# CONSIDERING THE INFORMATION OF THE NIÑO 3.4 INDEX IN THE OPERATION OF THE ELECTRICAL SYSTEM OF URUGUAY

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## 1 Introduction

It is well known that the El Niño – Southern Oscillation (ENSO) phenomenon [1]– a quasi periodic oscillation of the coupled ocean atmosphere system over the equatorial Pacific Ocean – conditions the climate of many parts of the world, including southeastern South America. During warm events or El Niño years, with seas surface temperatures in the equatorial Pacific higher than average, precipitation over Uruguay tends to be higher in certain seasons. Conversely, during cold or La Niña events, it tends to rain less [2-3].

In this work, we will represent ENSO by a scalar monthly index that consists of the sea surface temperature anomaly averaged over a box at the central equatorial Pacific called Niño 3.4 region [4]. Observed values of the N3.4 index are available for over a century.

The goal of this paper is to show the effect that the ENSO-induced bias in the precipitation has on the cost of energy supply in Uruguay. We further present a methodology to consider N3.4 index in the optimization tools that compute the optimal policy for the use of the water stocked in the hydroelectric subsystem.

We present the changes in the operation of the system induced by the consideration of N3.4 index in the optimization process. We focus on the operation of the reservoir of Rincón del Bonete because it is the biggest one in Uruguay. A case study was selected corresponding to the time horizon from August 2009 to July 2010. At the beginning of the selected period the development of an El Niño event was already clear and therefore more rains were expected in the region, in particular for local spring. The evaluation of the results shows the significance of the impact that this foreknowledge has on the operation of the system.

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# 2 The Uruguayan electricity system

## 2.1 Hydroelectric Plants

Uruguay has four hydroelectric plants: ”Bonete”, ”Baygorria” and ”Palmar” on the Negro River and “Salto Grande” on the Uruguay River, shared with Argentina. Bonete is upstream Baygorria which is upstream Palmar. The most relevant parameters of these plants are presented in Table 3.

| | *Bonete* | *Baygorria* | *Palmar* | *Salto-UY* |
|---|---|---|---|---|
| Minimum elevation of the reservoir [m] * | 70 | 53 | 36 | 30 |
| Maximum elevation of the reservoir [m]* | 81 | 56 | 44 | 35.5 |
| Discharge elevation [m]* | Baygorria | Palmar | 7.5 | 5 |
| Storage capacity of the reservoir [Hm3] | 8210 | 216 | 2575 | 3058 ** |
| Mean inflow from the basin [m3/s] | 567 | 0 | 290 | 2323** |
| Maximum discharge flow [m3/s] | 680 | 828 | 1373 | 4200 ** |
| Installed power [MW] | 155 | 108 | 333 | 945 ** |

Table 1. Hydroelectric plants of Uruguay. (*): ELEVATION IS MEASURED ABOVE SEA LEVEL (**): THIS VALUES CORRESPOND TO THE URUGUAYAN 50% PART OF THE PLANT.

## 2.2 Fuel fired Plants

In the time horizon of this study the fuel fired plants in operation are:

- 460 MW of aeroderivative gas turbine, burning diesel oil, with a generation cost of approximately 200 USD/MWh.
- 323 MW of steam turbines and moto-genenerators, burning fuel oil, with a generation cost of approximately 130 USD/MWh.

## 2.3 Distributed generation

In the horizon of this study there are approximately 60 MW of distributed generation composed of small wind farms and biomass fueled plants.

## 2.4 Interconnections

Uruguay is interconnected with Argentina through a 500 kV system with a capacity of 2000 MW and with Brazil through a 70 MW AC/AC converter that links a 150 kV, 50Hz subsystem in the Uruguayan side to a 230 kV, 60 Hz in the Brazilian side.

A new interconnection between Uruguay and Brazil is starting to be built and will be in operation in the 2$^{nd}$ half of 2012. This date is out of the horizon of this study.

## 2.5 The Load of the system

The load of the Uruguayan electricity system shows an hourly curve that has the maximum around 9 p.m. and the minimum near 4 a.m. The forecast of the annual energy consumption is displayed in Table 2.

| **Year** | **2009** | **2010** | **2011** | **2012** | **2013** | **2014** | **2015** |
|---|---|---|---|---|---|---|---|
| **GWh** | 8850 | 9204 | 9526 | 9860 | 10205 | 10562 | 10931 |

Table 2. Forecast of the Uruguayan energy load.

# 3 Methodology.

## *3.1 The optimal operation policy and the Future Cost function..*

The operation optimization of a hydrothermal system is a complex problem. This is because we are dealing with a system having reservoirs, so the issue of how to use the stocked resources is not only how much to use of each stock but also when to use them. This is a classical optimization problem [5]. A generic description follows to ease the explanation of the proposed methodology.

The problem can be stated as the optimal control problem of a dynamical system as the one sketched in Figure 1.

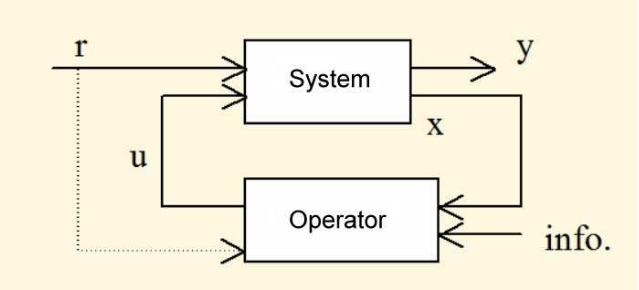


Figure 1. Sketch of the dynamical system that models the electric system and its operation.

The inputs of the system are classified in two groups: non-controllable ("*r*") and controllable ("*u*"). The state of the system is represented by a vector "*x*", while "*y*" is the set of outputs. The "info" input to the Operator takes into account additional information available to the Operator; in this study the climate forecast associated to N3.4 index. A forecast of the non-controllable inputs "*r*" is also used by the Operator and is represented by the dotted line.

The controllable variables "*u*" consists typically of: the committed power at each generation unit of the fuel fired plants, the amount of water spilled and turbined in the hydroelectric plants, and the power fluxes in the links with other power systems.

