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Practical Considerations For Customer-sited Energy Storage Dispatch On Multiple Applications Using Model Predictive Control

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Abstract:
Government subsidies for energy storage and renewable generation have led to the cost of energy storage come down during recent years. This has motivated people to deploy behind-the-meter energy storage units, to reduce their monthly electricity bill. For optimal control of the battery to incorporate maximum photovoltaic energy generation as well as demand charge reduction, data-driven and advanced Battery Energy Storage System (BESS) control strategies are required. This paper explores different use cases where customers could deploy energy storage systems for demand charge reduction as well as when customers could deploy energy storage systems for demand charge reduction while satisfying a utility set objective. From historical load and PV data, different use cases are simulated using a Model Predictive Control (MPC) based BESS control model. MPC requires machine-learning (ML) based forecasts of photovoltaic (PV) as well as load as inputs. A sensitivity analysis on the effect of different energy forecasts on the performance of MPC is presented in the paper. A degradation analysis with as a function of charge/discharge cycles is also presented in the paper to evaluate the trade-off between economic objectives and battery health.

Keywords: Energy storage control, energy forecasting, MPC, demand charge management, degradation analysis, benefit stacking, machine learning

1. INTRODUCTION

With the increasing world population, the demand for energy has increased significantly. It has been largely met by traditional sources of energy such as fossil fuels, however in the last decade, there has been a push towards renewable sources of energy. But, integrating renewable energy sources into the grid comes with its challenges. Due to their dependency on weather conditions, renewable energy sources are intermittent in nature, which makes it difficult to rely completely on these alternate energy sources. Energy storage offers a solution to this challenge. With recent government grants and incentives, the cost of energy storage has gone down in past few years (John, 2013). This has led to a drastic increase in the adaptation of energy storage.

Energy storage is flexible in its operation and can be deployed at various levels of the grid. A common use case for energy storage is customer-sited energy storage. Economically driven customers are deploying behind-the-meter energy storage systems for services such as demand charge reduction, maximizing renewable generation, market participation, among others. Electricity bill for customers such as large buildings, schools, offices, etc can be very large. Customers are motivated to use energy storage systems to reduce their monthly electricity bill. Electricity bills are made up of energy charges and demand charges, the later being derived from the peak power used during a billing cycle. A major share of the electricity bill can be due to demand charges (Neubauer and Simpson, 2015). Thus, using energy storage systems for demand charge reduction and energy charge reduction based on time-of-use rate can offer a solution to customers. Energy storage dispatch strategies for demand charge reduction have been explored in (Hanna et al., 2014; Zheng et al., 2015). As promising as battery storage can be, there are some operational nuances that must be considered, and are often overlooked. Battery degradation is a major driver of the storage system's value proposition. In many cases, battery cycling can be so costly that shifting energy over time to reduce a electricity bill can be a bad idea. However, it is uncommon in energy storage management literature to find works that directly incorporate the effect of degradation in the decision-making process. Moreover, there is little analysis on the degradation outcome due to different operational strategies.

Using energy storage systems for multiple objectives can be achieved by using an optimization-based control strategy. A Model Predictive Control (MPC) based controller with fast feedback offers a solution for optimal dispatch of the battery (Xie et al., 2012; Neubauer and Simpson, 2015). In MPC, at each time-step the controller solves an optimization problem. The solution of the MPC is updated using a fast feedback loop Wang and Boyd (2010). However, MPC requires future predictions as inputs, which have some level of error and uncertainty associated with them. Thus, for reliable control of the battery, accurate forecasts are required.

With development in machine learning and computational capacity, highly advanced techniques have been applied effectively in load and renewable forecasting. Techniques such as Artificial Neural Networks (ANN) (Drezga and Rahman, 1998; Sharma et al., 2018; Cali et al., 2009; Cali, 2011), Gradient Boosting (Taieb and Hyndman, 2014), Support Vector Machines (Chen et al., 2004) and Linear Regression (Hong et al., 2011) have been used in renewable and load forecasting. With energy forecasts being one of the most crucial inputs in the functioning of MPC, the accuracy of the forecasts going into the MPC would play an important role in the performance of the entire system. An analysis of effect of the forecast error on the performance of the MPC model has not been addressed in detail in literature. It would be of interest to observe the effect of forecast accuracy on the performance of MPC.

