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# Sensitivity to forecast errors in energy storage arbitrage for residential consumers

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**Abstract**—With the massive deployment of distributed energy resources, there has been an increase in the number of end consumers that own photovoltaic panels and storage systems. The optimal use of such storage when facing Time of Use (ToU) prices is directly related to the quality of the load and generation forecasts as well as the algorithm that controls the battery. The sensitivity of such control to different forecasts techniques is studied in this paper. It is shown that good and bad forecasts can result in losses in particularly bad days. Nevertheless, it is observed that performing Model Predictive Control with a simple forecast that is representative of the pasts can be profitable under different price and battery scenarios. We use real data from Pecan Street and ToU price levels with different buying and selling price for the numerical experiments.

**Index Terms**—Sensitivity, Arbitrage, Smart Grids, Battery, Load forecast

## I. INTRODUCTION

With new technological advances and an increase in Distributed Energy Resources (DER), exploiting end customer's flexibility becomes a feasible and important task. A major policy change in this direction was allowing end customers to sell their energy surplus and inject it to the grid.

In the face of such changes, a model that has grown in popularity is that of a household with a photovoltaic panel, a battery and possibly an electric vehicle (EV). The model requires an algorithm to operate the battery in the most efficient way possible. This usually means maximizing auto consumption.

The above model is similar to a pure arbitrage problem with two differences. First, the household has an inflexible load that has to be satisfied at all moments. Second, residential households are rarely faced with real time prices. Moreover, the types of tariffs faced by these customers consist, most of the time, of a selling price that is lower than the buying price at all moments (that is the case for the Parisian tariff *heures creuses*). This implies that arbitrage in the traditional sense is not possible.

This setting, in which an end customer owns a battery and faces a Time of Use (ToU) tariff has been studied in [1], where they use Model Predictive Control (MPC) paired with a persistence forecast to control the battery. The same setting

was used in [2], but the Reinforcement Learning technique used by the authors requires only a forecast for the next time slot, which they model as the true value plus a Gaussian noise.

If the household is subject to a Time of Use, the objective of arbitrage is to shift the consumption from the expensive period into the low price one [3]. As in the pure arbitrage model, stochasticity might prevent them from optimally utilizing of the battery. While in the pure arbitrage case the uncertainties are in the prices, for households they originate from renewable generation and consumption (load is external to the algorithm using the battery). This is an important point because unlike market price prediction which has received a lot of attention from many disciplines or forecasting the aggregation of several loads [4], [5], [6], [7]; forecasting the load of a single household is a difficult problem [8], [9]. Not only it is hard, but also expensive: unlike a market forecast that can be used by many, the forecast of a residential household has to be done independently for each house.

Sensitivity analysis for storage systems when the variability comes from the price (real time market prices) but ignore the load have been studied thoroughly: [10], [11]. Authors in [12], include a forecast of the load in addition to prices, but do not take it into account in their discussion.

Studies regarding sensitivity in the operation of a battery with respect to its different characteristics have been carried in the past. In [13], the authors perform a sensitivity analysis on the profitability of PV-storage systems for households but do not consider the impact of forecasts, which is the main goal in this work. A sensitivity analysis in the battery characteristics together with the evaluation of different optimization techniques to solve the problem has also been studied in [14]. Furthermore, it has already been shown that if the price of buying and selling are the same, then the load does not affect at all the operation of a battery [15]. For cases where selling price is not equal to buying price, the storage decisions are governed by price and load variations. In this work we consider energy storage arbitrage under ToU price and Feed in Tariff for excess production. Under such a case storage operation is affected by load variations. This work aims to answer how important is the forecast of the load when the tariff is a Time of Use. We

use data from Pecan Street, real ToU prices and forecast of varying degree of precision in order to obtain an estimate of the importance of such forecasts. We provide important insight on the relationship of the predictions and battery usage that will help future practitioners decide the accuracy of the model they are willing to work with.

