Using Smart-Grids Capabilities as a Natural Hedge Against Novel Risks Coming from Non-conventional Renewable Electricity Generation

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Abstract. Whether due to economic pressure or environmental concerns, the penetration rate of renewable energies has been increasing over recent years. Uruguay is a leader country in the usage of renewable energies, getting 98% of its electricity from such sources. Its lack of fossil energy resources has historically pushed this country to rely on hydro-energy. Recently, in a scenario where most natural hydro-resources have been deployed, Uruguay has moved to non-conventional renewable energies, to biomass and wind power mostly, although nowadays solar sources are rapidly increasing. As clean and financially stable as they are, non-conventional energies have weaknesses. Unlike thermic and most hydro-sources, wind and solar energies are not controllable, are intermittent and uncertain some hours ahead, complicating the short-term operation and maintenance of electrical systems. This work explores how to use smart-grids capabilities to adjust electricity demand as a natural hedge against novel short-position risks in the Uruguayan electricity market.

Keywords: Renewable energies · Smart-grids · Short-term power dispatch scheduling · Combinatorial optimization

1 Introduction

The absence of fossil energy sources, such as oil, coal or gas, spurred decades ago to Uruguayan authorities to invest in hydroelectric dams as its main source of electricity. Unlike fossil resources, the country accounted important hydraulic assets. Hence, Uruguay historically figured among top countries regarding the percentage of electricity coming from renewable sources. The national electric power matrix was complemented with conventional oil-fired thermal generation plants. Later on, the interconnection with its border neighbors (Argentina and Brazil) supplied and additional level of resilience and robustness to the system. As demand grew, the frequency at which thermal generation plants were used increased as well, so did the energy costs. Similar conditions were taking place in Argentina and Brazil, so importing electricity was as expensive as importing

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oil to keep thermal plants running. By 2007, the situation became critical and the national authorities started a process of diversification of the power sources, which aimed on biomass and wind power at early stages. Today, Uruguay is a world leader in the usage of renewable energies, serving 98% of its own demand of electricity from renewable sources (see [8]).

Table 1. Installed power plant by type of energy source [ADME: 2017]

Energy by type of source	Number of units	Installed power plant (MW)	Relative subtotal	Produced energy total 2017 (GWh)	Relative subtotal
Biomass	12	200	4.4%	900	7.1%
Wind-power	37	1.437	31.5%	4.400	34.9%
Solar	17	230	5%	200	1.6%
Hydroelectric	4	1.534	33.7%	6.200	49.2%
Combined Cycle	1	550	12.1%	100	0.9%
Other Thermal Units	4	604	13.3%	800	6.3%

Table 1 presents the main details regarding the Uruguayan power plant by late 2017. The source is ADME (Administración Del Mercado Eléctrico) and it is available at http://adme.com.uy. The extremely low dependence upon fossil energies isolates the Uruguayan electricity market from commodities volatility. On the other hand, and as it counts in Table 1, over one third of the total energy consumed comes from wind-power, which is highly volatile in the short-term. Variable renewable energies (VRE) have a negative impact in the operation costs of the system. Real-world examples (UK and Germany) of such problems are described in [2]. Managing the electric grid of a country is a challenging task that must be carried out carefully and optimally. In order to accomplish that, multiple problems are to be solved, spanning different scales of time and components. Main objects are: generating plants, the transmission and distribution networks. Long-term planning usually applies to assess the return of investments over those objects along many years ahead. Medium-term planning usually refers to the valuation of intangible resources, such as the height of the lake in an electric dam accounted as an economic asset. Short-term planning consists in crafting optimal dispatch schedules some days ahead, in order to efficiently coordinate the usage of available resources. Beyond that time scale, there are almost real-time models to keep the physical variables of the system (e.g. frequency, active and reactive power) under control. This work aims on the short-term power dispatch of the grid, whose results set the prices of energy in the electricity market. Due to its short scale of time (a few days ahead), such models can assume many sources of uncertainty as deterministic. For instance, oil prices can be considered as fixed along some days to follow, and although sudden/unexpected rains could arise, they hardly change the level of water reservoirs to a significant point.