The state vector "*x*" captures all past and current information that is relevant to compute the future evolution of the system with known future inputs. It comprises the volume of water in the reservoirs, the information that represents the wet or dry condition and any other necessary information to compute the future system. The state of the system results from its

We formulate an optimization problem where the objective is to minimize the operation cost: fuel consumption plus imports plus the country cost of fail in supplying the energy demand. The computation is discretized in a set of consecutive stages or time steps. The production costs of each thermal unit and the cost of fail is known at each time step. Water in the reservoirs does not have an explicit cost so the production cost of hydroelectric plants is not predefined.

The present use of stocked water potentially increases future productions costs. The preservation of water today for a later use may reduce production costs in the future, but it certainly increases the cost today due to the additional thermal generation that will be needed. This is the core of the problem, to find a policy of use of stocked resources that balance present and future costs.

We thus face an optimization problem: to minimize a cost function subject to several constraints -including the dynamic of the system- where the solution must be the expected minimum cost over the ensemble of possible realizations of the stochastic process "*r*". A good introduction on how to build the problem equations can be found in [6].

There are well known strategies to face this problem. The most classical is called Stochastic Dynamic Programming (SDP)[5]. For this study, the SimSEE software [7] was used to run a classical SDP algorithm, which computes the cost function from future back to present. To proceed with the calculations, a time and space discretization is defined for each of the state variables of the system.

The SDP algorithm gives as a result the Bellman function [5], also called Future Cost function, denoted in this work as FC(x, t), where "*x*" is the state of the system and "*t*" is time. FC(x,t) gives, at each time "*t*" and for each state "x", the minimum expected cost of operation, from the time "t" to the end of times.

The FC function implies the system operation policy. At each time step, when the optimization problem of operation is posed, it must be decided how much of each resource has to be committed. Storable resources that do not have an explicit cost (e.g., water in the reservoirs), instead have a future value that is minus the derivative of FC with respect to the resource, at the end of the time step. If the use of a volume dV at this stage implies savings in direct costs (fuel, fail, imports) that are larger (smaller) than the increase caused in FC due to the variation of the system state associated to the extraction of dV, the decision will be to (not) use that volume. For this reason, an operation policy is equivalent to an FC function.

In this study, we are comparing the performance of two operators, each one with its own optimal operation policy resulting of the information known. The difference among them is that one is more informed than the other.  We shall call the less informed operator OPLI and OPMI to the more informed operator.

The information that makes the difference among operators is related the climate forecast associated to the conditioning of inflows due to ENSO (represented byN3.4 index). For the computation of its optimal operation policy (or FC function), OPLI does not consider N3.4 information, while OPMI does.  This info is considered in the model of hydraulic inflows to the reservoirs.

SimSEE includes a model of these stochastic processes that generate synthetic series of inflow to the reservoirs. These series are used in a Monte Carlo simulation in the SDP algorithm. The difference between operators is reflected in these models of stochastic processes. When considering the expected inflows to the reservoirs, each operator visualizes them as a "cone" of possible values; the larger the uncertainty, the wider the cone. It is expected that the better informed OPMI has a lower variance than OPLI, and therefore a narrower cone, as shown in Figure 2.

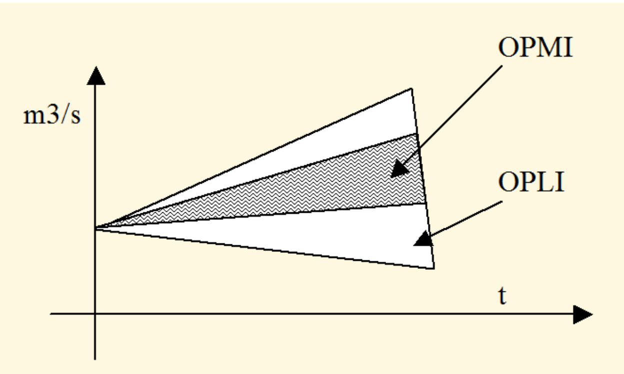


Figure 2. Uncertainty cones of non-controllable variables "*r*" -represented in the model by stochastic processes- associated with each operator

These uncertainty cones should be conceived associated to probabilities. For example, it can be thought that, from the whole set of realizations of stochastic processes synthesized by the corresponding models, the cones represent values having a 90% confidence of not being exceeded, both in the sense of falling above the upper limit or below the lower limit.

SimSEE has a tool -called "CEGH"- that identifies models for the stochastic processes, see the apendix of [8]. In the scope of this work, the stochastic processes of concern are mainly those that generate the water inflows to the reservoirs. The historical available data is a 100-year long time series of the average weekly values of the inflows to the reservoirs of the three most important hydroelectric plants in the country.

The model should be capable of generating synthetic series with the same properties as those of historical data, meaning that, at least, these synthetic series should maintain the amplitude histograms of the original series and that the inertia of the hidden stochastic processes is properly represented. The idea behind CEGH modelling is to build a set of non-linear transformations (NLT) and their inverses so as to be able to work in a “Gaussian world”. The reader can think of the NLT as a set of “lenses” that distort the amplitudes of the time series, making them look Gaussian. Since the linear transformation of a Gaussian process is also Gaussian, once in the distorted Gaussian world, we can make use of all the tools of linear system identification without losing the shape of the histograms. Once a linear model is obtained that captures the inertias and correlations of the (transformed) data series, we can use it to synthesize series in the Gaussian world and then apply the set of inverse NLT to transform those synthetic series to the real world.

Two different CEGH models are built in this study. The first one considers the full 100 year of the historical data series in the design of the nonlinear transformations (NLT). The second one considers only a subset of 30 years of the historical data series, the analog years, selected based on the condition of ENSO (see section 3.3).

The optimal policy obtained with SDP using the first model corresponds to the OPLI (Less Informed OPerator), which does not take into account the ENSO-related climate forecast, while the optimal policy obtained with the second model corresponds to an OPMI (More Informed OPerator), which considers ENSO conditioning of inflows.

If we consider the distribution of inflows conditioned by N3.4 as a more accurate characterization of the expected inflow, we can say that the OPMI is more informed than the OPLI and therefore constitutes a better operation policy. This does not imply a lower cost of operation of the system for a particular realization, since the forecast is probabilistic and chance may favor the OPLI. However, if we consider expected values, the operation of OPLI is bound to be more costly than the operation of OPMI.