The rest of the paper is organized as follows: in Section II the mathematical model of the problem is formulated. Section III describes the methodology and problem setup used for our analysis. Numerical results with the appropriate discussion are presented in Section IV. Finally, Section V includes closing remarks.

## II. MODEL DESCRIPTION

This study focuses on households that own a battery. Such battery will be modeled by the difference equation (1) in discrete time:

$$b_{t+1} = b_t + x_t, \quad (1)$$

where  $b_i$  is the State of Charge (SoC) of the battery at time  $i$  and  $B_0$ , the initial SoC, is given. In Equation (1),  $x_t \in \mathcal{X}(b)$  denotes the energy charging (positive) or discharging (negative) the battery. The set  $\mathcal{X}(b)$  of feasible actions depends on the SoC and is defined in Equation (2) where  $\delta_{max}$  and  $\delta_{min}$  denote the maximum charging and discharging rate (in power),  $h$  is the length of each time interval and  $b_{max}$  and  $b_{min}$  are the maximum and minimum SoC of the battery.

$$\mathcal{X}(b) = [\max\{\delta_{min}h, b_{min} - b\}, \min\{\delta_{max}h, b_{max} - b\}] \quad (2)$$

Because we consider efficiency losses, the actual energy required to charge the battery an amount  $x_t$  is  $\frac{x_t}{\eta_c}$  ( $\eta_c \in (0, 1]$ ) while the energy seen from outside the battery when it discharges  $x_t$  is  $x_t\eta_d$  ( $\eta_d \in (0, 1]$ ). In what follows, we will denote the energy seen from the outside of the battery  $s_t$ .

Each time slot  $t$ , consumers are faced with a buying price  $p_t^b$  and a selling price  $p_t^s$ . The inflexible load of the consumer at time  $t$  is denoted  $z_t$  (a positive value represents consumption while a negative value represents surplus of generation).

For a given and finite time horizon  $T$ , the consumer is interested in solving the optimization problem given as

$$P) \quad \underset{x_0, \dots, x_{T-1}}{\text{minimize}} \quad f(x) = \sum_{i=0}^{T-1} p_i^b [s_i + z_i]^+ - p_i^s [s_i + z_i]^- \quad (3a)$$

subject to

$$b_{j+1} = b_j + x_j \quad j = 0, \dots, T-1, \quad (3b)$$

$$x_j \in \mathcal{X}(b_j) \quad j = 0, \dots, T-1 \quad (3c)$$

where  $[\cdot]^+ = \max\{\cdot, 0\}$  and  $[\cdot]^- = \max\{-\cdot, 0\}$ .

Problem P) was studied in [15] where the authors proved that the optimal policy has a threshold structure and propose an algorithm to solve the optimization problem efficiently.

The solution of the optimization problems depends on the battery characteristics, the price of electricity (both of which are known) and on the electricity load profile  $z$ . Denote  $x^* = x^*(z)$  the optimal solution of the optimization problem when

the load profile  $z$  is used as input and  $f^* = f(x^*(z))$  ( $f$  is the electricity cost incurred by a household in a day). If instead of the original profile  $z$  there is access only to an approximation of it,  $\hat{z}$ , we seek to understand how  $x^*$  and  $\hat{x} = x^*(\hat{z})$  are related, as well as  $f^*$  and  $\hat{f} = f^*(x^*(\hat{z}))$ .

### A. Model Predictive Control

A natural idea in this kind of iterative problems where information becomes available as time goes by, is to use a receding horizon and solve the problem iteratively, as new information arrives. In the next sections we will make use of Model Predictive Control (MPC). Here we briefly describe some of the conventions used. Let  $j \in \{0, 1, \dots, T-1\}$  index the time slots of a given day. For  $j = 0$ , problem P) is solved using  $[z_0 \hat{z}_{1:T-1}]$  as the load profile (where  $[\ ]$  denotes the concatenation of the two vectors). We denote the optimal solution  $x^{0*}$ . In general, at timeslot  $j$ , problem P) is solved using  $[z_{0:j} \hat{z}_{j+1:T-1}]$  as the load profile and also imposing that the first  $j$  coordinates of  $x^{*j}$  are the decisions already taken, i.e.,  $x_{0:j-1}^{*j} = x_{0:j-1}^{*j-1}$ . We refer to this as MPC(1).