The former premisses are actually quite realistic when applied to conventional and some non-conventional energy sources (e.g. biomass). Regarding wind and solar power however, those hypotheses become erroneous. The intrinsic stochastic nature of wind and solar power turns out the short-term dispatch of the grid into a much harder challenge, which is object of academic and industrial interest (see [3,6]). In its economical dimension that volatility indicates that wind-energy constitutes a risk position. Under steady conditions (energy prices, weather conditions, date of a year) demand is highly predictable, so given a particular date of the year and an accurate weather forecast, the demand over the grid is among those variables that could be considered as known. This is due to low deviations associated with a large number of users under a stationary behaviour. As a consequence, legacy short-term optimal schedules models are deterministic, or deal with narrow variance in the variables. In addition, traditional instruments to modulate demand with economic measures go by setting different prices between hours on a day, intending to move a fraction of energy consumption from the demand's peak hour towards demand valleys (night-valley filling). Such instruments are based on the premisse that energy is scarce, while the truth is that non-conventional energies, especially wind-power, can be either lower or higher than forecasted. Smart-grid technologies are a cornerstone for Smart-cities paradigm. Smart-grids allow to coordinate important portions of the demand, which could now be directed in opposite direction to wind-power variations and accounted as a hedge instruments against generation risks (demand response). There are many ways to get benefits from demand control. For instance, works [4,5,7] are inspired in a free-market environment, with a kind of underlying stock exchange where energy offers are traded. Sometimes this is not possible due to regulatory or scalability issues. Besides, wind and solar power fluctuate so rapidly, that implementing classical financial contracts (e.g. forwards or swaps) is not always optimal, even a-day-ahead. Using batteries is another instrument to compensate power variations in the offer with demands. This document explores the benefits of using smart-grid technologies and residential energy storage, to coordinate part of the residential demand with the uncertain offer of energy in the system. The application case is based on the particulars of the Uruguayan market, where only large-scale energy consumers are allowed to trade in the electricity market, while residential users only can get electricity from the state-owned company. In this wholesale electricity market, the price is not set by pairing bids and offers. Instead, their production parameters of generators (e.g. minimum and maximum power, fixed and variable costs) are public, and up from them, the authorities that operate the system dictate when and how much energy is going to be produced by each unit. Production decisions are driven by a short-term reference optimization model, whose objective function aims on minimizing the total cost of generation. Such premisses are ideal for the approach presented in this work, which is stated from a short-term point of view optimization. These results show how the existence of smart-grid technologies allow to improve the efficiency of the system, not the return of the investments necessary to achieve such smart-grid grade. Problem instances are based on real data of the Uruguayan market, chosen to be representative of different scenarios. The remaining of this document is organized as follows: Sect. 2 shows the shot-term volatility of wind power and the techniques used to master it; Sect. 3 describes the main characteristics of the optimization models used to estimate the benefits of counting with smart-grid technologies; Sect. 4 presents the set of test scenarios used as instances of the previous models; while Sect. 5 summarizes the main conclusions of this work and lines of future work.

2 Dealing with Wind Power Uncertainty

This section shows how variable wind-power is, when described as a stochastic process, and it briefly presents some of the techniques used to likely fence its realizations. The historical of wind-power data in Uruguay has a few years, and along this period the installed power plant was firmly growing, so instead of expressing power in term of MW we use the Plant Load Factor (PLF), which corresponds to the actual power generated at each time, divided by the sum of the installed power capacity of each wind turbine in the system at each moment. So, $0 \leq \text{PLF} \leq 1$ for each hour. Hence, information is normalized, and we can disregard of changes in the installed capacity during the period of analysis.

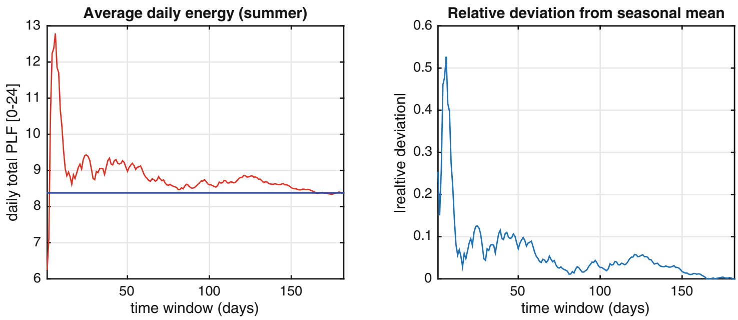

Fig. 1. Time window average for daily wind energy on summer days

Figure 1 shows the daily cumulated PLF (the sum of hour PLFs, which then ranges from 0 to 24) along two consecutive years of summer days. We have selected days of one season to avoid deviations coming from seasonal behaviour. The figure shows how after a week or two the process goes inside the 10% error band, respect to the expected value for that season.

Therefore, wind-power is fairly regular when used in medium-term planning. For shorter periods of the time, the situation is quite the opposite. The leftmost of Fig. 2 sketches the distribution of daily cumulated PLFs, while the rightmost part plots actual daily realizations of the process (blue curves) along one and a half years and the average PLF at each hour (black asterisks). Complementarily, there are approaches for short-term wind power forecasting based on

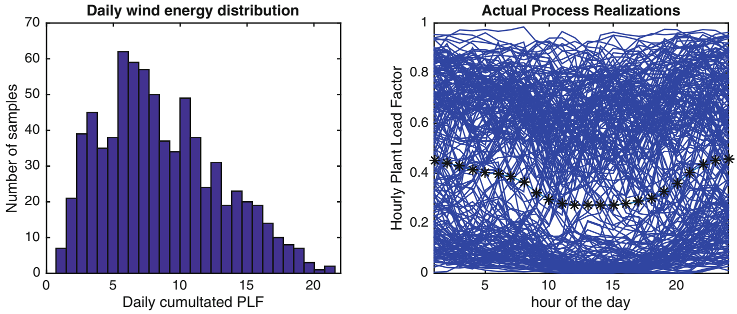

Fig. 2. Histogram of daily wind energy samples [leftmost] and 30% most atypical realizations for Uruguayan wind-power [rightmost] (Color figure online)

numerical simulations of atmosphere's wind flows. For a day ahead period, or even larger time windows, numerical simulations are usually more accurate than purely statistical models. Figure 3 presents 72 h ahead forecasts (blue curves) and actual power series (red curve) for two samples within the actual data-set. These and other historical series are available at: http://www.ute.com.uy/SgePublico/ConsPrevGeneracioEolica.aspx.

