Impact of forecast on control methods for customer-sited battery storage

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ABSTRACT

This work explores the effect of forecast on model-based methods for control of energy storage. There are high-value applications of energy storage that require advanced control. Model Predictive Control (MPC), an optimization-based technique is a widely used example of model-based control. Depending on the application, MPC requires forecast of variables like demand, renewable generation, and electricity prices. We explore the performance of MPC using different forecast techniques, with varying levels of error. We analyse the deterioration of system performance when forecast error increases, for a customer-sited storage system under different settings.

INTRODUCTION

Along with ever increasing demand of energy, there has been an increase in energy resources in the distribution grid and customer's premises. Because of these distributed resources, storage is expected to play a significant role due to its operational flexibility that allows to provide services to different domains and stakeholders of the grid: transmission/distribution operators, residential, commercial and industrial consumers. A large share of the energy storage connected to the grid corresponds to customer-sited battery storage. Storage at customer end has multiple benefits. Few of these benefits include reducing time of use energy cost for the customer, demand charge reduction, electric service reliability, improvement in power quality, reduction in peak demand, frequency regulation etc [1]. Owing to the problem of uncertainty and high variability of renewable generation like solar photovoltaics (PV), coordinated optimal dispatch becomes a challenging task to handle [2]. Coordinated control can be achieved by schedule-based, rule-based and model-based methods. While schedule based method provides control for a given objective, it lacks the ability to update the dispatch according to the real time grid conditions and needs. Another type of dispatch used is rule-based, although it updates the set point according to grid condition it lacks to perform multiple services and other grid constraints together. Thus, rule-based strategies lack in providing optimal control for the operation of grid under additional constraints related to hosting capacity, interconnected grid, varying demand, regulation services, etc. [3] The rule-based techniques are sub-optimal and in many cases, do not handle real-time conditions. Concerns on hosting capacity will lead to more complicated interconnection requirements that may require self-limitation of the system.

To address all the objectives and design parameters of load and generation, an optimization-based optimal control technique can be deployed. Using an optimal controller all stacked services of storage can be utilized along with increasing the time of utilization of battery by adding it as a constraint to the control method and thus improving power quality and system reliability [4]. One of the methods used for optimal control is model based predictive control with fast feedback control loop [5]. Optimization-based strategies are a good way to handle complicated constraints, however, they require load and generation forecast at each time step. Owing to the problem of uncertainty of renewable generation, the dispatch becomes unstable and unpredictable [6]. The sizeable degree of uncertainty creeps into the decision-making process for the control operation. Decision makers use energy demand forecasting as one of the most important policy tools for making the grid reliable and stable. One of the decision makers dilemmas is how to forecast electricity demand and generation. Thus, an efficient forecasting tool needs to be implemented to achieve a stable and accurate prediction.
There are various forecast models available in literature that include parametric models like artificial neural network based model [7], fuzzy logic based model [8], exponential smoothing model [9], Holtz-Winter model [10] and non-parametric models such as k-nearest neighbors [11]. Each forecast model forecasts the input load or generation differently and has different error values for each method.

This paper focuses on analyzing the impact of forecast on optimization-based control strategies. Forecast is carried out for varying hours ahead prediction. Error variation can be analyzed for each of the time ahead hours of prediction. In this paper use case for energy and demand charge reduction for electricity customers is analyzed which are modeled using load, PV generation, and tariff rate data. One of the main objectives of storage taken into consideration is to reduce electricity bill of consumer and increase self-consumption of PV. The load and generation are forecasted using parametric forecast of Holtz-Winter method and non-parametric kNN approaches coupled to the control scheme. The use case addresses the case of interconnection rules with power export at point of common coupling under stringent power limits.

This manuscript is organized as follows. Section II explains in detail the approach and methodology for the analysis. It explains the MPC based control and forecast models used in analysis; the approach to evaluate the impact of forecast. Section III evaluates the results and dispatch estimation for each method; points out the inferences. Section IV draws conclusion and future scope of work in this area.

METHODOLOGY

This study is comprised of two major steps: i) analyze the forecast error for two widely used forecast techniques, and ii) analyze the performance of an MPC-controlled energy storage system for a customer application, using the foreacast techniques, an perfect foresight as a performance benchmark.

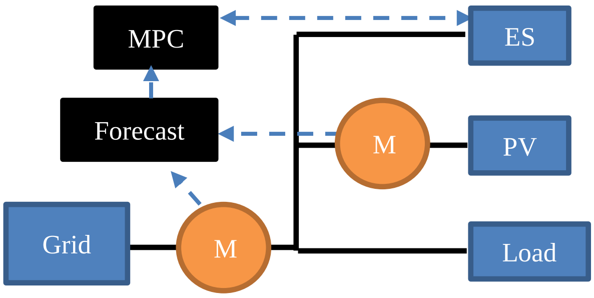

Figure 1 Diagram of the control system. The forecast uses measurements to update prediction, and feeds it to the MPC controller.