In this work, we also consider MPC with updates that can be made only at time steps  $j \in \{0, d, 2d, \dots, T-d-1, T-1\}$ , where  $d$  is a divisor of  $T$ . We will denote this version of MPC with decreased sampling time as  $MPC(d)$ .

Because we will sometimes need the error of the forecast used while doing MPC(X), we will adopt the following convention: the error associated with MPC(X) is the weighted average of all the errors of the forecasts used, where each weight corresponds to the number of decisions taken with it.

## III. EXPERIMENT SETUP

In this section we will describe the experiment design and the parameters chosen for it. This involves the tariff structures, the battery parameters, the consumption profiles, the forecasting techniques and the algorithms to solve the minimization problem. Whenever it is possible, we try to use real data as to get "practical" results.

To begin with, the Parisian two-period ToU *heures creuses* was used. During the cheap period *heures creuses* (23 to 7), the price of energy is 12.3c/KWh and during the expensive period *heures pleines* (7 to 23) the price is 15.8c/KWh. Moreover, photovoltaic energy can be sold back to the grid at the *tarif rachat* or Feed in Tariff (FIT), which as of March 2019 is 10c/KWh. In order to understand how different tariffs affect the profitability of arbitrage we considered four additional tariffs, based on the Parisian ToU. Table I summarizes them. In all of them, the low price period is from 23 to 7.

TABLE I  
TARIFFS USED IN THE EXPERIMENT

Name	Price Low	Price High	Selling Price (FIT)
P1	12.3	15.8	10
P2	12.3	15.8	5
P3	12.3	15.8	1
P4	12.3	20	10
P5	12.3	20	5

The battery parameters are modeled after Tesla’s Powerwall 2 [16], arguably the most well known storage product in the market as of writing this. The parameters of the battery are described in Table II. It has been shown that the performance of a battery doing arbitrage with real time prices depends on the speed of it (the time it takes to charge or discharge) [15]. To take this phenomenon into account, we also used a modified versions of the Powewall 2 with  $B_{max} = 25$  and  $\delta_{max} = -\delta_{min} = 100$ . We will refer to this new battery as **Fastbat**.

TABLE II  
POWERWALL PARAMETERS

$\delta_{max}$	$\delta_{min}$	$b_{max}$	$b_{min}$	$\eta_c$	$\eta_d$
5	-5	13.5	0	0.95	0.95

For the user profiles, data was obtained from the PecanStreet project [17]. Data from two users: one with solar generation (id 5403) and another one without it (id 821) was used. The granularity of the data used was 15 minutes and for the experiments, only weekdays from July 2015 were considered. That is, all weekends were removed from the dataset. In what follows, when referring to a previous day, we mean the previous day in the dataset, i.e, the previous day of Monday is Friday.

To run the experiments we solved problem P) using Model Predictive Control with 4 different sampling times: every 15 minutes (MPC(1)), every hour (MPC(4)), every 12 hours (MPC(48)) and only once every day (MPC(96)). We expected to see a natural trade-off between accuracy and increased computational time.