This paper looks into the practical aspects of MPC for energy storage control: effect of forecast accuracy and degradation management. An MPC based controller with fast feedback to reduce the customers electricity bill and maximize the use of photovoltaic generation is present. A scenario when the customer deployed the battery for its bill reduction (customer-benefit) is explored, moreover a scenario where the energy storage system reduces the customers electricity bill as well as supports the utility to use the battery to avoid the feeder load exceed the thermal limit (stack-benefit). Three different types of forecasting techniques–namely, persistence, Support Vector Machines and perfect forecast were developed and their effect on the performance of the MPC controller were studied. Customer electricity bill and the number of violations at the feeder are analysed for customer-benefit and stacked-benefit scenarios for different forecasting techniques. Subsequently, a degradation analysis of the battery is also presented, to understand the effect of a relaxed degradation model in the optimization algorithm.

2. PROBLEM FORMULATION

The system configuration for this analysis is that of a commercial or industrial customer with PV solar generation and a battery system. Without loss of generality, the battery system and the PV system are AC-coupled. An orchestrating system has been deployed on the site to control both the PV as well as the battery system. This control is capable of running linear programming models, and diverse machine learning algorithms. The controller is connected to different power meters that monitor the AC power flowing into the customer load, in and out of the battery system, and out of the PV system.

The controller is used to carry out smart management of the customer's bill, while being able to support interconnection constraints that can be imposed by the distribution utility. These constraints can be aimed at stopping the back-flow into the grid, or requesting an increase in the customer's generation to support a grid capacity need. The customer's bill may have a time of use (TOU) energy charge, and multiple demand charges that affect different times of the day. The controller must generate dispatch setpoints that reduce the customer's bill, while ensuring that the battery system is able to support interconnection constraints, and ensuring that the battery degradation is taken into account in all dispatch decisions.

2.1 Mathematical model

The customer site is modeled as an AC bus where power is injected by a set Γ of elements that includes the customer load, the PV generation, and the battery system. The power balance in the bus is given by:

$$\sum_{q\in\Gamma} P_t^q = P_t^{PCC}, \tag{1}$$

where P_t^{PCC} is the power flowing between the grid and the customer at time t. A negative value corresponds to power flowing from the customer to the grid, and a positive value corresponds to power flowing from the grid to the customer.

Battery model: The battery model captures the main aspects of a Li-ion battery system that are needed for a quasi-steady state time series (QSTS) simulation: i) state of charge SOC evolution, roundtrip efficiency η_{RT}, power capacity P_{max}^{Batt} which limits the charge and discharge power, and energy capacity E_{max} which limits the maximum energy that can be stored in the battery.

State of Charge (SOC) State of charge is defined as the ratio of the available energy in the battery by its maximum energy capacity. Energy storage operates between certain limits (max/min) of charge based on its capacity. This affects the operation of the battery as the SOC must always remain in certain limits at all time for proper functioning of the battery.

Charging and discharging Energy storage can function within certain boundaries of maximum and minimum charging and discharging capacities. The charging and discharging values depend on the maximum and minimum state of charge (SOC) and the maximum available battery capacity.

Efficiency There is a loss of energy while operating the battery which affects the operation of the battery. Efficiency directly affects the loss of energy during charging and discharging.

The SOC evolution is modeled as follows:

$$E_t = E_{t-1} + (\eta_{RT} * C_t - D_t)\Delta t \tag{2}$$

$$SOC_t = E_t/E_{max} \tag{3}$$

The non-negative variables C_t and discharge D_t represent the battery power dispatch $P_t^{Batt} = C_t - D_t$ during a time period t. The variables SOC_t and E_t correspond to the state of charge and state of energy respectively at the end of the time period t. The term Δt is the length of the time period t in hours. In order to respect the physical limits of the system, it must hold that:

$$SOC_t \in [0, 1] \tag{4}$$
$$C_t \in [0, P^{Batt}_{max}] \tag{5}$$
$$D_t \in [0, P^{Batt}_{max}] \tag{6}$$

State of Health (Degradation) Battery degradation is the loss of retention capacity available for charging. With continuous charging and discharging cycles, there is a loss or degradation in the maximum available capacity and the efficiency of the battery. Battery degradation is a crucial factor in calculating the economic benefit of energy storage as the battery might need replacement after some years.

