Forecasting and technoeconomic optimization of PV-battery systems for commercial buildings

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Abstract

The cost structure of electricity tariffs varies among countries. In Norway, it is being modified from a two-part tariff, where the cost is divided between a fixed installation cost (EUR/installation) and a cost for consumed electricity (EUR/kWh), to a three-part electricity tariff where customers additionally pay demand charges for capacity usage (EUR/kW). To combat demand charges, commercial customers are looking into supplementing PV installations with batteries to more efficiently reduce peak electricity demand, i.e. peak shaving. A crucial part of the complete energy system is also the energy management, where forecasting improves efficiency and economics. The objective of this work was to investigate the profitability with peak shaving in Norway for a commercial building. A forecasting algorithm for load prediction was developed, and the economic value of forecasting was determined for a PV-battery system. The load forecasting was developed using component-wise gradient boosting and the results from the model were verified against a renowned benchmarking load forecasting model. The economic value of forecasting was determined through simulations with Homer Energy Software that optimizes the net present cost of the systems. The results showed that battery storage was only economically beneficial when forecasting was deployed. Moreover, the cost savings came mainly from reduced demand charges, not from increased self-consumption of PV electricity. It was also discussed that the application of forecasting in an energy management system could be divided into three phases. One phase where forecasting is deployed to dimension energy system components in an early stage, one monthly forecast overview that identifies height and frequency of maximum peaks, and finally one high-resolution forecast that operates the battery on an hourly basis. Altogether, such an energy management system could additionally also be used by utility grid owners to schedule demand response actions for power quality control.

Introduction

The cost structure of electricity tariffs varies among countries. In Norway, it is being modified from a two-part tariff, where the cost is divided between a fixed installation cost (EUR/installation) and a cost for consumed electricity (EUR/kWh), to a three-part electricity tariff where customers additionally pay demand charges for capacity usage (EUR/kW). The demand charge reflects purchased energy per time unit, i.e. kWh/h. Simshauser (2016) argues that this three-part tariff is more efficient and reflects both cost elements of electricity distribution, capacity and energy. Fridge et al. (2018) took this study further and performed an analysis of how different electricity tariffs affect cost distribution between micro-grid owners and electricity distribution grid owners. They found that two-part tariffs encourage grid destabilization. Although the three-part tariff has not been fully implemented in Norway, commercial customers are billed for demand charges. A shift to the three-part tariff would create winners and losers (Simshauser 2016), and thus, there is a need for assessing the potential for cost savings by cutting the peak demand, i.e. peak shaving.

To combat demand charges, commercial customers are looking into supplementing PV installations with batteries to more efficiently perform peak shaving. However, the current PV installations do not usually include batteries, but as battery prices decline (IRENA 2017), it becomes interesting to consider a co-optimization of PV-battery systems. Comello et al. (2018) analyzed the profitability for PV-battery systems and found that systems with low-cost storage would be profitable. Indeed, the cost of storage is vital for profitability. To the authors' knowledge, no similar study has been conducted for the commercial sector in Norway.

Installation of the physical PV and batteries alone will not result in optimal solutions. A crucial part of the complete system is also the energy management, which is the control that eventually will improve efficiency and economics while reducing emissions. One conceptual framework for such a system was presented by Zhao et al. (2010) and includes both a cyber and a physical system. Forecasting is a crucial feature of the cyber-part and it has been shown to increase revenues from PV-battery systems, although it was highlighted that the actual benefits are strongly dependent on site-specific boundary conditions such as feed-in-limit, feed-in-tariff etc. (Litjens 2018).

Therefore, this work was initiated to investigate the profitability with peak shaving in Norway for a commercial building. There were two specific objectives, first to develop a forecasting algorithm for predicting electric load, and second to determine the economic value of using forecasts for efficient battery control.

Method

LOAD FORECASTING

To forecast the energy load for 2018, data from 2017 was used to train the model. Hourly electricity usage was collected from electric meters from the advanced metering infrastructure (AMI) system. Further, weather data on an hourly level was collected from the Norwegian Metrological Service[1].