To generate forecasts, the four following methods were used:

- 1)  $\hat{z}(d) = z(d-1)$
- 2)  $\hat{z}(d) = z(d) + w$ ;  $z, w \in \mathbb{R}^T$ ;  $w_i \sim \mathcal{N}(0, \Delta)$  i.i.d
- 3)  $\hat{z}(d) = \frac{1}{|S|} \sum_{j \in S} z(s)$ ,  $S = \{j : j \equiv d \pmod{\tau}, j < d\}$
- 4)  $\hat{z}(d) = \text{SARIMA}(2, 1, 1)(0, 1, 1, 96)[z(d-1), \dots, z(d-4)]$

where the notation  $z(d)$  means the real profile of the day  $d$ <sup>1</sup> and  $\Delta$  is exactly half of the the 3rd quantile of the user consumption (in absolute value). Method 1 is the standard *persistence forecast* or also known as day ahead. It assumes that the profile is going to be exactly as the real profile of the day before. Method 2 (*Gauss*) corresponds to adding additive noise equally distributed and independent to all coordinates. We emphasis that we do not consider this to be a realistic forecast (as it requires knowledge of the future), but it acts as a placeholder for more accurate forecasts. Method 3 (*AvgPast*), consists on an average of all past days in the dataset that fall in the same weekday, i.e, the average of all consumption on the past Mondays, Tuesdays, etc. Finally, for the last method we trained a Seasonal ARIMA (*SARIMA*) model. Each time a forecast had to be issued, the previous four days in the dataset where used to fit the parameters of the model and an out-of-sample forecast was produced.

<sup>1</sup>We enumerated all days in the dataset starting form 0.

To evaluate the quality of the forecasts, we used two methods usually encountered in the literature: MAPE (defined in Equation 4) and NRMSE (defined in Equation 5), where  $\bar{z}$  denotes the average of the coordinates of  $z_{T-k+1:T}$ .

$$MAPE(\hat{z}_{T-k+1:T}, z_{T-k+1:T}) = \frac{100\%}{k} \sum_{i=T-k+1}^T \left| \frac{\hat{z}_i - z_i}{\bar{z}} \right| \quad (4)$$

$$NRMSE(\hat{z}_{T-k+1:T}, z_{T-k+1:T}) = \sqrt{\frac{1}{k} \sum_{i=T-k+1}^T \left( \frac{\hat{z}_i - z_i}{\bar{z}} \right)^2} \quad (5)$$

The NRMSE of the forecasts used in the dataset is illustrated in Figure 1. For each of the 22 days considered in the experiment, we include 16 forecasts, one for each combination of forecasting technique and sampling time. To obtain the forecast error for a sampling time lower than 96, the weighted average as described in section II.A was used.

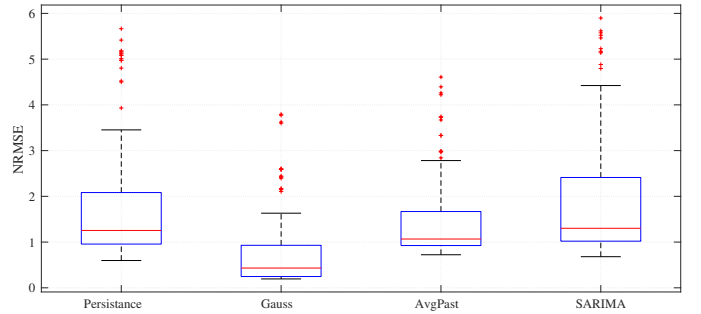


Fig. 1. NRMSE for the forecasts used in the study

As a benchmark, we compare the results obtained with [8], where the authors show that their forecasts have a NRMSE of approximately 2.

## IV. RESULTS

In this section the numerical results obtained are presented. First, we will look at the opportunity of arbitrage with perfect information. Second, we will show how the different sampling and forecasting techniques affect the earnings obtained as well as the optimal battery actions. Thirdly, the relationship between the forecast error metrics and the arbitrage gains is studied. Finally, a profitability study is included, as a summary of our findings.

### A. Arbitrage opportunity with perfect information

The arbitrage opportunity with perfect information (AO) can be defined as the difference in electricity cost in a single day between a scenario without battery (CwB) and a scenario with a battery and perfect information (CBPI). This metric will enable us to better understand the results obtained by performing arbitrage. What is more, this metric could suffice to determine whether the investment in a battery is profitable.