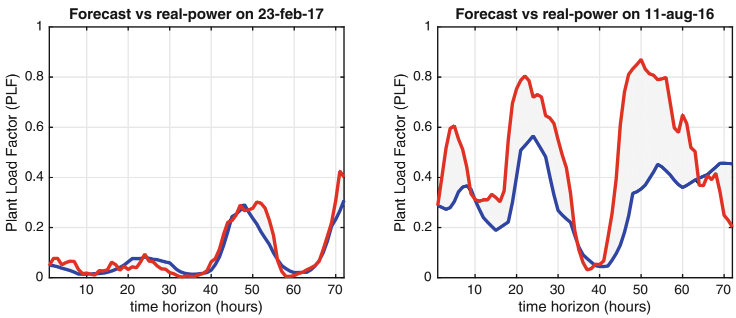

Fig. 3. Examples of 72 h forecasts (blue) and the actual power registered (red) (Color figure online)

Although numerical simulations perform better than purely statistical methods to follow the process whereabouts at early stages, they are far from being trustworthy in what respects to the construction of likely scenarios at larger times. On the rightmost of Fig. 3 there is an example where the difference of energy between forecast and actual processes (i.e. the grey area), accounts 57% of the average PLF for the period.

Besides assessing potential savings coming from using smart-grids, this work benchmarks the performance of deterministic and stochastic optimization models over the same test scenarios. Therefore, confidence bands were used to fence

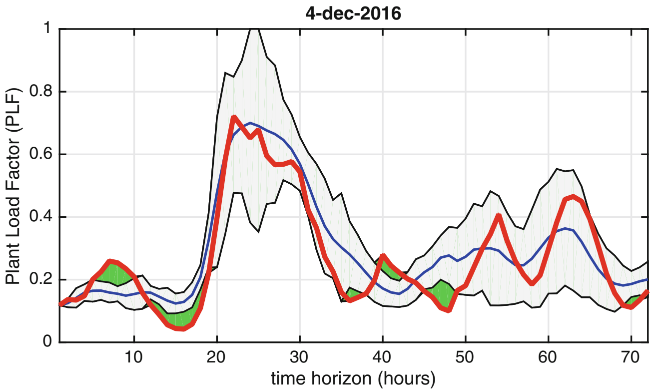

Fig. 4. A confidence band (grey) crafted after forecast and the actual process (red) (Color figure online)

wind-power process with a high degree of certainty. Those bands were crafted up from the combination of three independent sets of forecasts and the correspondent actual power series. As an example, Fig. 4 shows the confidence band for a particular day within the test-set. Bands were calibrated seeking for the average off-band energy (i.e. green areas in the figure) to be below 10% of the average PLF. Besides, bands are adjusted so less than 10% of the days violate the previous condition. The calibration whose average band width is minimal while fulfills the previous conditions, has an average width deviation respect to the centroid (i.e. blue curve) slightly above 10% of the average energy demand (the fact this final figure replicates the previous is just a coincide). The details of the technique used to craft these bands are documented in [9].

3 Optimal Short-Term Optimization Model

This section describes the main entities of the Uruguayan electricity market and examples about how some of them are modeled, and how their instances are combined into a single optimization model.

Over the upmost part of Fig. 5 is represented the power offer of the system. Renewable (green) energies comprise: wind and solar power (non-cumulative renewable/NCR), Hydroelectricity (HYD) and the Biomass, whose units are basically thermal generation plants (TER). The installed power plant is completed with fossil thermal generation units. Upon the rightmost-bottom of Fig. 5 non-manageable demands are represented. They are typically associated (though not limited) to some residential appliances. Such inelastic appliances (IAP) are considered hourly predictable demands over the time horizon to optimize, which is 72 h ahead in this work (i.e. the time horizon of wind-power forecasts). In other words, inelastic appliances impose a power requirement to the system. Variants of the basic model introduce: elastic applications (EAP) or active applications