## *3.2 Quantifying the economic value of the climate forecast.*

Given the two CEGH models and the corresponding operation policies, we can assess the economic impact associated to the information given by the N3.4 index regarding the expected inflows. We need to compare the operational costs associated with each operation policy in a given timeframe and for the same set of realizations of the stochastic processes. We carried out two set of simulations of the system, one with each of the operation policies, but with the same stochastic model, the one that considers only the analog years in the NLT, since it is our best model for the simulation period. Since OPMI was trained in that environment of uncertainty it will inevitably outperform –in a mean sense- OPLI, which resulted from the optimization in a broader uncertainty cone. In other words, the expected cost of operation should be lower for OPMI; we want to quantify how much lower.

For each realization, operation policy and time step, the total cost of operation results from the sum of the direct costs (fuel + fails + imports) already incurred since the beginning of the simulation period to date, plus the value of the future cost function CF(x,t) evaluated at the state reached by the system at that instant. The future cost function was previously determined in the optimization process and depends on the uncertainty cone, so that CF(x,t) are different in each operation policy. Since OPMI is better informed, we consider $CF_{OPMI}(x,t)$ to be a better estimate of future costs.

Therefore, we can compute total cost function in different ways with different interpretations:

*Total cost predicted by OPLI*

$CT_{OPLI\_p}(t) = \left\langle \int_{t=t0}^{t} cd_{OPLI}(u,r,t).dt + CF_{OPLI}(x,t) \right\rangle_R$ , where $cd_{OPLI}(u,r,t)$ are the direct costs incurred during the operation and $u$ the control variables associated with OPLI policy. The system reaches state $x$ at time $t$ as a consequence of the operation and the uncontrolled variables $r$. Brackets denote expected value over the ensemble of realizations $r(t)$.

*Expected total costs for OPLI*

$CT_{OPLI\_e}(t) = \left\langle \int_{t=t0}^{t} cd_{OPLI}(u,r,t).dt + CF_{OPMI}(x,t) \right\rangle_R$ , which differs from the previous one in that the future cost at the state $x$ that results from applying OPLI policy is estimated with OPMI.

*Expected total costs for OPMI*

$CT_{OPMI}(t) = \left\langle \int_{t=t0}^{t} cd_{OPMI}(u,r,t).dt + CF_{OPMI}(x,t) \right\rangle_R$ . Note that the future cost for the same time step $t$ differs from the one in the previous case through the dependence on the state $x$, which in turn depends on the previous operation policy.

We can quantify the value of the climate forecast in two complementary ways.

First we can compute the expected Value due to Reduction in Costs:

$$VRC(t) = CT_{OPLI\_e}(t) - CT_{OPMI}(t), \qquad \text{Eq. (1)}$$

which is null at $t=t_0$, becomes non-zero as the system is operated with the different policies (OPMI and OPLI.) and reaches a final value at the end of the simulation period $VCR(t_f)$ which accounts for the expected total reduction in cost due to the additional information provided by N3.4 index.

We can also compute the value of the information due to a more accurate prediction of total costs at the beginning of the period, which has an associated financial benefit since a more accurate amount of capital is frozen for the operation of the system. The error in the prediction of costs at the beginning of the period is given by:

$$ErrP(t_0) = CT_{OPLI\_p}(t_0) - CT_{OPMI}(t_0), \qquad \text{Eq. (2)}$$

which is -in general- nonzero due to the different future cost functions associated with each operation policy, since direct costs are zero at the initial time. The financial cost associated with the error in the prediction of costs can be estimated assuming a 4% annual interest rate as: $\alpha \times ErrP$ , with $\alpha = (1.04)^{Years} - 1$ and *Years* the length of the simulation period.

Therefore, the total value of the information is:

$$VInfo = VRC(t_f) + \alpha \times ErrP \qquad \text{Eq. (3)}$$

## *3.3 Subset of analog years.*

Extreme events of El Niño-Southern Oscillation (ENSO) peak towards the end of the calendar year, reaching the maximum amplitude of sea surface temperature anomalies respect to the mean annual cycle. The ENSO state for the entire period of interest (August 2009 to July 2010) was therefore characterized by a single number, the value of N3.4 index averaged from November 2009 to January 2010. In view of the known relation between N3.4 and inflow to Rincón del Bonete [9], we consider that the historical inflow distribution limited to those years that share a similar value of N3.4 for the November to January trimester better represents the expected value compared to the entire historical set. We call this subset of years, the analog years.

With this methodology, all weeks of the simulation period share the same subset of analog years, since these are determined by the N3.4 index during a fixed trimester of the year. We are aware of the strong seasonality of ENSO influence on regional precipitation [10]. However, we chose to adopt this simple definition of analog years for an initial study and leave seasonal variations for future work. The distribution of inflow values in the analog years is significantly different from the universe of inflows on record only for specific parts of the years, those seasons in which N3.4 is known to condition the local climate. On other seasons the two distributions (entire record and analog years) are very similar and the limitation in the sampling cannot be justified. However, precisely because of the similarity in the distributions, no major influence in the results is expected from this simplification in the methodology.

There is a tradeoff in the definition of the size of the subset of analog years. On the one hand, if it is too small, the interannual variability of inflow within years with similar ENSO conditions is not well captured. On the other hand, as the subset gets larger, it starts to incorporate analog years with increasingly different ENSO conditions. Experience shows that for a century long dataset it is reasonable to limit the size to 30 years, and that results don’t change substantially with small changes in the number of analog years.

Of course, the value of N3.4 for November 2009 – January 2010 was not known in August 2009, at the beginning of the period of the retrospective simulation. Instead, we took the best prediction available at the time. NCEP climate forecast from August 2009 predicted a mean anomaly of 1.7ºC for N3.4 index for the target trimester. It proved to be quite a skillful prediction since the observed anomaly turned out to be 1.68ºC.

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1911 | 1912 | 1913 | 1914 | 1915 | 1918 | 1919 | 1923 | 1925 | 1926 |
| 1929 | 1957 | 1958 | 1963 | 1965 | 1968 | 1969 | 1972 | 1977 | 1980 |
| 1983 | 1986 | 1987 | 1991 | 1992 | 1994 | 2002 | 2003 | 2004 | 2006 |

Table 3. List of analog years, those with ENSO conditions in Nov.-Jan. similar to the ones during the simulated period.