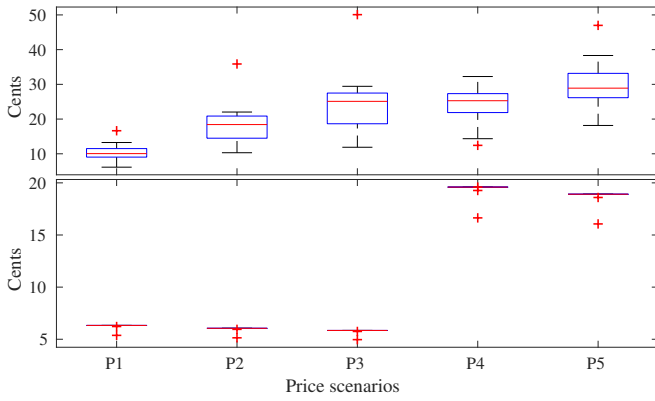


Fig. 2. AO using a Powerwall 2 for households: 5403 on top, 821 below.

As the AO is the optimal case, if a particular storage is not profitable under these circumstances, it will not be at all.

Figure 2 shows the AO for the two household (5403 with generation on top and 821 without generation on the bottom). For the household with id 5403, it can be seen that the AO increases as the selling price decreases ( $P1 \rightarrow P2 \rightarrow P3$ ). This effect can be explained as follows: when the FIT is high enough, the advantage between storing for later consumption and selling to the grid and re buying later is less compared to the scenario when the selling price is very low. On the contrary, for a consumer without generation, a high selling price helps mitigate forecast errors: if energy was bought but it was not needed, it can be resold again for a small loss.

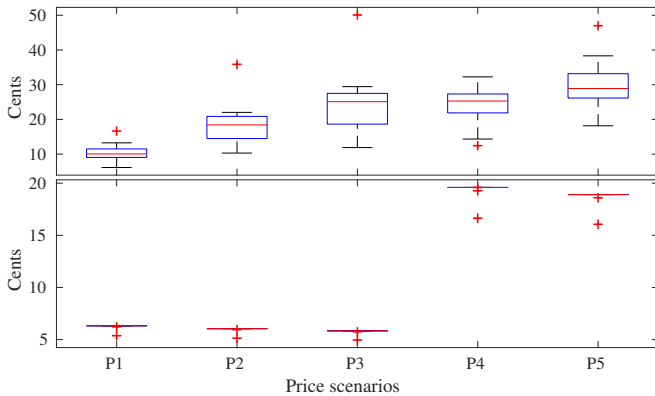


Fig. 3. AO using **Fastbat** for households: 5403 on top, 821 below.

Figure 3 shows the equivalent results when **Fastbat** is used instead. It can readily be seen that while the overall gains increase, the trend persists. Also, the difference between scenarios P4 and P5 with the other three is easily explained. In those cases, the gap between low buying price and the high buying price is bigger and so the AO is bigger as well. Recall that for a ToU tariff, arbitrage is mostly equivalent to switching consumption from the expensive period to the cheap one.

### B. Arbitrage opportunity without perfect information

Having assessed the potential of arbitrage for the different prices and households, we turn our attention on how those

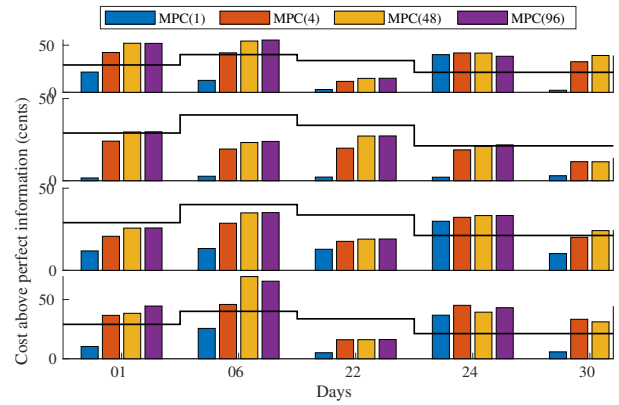


Fig. 4. AOF for 5403 for some days under tariff P1. Each row corresponds to a different forecast technique. From top to bottom: persistence, Gaussian, AvgPast and SARIMA.