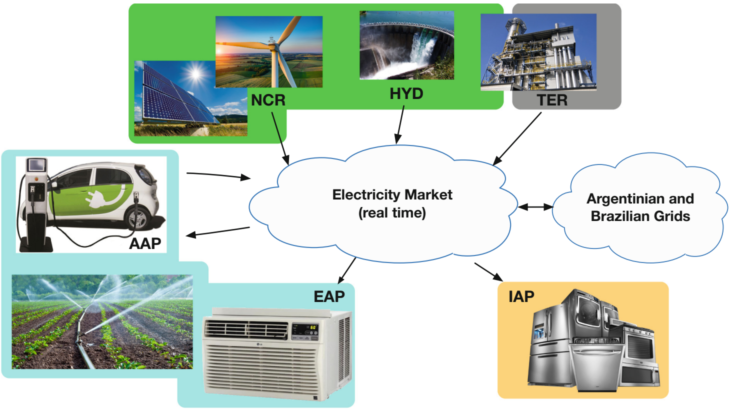

Fig. 5. Entities of the wholesale electricity market

(AAP). Elastic applications are those where requirements are better expressed in terms of energy rather than power. A fraction of what they need could be expressed as a power constraint, but the idea is that substantial portions of the required energy within certain time windows could be either deferred or advanced into that window. Finally, in addition to being elastic, active applications can return power to the network when necessary. In all the models explored in this work, elastic and active applications are at the service of the system (i.e. social-welfare). We assume they can be remotely controlled, so as long as basic power requirements are fulfilled, the gaps of energy to complete those demands constitute control variables just as those of the installed power plant, and they are also used to get the most of the optimization.

3.1 Thermal Units

Each entity has a reference mixed-integer optimization sub-model or block. All these blocks combined and instantiated for a particular data-set define the whole optimization problem for that instance and variant. For example, Eq. 1 is the framework to model simple thermal plants, labeled as *Other Thermal Units* in Table 1.

$$\begin{cases} \min\limits_{x_t^g, w_t^g} a \sum\limits_{t \in T} x_t^g + b \sum\limits_{t \in T} w_t^g + \alpha \sum\limits_{t \in T} y_t^g & & \\ m_{GT} \cdot x_t^g \leq w_t^g, & t \in T & (i) \\ w_t^g \leq M_{GT} \cdot x_t^g, & t \in T & (ii) \\ y_t^g \geq x_t^g - x_{t-1}^g, & t \in T & (iii) \\ 2x_t^g - 2x_{t+1}^g + x_{t+2}^g + x_{t+3}^g \geq 0, & t = 1, \ldots, T_m - 3 & (iv) \\ 2x_t^g - 2x_{t+1}^g + x_{t+2}^g + x_{t+3}^g \leq 2, & t = 1, \ldots, T_m - 3 & (v) \\ x_t^g, y_t^g \in \{0, 1\} & & \end{cases} \qquad (1)$$

Boolean variables x_t^g indicate whether the unit g is active or not at the time moment t. The period of activation of a small thermal unit is bellow 10 min, so it can be considered instantaneous for a time slot of one hour. Whenever active ($x_t^g = 1$) the power generated by each unit must be between technical minimum (m_{GT}) and maximum (M_{GT}) values. This is imposed with constraints (i) and (ii). Boolean variables y_t^g identify the instants of time t at which a unit g is activated, which is forced by constraint (iii). The terms in the objective function respectively correspond to: the hourly fixed cost of operation when the unit is active; the variable cost incurred by the level of power generated; and the operational costs incurred in by activating the unit, i.e., fuel expenditures for warming up the unit plus a maintenance share per operation cycles. Besides of being costly in terms of maintenance, the process of frequently activating thermal units is not operationally friendly. Therefore, we added constraints to guarantee that once started, a unit should be active (for instance) at least 3 h (constraints (iv)), and also to force it to be inactive for at least 3 h after stopped (constraints (v)). The last sets of constraints should be complemented with boundary constraints when the initial or final activity states are inherited as part of the instance. Table 2 shows a possible set of parameters for those simple thermal units, for a particular oil price during 2016. We could not find public data to valuate parameters α.

Table 2. Parameters for simple thermal units

Name of each thermal unit	Number of power subunits	Power min	(MW) max	a USD	b $\frac{USD}{MWh}$
Central Batlle (Motores)	6	6	60	0	82
Punta del Tigre: 1 to 6	6	90	288	7423	86
Punta del Tigre: 7 and 8	2	0.6	48	1619	88
Central Térmica Respaldo	2	40	208	6819	103

Unlike simple thermal units, the *Combined Cycle Plant* (or CCC) has slow time commitments, of around four hours till full operation, so its start-up details should be integrated into the model. To model such type of unit we used four types of variables and over twenty types of constraints. Elaborating into those details would deviate the focus of this document, so they were intentionally left outside of the scope. Reference parameters are: $m_{GT} = 58\,\text{MW}$, $M_{GT} = 550\,\text{MW}$, $a = 5240\,\text{USD}$ (hourly fixed cost), $b = 63\,\text{USD/MW}$ (variable cost) and $\alpha =$ 5500 USD. Along the four hours it takes the CCC to attain its full operation, the plant gradually increases the output power following a predetermine ramp. During that ramp-up, the efficiency is lower, so b is 35% higher. Once in full operation condition, the CCC should not be stopped until four hours later (i.e. eight hours since started), and once stopped there should be a period of at least 6 h until start it up again. The CCC is the most efficient among the thermal units. However, it is not always chosen by the optimization process because of its complex commitment times, which sometimes does not fit system needs.