Two different modelling techniques were used. First, the Tao vanilla benchmark model (TVB). This model was first published in Hong (2010) and was later used as a benchmarking model in the GEFCom2012 load forecasting competition (Hong, Pinson, and Fan 2014). The model performed among the best 25 of 100 teams. In the commercial software package SAS Energy Analytics, the TVB model is integrated as a standard load forecasting method. Further, because of the relatively straightforward specification and proved predictive performance the model is a good candidate to test other models against. The model is a multiple regression model

$$\begin{aligned} Y_t &= \beta_0 + Y_{t-1} + \beta_1 M_t + \beta_2 W_t + \beta_3 H_t + \beta_4 W_t H_t + \beta_5 T_t \\ &+ \beta_6 T_t^2 + \beta_7 T_t^3 + \beta_8 T_t M_t + \beta_9 T_t^2 M_t + \beta_{10} T_t^3 M_t \\ &+ \beta_{11} T_t H_t + \beta_{11} T_t^2 H_t + \beta_{11} T_t^3 H_t \end{aligned} \tag{1}$$

where Yt is the load forecast for hour t, β_i are the estimated coefficients from the least squares regression method; M_t, W_t and H_t are month of year, day of the week and hour of the day. Further, T_t is the temperature corresponding to time t. Note that we make two different TVB models, one with and one without the lagged dependent variable, Y_{t-1}.

This has some very important implications for how it is possible to apply the model in production. Without Y_{t-1} it is possible to predict as long as a year ahead (given that the model was trained on one year of data) and that the model is fed some realistic temperatures series for the different seasons. However, using Y_{t-1} we have to continuously score the model based on the latest data each hour. This will 'predict' any sudden "peaks" after the actual "peak".

In the next section, we present the gradient boosting approach. Previous research with boosting demonstrates excellent prediction performance within statistics and machine learning (Schapire and Freund 2012). Further, Bühlmann and Yu (2003) developed *component-wise gradient boosting (CW-GB)* to handle models with a large set of independent variables. In this paper, we use *component-wise gradient boosting with penalised splines* (P-splines) (Bühlmann and Hothorn 2007). Also, boosting is robust against multicollinearity and flexible in terms of modelling different types of effects (Mayr and Hofner 2018). A similar approach was used by Taieb and Hyndman (2014) in the Kaggle global energy forecasting competition 2012 and ranked fourth out of 105 participating teams. Next, we provide a more detailed overview of the procedure.

We label the outcome variable, energy consumption, y and the predictors (temperature variables and calendar data) x_1, …, x_p. The objective is to model the relation between y and $X :=(x_1, \dots, x_p)^T$, and to estimate the "optimal" prediction of y given x. To achieve this objective, we minimize the loss function $\rho(y,f) \in \mathbb{R}$ over a prediction function f depending on x. Since we use a generalized additive model the loss function is the negative log-likelihood function of the outcome distribution. In the gradient boosting the objective is to estimate the optimal prediction function f^*, defined by

$$f^* := argmin_f \mathbb{E}_{y,x}[\rho(y, f(x^T))], \tag{2}$$

where it is assumed that ρ the loss function, is differentiable with respect to f.

1. Initiate the function estimate $\hat{f}^{[0]}$.
2. Determine the set of *base-learners*. Each of the base-learners acts as a modelling alternative for the predictive model. We set the number of base-learners equal to P and $m = 0$.
3. Increase m by 1
   a. Compute the negative gradient $-\frac{\partial \rho}{\partial f}$ of the loss function and evaluate it at $\hat{f}^{[m-1]}(x_i^T), i = 1, \dots, n$. This gives us the negative gradient vector

   $$\mathbf{u}^m = (u_i^{[m]})_{i=1,\dots,n} := (\frac{\partial \rho}{\partial f}(y_i, \hat{f}^{[m-1]}(x_i^T)))_{i=1,\dots,n} \,.$$

   b. Fit each of the base learners individually to the negative gradient vector. We estimate the negative gradient $\mathbf{u}^m$ for all the vectors of the predicted values P.

   c. This step selects the base-learner that fits $\mathbf{u}^m$.