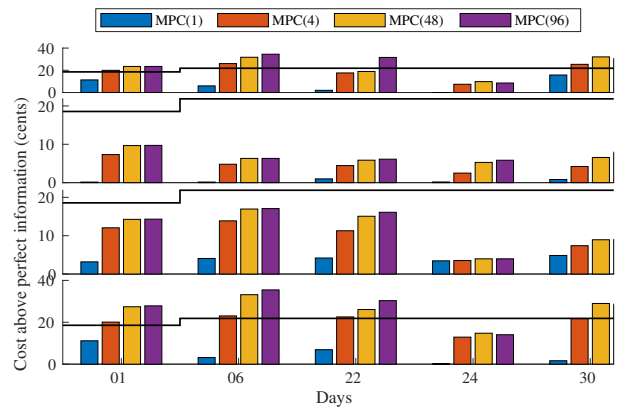


Fig. 5. AOF for 821 during some days under tariff P1. Each row corresponds to a different forecast technique. From top to bottom: persistence, Gaussian, avgpast and SARIMA.

benefits are affected when forecasts are used instead. For household 5403, these results while using a Powerwall 2 are shown in Figure 4. In it, each bar represents the cost incurred using a forecast (CF) minus the cost of having perfect information (CBPI) while the black line depicts the cost of not having a battery (CwB) minus the CBPI. In this way, all results between the x-axis and the black curve imply that profit was obtained when using the forecast while bars above the black line stand for days in which **doing nothing would have been a better choice**. As it can be seen in Figure 4, July 24 th is a particularly bad day. Only with a very accurate forecast losses could have been avoided.

In Figure 4, each subplot shows the result for a different forecasting technique. For top to bottom: persistence, Gaussian, AvgPast and SARIMA. Moreover, each color stands for the frequency of sampling used for running MPC. The blue bars (1) are standard MPC taking actions every timeslot while the purple bars (96) are cases when all actions were decided at the beginning of the day. As it was to be expected, the most frequent the sampling time is while running MPC, the lower the incurred cost is. There is a natural trade-off between

CPU usage and accuracy. It can be observed that using a more frequent sampling is more important than using a good forecast.

In contrast with household 5403 who is a producer, household 821 can operate closer to optimality using less accurate forecasts. This is evidenced in Figure 5 where the same information as in Figure 4 is plotted for household 821. MPC(1) performs remarkably well.

Turning our attention to the optimal actions, for household 5403 and the forecasting technique AvgPast, Figures 6 and 7 plot the different usages of the battery for days 1st and 24th of July respectively.

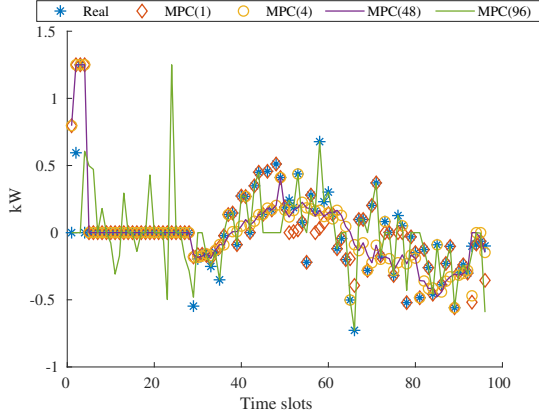


Fig. 6. Differences in optimal battery operation during the 1st of July using the AvgPast forecast for household 5403

In Figure 6, only MPC(96) differs strongly from the real data at the beginning of the day. During July 1st all sampling frequencies were profitable using the AvgPast forecast. In Figure 7 however, it can be seen that all techniques made the wrong decision at the beginning and near the end of the day, resulting in an overall loss. This can happen if the day in question is very different to the previous ones.