3.2 Hydroelectric

A third of the installed power plant and a half of the energy produced in Uruguay still come from hydroelectricity. Hydroelectric dams are geographically distributed over the mid-north of the country, as sketched in Fig. 6. Three of them are in tandem over an internal river (Río Negro), while the fourth, placed over the Uruguay River, is a binational joint project with Argentina. The main state variable of a hydroelectric dam is the volume of water in its storage lake. That volume determines the *head* (i.e., the height difference between the surface of the reservoir and the turbines). Control variables regard with how much water flows through the turbines, and how much is spilled. The higher the head, the most energy obtained by volume of water turbinated. Actually, this also depends on the level the river after the dam, which in Uruguayan low steep river courses is highly dependent on the total flow itself (i.e. turbinated and spilled), so the production function is far from being linear. Natural influxes into the reservoir increase the volume of water in it, while turbinated water decreases it. Intuition suggests that production efficiency passes by keeping the head as high as possible, while waters flow turbines downwards. However, whenever the head surpasses a security threshold, water must be spilled. Spilling not only wastes the resource, but, as mentioned before, increases the level downstream, what reduces the efficiency for the fraction of water really passing through the turbines.

Table 3. Parameters of the hydroelectric Uruguayan power plants

Hydroelectric power plant	Power	Empty	Influxes
Rincón del Bonete	148 MW	20 weeks	Río Negro
Baygorria	108 MW	1 day	Bonete's outflux 6 h earlier
Palmar	333 MW	2 weeks	Yí river and Baygorria 10 h earlier
Salto Grande	1/2 1890 MW	2 weeks	Uruguay river

As it counts in Table 3 and can be observed in Fig. 6, the sequence of dams over the Río Negro binds influxes of some dams with the outflux of the previous.

Table 3 also shows the emptying time when the unit is used at its maximum power. Within an optimization horizon of three days, control decisions hardly affect the efficiency (head or spilling) in Bonete, Palmar or Salto. Baygorria on the other hand must be finely tuned.

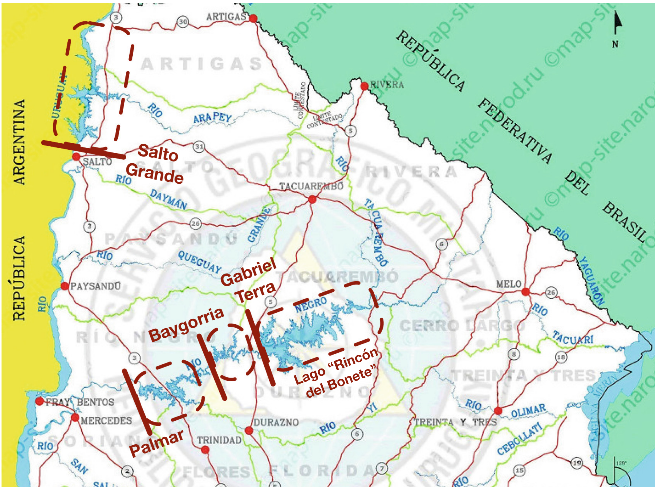

Fig. 6. Geographical distribution of hydroelectric dams in Uruguay

3.3 Storage Batteries

Units of energy storage are modeled without an objective function, i.e., without a direct profit. So they are at the service of the system.

$$\begin{cases} b_t = b_0 + \delta \sum_{\tau=1}^{\tau=t} r_\tau^c - \sum_{\tau=1}^{\tau=t} r_\tau^d & (i) \\ 0 \leq r_t^c \leq \overline{r_c} & (ii) \\ 0 \leq r_t^d \leq \overline{r_d} & (iii) \\ 0 \leq b_t \leq \overline{b} & (iv) \end{cases} \tag{2}$$

The state variable b_t indicates the level of charge of the battery, i.e., the energy cumulated in it at time t. Control variables r_t^c and r_t^d indicate how much power is used at time t to respectively charge or discharge the battery. In the first case the power is taken from the grid (as a demand), while in the second is returned (as generation). There are upper limits for control and state variables. The parameter δ<1 represents the inefficiency (loss of power) of charge/discharge cycles. There are no storage units in the Uruguayan grid, so as a reference, we used parameters as in a real-world project ("Neoen & Tesla Motors" in Australia). They are: $\overline{r_c} = 35$ MW, $\overline{r_d} = 100$ MW, $\overline{b} = 140$ MWh y $\delta = 0.9$.

