elevations were represented by 4th degree polynomial functions and the penstock head loss $\xi$ by a quadratic function.

A deterministic optimization for the period encompassed by the historical records provides the perfect foresight (PF) solution, which was also computed to establish an upper bound for the performance of the operational policies to be compared.

Table I summarizes the simulation results in terms of average values of generation, operational cost, spillage, and hydropower efficiency. Standard deviation of generation is also given.

TABLE I
Simulation Results

| | Cost ($) | Hydropower [MW] Avg. | Hydropower [MW] Std. Dev. | Spillage (m³/s) | Efficiency (MW/m³/s) |
|---|---|---|---|---|---|
| PF | 8292.85 | 562.5 | 135.1 | 0 | 1.170 |
| SDP | 8974.48 | 540.9 | 160.5 | 17.1 | 1.156 |
| PCFIS-M | 9041.40 | 542.4 | 173.3 | 18.1 | 1.163 |
| PCFIS-A | 8776.53 | 551.7 | 169.8 | 10.2 | 1.163 |

As was expected, the PF solution provides the lowest cost, highest average and lowest standard deviation for hydropower generation, the highest hydropower efficiency, and no spillage at all. This high performance was guaranteed since the decision maker had perfect foresight of future inflows.

In terms of cost, the performance achieved by SDP was 8.22% higher than that of PF. This sub-optimality index can be interpreted as the “cost of uncertainty”, since it measures the additional cost due to decision-making faced with the uncertainty of inflows. For SDP this cost reflects an increase of 17.1 m$^3$/s in water spillage, a decrease of 0.0014 MW/(m$^3$/s) in hydropower efficiency, and a reduction of 22.4 MW in average hydropower generation.

The proposed PC approach using the FIS inflow forecasting model on a monthly basis (PCFIS-M) leads to a “cost of uncertainty” of 9.03%, slightly higher than that of the SDP. It is interesting to note, however, that although the PCFIS-M solution leads to 1 m$^3$/s more spillage than does the SDP, it provides an increase of 0.6% in hydropower efficiency and of 1.5 MW in hydropower generation. However, this higher hydropower generation is provided on a less stable way, as indicated by the higher standard deviation. In the end, the

PCFIS-M approach leads to an increase in cost of 0.75% over that of the SDP approach. These results indicate that OLFC approaches with inflow forecasting on monthly basis perform slightly worst than CLFC approaches [8].

The PC approach using an FIS model on an annual basis, then disaggregated on a monthly basis (PCFIS-A) involved only a 5.83% "cost of uncertainty", a significant improvement with respect to the two other approaches considered. This is due to the fact that the PCFIS-A solution maintains the high hydropower efficiency of the PCFIS-M while simultaneously achieving a drastic reduction in spillage, thus resulting in an increase of 10.8 MW in generation in relation to the results of SDP.

The superior performance of the PCFIS-A approach can be atributed 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 any one month.

Fig. 4 shows the reservoir trajectories of the Emborcação hydro plant provided by the deterministic nonlinear optimization model considering a planning period of 22 months from September to April of the second year, starting with 70% of usable storage and ending with 100%, according to the design of PCFIS decision-making approach proposed here. Two different inflow sequences with similar total values were considered, one starting in 1957, with an average inflow of 457.5 m³/s, and the other starting in 1993, with an average inflow 457.6 m³/s. The historical inflows and discharges resulting from the optimization over these periods are presented in Fig. 5.

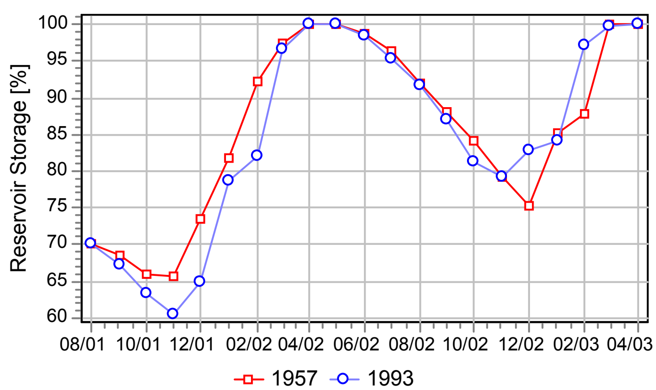


Fig. 4. Reservoir storage based on optimization for similar average inflows.