1. www.met.no

d. The current estimate is updated by setting $\hat{f}^{[m]} = \hat{f}^{[m-1]} + \nu\hat{u}^{[m]}$ where $0 < \nu \leq 1$.

4. Steps 3 and 4 are iterated until m_{stop} is reached.

and p is the number of features in the model. In step 3c) and 3d) the algorithm performs variable and model selection. There are two hyperparameters that need to be estimated, M, the number of steps, and ν, a step length factor. However, Friedman (2001) shows that a small ν can prevent over fitting. We set ν=0.15 and M=400. Further, the CW-GB had 32 different variables available (temperature data, holidays, calendar data) and the algorithm then chose the best set of variables from these.

ENERGY SYSTEM OPTIMIZATION

A grid-connected commercial building in the retail sector located in Norway was chosen for this study. The yearly electricity consumption was about 2,900 MWh. The volatility of the consumption profile can be used as an indication of the profitability with peak shaving. Lind et al. (2017) found that the coefficient of variation (CV) can be used to give the consumption profile a score, where buildings with high CV-values have a higher probability of benefiting from peak shaving. CV-value is calculated as the standard deviation to the average value, and the object in this work had a low score of 0.37.

Homer Energy

The economic value of forecasting was determined using the commercial software Homer Pro and Homer Grid. Homer is an acronym for Hybrid Optimization of Multiple Energy Resources. Both software programs were developed by Homer Energy to simulate, optimize, and perform a sensitivity analysis of on- and off-grid micro grids (Lambert et al., 2006, Bahramara et al. 2016]. Homer optimizes the system based on minimizing the objective function Net Present Cost (NPC), which is the value of all the costs the system incurs over its lifetime, minus the present value of all the revenue it earns over its lifetime. Costs include capital costs, replacement costs, O&M costs, and the costs of buying power from the grid. Revenues include salvage value and grid sales revenue.

Economic value of forecasting

Four cases were designed to determine the value of forecasting.

Case A was simulated in Homer Pro with a cycle charging dispatch strategy, which is common today in systems with little renewable power generation. Cycle charging means that whenever a generator is running, in this case, grid or PV, the battery is charged until it reaches a specified state of charge, in this case, 95 %. Moreover, there is no forecasting applied, and hence no control to capture excess PV electricity or to avoid grid charging of battery. During case A, the capacity of both PV and battery were optimized to determine optimal component dimensioning for a case without forecasting.

Case B was simulated in Homer Grid with a forecasting dispatch controller. The forecasting feature is not included in Homer Pro. The intention with case B was to determine the optimal battery size if forecasting was applied to a building where PV had already been installed based on optimization without forecasting. Therefore, the optimal PV size from case A was applied and only the battery component was optimized. The forecasting controller sees 48 h ahead and determines how to use the system components for demand charge reductions and energy arbitrage while serving the electrical load.

Case C was similar to Case B but here also the PV component was optimized, thus a complete co-optimization of PV and battery using the forecasting controller in Homer Grid.

Case D was simulated in Homer Pro to show how the project economics are affected if forecasting is not applied to a system that was dimensioned based on an optimal case, i.e. case C.

Modelling constraints

The system components included in the optimization are PV, battery, converter, load, and power grid. The PV component is modelled as polycrystalline silicon 60 cell module (Jinko JKM275-60). The model included temperature effects and a derating factor (losses from wiring, soiling, snow cover, and degradation) of 92 %. Solar irradiance and temperature data were imported through Homer from the NASA Surface Meteorology and Solar Energy database and included monthly global horizontal radiation, averaged from July 1983 to June 2005. The modules were simulated to face south with a tilt of 20 °. The installation cost was set to 1,020 EUR/kWp and the costs related to operation and maintenance were neglected. Lifetime was set to 25 years, even though the effective lifetime of the PV system may be substantially longer.