3.4 Demands

Demands are the entities that bind all sub-problems into one. When demands are hourly determined, they form part of the data-set of the instance and are integrated into problem as set of T constraints: $\sum_{g \in G} w_t^g \geq d_t$, $t \in T$. Being T the number of hours along which we are optimizing, d_t the expected demand at the hour t, G the set of generation units and w_t^g the power produced by the unit g at time t (plus storage's uncharging). In more general terms, consider an application j in a set of applications J, and A^j a set of c_j disjoint time intervals $A^j = \{A_1^j, \ldots, A_{c_j}^j\}$ proper of that application. Let D_p^j be the energy requirement of the application j along the p^{th} interval ($1 \leq p \leq c_j$), and consider the control variable z_t^j, the power supplied by the grid to fulfill demand j at hour t. Besides, let $\underline{z}_t^j$ and $\overline{z}_t^j$ respectively be the lower and upper power bounds. Expressed so, an elastic demand is satisfied whenever constraints in Eq. 3 are satisfied.

$$\begin{cases} \sum\limits_{t \in A_p^j} z_t^j \geq D_p^j, & 1 \leq p \leq c_j, j \in J \quad (i) \\ \underline{z}_t^j \leq z_t^j \leq \overline{z}_t^j & \forall t \end{cases} \tag{3}$$

The new power balance condition is $\sum_{g \in G} w_t^g \geq \sum_{j \in J} z_t^j$, for every $t \in T$. Observe that traditional (hourly fixed) demands can be easily expressed using $A = \{1, \cdots, T\}$ and setting $D_t = d_t$. In this document we derive two flavors from this general model for demands. One of them is the traditional, where there is only one kind of demand, whose hourly requirements are known. In the other, we assume that 30% of the residential demand is elastic within each day. Almost 52% of the total energy in Uruguay is dispatched for residential use. So, power demand is first disaggregated between residential (d_t^R) and large scale energy consumers (d_t^L). Next, we set $\underline{z}_t = 0.7d_t^R + d_t^L$, $\overline{z}_t = \infty$, $A = \{A_1, A_2, A_3\}$ where $A_1 = \{1, \ldots, 24\}$, $A_2 = \{25, \ldots, 48\}$ and $A_3 = \{49, \ldots, 72\}$. Finally, we assign $D_1 = \sum_{t=1}^{24} 0.3d_t^R$, $D_2 = \sum_{t=25}^{48} 0.3d_t^R$ and $D_3 = \sum_{t=49}^{72} 0.3d_t^R$.

4 Experimental Results

In addition to opening models by demand elasticity, we branch them by using deterministic or stochastic versions of the problem. So the number of versions totalizes four. Since solar power was incipient by the time this work was being developed, we only consider uncertainties coming from wind-power. In every case, confidence bands (see Fig. 4) are used to bound process realizations. Deterministic versions assume the wind power will be as the centroid of the band (blue curve in Fig. 4). Stochastic versions use the classic stochastic programming framework (see [6]) with four stages. Time intervals (in hours) for each stage are: [1, 6], [7, 24], [25, 48] and [49, 72]. Assuming a power assimilation preprocessing, forecasts are proven accurate during the first six hours (see [1]), so we can model stage-1 as deterministic. For the rest of the stages, trajectories are built to explore the confidence bands in order to reproduce different realizations. For stochastic programming versions of the problems we used 27 trajectories. In summary, for each representative scenario four versions of the problem are solved. They are defined by combining "inelastic" or "elastic+inelastic" demands, in their deterministic or stochastic versions. Historical data about actual dispatch is not available (they are considered confidential by authorities). However, since the historical information for the actual wind-power is available, we tested the convenience of the optimal schedule crafted, by comparing it with results of simulations of the real cost the system would have incurred in by using that plan as a guide. We remark that no algorithm was developed to tackle down these problem instances, since all of them were solved using a generic comercial MIP optimizer: *IBM(R) ILOG(R) CPLEX(R) Interactive Optimizer 12.6.3.0*, on an *HP ProLiant DL385 G7* server with *24 AMD Opteron(tm) 6172* processors, 72 GB of DDR3 RAM and running *CentOS 6.10* Linux operating system.

4.1 Problem Instances

Instances were defined up from scenarios particularly interesting to analyze sensibility against some key aspect the problem. Due to the importance of hydroelectric energy for the country, the availability of hydraulic resources is one the dimensions to explore. We defined five hydro-scenarios to test, they are as follows. *HB1* is the historically typical scenario, with a good head of water in the reservoirs and high expectations of new influxes the next weeks to come. *SH1* assumes a drought condition, with medium resources in the reservoirs and poor expectations about the new influxes. *SH2* is a worse drought condition than in SH1, since now the head level in reservoirs is critical. *EHT1* is an intermediate situation to HB1 and SH1. Resources are good but important new influxes are unlikely, so the valuation of the water (that comes from mid-term planning models) pushes prices towards those of fossil fuels. The valuation gives lowest prices for those reservoirs over Río Negro. *EHT2* is similar to EHT1, but now Salto Grande reservoir has lower prices than those of Río Negro. Although not representative regarding the typical volume of rains in a year, SH1, SH2, EHT1 and EHT2 are important to stress the model. The second dimension for scenarios is defined by the second power source by importance: the power-wind. We selected four "forecasts+actual power" among the set of historical series.