## *3.4 CEGH model calibration.*

SimSEE simulator includes a module that trains linear stochastic processes on given temporal time series, in our case inflow to the reservoirs. This results in a calibration of the linear system that will in turn be used to simulate the stochastic processes during optimization and simulation phases. This calibration, that accounts for the short term memory and cross correlations of the uncontrolled variables, takes place in “Gaussian space”. CEGH (for Correlation in Gaussian Space of amplitude Histograms) therefore includes the set of nonlinear transformations (NLT) previously mentioned that transforms temporal series from the real to Gaussian space and back.

The identification of the model (determination of the NLT and the coefficients of the linear system) was separately done based on the whole set of 100 years of historical time series and on the 30 analog years only. Figure 3 shows the expected inflows to Bonete (B), Salto (S) and

Palmar (P) for the simulation period (August 2009 – July 2010) based on the entire dataset and on the analog. The larger inflows in analog years reflect the wetter conditions associated with El Niño years.

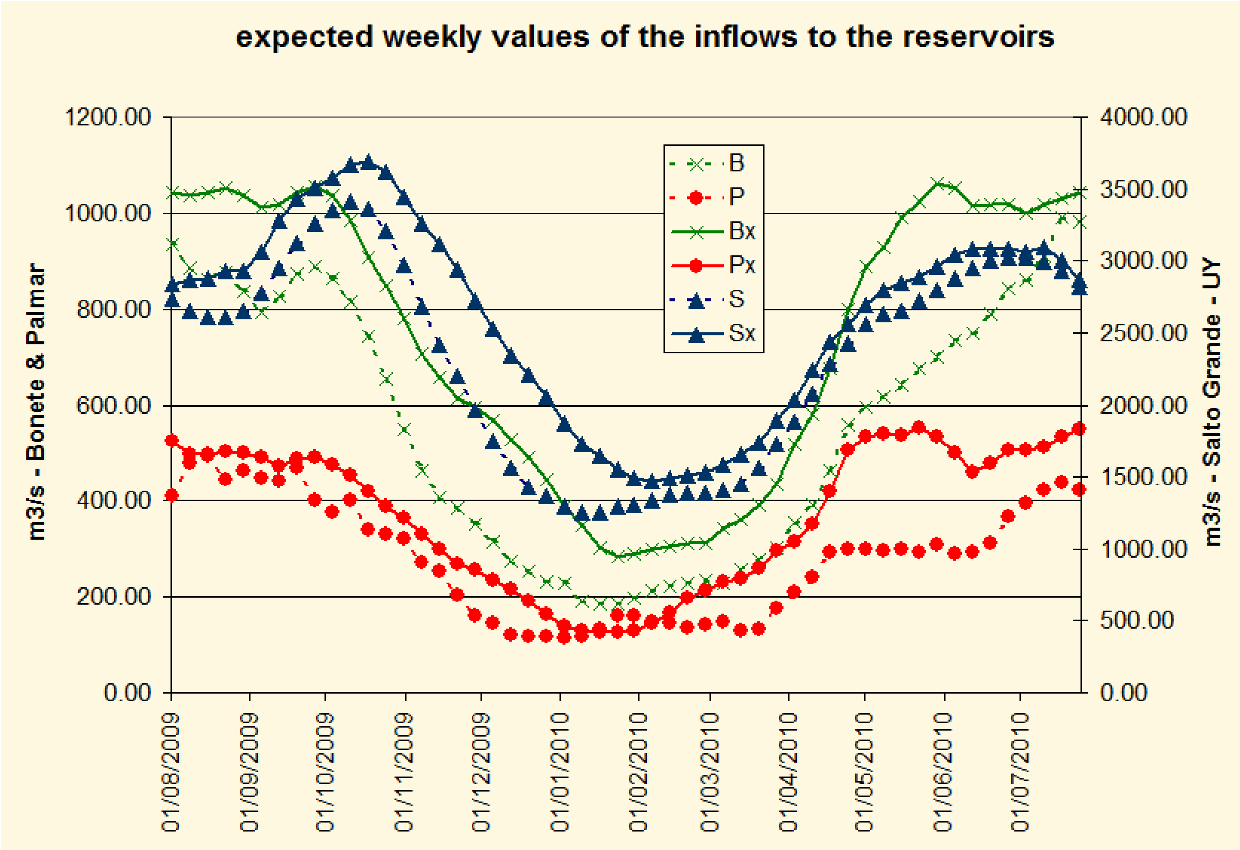


Figure 3. Expected inflows for to Bonete (B), Salto (S) and Palmar (P) during the simulation period considering the entire dataset (dashed lines) and the analog years only (solid lines).

The linear system in Gaussian space is of the form: S(k+1) = A* S(k) + B* W(k), where S is the state of the stochastic process and W a vector of Gaussian cross-independent white noise. Training such system in the two cases considered, renders the following set of coefficients (the matrices are three-dimensional because we are considering three reservoirs: Bonete, Salto and Palmar):

**Identified coefficients for the system trained in the entire 100 record**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 0.761 | 0.025 | 0.076 | | 0.380 | -0.181 | -0.397 |
| **A** = | 0.158 | 0.626 | 0.010 | **B** = | 0.614 | 0.253 | 0.174 |
| | 0.121 | -0.033 | 0.780 | | 0.182 | -0.477 | 0.243 |

**Identified coefficients for the system trained in the 30 analog years**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 0.680 | 0.038 | 0.099 | | 0.496 | -0.179 | -0.392 |
| **A** = | 0.111 | 0.606 | 0.020 | **B** = | 0.617 | 0.356 | 0.197 |
| | 0.088 | -0.005 | 0.748 | | 0.261 | -0.500 | 0.280 |

Table 4. Coefficients of the linear system trained under the two cases considered.

The two set of coefficients are similar, indicating that the main influence of ENSO conditioning on inflows is not in the short term memory and cross correlations but in the amplitude of inflow histograms, as can be deduced from Figure 3. This dominant effect is captured in the set of nonlinear transformations.