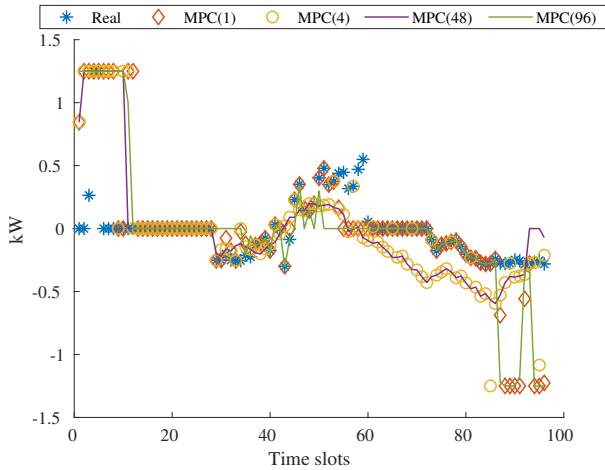


Fig. 7. Differences in optimal battery operation during the 24th of July using the AvgPast forecast for household 5403

### C. Sensitivity of the gains to NRMSE and MAPE

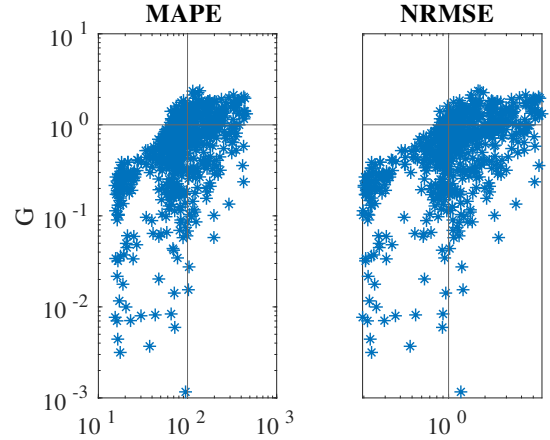


Fig. 8. Average savings as a function of the forecasting error metrics.

In a sensitivity analysis, it is natural to consider how does the output vary in response to the input. In this setting, we are interested in understanding the arbitrage gains as a function of the precision of the forecast. Figure 8 provides insight in this matter. In the x-axis the two error metrics are plotted: MAPE in the left and NRMSE in the right. The y-axis represents the linear mapping defined as

$$G(\hat{z}) = \frac{\hat{f} - f^*}{CwB(z) - f^*} \quad (6)$$

It is 0, when the forecast performs as having perfect information, 1 when it performs as not having a battery and values greater than 1 are worst than doing nothing. Observe that although there is not a clear correlation between both axes, it is possible to find a threshold (vertical bar) for which all forecast with less error than the threshold (to the left of it) perform better than not having a battery (below the horizontal line).

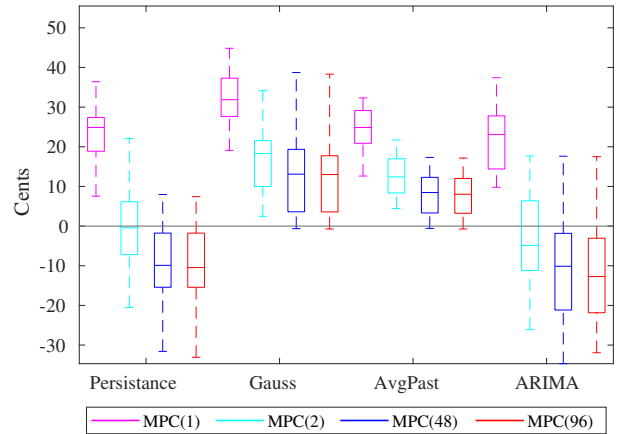


Fig. 9. Savings using the Powerwall 2 battery for household 5403 and price scenario P1