The degradation aspect of the battery system is captured by the sum of two elements: calendar degradation and cycling degradation. Degradation is measured as the loss of state of health SOH. SOH is a variable in $[0, 1]$, which is 1 when the battery system is new, and 0 when it needs replacement. Cycling degradation is a function of the SOC evolution over a given time period. Each cycle is the event of the SOC variable going back to an initial value after having gone sufficiently far from it. This movement is referred to as depth of discharge. Each cycle within the SOC evolution will affect the SOH differently, according to its depth of discharge. Let $SOC_{[0,T]}$ be the evolution of the SOC of a battery over the time interval $[0, T]$. Let $i \in I_{[0,T]}$ be all the cycles existing in $SOC_{[0,T]}$. The depth of cycle i is denoted by $\delta(i)$. The loss of SOH due to cycling is modeled as:

$$SOH^{cycling}_{loss} = \sum_{i \in I_{[0,T]}} \frac{1}{f_{DoD}(\delta(i))} \tag{7}$$

where f_{DoD} is a function that represents the number of cycles of a fixed depth of discharge that the battery system may undergo before needing replacement. The function f is known from battery cycling experiments. The number of cycles and the corresponding depth of discharge of each cycle is calculated using a Rainflow Counting Algorithm, which takes the SOC signal for a given time interval and return the depth of discharge of each cycle found within the signal. We omit the details on the Rainflow Counting Algorithm for brevity. However, the algorithm is a highly non-convex function, making it difficult to incorporate directly in an optimization algorithm. In a subsequent section, we introduce a relaxation to indirectly account for degradation in the decision-making process, and then in the simulation analysis, we evaluate the effect of the operation in the non-convex model.

PV solar model: The PV solar model is simply a stochastic process that represents the AC solar power availability at any time t. It is given by $P^{PV}_{max,t}$, and for the controllable PV inverter, the AC power output is the non-positive variable P^{PV}_t. The physical limits of the PV system are represented by the equation:

$$P^{PV}_t \in [-P^{PV}_{max,t}, 0] \tag{8}$$

Load model: The load is modeled as a non-negative stochastic process $Load_t$. Much like the PV solar model, the stochastic processes associated to these phenomena are assumed to have certain predictability. The power associated to the load during the time t is $P^{load}_t = Load_t$.

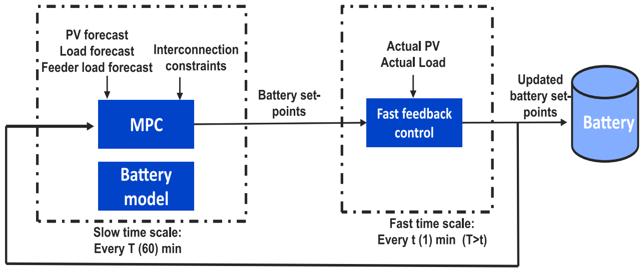

Fig. 1. MPC architecture

Tariff rate: The most complicated tariff rates in the United States can be modeled in the framework presented in the following. For each month $m \in \{1, \ldots, 12\}$, metering intervals $t \in \Lambda_m$, and demand charges $l \in \Lambda_m$, the customer bill is given by:

$$\text{Bill}_m = FR + \sum_{t \in_m} c^e_t P^{PCC}_t + \sum_{l \in \Lambda_m} c^D C_l \max_{\sigma \in_m (\Lambda_m)} P^{PCC}_\sigma \tag{9}$$

The first term is the customer's fixed charge (FR), the second term is the energy charge, and the third term is the sum of all demand charges in the tariff.