# 4 Results

Figure 4 shows the two optimal policies (OPMI and OPLI) for the use of the stocked water of the Bonete reservoir during January-February 2010. The horizontal lines, TV and TG, correspond to the variable cost of the fuel fired units, Vapor Turbines using fuel oil and Gas Turbines using gasoil, respectively.

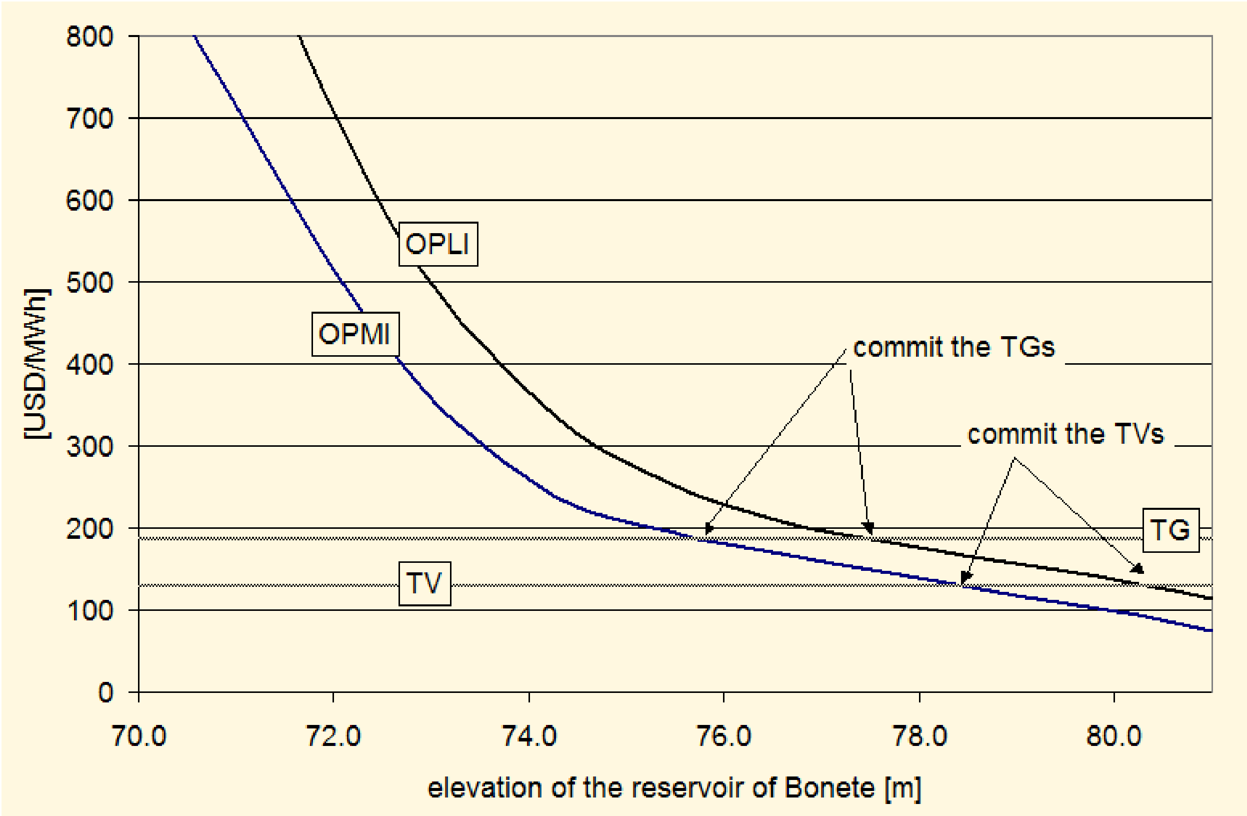


Figure 4. Comparison of the policies of the operation of the Bonete reservoir, average for January and February 2010 in the expected hydrological state.

The information provided by N3.4 index changes the policy of use of the reservoir at the beginning of 2010, lagging the dispatch of thermal units until the elevation of the reservoir is reduced 1.6 meters below the elevation at which the same thermal plant would be committed using the OPLI policy (see Figure 4). This is only an example, for a given state of the system, of the differences induced by the knowledge of Niño 3.4 index in the optimal operation policy. It implies that the estimation of the value of the stocked water at that time is higher for OPLI as compared to OPMI, which is confirmed in Figure 6. Other consequences of the different information considered by the operators of the system are shown below.

Figure 5 shows the expected value of the Bonete reservoir level for both operation policies. The upper curve corresponds to the OPLI operation, which does not consider ENSO-related wet climate forecast and is therefore more conservative with water management. The initial level is set to be the same in both simulations. The final levels are also the same for both operators, which is consistent with the fact that by the end of the period (one year) the impact of the different information considered by the operators at the starting time vanishes.