Figure 1 shows a block diagram representation of the system that will be analyzed in this study.

The following forecasting techniques have been selected for this study :

- Non-parametric forecast : k-nearest neighbors forecast (KNN)
- Parametric forecast : Holtz-Winter forecast

Model Predictive Control (MPC)

Model predictive control is a control technique that uses optimization models to estimate the future state of the controlled system and the optimal control strategy. The control is run periodically, with a period shorter than the prediction horizon. For example, the control could be recalculated every hour, and it should yield control values for the next 24 hours. In this case then, only the control for the first hour is applied to the system. The rest of the control values is only used to estimate the effect of the first control step in the future behavior of the system.

In the case of energy systems, some variables like load and solar generation can be predicted outside the MPC model, without losing any of the underlying assumptions of the approach.

Forecast error analysis

Different forecast techniques are expected to perform differently for datasets that are relevant to energy storage control, particularly load and renewable generation [13].

The type of forecast that is used for energy storage applications is usually slow time resolution (greater than 15 minutes) and multi-step (for instance, one day worth of estimate).

The forecast error is expected to be larger as the number of hours ahead increases. Estimating at 10 am the average solar available power between 2 pm and 2 15 pm should be less accurate thn estimating it at 1 45 pm. We will use one year of load data and one year of solar generation data to calculate hourly forecast for the next 24 hours. This will allow us to establish minimum and maximum error trends for the entire forecast horizon.

Impact of forecast error in control performance

Effects of the forecast inaccuracy on the performance of MPC techniques are little studied. Intuitively, knowing that there will be more solar resource during mid day than later in the afternoon, should lead to charging during at noon. This reasoning is valid for an energy arbitrage application. In this case, it might not be that important to know exactly the solar generation, but the relative differences between different times of the day.

If the application also includes demand charge reduction, the operation driver is the peak load, and the solar generation forecast accuracy will have less overall impact.

To analyze the effect of forecast accuracy in the MPC performance, we will simulate a behind-the-meter system, with load, storage, and solar generation. An MPC control will be used for the energy storage system. We will run simulations using the different forecast techniques to provide input to the MPC control. We will also include the simulation of an MPC control receiving a perfect forecast of the load and solar generation.

Then, the results will be analyzed in terms of the electricity bill of the studied customer. To this end, we will use the PG&E tariff structure E-19, which includes Time-of-Use energy and demand charges.

RESULTS AND INFERENCE

For evaluating the use case of energy and demand charge reduction, parametric and non-parametric based models of load and generation forecasting were analysed. The predicted load and generation was fed into the MPC controller to compare the dispatch and electricity bill in both cases.

Parametric based forecast

Our parametric technique for this analysis is the Holtz-Winter model. Holtz-Winter method consists of three variables that take into consideration exponential component, trend component and seasonal variation. These variables are linearly related and predict the forecast next t hours [12]. To take care of both load and PV generation's seasonal trend the method was quite applicable. The forecast was evaluated in Python using inbuilt libraries of statsmodels. The forecast was calculated for day ahead simulation and error was evaluated as given below

$$error(t) = \frac{f(t) - x(t)}{\max_{t}[x(t)]}$$

Where $f(t)$is the forecasted value and $x(t)$ is the actual measured value. In this analysis for a hourly input profile 48 hours of previous data was taken as input to forecast for next 24 hours. This value might change according to the profile and shape of input data. Fig.1 and 2 shows the forecast error box plot for load and PV generation for a summer month (May) data. It is seen as the hours ahead of forecast increases the prediction error also increases. PV error is seen to reduce a little and then increase again this might be because of high uncertainty in generation. According to the standard deviation of error plot shows an increasing trend for larger hours of ahead prediction.