2.2 MPC approach for PV and battery management

The decision-making approach followed in this work is a model predictive control (MPC) that uses a system model, along with forecast of the solar PV generation and customer's load to determine the best setpoint for the battery system and PV. There are two advantages of this approach. First, the optimization formulation makes it possible to capture the economic objectives of the customer, while addressing the constraints related to the system technical features and interconnection constraints. It also allows to include degradation management in the decision-making process. Second, recalculating the set-points frequently allows to incorporate new information from refreshed forecast, new measurements, and latest system state into the new decision.

The formulation for this analysis is flexible in terms of the prediction horizon and the control step, but for convenience, we present it with a fixed control step of 1 hour and a prediction horizon of 24 hours. It means that the optimization problem must run every hour, and calculate system variables for up to 24 hours later.

$$
\begin{aligned}
\text{minimize} \; & \sum_{s\in[t,t+24]} c_t^e P_t^{PCC} + \\
& \sum_{l\in\Lambda_m} c^D C_l \max_{\sigma\in[t,t+24](\Lambda_m)} P_\sigma^{PCC}, l_t^{max} + \\
& \kappa \sum_{s\in[t,t+24]} D_t \\
\text{subject to:} \; & \\
& E_s = E_{s-1} + (\eta_{RT} * C_s - D_s)\,\Delta s \\
& SOC_s = E_s/E_{max} \\
& SOC_s \in [0,1] \\
& C_s \in [0, P_{max}^{Batt}] \\
& D_s \in [0, P_{max}^{Batt}] \\
& P_s^{PV} \in [-P_{max,s}^{PV}, 0] \\
& P_s^{load} = Load_s \\
\sum_{q\in\Gamma} P_s^q = {} & P_s^{PCC} \text{for all } s \in [t, t+24].
\end{aligned}
$$

Since the effect of operation on degradation is highly non-linear and non-convex, we use a simplified convex approach. The term $\kappa \sum_{s\in[t,t+24]} D_t$ is used to manage battery degradation by setting a penalty on the battery discharge. The terms l_t^{max} correspond to the maximum demand seen in month m before time t associated to demand charge l. It allows to reduce battery activity when there is no value in reducing subsequent peaks. In the simulation analysis, we analyze the actual degradation produced by the operational profile in the non-linear degradation model.

The values of $P_{max,s}^{PV}$ and $Load_s$ for the next 24 hours come from forecast processes, which will not be discussed in detail in this work.

3. SIMULATION CASE

The proposed system is evaluated and analysed with different sensitivities. For each sensitive analysis, the system is run for two cases:

Customer benefit: In this case, the aim of the system is to reduce the customers monthly electricity bill. This is done by reducing the amount of electricity bought during peak hours by utilizing PV and storage to reduce the customer's electricity bill.

Benefit Stacking: In this case, the primary aim of the system is to control the battery such that there are no violations at the feeder while trying to reduce the customer's electricity bill. Since two objectives are stacked on top of each other, this adds more value to energy storage.

3.1 Data

The data consists of a virtual feeder with five customers. Each customer has load, PV generation and tariff rate data associated with them. The data consists of 1 year of load and PV values with an hourly horizon from 1st January . The thermal limit at the feeder is assumed to be 17MW. The battery is modeled be a 4 hour battery with 90% efficiency.

3.2 Energy Forecasting

Energy forecasting is the process of estimating the future values of an energy time-series using historical values of the time-series. In this paper, the available one year of data is split into training and testing sets. The training set consists of 3 months of data and testing set consists of 9 months of data. The following forecasting techniques are implemented to generate forecasts of feeder load, load and PV generation.

Perfect Forecast: A perfect forecast is one in which the forecasted values are equal to the actual values for each point in the data set. No forecasting model can create a perfect forecast. Using a perfect forecast actually means assuming that we can peak ahead into the future.

Persistence Forecast: In persistence forecasting method, the forecasts are generated by taking the last observation in the training period and using it as the forecast for each of the points of the forecast horizon. The persistence method assumes that there will be no change in the conditions at the time of the forecast.