The battery component was modelled as a generic Li-ion with 90 % round-trip efficiency and with a C-rate of 1 and 3 for charging and discharging, respectively. The initial state of charge was set to 50 % and minimum state of charge to 10 %. The lifetime of the battery was set to either 15 years or 3,000 cycles, whichever comes first. The cost of installation was set to 310 EUR/kWh and replacement of the battery was set to 150 EUR/kWh (IRENA 2017). The converter was modelled as a generic system converter with an efficiency of 96 %. The inverter and rectifier capacities were equally large and the installation cost was included in the cost of PV and battery components.

The grid component was designed to reflect the local conditions. Electricity prices (EUR/kWh) consisted of spot prices, utility fee, demand charge fee, and a specific cost/benefit price for the building owner. Historical prices from 2017 were imported from Nordpool (Nordpool). The cost of power (EUR/kW) was set to 15 EUR/kW for December–February, 8 EUR/kW for March and November, and 2 EUR/kW for April–October.

The project lifetime of the simulation was set to 25 years, the interest rate to 3.5 %, and the inflation rate to 2 %. The forecasting dispatch strategy applied in the optimizations uses both load, PV, and price forecasting. This paper shows results on successful load forecasting, but do not analyse the possibilities of PV and price forecasting. However, price forecasts for the next 24 h are available on Nordpool (Nordpool) and can be incorporated into an actual dispatch strategy. Forecasting of PV production has been studied elsewhere (Chun Sing et al. 2017) and seems to give accurate results. The incorporation of these three forecasting algorithms would enable an optimization similar to the one used by Homer Grid. It should still be mentioned that real forecasts are not 100 % accurate, in contrast to the "perfect foresight" that Homer applies.

Results and discussion

LOAD FORECASTING

The results of the forecasts from the two different modelling strategies are described in the following figures. Figure 1 shows the TVB and the CW-GB model when the dependent variable lagged one hour is used as an explanatory variable. The TVB model is included because it has a previous track record of good load forecasting abilities; hence it is useful to compare the CW-GB results against a benchmark. As can be seen from Figure 1 both the TVB and the CW-GB models follows the actual load (kW) closely. The CW-GB and the TVB has a CV(RMSE) equal to 0.114 and 0.124, respectively. For example, 'ASHRAE' specifies that the CV(RMSE) should be less than 25 % if 12 months of post-measure data are used (American Society of Heating, Refrigeration and Air Conditioning Engineers 2014). The CV(RMSE) for both the models are well below the ASHRAE requirements. However, from a practical perspective using Y_{t-1} is challenging in production. The models need to be updated every hour and will not be able to predict a sudden "peak" in demand.

Figure 2 shows the TVB and the CW-GB model without Yt-1 as an explanatory variable. Both the models follow each other relatively close, but the predictions are not as good as the models with the lagged dependent variable. Also, the predictions are far from the actual loads the first 9 days of January but perform somewhat better for the rest of January. The CV(RMSE) for the CW-GB is 0.323 and 0.367 for the TVB. However, the actual building that these two models were developed for had a lot of different equipment installed, many of which were used on an ad hoc basis, thus difficult to predict.

ECONOMIC VALUE OF FORECASTING

Table 1 presents the four different cases that were evaluated and highlights four main points based on optimization of NPC. First, the NPC was lowest for case C where all components were co-optimized using a 48 h forecasting horizon. During a 25-year period it would save about EUR 10,200 compared to case A with standard cycle charging battery control, and EUR 61,300 compared to case D where forecasting is not applied. Second, the battery is only economically beneficial if forecasting is applied. The difference in NPC is small but applying forecasting do also allow for a larger PV capacity. Third, PV and battery should be co-optimized since battery size affects optimal PV capacity. Fourth, installation of a system optimized using forecasting results in the highest NPC if standard cycle charging control is used.