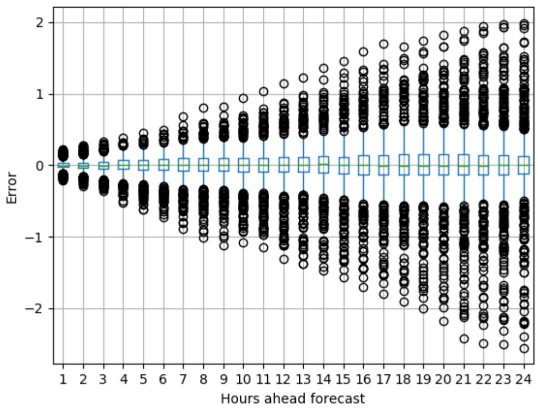

Fig 1 – Box plot for 24 hours ahead load forecast for May data

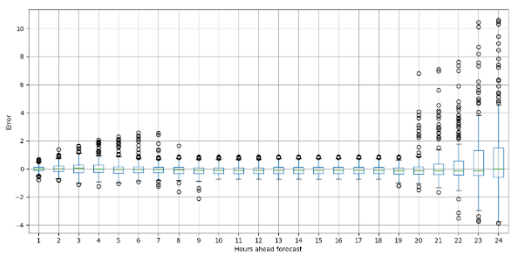

Fig 2 – Box plot for 24 hours ahead PV forecast for May data

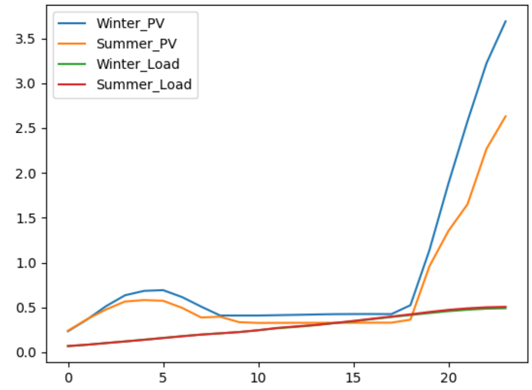

Fig 3 – Standard deviation of forecast error for summer and winter months

Non-parametric based forecast

We implement kNN based forecast as a choice of non-parametric technique. kNN based model uses historical load data to from a number of « *neighbours* « to predict the forecast data. Neighbours (k) are evaluated by calculating the Euclidean between the training data and historical load data to find the number of closest neighbours. The load is predicted as a mean of measured data from these k neighbours. The forecast framework is shown in Fig 3.

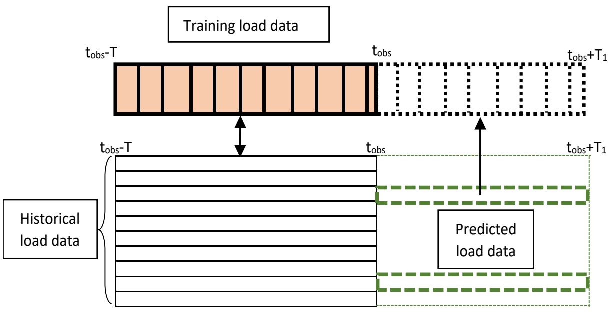

Fig 4- Framework for forecast load and generation

Same data as used for Holtz-Winter forecast model was used for analysis in kNN based forecasting. Fig. 5 and 6 shows the forecast error box plot for load and PV generation for a summer month (May) data. It is seen as the hours ahead of forecast increases the prediction error also increases. Standard deviation of forecast error for load and generation in summer and winter months is shown in Fig 7. By this method of forecast as well the error is seen to increase in general as the hours ahead of prediction increases.

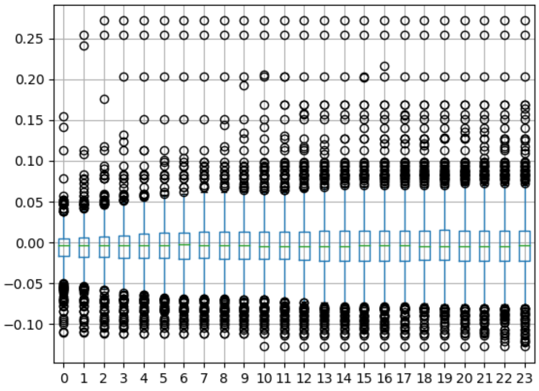

Fig 5 – Box plot for 24 hours ahead load forecast for May data

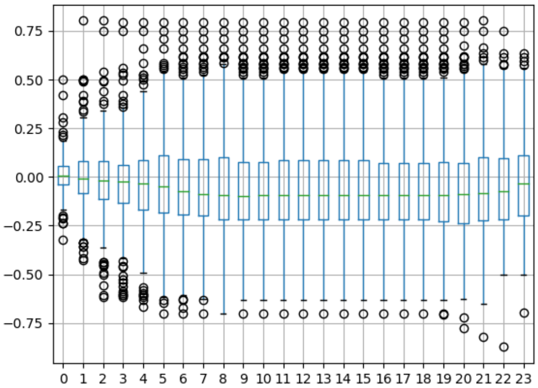

Fig 6 – Box plot for 24 hours ahead PV forecast for May data

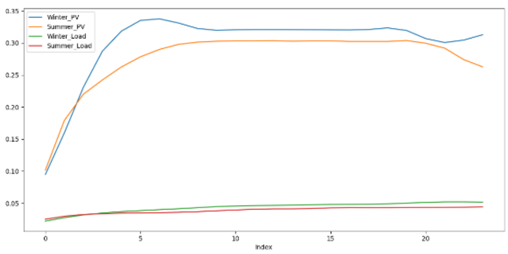

Fig 7 – Standard deviation forecast for summer and winter load

Optimization results

Comparing the forecast results of the two methods kNN based forecast has lower mean error as compared to Holtz-Winter forecast for a given set of input parameters. The results are given in Table 1. A comparison between each forecasted load and generation values is carried out with day ahead forecast using MPC optimization model. The objective is set as to reduce demand peak charges with battery and power constraints.