Support Vector Regression: Support vector regression (SVR) is an extension to support vector machine (SVM) classification introduced by Müller et al. (1997). In SVM, a hyper-plane is found such that a given data-set is divided into two parts, maximising the distance between the hyper-plane and the nearest point from either group. We omit the details of SVM in this manuscript for brevity, a detailed explanation can be found in (Smola and Schölkopf, 2004).
The inputs for training the SVR model were 3 months of historical load or PV values and a 24-hour lag time series of the historical load or PV values. The lag time-series provides the model information about the recent trend of the time-series, giving more importance to the newer information.

3.3 Forecast error analysis

The aim of this study is to analyse the effect of forecast accuracy on the control system. Feeder load, customer load and PV generation forecasts using different forecasting techniques with different accuracy are modelled and are given as inputs to the MPC and their effects are analysed. For this analysis, an SVM forecasting model is developed and compared to two benchmark forecasts, namely persistence forecast and perfect forecast. The forecast accuracy of the SVM model lies between the accuracy of perfect forecast and persistence forecast. The forecasts are made at each hour of the day for the next 24 hours. Since there is no information regarding the future going into the forecasting model, the forecasts for the recent hours are more accurate than for the later hours. To present a comparison of the different scenarios, a base case without energy storage is simulated. This case is the the no-control scenario. Figure **??** shows the plot comparing the forecasts for 24 hours. From Table 1 and Table 2 it can be observed that the customer's bill savings decrease with decrease in

Table 1. 9-month customer bill saving from stacked benefits

Stacked benefit	Customer 1	Customer 2	Customer 3	Customer 4	Customer 5
Perfect forecast	$143,230	$107,894	$124,564	$142,015	$172,450
SVM	$96,814	$106,734	$89,561	$113,277	$111,498
Persistence	$91,408	$102,072	$83,465	$106,286	$110,597

Table 2. 9-month customer bill saving from customer benefits

Customer Benefit	Customer 1	Customer 2	Customer 3	Customer 4	Customer 5
Perfect forecast	$153,557	$111,783	$135,296	$140,917	$183,550
SVM	$110,817	$111,175	$101,431	$111,018	$121,147
Persistence	$109,216	$108,053	$101,905	$108,228	$125,116

forecast accuracy. The electricity bill savings reduce by 23% in case of SVM and approximately by 27% in case of persistence forecast for stacked benefit. For customer benefit, the electricity bill savings reduce by 22% in case of SVM and approximately by 23% in case of persistence forecast. Another important parameter while evaluating the performance of the system is the number of violations. In case of customer benefit, the system does not try to reduce the number of violations, but for the stacked benefit case, the primary objective for the system is to avoid any violations. Similar to the customer bill evaluation, the number of violations in each case is compared to the no-control scenario. From Table 3, it can be seen that for the no-control case there are 83 violations. The number of violations for each customer are reduced with energy storage and control. The number of violations occurring in case of persistence forecast and SVM forecast is due to the error in the forecast. In principal, SVM is more accurate than persistence forecast but since the SVM model does not have any information about the future (e.g. weather forecast), there can be an error in predicting the peaks in the next 24 hours that might results in a violation at the feeder. In case of perfect forecast, there are no violations observed.