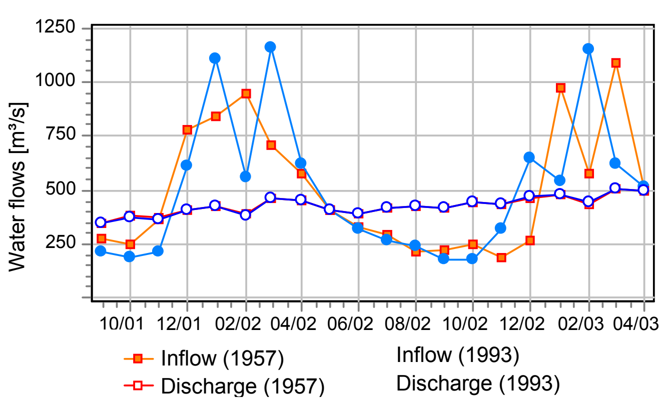


Fig. 5. Water flows based on optimization for similar average inflows.

As can be seen, the differences in reservoir storage trajectories reflect the different profiles of the inflow sequences considered, but the discharge decisions are practically the same, because the average inflow of the two sequences was almost the same.

Therefore, since forecasting errors on an annual basis are lower than on an monthly basis, forecasting approaches based on annual inflows (with subsequent disaggregation to monthly basis) yield better information for optimal decision-making then do forecasting approaches based on monthly values, within the framework of OLFC operational policies.

Fig. 6 illustrates the variation in Mean Absolute Percentage Error (MAPE) considering different forecast horizons (*h=1,..12*) on a monthly basis as well as for the two different inflow forecasting approaches evaluated, FIS-A and FIS-M.

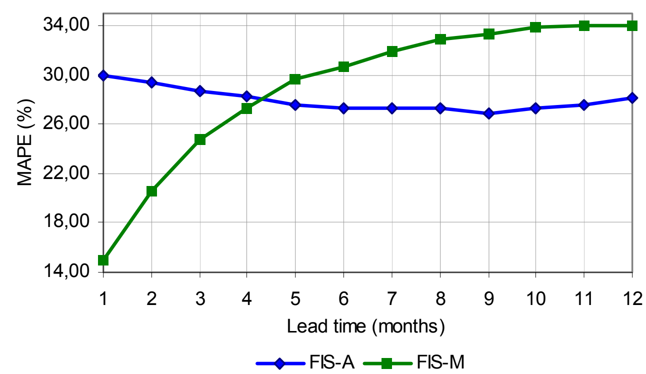


Fig. 6. Evolution of MAPE for FIS approaches, based on different forecast horizons.

Based on this figure, one important observation is that the FIS-M obtains a better performance for forecast horizons for one to four steps-ahead than does FIS-A. Nevertheless, its performance gets worse for more future steps ahead although the FIS-A maintains an almost constant performance for all lead times. Thus, the FIS-A exceeds the FIS-M in performance for the steps ahead.

Thus, a partial conclusion, based on this figure, is that the FIS-A model is more efficient on the long run than the FIS-M, and despite its poor performance for $h \leq 3$, it provides the best long-term forecasting for monthly inflow samples up to $h=12$.

Table II presents the forecasting errors for the aggregate of the twelve future monthly inflow samples: the Root Mean Square Error (RMSE), the MAPE and the Mean Absolute Error (MAE). All error measures are lower for the FIS-A model, to be expected since it was designed to predict such aggregated values.

TABLE II
STREAMFLOW FORECAST ERRORS.

| | RMSE (m³/s) | MAPE (%) | MAE (m³/s) |
|---|---|---|---|
| FIS-A | 933.05 | 10.69 | 545.42 |
| FIS-M | 1450.57 | 20.00 | 1101.20 |

In general terms, despite the lower performance of the FIS-A for the first few steps ahead on a monthly basis, its performance for the year surpasses that of the FIS-M.

A more detailed comparison of the SDP and PCFIS approaches is provided in Fig. 7, showing the water reservoir storage trajectories simulated for the period from 05/1965 to 04/1970. This period comprises 5 years. The third year was hydrologically average, whereas the fourth was a dry year; the other three were above average, hydrologically. This can be seen in Fig. 8, where historical inflows for the period are presented, along with average monthly values.

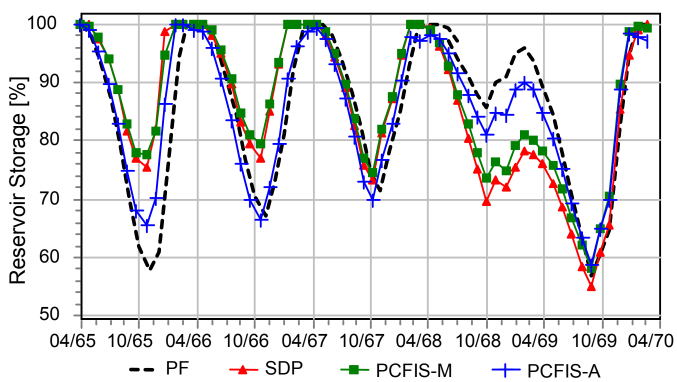


Fig. 7. Reservoir storage from simulation for 1965-1970 historical inflows.