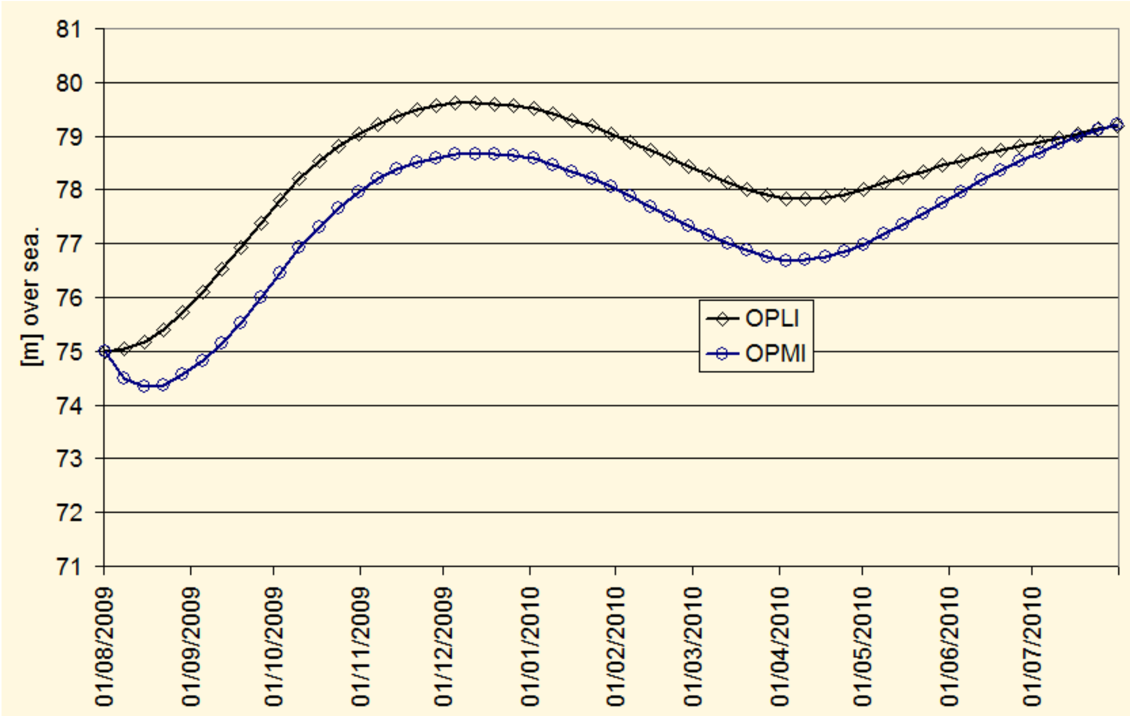


Figure 5. Expected evolution of the elevation of Bonete reservoir.

Fig. 6 shows the expected value of water in the Bonete reservoir. It can be seen that the OPLI operation (black curve) is significantly more conservative (higher value of water) compared to OPMI during the first several months of the simulation. Since both operators start from the same initial condition, the more conservative management of OPLI results in higher levels of the reservoir (Figure 5). The larger volumes of stocked water affect the value of water which thus starts to decrease. Only by March 2010 does the expected value of water for OPLI fall below that of OPMI. At this point OPLI will start, for the first time in the period, to turbine more water than OPMI (see Figure 7).

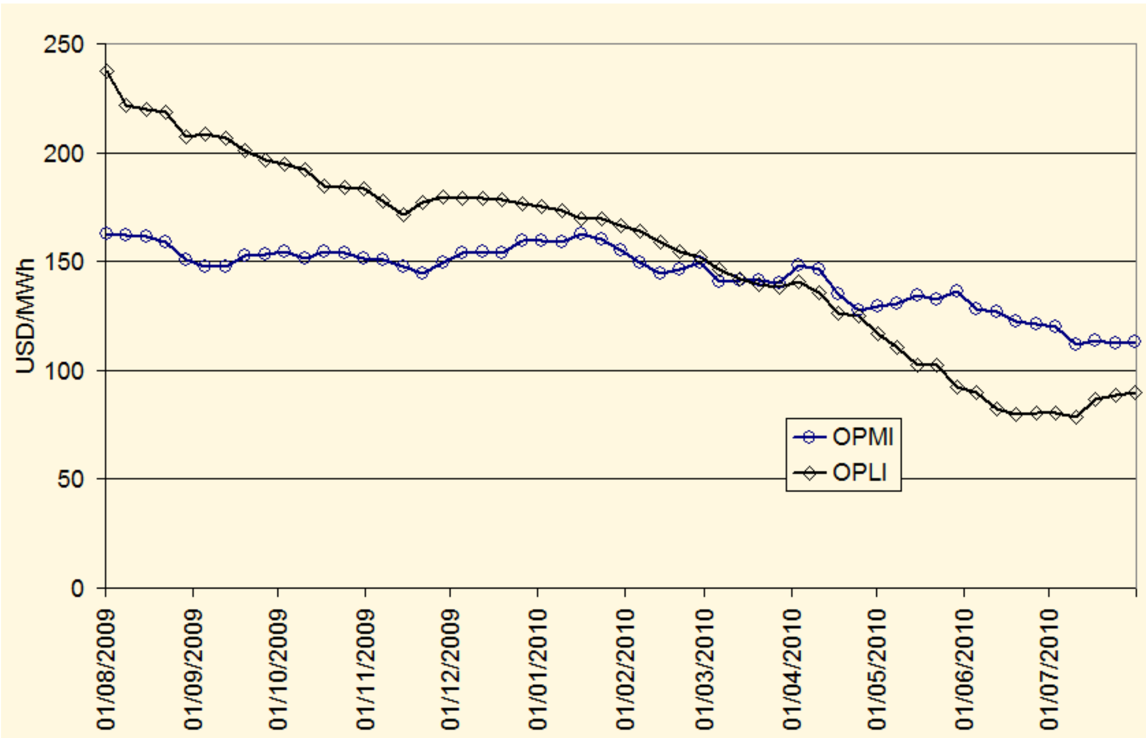


Figure 6. Expected evolution of the value of the water stored at Bonete reservoir.

Figure 7 shows the expected weekly average of turbined and spilled flow rates for both operations and inflows to Bonete reservoir. At the beginning of the period, it is observed that the OPMI starts turbining far more water than OPLI in an attempt to reduce future spilling. This is because, based on the Niño 3.4 index information, OPMI expects a wetter season and higher inflows than the OPLI.