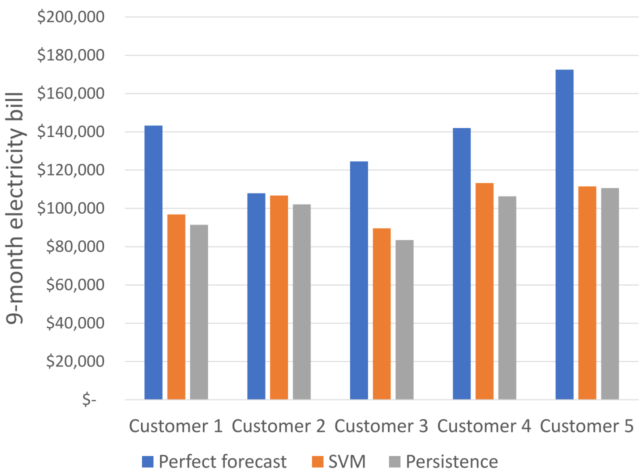

Fig. 2. Benefit stacking: 9-month electricity bill savings

3.4 Degradation sensitivity analysis

Energy storage systems are a relatively expensive asset to own and maintain for a customer and hence its longevity becomes one of the most important factor to consider while managing the energy system. The health of the battery is affected by the number of charging and discharging cycles in its operation. In the present work, a sensitivity is run on the MPC system by adding a penalty term on battery discharge. The penalty term is varied to run a sensitivity analysis for different penalties. The reduction in the state of health of the battery is evaluated for different penalties. The results are present in Figure 4 and Figure 5. Ideally, as the penalty is increased to a higher value, the percentage of degradation in the state of health of the battery should decrease due to conservation in the charging-discharging cycles. For the customer benefit, the results are observed to be consistent with the ideal scenario but for benefit stacking, there is very less variation in degradation values with change in the penalty term. This needs to be further analysed in future work.

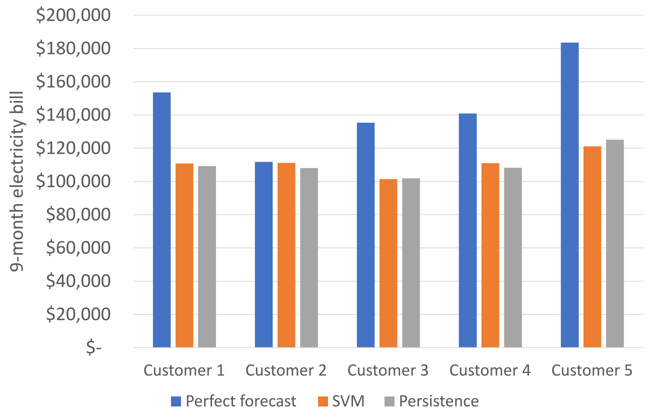

Fig. 3. Customer benefit: 9-month electricity bill savings

Table 3. Number of violations for different forecast accuracy

	No Ctrl	Persist.	SVM	Perfect
Customer 1	83	5	5	0
Customer 2	83	18	20	0
Customer 3	83	11	13	0
Customer 4	83	13	12	0
Customer 5	83	0	0	0

4. CONCLUSION

This work looks into the practical implementation of an MPC based energy dispatch control algorithm for a system consisting of solar plus storage. The effect of forecast

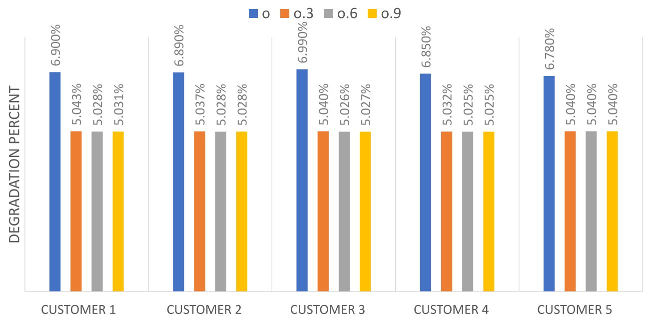

Fig. 4. Benefit stacking: Degradation sensitivity analysis

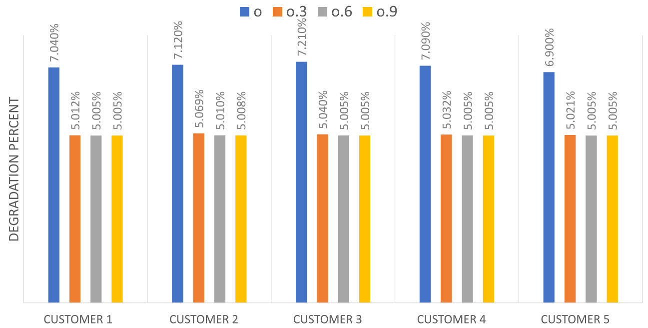

Fig. 5. Customer benefit: Degradation sensitivity analysis

accuracy on the performance of the system is analysed by using different forecasting techniques with varying forecast error. Secondly, a battery degradation analysis is done by introducing a penalty term associated with each discharging cycle. A sensitivity analysis of the effect of discharge penalty on the battery degradation is also presented.