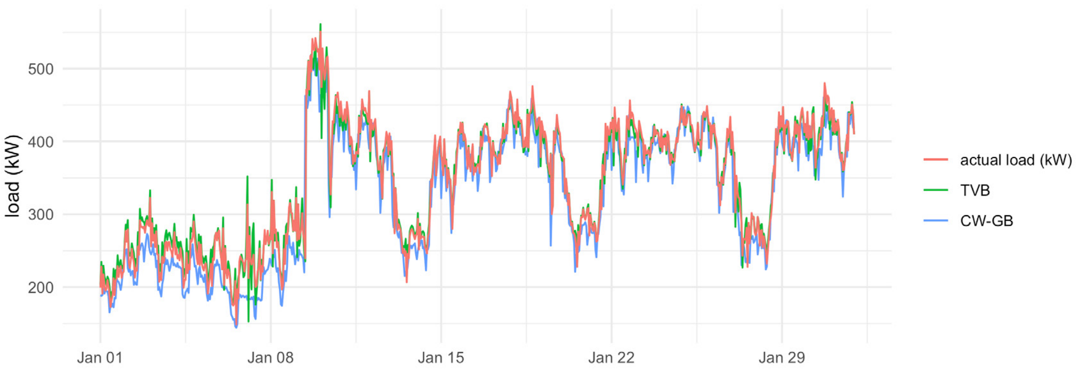

Figure 1. Actual loads (kW) for January 2018, and the predicted loads from TVB and CW-GB models, both models with the dependent variable lagged 1 hour.

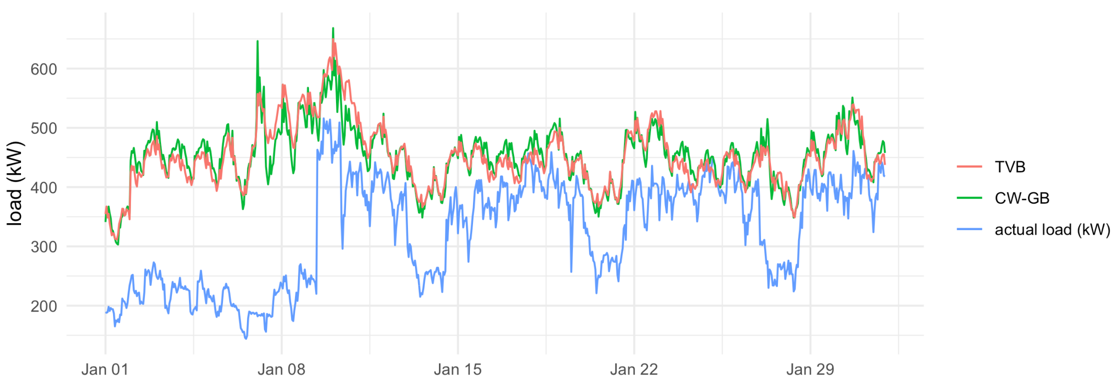

Figure 2. Actual loads (kW) for January 2018, and the predicted loads from TVB and CW-GB models, both models without the dependent variable lagged 1 hour.

Table 1. System dimensioning and project lifetime economics.

Control	PV (kWp)	Battery (kWh)	COE* (EUR/kWh)	NPC** (M EUR)	Optimization
A) Cycle charging	240	0	0.0652	3.92	All components
B) Forecasting	240	135	0.0650	3.91	Only battery
C) Forecasting	322	135	0.0649	3.91	All components
D) Cycle charging	322	135	0.0658	3.97	No components

** COE denotes Levelized Cost of Electricity. ** NPC denotes total Net Present Cost.*

Table 2. Monthly level of peak shaving reduction for the different cases, in % and in EUR.