Table 1: Mean standard deviation error

Mean standard deviation error (%)	Winter _PV	Summer _PV	Winter_ Load	Summer_ Load
Holtz Winter	89.53	67.89	28.35	28.78
kNN	29.88	27.64	4.33	3.86

According to the simulation results, it is seen that the number of power constraint violations for Holtz-Winter forecast are larger as compared to kNN based forecasting. Moreover, deeper and more number of battery cycles are seen in the case of Holtz-Winter forecast. Snapshot of these results are shown in Fig 8,9 for the month of June.

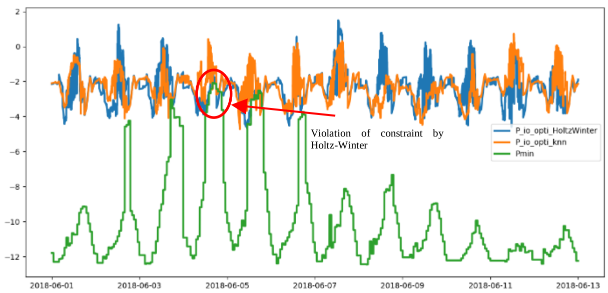

Fig 8 – Power at interconnection for Holtz-Winter and kNN forecast

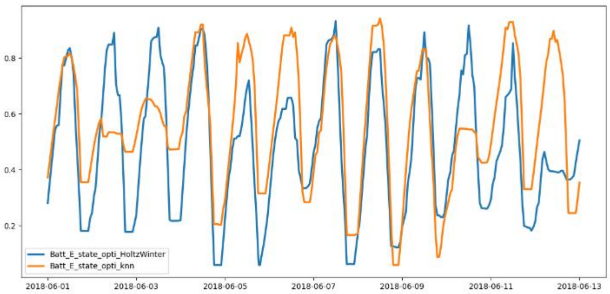

Fig 9 –Battery state of charge for Holtz-Winter and kNN forecast

Table 2: Bill charges for different forecast techniques

Charges ($)	kNN	Holtz-Winter	Perfect foresight with battery
Peak demand charge	382,270	470,080	464068.8
Peak demand charge savings	100,950	13,140	19,150
Energy charge	452,770	451,270	452,080
Energy charge savings	3,880	5,390	4,580

In each simulation bill charges are estimated as shown in Table 2. Savings are estimated as a difference of demand/energy charges for each simultion with respect to the system operation with load and generation, without battery. It is seen that kNN based simulation is more cost effective as compared to Holtz-Winter forecast. Moreover, for a perfect foresight the peak demand charges are a little larger as compared to kNN as no violations of power constraint is seen. But on a whole kNN performs the closest to the optimal dispatch i.e. with battery in perfect foresight of PV generation and load.

Inference

In summary, it is seen that with higher forecast error the electricity bill of the customer becomes larger. Moreover, battery has more and deeper cycles for a poor forecast. In terms of power dispatch both the methods have very few power violations although poor forecast gives more violations. Comparing these to perfect foresight the results with lower forecast error performs closest to optimal dispatch. Thus, forecast plays an important role on optimization results, yet these variations vary according to the objective and input data at hand.

CONCLUSION

This work explores the impact of forecast accuracy in the performance of energy storage control. The analysis focuses on understanding the behaviour of parametric and non-parametric forecast techniques applied to load and solar generation. Then, a further step is taken to analyse the impact of forecast on the performance of Model Predictive Control (MPC) for customer-site storage. MPC uses optimization models to calculate the charge/discharge profile of storage during a given time horizon. Then, the control is recalculated after the first setpoint is applied. Recalculation allows to include new information provided by new measurements and new forecast.

The case study assumes a complicated tariff rate structure with Time of Use energy and demand charges. Demand charge reduction is particularly sensitive with respect to forecast, and errors can lead to heavy costs to the user.

Future analysis must include the effect of time horizon on the MPC performance, as well as effect of fast variations of the load and solar generation in the overall result. Additionally, a taxonomy of MPC variations that help model and address structured uncertainty can be analyzed to identify the most effective solution to the problem.

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