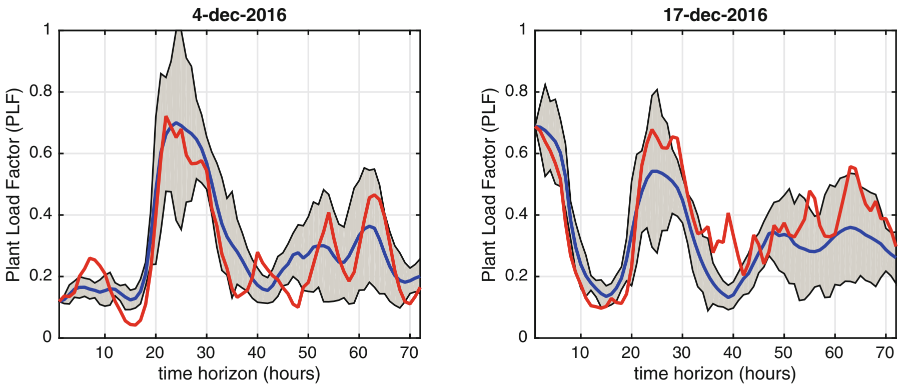

Fig. 7. Representative wind-power samples

Days in Fig. 7 were chosen because they are typical, i.e., they are close to the medians of: off-band error, effective wind-power produced, and width of their confidence band. Days in Fig. 8 on the other hand were chosen to stress the model. The leftmost sample for having the confidence band with the larger width, and the rightmost one for being among the samples with the higher off-band energy, i.e., for being among those bands with the poorest performance.

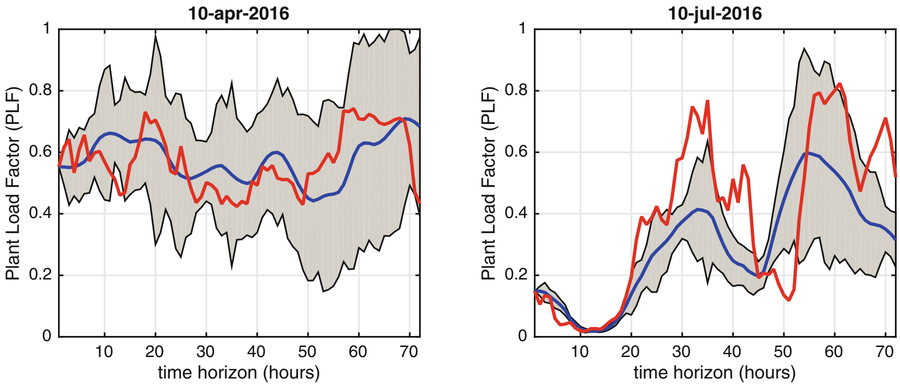

Fig. 8. Stressing samples regarding forecast and wind-power series

In addition, the last sample has a particularity regarding power. Observe that in the period between the hour 51 and 54 rises almost 70% of the PLF, which rounds 1GW, close to the average power consumption of the country.

Therefore, 80 problems were solved to explore those scenarios over different models (4 models × 5 hydro-scenarios × 4 wind-scenarios). In the first place, we show the results for the deterministic models over all hydro and wind scenarios.

Table 4. Cost [USD] deterministic optimization 72 h ahead. [HB1]

	4-dec	17-dec	10-apr	10-jul
Inelastic demand	348,930	334,760	241,230	359,730
Elastic demand	327,200	311,240	239,350	344,780

Complementing the information in Tables 4 and 5, we must add that after simulating the system dispatch using actual wind-power values, the absolute difference between the projected schedule and the simulation of the operation was between 3% and 6%.

Instances for hydro-scenario HB1 do not require the usage of thermal generation. This fact explains the low production costs. Conversely, several thermal units are to be activated in hydro-deficient scenarios EHT1, EHT2, SH1 and SH2,

Table 5. Cost [thousands of USD] deterministic optimization 72 h ahead

	EHT1				EHT2			
	4-dec	17-dec	10-apr	10-jul	4-dec	17-dec	10-apr	10-jul
Inelastic demand	5,389	5,120	3,737	5,448	4,091	3,869	2,850	4,126
Elastic demand	5,281	5,026	3,660	5,338	3,951	3,761	2,667	3,958
	SH1				SH2			
	4-dec	17-dec	10-apr	10-jul	4-dec	17-dec	10-apr	10-jul
Inelastic demand	5,696	5,419	3,857	5,731	5,706	5,428	3,857	5,742
Elastic demand	5,602	5,316	3,735	5,630	5,621	5,337	3,735	5,646

Table 6. Relative deviation stochastic vs deterministic models [HB1]

	4-dec	17-dec	10-apr	10-jul
Inelastic demand	−0.01%	−0.24%	−0.12%	−0.09%
Elastic demand	0.18%	−0.01%	−1.00%	−0.21%

Table 7. Relative deviation stochastic vs deterministic models

	EHT1				EHT2			
	4-dec	17-dec	10-apr	10-jul	4-dec	17-dec	10-apr	10-jul
Inelastic demand	−0.28%	−0.29%	−0.19%	−0.13%	−0.45%	−0.21%	−1.41%	−0.30%
Elastic demand	−0.42%	−0.41%	−0.36%	−0.10%	−0.44%	−0.34%	−0.25%	−0.14%
	SH1				SH2			
	4-dec	17-dec	10-apr	10-jul	4-dec	17-dec	10-apr	10-jul
Inelastic demand	−0.34%	−0.33%	−0.04%	−0.09%	−0.33%	−0.34%	0.00%	−0.10%
Elastic demand	−0.51%	−0.45%	0.05%	−0.02%	−0.50%	−0.47%	0.09%	−0.01%

then costs increase over the order of magnitude. Observe that although costs and other conditions are similar, the system manages much more efficiently hydro-scenarios ETH2 than their homologous in EHT1, whose figures are similar to those of SH1 and SH2.