Month	Case A	Case B	Case C		Case D
	Peak reduction (%)	Peak reduction (%)	Peak reduction (%)	Demand Charge Saving (EUR)	Peak reduction (%)
January	0	12	12	1,680	5
February	0	9	9	950	0
March	0	11	11	630	0
April	0	6	6	60	0
May	9	15	15	170	9
June	10	27	27	350	10
July	6	17	18	170	8
August	7	20	22	200	8
September	14	23	24	170	15
October	7	29	32	220	9
November	9	26	26	830	11
December	0	17	17	1,580	0

The benefits of forecasting arise from both increased self-consumption of PV electricity and reduced costs with peak shaving. Sales of PV electricity was reduced from 512 kWh (Case A) to 94 kWh (Case B) when forecasting was applied and shows consequently that increased self-consumption is not the reason to why battery and forecasting make economic sense. Total PV production for Case C was about 338 MWh. Table 2 summarizes monthly peak shaving levels for the different cases, as well as monthly demand charge savings for Case C. The maximum peak shaving occurred for Case C in October where the co-optimized PV-battery system shaved 32 % of the monthly peak, which is in line with results from Leadbetter and Swan (2012) that presented peak reduction between 28 and 49 %. There was however some months with low peak reductions. In terms of economics, it is seen in Table 2 that Case C saves between 1,680 and 60 EUR/month due to reduced demand charges. Table 2 further shows that Case D did not achieve efficient peak shaving even though the system components were the same size as Case C. This shows that accurate forecasting is crucial to achieving a low-cost system.

Energy storage behind-the-meter, as shown in this paper, is a way to cut costs for the building owner through peak shaving. Another possibility for building owners to cut payback time of behind-the-meter storage is to rent storage capacity to the power grid to enable control of power grid stability in front-of-meter. Whether the battery capacity presented in this paper would be useful for this purpose, was not analysed. Chun Sing et al. (2017) studied large-scale PV-storage installations and concluded that energy storage could limit stability issues related to frequency and voltage. A lab-scale experiment for such a system was conducted by Young-Jin et al. (2017) with promising results. The implementation of such features would require new business models, but it is speculated that through an energy management solution as presented in this work, it would be possible for buildings to have a time-stamped forecast of net power purchase from the grid. This way, it would be possible to schedule actions to control power grid stability, not only by the temporal shutdown of equipment as is the case for certain larger industrial customers, but also by distributing power from behind-the-meter battery to power grid. Ranaweera et al. (2017) presented a battery control method that could serve such a purpose.

Setting up an efficient energy management system for a building might consist of three phases. First, a robust dimensioning of system components (PV, battery, inverters) in an early stage. This phase is covered in the current paper. Second, there is a need for a monthly overview that identifies the maximum peak that will set the cost for the month. Both height of peak (kW) and timing (day) of month should be identified. This forecast should also provide a frequency of these peaks, i.e. whether they occur once or several times a month. Results from this paper show that both TVB and CW-GB with Yt-1 is efficient for this overview. Third, a higher resolution forecast, preferably down to 15 minutes, should identify how to operate the battery on a day-to-day basis. Results from this paper show that model TVB and CW-GB without Yt-1 may have potential, but the building in the current study had some unexplained variation that was difficult to predict. Forecasting both the monthly peak and the day-to-day high-resolution peak is important to get the most economic gains out of the system. There might be no reason to discharge the battery during hours where the demand is much lower than the monthly peak, although it might be beneficial to charge the battery during hours with low electricity price or to capture excess PV electricity. However, if new business models are introduced that allows the energy storage owner to sell electricity back to the power grid in order to control power grid quality, it might be more beneficial to use the battery for both peak shaving and power grid control.

Conclusion

Based on the results from this work, the following conclusions are highlighted:

- Accurate forecasting of electricity demand can be performed with both the TVB and the CW-GB model, but for the building in this study Yt-1 is crucial as a predictor, hence the model will be challenging in production
- During the design of PV-battery systems, the components should be co-optimized.
- Battery storage was only economically beneficial when forecasting was deployed.
- Energy management with forecasting improved profitability and potentially between EUR 10,200–61,300 can be saved during a 25-year period.
- For the optimal case, most of the savings came from peak shaving, not from increased self-consumption.

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