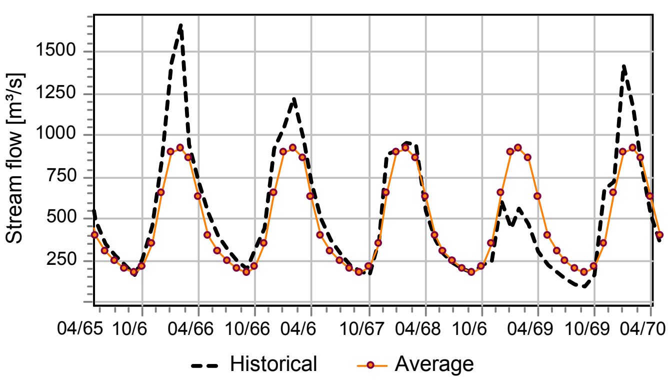


Fig. 8. 1965-1970 historical inflows and average monthly values.

First of all, the PF solution corresponded to a reduction in storage for the period from May to October for all the years, with an increase for that from November to April, thus presenting five independent hydrological cycles.

Each year the reservoir reduced its storage in the exact amount necessary to provide refilling without spillage. The only year that the reservoir did not refill completely was the dry one because the optimization model, knowing that the next year would be more wet, stopped refilling at 96% of storage capacity at the end of the wet season, but this is still a high storage level. Only with perfect foresight of inflows is it possible to achieve such perfection for maximization of water head without spillage.

Comparing the trajectories of the different operational policies, it is quite clear the best performance was that of the PCFIS-A. When inflows are above average, as they were in the fist two years, the PCFIS-A reduces the storage more than do the other approaches, approximating the PF solution more closely. On the other hand, when inflow is below average, as in the 4th year, the PCFIS-A reduces the storage less than do the other approaches, again approximating more closely to the PF solution. In average years, such as the 3rd year, the three approaches provided equivalent performance, quite close to the PF solution.

Numerical results of the simulation for the 1965-1970 period are presented in Table III.

TABLE III
SIMULATION RESULTS FOR 1965-1970 PERIOD

| | Cost | Hydropower [MW] | | Spillage | Efficiency |
|---|---|---|---|---|---|
| | ($) | Avg. | Std. Dev. | (m³/s) | (MW/m³/s) |
| PF | 6954.18 | 614.1 | 118.0 | 0 | 1.167 |
| SDP | 7483.84 | 601.2 | 159.8 | 15.92 | 1.168 |
| PCFIS-M | 7463.05 | 606.6 | 176.0 | 12.54 | 1.172 |
| PCFIS-A | 7099.57 | 615.4 | 151.5 | 2.53 | 1.167 |

For this period, the cost of PCFIS-A was only 2.09% higher than that of the PF, whereas in month-based models it indicates over 7.3% of sub-optimality. The water spillage in the PCFIS-A approach was also different since it was able to avoid 84.1% of the spillage incurred by SDP.

A gain of 0.36% hydropower efficiency was achieved with the PCFIS-A approach, for which the hydropower average generation exceeded that of the PF. However, the stability of its generation was similar to that of the other operational policies, as indicated by the variations in standard deviation (5% lower than in the SDP and 49% higher than in the PF).

## VII. CONCLUSION

This paper has presented an operational policy for long-term hydropower scheduling based on deterministic nonlinear optimization and annual inflow forecasting models using an open-loop feedback control framework.

A predictive control operational policy was implemented using a fuzzy inference system that provides both monthly and annual inflow forecasts. A single-reservoir hydropower system was adopted for a case study so that the stochastic dynamic programming approach could be compared.

The simulation results using historical inflows have demonstrated the superior performance of the predictive control approach based on annual forecasts in relation to those based on monthly inflows. Indeed, both stochastic dynamic programming and predictive control with monthly forecasts performed quite similarly.

It was also shown that the discharge decisions of the optimization model are much more sensitive to the total annual inflow than are those based on specific values for a particular month. This in fact explains the expressive improvements obtained by the use of the preditive approach with inflow forecasting on annual basis in relation to all measures.

Therefore, since this annual inflow forecasting model provides better information for optimal decision-making, it significantly increases hydropower generation and reduces operational costs. This reflects the efficiency of the approach for the management of the reservoir in order to accomodate possible spillages and gain more hydropower efficiency.

Morover, the proposed approach can also be applied to more complex problems, such as multireservoir systems, maintaining a precise representation of the system's non-linearities, without the need for simplification. This leads to more stable scheduling, and thus to more economic and reliable operation.

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