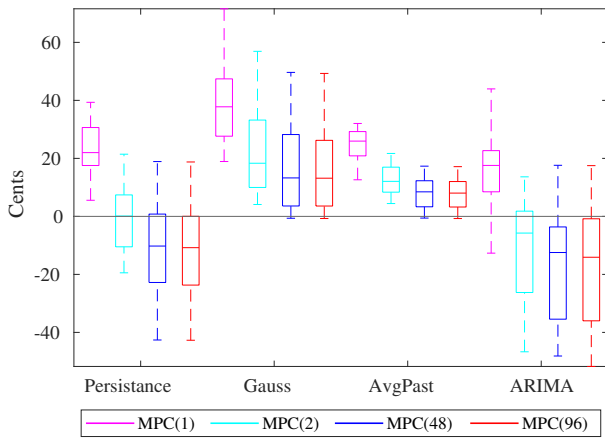


Fig. 10. Savings using the **Fastbat** for household 5403 and price scenario P1

TABLE III  
NUMBER OF YEARS THAT IT WOULD TAKE HOUSEHOLD 5403 TO RECOVER ITS INVESTMENT IN A POWERWALL 2 FOR THE DIFFERENT PRICE SCENARIOS AND FORECASTING TECHNIQUES

	Persistence	Gaussian	AvgPast	SARIMA	Perfect
P1	89.0	58.0	83.0	94.0	54.0
P2	51.0	31.0	45.0	63.0	29.0
P3	39.0	23.0	33.0	49.0	21.0
P4	26.0	19.0	27.0	26.0	18.0
P5	21.0	<b>15.0</b>	<b>21.0</b>	24.0	<b>14.0</b>

#### D. Profitability analysis for Powerwall 2

We conclude the analysis with the evaluation of the average performance of each forecasting technique and each sampling frequency using MPC for household 5403. Figure 9 and 10 depict the savings obtained by having a battery with respect to not having one in a given day for the two batteries, respectively. As expected, gains decrease with less sampling, but interestingly enough for a simple forecast as AvgPast, it would be possible to use a less coarse sampling time and still obtain profits. Regarding both batteries, it can be seen that while SARIMA and the persistence forecast are not profitable with the Powerwall 2, they are with the **Fastbat**. Finally Table III shows the number of years it would take consumer 5403 using MPC(1), for the different forecasting techniques and price scenarios, to recover the investment in a Powerwall 2<sup>2</sup>. Unfortunately, it does not seem likely that under any scenario the investment will be profitable. With perfect information and the best price structure (P5) it will take 14 years to get the Return of Investment while with a good but imperfect forecast the time increases from 1 to 5 years.

#### V. CONCLUSIONS

Consumers facing a Time of Use can perform arbitrage by shifting their consumption in the expensive period to the cheap period. If it is possible to sell back to the grid, a consumer with generation will obtain a bigger reward from a battery if such selling price is low. The contrary occurs for

a consumer without generation. Even then, as prices do not spike, the margins are low. Such low margins imply that for some days, even with very accurate forecast it will be very hard not to lose money. That is the case of household 5403 during the 24th of July. It is found that the sampling time greatly impacts the profit and only very good forecasts can avoid losses with a sampling frequency greater than one. In spite of such negative results, on average, running MPC(1) with the AvgPast forecast seems to be sufficient to guarantee profit. We conclude that forecasting does have a big impact on the profits obtained facing a Time of Use. However, since such profits are low, the gap between the AvgPast and very accurate Gaussian approximation of forecast do not yield a very big difference.

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<sup>2</sup>The cost of a Powerwall 2 is 7000 euros in France.