MPC based energy dispatch control, using real data from five different customers is simulated for two scenarios: Customer benefit, when the system tries to minimize the customer's monthly electricity bill; and Benefit stacking, when the system reduces the customer's electricity bill while supporting the utility's objective. It is observed that the customers make significant savings by deploying the proposed system for demand charge reduction while supporting the utility as well. The accuracy of the forecast highly affects the performance of the model which can be measured by the customer's electricity bill. Secondly, the degradation in the state of health of the battery is much more for lower penalty terms and it is less for higher penalty terms. The penalty on the discharging cycles, increases the life of the battery by reducing its degradation. For future research, different forecasting algorithms can be explored. Using Numerical Weather Prediction (NWP) data to make load and solar forecasts can significantly increase the accuracy and the quality of the forecasts. The length of the testing data can also impact the accuracy of the forecasts. using more amount of data for training the models can improve the accuracy of the models. Further research is required to completely understand the impact of the penalty associated with discharging cycles on the degradation of the battery.

REFERENCES

Cali, Ü., Speckmann, M., and Saint-Drenan, Y. (2009). Energy economical benefits of wind power forecasting and utilisation of intraday trading. *Proceedings of the EWEC, Marseille (FR)*, 16–19.

Cali, Ü. (2011). *Grid and Market Integration of Large-Scale Wind Farms Using Advanced Wind Power Forecasting: Technical and Energy Economic Aspects*, volume 17. kassel university press GmbH.

Chen, B.J., Chang, M.W., et al. (2004). Load forecasting using support vector machines: A study on eunite competition 2001. *IEEE transactions on power systems*, 19(4), 1821–1830.

Drezga, I. and Rahman, S. (1998). Input variable selection for ANN based short-term load forecasting. *IEEE Transactions on Power Systems*, 13(4), 1238–1244.

Hanna, R., Kleissl, J., Nottrott, A., and Ferry, M. (2014). Energy dispatch schedule optimization for demand charge reduction using a photovoltaic-battery storage system with solar forecasting. *Solar Energy*, 103, 269 – 287.

Hong, T., Wang, P., and Willis, H.L. (2011). A naive multiple linear regression benchmark for short term load forecasting. In *2011 IEEE Power and Energy Society General Meeting*, 1–6. IEEE.

John, J.S. (2013). California sets energy storage target of 1.3 gw by 2020. june 11.

Müller, K.R., Smola, A.J., Rätsch, G., Schölkopf, B., Kohlmorgen, J., and Vapnik, V. (1997). Predicting time series with support vector machines. In W. Gerstner, A. Germond, M. Hasler, and J.D. Nicoud (eds.), *Artificial Neural Networks — ICANN'97*, 999–1004. Springer Berlin Heidelberg, Berlin, Heidelberg.

Neubauer, J. and Simpson, M. (2015). Deployment of behind-the-meter energy storage for demand charge reduction. Technical report, National Renewable Energy Lab.(NREL), Golden, CO (United States).

Sharma, V., Cali, U., Hagenmeyer, V., Mikut, R., and Ordiano, J.A.G. (2018). Numerical weather prediction data free solar power forecasting with neural networks. In *Proceedings of the Ninth International Conference on Future Energy Systems*, e-Energy '18, 604–609. ACM, New York, NY, USA.

Smola, A.J. and Schölkopf, B. (2004). A tutorial on support vector regression. *Statistics and computing*, 14(3), 199–222.

Taieb, S.B. and Hyndman, R.J. (2014). A gradient boosting approach to the kaggle load forecasting competition. *International journal of forecasting*, 30(2), 382–394.

Wang, Y. and Boyd, S. (2010). Fast model predictive control using online optimization. *IEEE Transactions on Control Systems Technology*, 18(2), 267–278. doi: 10.1109/TCST.2009.2017934.

Xie, L., Gu, Y., Eskandari, A., and Ehsani, M. (2012). Fast MPC Based Coordination of Wind Power and Battery Energy Storage Systems. *Journal of Energy Engineering*, 138(2), 43–53.

Zheng, M., Meinrenken, C.J., and Lackner, K.S. (2015). Smart households: Dispatch strategies and economic analysis of distributed energy storage for residential peak shaving. *Applied Energy*, 147, 246 – 257.