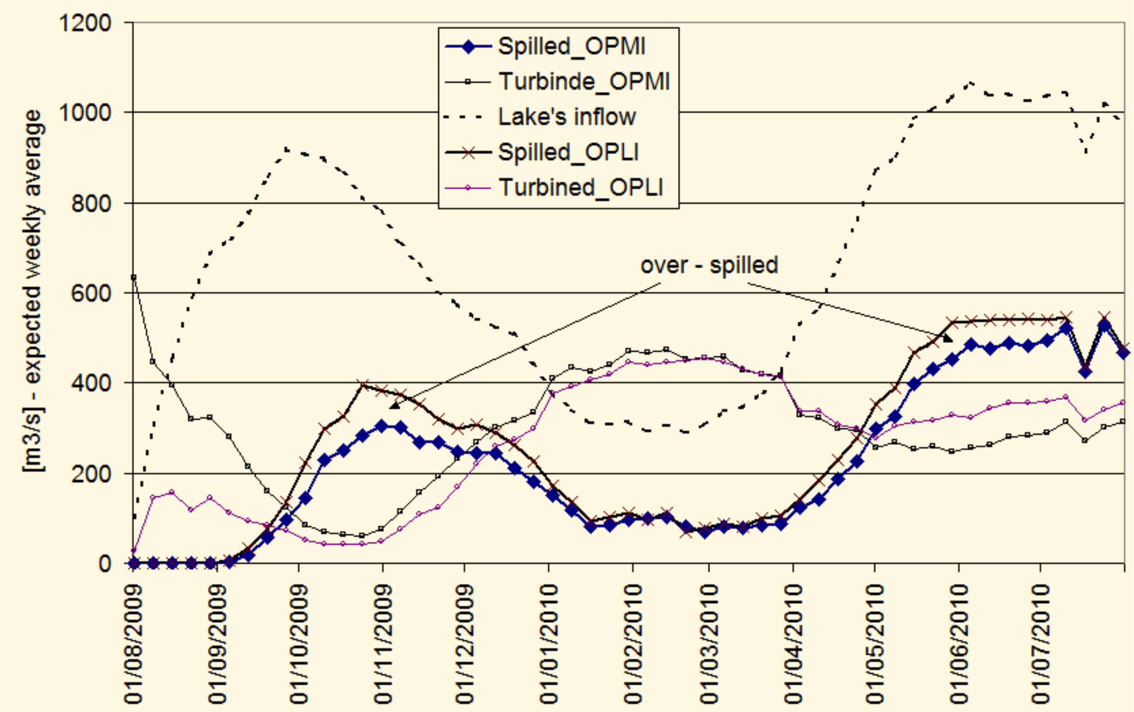


Figure 7. Expected operation of the Bonete hydroelectric plant.

We can see that, in November and December 2009, both operators have considerable spilling. However, those of OPMI are somewhat lower. The same happens at the beginning of 2010 winter when high inflows are expected once more. Again, thanks to the lower level of operation of the reservoir, OPMI manages to have lower spilling rates even though the operator is turbining less water than OPLI at that time.

Table 5 shows the different use of water during the whole period for both operators, OPMI and OPLI, as percent of the incoming volume and the relation among them.

| | **Spilled** | **Turbined** | **Stored** |
|---|---|---|---|
| **OPMI** | 33% | 46% | 21% |
| **OPLI** | 38% | 40% | 21% |
| **OPLI/OPMI** | 1.17 | 0.89 | 0.99 |

Table 5. Use of the water for each operation policy (see text)

The OPLI spills 17% more water and turbines 11% less than the OPMI. Both operators store 21% of the inflow volume, which is consistent with Figure 5 where it is shown that both the initial and final levels are the same for both operators. It is important to note that the OPMI succeeds in reducing the spilled water.

Fig. 8 shows the expected value of operation cost accumulated since the beginning of the period for each operator (left axis) and its difference (right axis). The expected values of operation costs (fuel + fail + imports) during the year add up to 360 MUSD and 331 MUSD for the OPLI and the OPMI respectively. The accumulated over cost of the OPLI with respect to the OPMI is 30 MUSD (about 10% of the yearly cost).

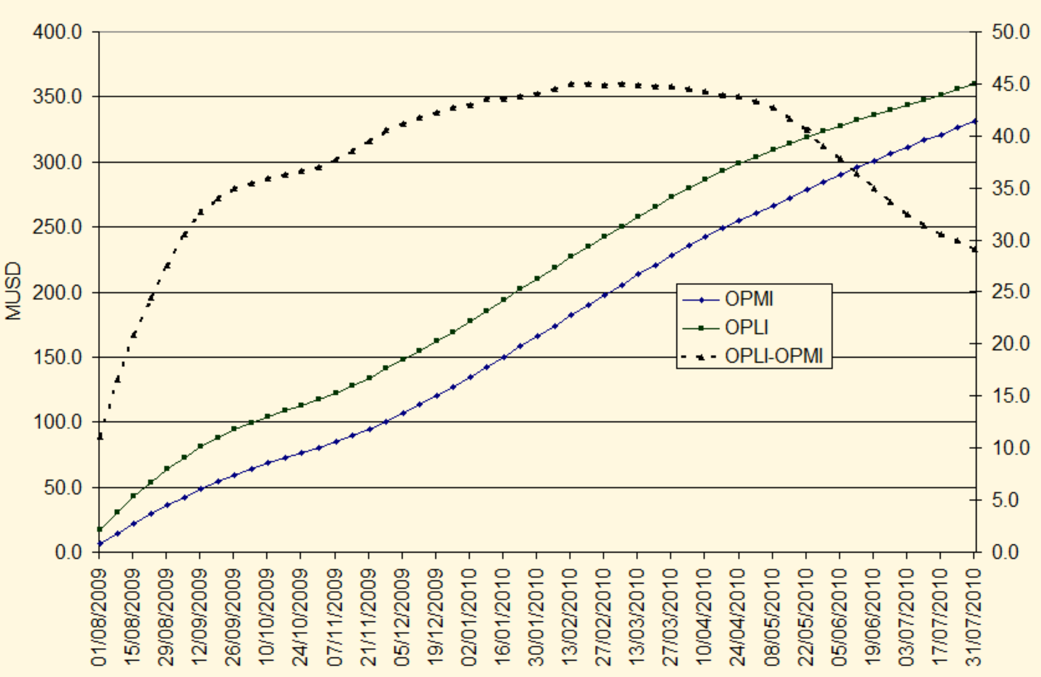


Figure 8. Expected evolution of the expected value of the accumulated operational costs.

Figure 9 shows, for each time step, the Value due to Reduction in Costs (VRC), and the Error in the Prediction of costs (ErrP), as defined in Eqs. 1 and 2 respectively.