Regardless of the hydro-scenario or demand elasticity, Apr/10/2016 always gets the lowest cost, with reductions in the order of 30%. That date corresponds with three windy days in a row and evinces how sensible the system cost is to the power coming from wind farms.

Focusing now on the expected cost for stochastic versions, the values are quite similar to the corresponding deterministic instance, so Tables 6 and 7 present the relative difference with respect to figures in Tables 4 and 5.

Observe that in 36 out of 40 instances, the stochastic version gets schedules with lower expected values than those of the deterministic version. This fact by itself is not relevant, however, a-posteriori simulations run to assess models' robustness, show that differences between projected schedules and simulations are always under 3.5% for the stochastic version. Thus, the stochastic version is not only better in quality but in confidence, so we use its figures as a reference to valuate the benefits of having smart-grids capabilities to control up to 30% of the residential demand of energy. Those figures show that having such control allows to reduce costs in all the hydro-scenarios: 4.7% (HB1), 3% (EHT1,2) y 2.1% (SH1,2). Saving are relative higher in the hydro standard HB1 scenario, but in absolute terms are much higher in those of drought. If all those savings were transferred to elastic demands, reductions of price could round 25%.

5 Conclusions and Future Work

This document presents how classical optimization models were used to quantify the benefits of having smart-grids technologies, a fundamental component of smart-cities. Such benefits were computed upon a real-world scenario, the Uruguayan electricity market, a world leader in the usage of renewable energies, which is facing the challenge of getting over 35% of its electricity from wind-power, a volatile source of energy. Experimentation was realized assuming that 30% of the residential demand can be controlled, showing that if billed differentially, discounts could round 25%. Large scale energy consumers can trade in the wholesale electricity market according on their needs. Residential users however, must contract with the public owned company (UTE), so a centralized mechanism as that described in this document is viable in Uruguay.

Regarding the particulars of the dispatch schedules, their results show that smart-grids not only allow to reduce production costs, but also softness the stress to operate the grid. A secondary but highly desirable consequence of controlling demands to reduce costs, is that the set of components necessary to provide power to the grid, is lower than in regular conditions. In addition, there are fewer cycles of activation/deactivation of components. As a consequence, spot prices are also more regular for smart-grid based dispatch schedules, turning the wholesale market less volatile for all of the users.

Experiments realized so far are punctual, and simulate specific days taking its parameters from historical data sets. A promising line of work consists in expanding the software components developed so far, to run instances along larger periods of time. Hence, historical information could be used to evaluate results over months or years. The analysis of the solutions shows that most of the savings are consequence of a better use of hydraulic resources. Therefore, it is probable that the sustained application of such controls makes the system more immune against falling in drought conditions, in which costs are much higher. Another line of future work is the integration of solar-power among the sources of uncertainty.

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References

1. de Mello, S., Cazes, G., Gutiérrez, A.: Operational wind energy forecast with power assimilation. In: 14th International Conference on Wind Engineering (2014)
2. Joos, M., Staffell, I.: Short-term integration costs of variable renewable energy: wind curtailment and balancing in britain and germany. Renew. Sustain. Energy Rev. **86**, 45–65 (2018)
3. Karki, R., Billinton, R.: Cost-effective wind energy utilization for reliable power supply. IEEE Trans. Energy Convers. **19**(2), 435–440 (2004)
4. Li, N., Chen, L., Low, S.H.: Optimal demand response based on utility maximization in power networks. In: 2011 IEEE Power and Energy Society General Meeting, pp. 1–8, July 2011
5. Mohsenian-Rad, A.H., Leon-Garcia, A.: Optimal residential load control with price prediction in real-time electricity pricing environments. IEEE Trans. Smart Grid **1**(2), 120–133 (2010)
6. Morales, J.M., Conejo, A.J., Madsen, H., Pinson, P., Zugno, M.: Integrating Renewables in Electricity Markets, vol. 205, No. 1. Springer, Boston (2014). https://doi.org/10.1007/978-1-4614-9411-9
7. Paganini, F., Belzarena, P., Monzón, P.: Decision making in forward power markets with supply and demand uncertainty. In: 2014 48th Annual Conference on Information Sciences and Systems (CISS), pp. 1–6, March 2014
8. REN21. Renewables 2018 global status report. Technical report, REN21 Secretariat, Paris (2018)
9. Risso, C., Guerberoff, G.: Nonparametric optimization of short-term confidence bands for wind power generation. ArXiv e-prints, May 2018