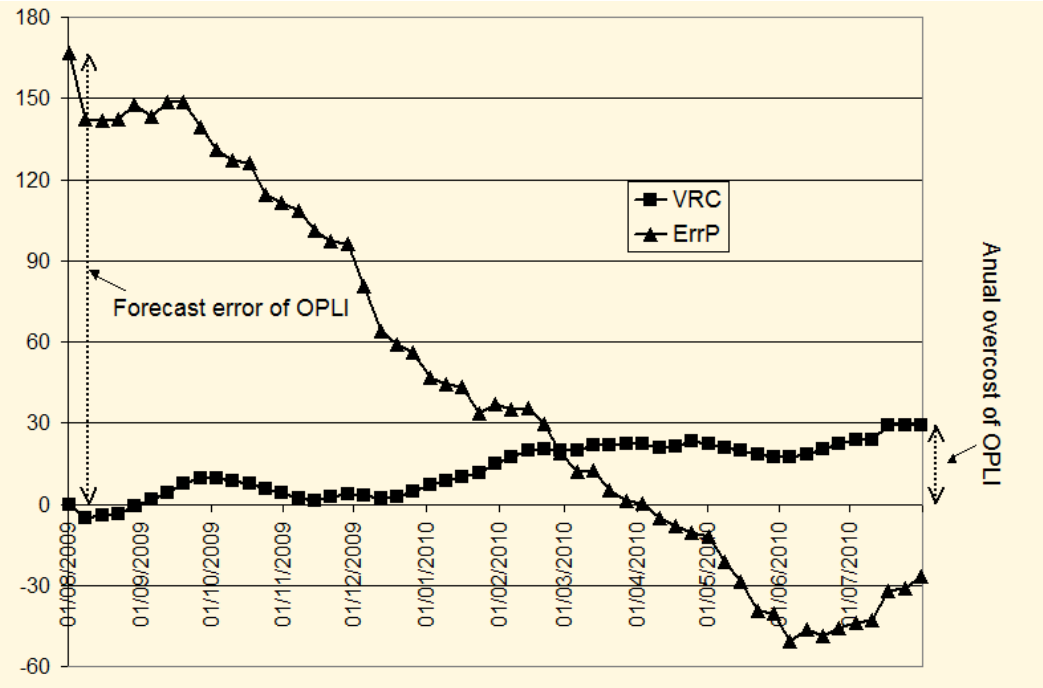


Figure 9. Value of N3.4 index information available on August 1st 2009. Evolution of the VRC and ErrP measures.

“ErrP” measures the prediction error in the total cost of the OPLI with respect to OPMI. At the beginning of the period, that value reaches 167 MUSD. This means that, at that time, the OPLI makes a cost estimate for the year, which is 167 MUSD higher than the OPMI estimate. “VRC” shows, at each time, the over cost attributable to the OPLI lack of climatic information. As was already mentioned, at the end of the period over cost equals 30 MUSD. The value of information provided by N3.4 index on August 2009, as given by Eq. 3, amounts to 30 + 0.04*167 = 36.7 MUSD.

# 5 Discussion, conclusions and future work.

ENSO is known to affect precipitation and therefore influx to the reservoir of the hydroelectric dams in Uruguay. A methodology was developed to take consideration of this information (through the N3.4 index) in the optimal dispatch planning of Uruguayan energy system. Optimization and simulations were carried out for a one-year-long case study starting in August 2009 when a warm event (El Niño) was developing in the equatorial Pacific.

The results for the case study implemented are quite significant. The operator that takes into account N3.4 information has an expected saving of 30 MUSD when compared with the operator that ignored the climate forecast associated to ENSO. This saving is approximately 10% of the expected operation cost for the 12 months considered. A component of this savings is financial, due to do the better capacity of the informed operator to forecast the operation cost of the period. For this case, the less informed operator overestimates the operation cost of the period in 150 MUSD, equivalent to 45% of the operation cost estimated by the more informed operator. The rest of the savings comes from lower direct costs due to a better management of the reservoirs, where spilling is reduced in 17%. In years of very low inflows, there is very little room for water management and no risk of spilling water from the reservoirs, so different operation policies will have little differences in the direct costs incurred in the long run. However, the savings due to a better initial prediction of total costs remain valid even if the climate forecast is a dry one rather than a wet one.

This individual case study is highly promising of the potential usefulness of climatic information to improve the operation of the electrical system of Uruguay. Nevertheless, there are many shortcomings in the methodology that limit the scope to which these results can be generalized. Each of these shortcomings in turn indicates a possible line of future development. We end up by addressing a few of them.

*Skill of the climate forecast*. We assumed that the more informed operator is indeed better informed. Given a methodology to incorporate climate forecasts to the operation of the system, which in this study consists on the simple N3.4 analog years approach, its skill and impact needs to be assessed in a large number of cases to account for the probabilistic nature of the climate forecast. In this study we entirely skipped this issue concentrating on the impact of the forecast on the operation and economic outcome for a particular case. It is worth mentioning that precipitation over Bonete basin was larger than climatology in each of the first 7 months of the period considered and that the total precipitation for that period was more than twice the climatological value. Still, this information is only anecdotal and does not substitute for a rigorous analysis of skill and impact of forecasts.

*Non-deterministic forecast of ENSO*: ENSO predictions are subject to errors, although the skill has consistently improved over the years. This depends partly on forecast lag, but also on the state of the coupled ocean-atmosphere system over the equatorial Pacific. In the future, a probabilistic prediction of ENSO (through N3.4 index or other) could be included in the generation of the stochastic processes. This approach will become inevitable if the optimization and simulation period extends beyond the predictability threshold for ENSO, which has already been stretched in this study. In particular, for multiyear planning simulations, there will be a need to incorporate a model that captures the dynamics of ENSO.

*Seasonality and lack of predictability*. Both shortcomings were already highlighted previously. The analog year approach needs to be generalized to account for the seasonality of ENSO signal in the regional climate. One way could be to define the analog years for each week of the year. During many weeks, though, there will not be a defined signal and the conditioned distribution may not differ from the entire historical record, in particular during ENSO neutral years. In principle, this does not constitute a problem for the methodology. Should there be other predictor of the local climate (i.e. the Atlantic Ocean), different indeces could easily be incorporated to this methodology as well.

*After the fact evaluations*. This study was performed entirely with information available on August 2009. Once the influx time series for the period becomes known, it is interesting to perform evaluations incorporating the new information. The total cost with each of the operation policies, OPLI and OPMI, could be computed for the realized influx time series. Moreover, a Perfect OPerator (OPP) policy could be assessed assuming the realized time series known at the initial time, redoing the optimization and, finally, computing the cost of OPP with the realized (and previously known) inflow. In this way, an upper bound of the value of the unknown information can be found.

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