Shaving the peaks through statistical learning: smart use of solar energy and storage solutions

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Keywords

storage, energy systems, energy demand, energy cost, energy supply and demand, statistical learning, load management

Abstract

This paper demonstrates how big-data, statistical learning and simulation of local energy production and storage, can contribute to reduce costs and shift energy consumption from the main power line to locally produced solar energy and battery storage during peak hours. This is demonstrated by using more than 5 million of hourly energy meters readings from 600 Norwegian grocery and large hardware stores. Many of the Norwegian grid operators use fixed peak-load tariffs, thus shaving the peaks will result in decreased energy costs. Our aim is to find the largest peaks; where the most potential for cost reductions can be found. To isolate the stores with the largest variation from hour-to-hour we suggest using the coefficient of variation (CV); we demonstrate this by calculating CV for 600 stores and use the results to rank and identify stores with both large variation and little variation in energy consumption. Further, three of these stores are used in solar photovoltaic (PV) production and energy storage simulations. The simulations will highlight the cost savings between stores with different CV values. Results suggest that by using such methodology, we can reduce total energy costs, and at the same time lower energy loads through peak shaving and phase shift.

Introduction

The availability of hourly energy metering, in particular for electricity consumption, have great potential to contribute to more efficient energy use in buildings. However, in order to achieve its full potential, there is a need to improve data management and data analysis methods to visualize the economic opportunities. Analysis of annual and monthly time series data has a long history and well-established procedures, while techniques to analyse hourly energy data are still immature (Ferreira 2014). Additionally, most previous studies of the economic consequences of tariff switching using real power demand data have been made for residential consumers (Granell 2016). The main purpose of this paper is to demonstrate a methodology for reducing electrical energy costs in commercial buildings. Such cost savings are achievable through peak demand shaving, utilizing local PV energy production and storage. We analyse the energy profile of 600 different stores to find those with the most potential for cost savings. The first part of this paper outlines the tariffs' policy of the studied Distribution Grid Operator (DSO). Then, a method for analysing the energy consumption using the coefficient of variation (CV) is introduced, and consecutively used to rank the 600 stores/buildings in terms of variation in energy consumption. Based on the analysis and the selection of one common DSO, three stores are chosen for PV energy yield and storage (battery) simulation. Results and conclusions derived from the simulations and the associated cost scenarios are discussed in the final sections.

Method

While not all the stores in our study have the same grid operator, we focus on the largest operator, i.e. Hafslund. In Norway, Hafslund has more than 700,000 customers (private and business customers) and their grid distributes about 18,000 GWh of electricity each year, through 44,000 km of cables. As Table 1 shows, the tariffs from Hafslund are fixed within seasons; winter months feature the highest tariff, with a peak load charge of NOK 150. The winter tariff is 14 times more expensive than the corresponding summer tariff of NOK 11. Further, the peak load tariff is calculated on the basis of the highest load drawn by the system per calendar month. For example, if a commercial energy customer reaches 250 kWh in a particular hour in January, the calculated tariff will be 250 × 150 = NOK 37,500. This regardless of the average load profiles. Thus, if for example, customer A draws on average 220 KWh each January, while customer B only 120 kWh for the same period, the applied tariff will be exactly the same, in case both customers feature a similar peak in their consumption, within this period. Due to such fixed tariff policy, it is important for a building owner to find the largest peak every month, particularly in winter months and to analyse the reasons behind the peak. Evidently, any reduction of the peak consumption will directly reduce the overall cost. However, if the average energy consumption is close to the peaks, the potential of cost reduction will be substantially less than if the peak has larger deviation from the average. The first step for owners of a large number of buildings, therefore, will be to find those stores that feature large variations between the average and peak consumptions/loads; and select those stores as "candidates" to investigate an optimized strategy for potentially shifting the load.

Our database contains energy consumption data from 600 Norwegian retail stores, with a total of 5.3 million hourly observations for 2016. In order to identify stores with high potential of shaving peaks in their energy consumption profile, we propose using the coefficient of variation (CV). The *CV* is a standardized measure of dispersion, defined as the ratio of the standard deviation σ to the mean μ (Everitt, 1998):

$$CV = \frac{\sigma}{\mu}$$

CV is independent of the unit in which the measurement has been taken, thus it can be used to compare data with different units or means. Figure 1 depicts the distribution of CV scores in a boxplot for the three winter months, i.e. December (12), January (1) and February (2), when the tariff is highest.

For PV systems sizing and energy yield simulations, the licensed software PVsyst is used. The PV systems under study, are sized and modelled, given the available roof area of the three selected stores. For stores hosted in buildings with tilted roof, the PV modules are assumed to be roof-integrated, thus with negligible spacing between them. For cases of flat roofs, we assume modules mounted on fixed structures at an inclination of 45 ° and azimuth α = 180 ° ("south"). Simulations of energy yield production were based on the irradiation data provided by the Climate-SAF PVGIS database. As incurring system losses, we assumed the standard ones suggested by PVSyst, namely: Incidence Angle Modifier (IAM) factor, near-shadings and irradiance level losses; module temperature losses; light-induced degradation (LID); module array mismatch; ohmic wiring and inverter losses. Due to lack of detailed information, no shading effects from possible nearby objects were taken into account. The chosen module inclination angle (45 °) for the fixed structure-mounted systems has been identified as the average optimal one, for the geographic locations of the studied buildings.

All the modelled systems are grid-connected and a polycrystalline silicon (poly-Si) module, type REC 265TP-26V, with a nominal power of 265 W_p is used, representing a typical module, with respect to efficiency and cost. In particular, the following three cases of buildings (and respectively rooftop PV systems) were defined and simulated:

- *Store id 2703*: The modelled system consists of 1,065 poly-Si modules, covering an overall surface of 1,757 m^2 (78.5 % of the available roof area) and providing a total array power P_{inst} = 282 kW_p nominal (at STC) or 255 kW_p at operating conditions (50 °C). Shading profiles through the year between the modules, were simulated and taken into account, thus adjusting the spacing between the module tables (rows). The modules were arranged in 71 strings of 15 modules per string. In total, 19 inverters of 12 kWac each, were suggested. As an example, a generic model from the PVsyst database, type 12 kW 350–600 V TL, was chosen.
- *Store id 2487*: The system here consists of 980 poly-Si modules, covering an overall surface of 1,617 m^2 (73.5 % of the available roof area) and providing a total array power

Table 1. The peak-load tariffing policy applied by Hafslund.

Commercial customer: peak-load tariffs	Price	Unit
Fixed charge per installation	340	NOK/month
Peak load charge (Winter 1, Jan–Feb, Dec)	150	NOK/kW/month
Peak load charge (Winter 2, Mar and Nov)	76	NOK/kW/month
Peak load charge (Summer, Apr–Oct)	11	NOK/kW/month
Energy charge (Winter, Jan–Mar, Nov–Dec)	5.2	NOK/kWh
Energy charge (Summer, Apr–Oct)	3	NOK/kWh

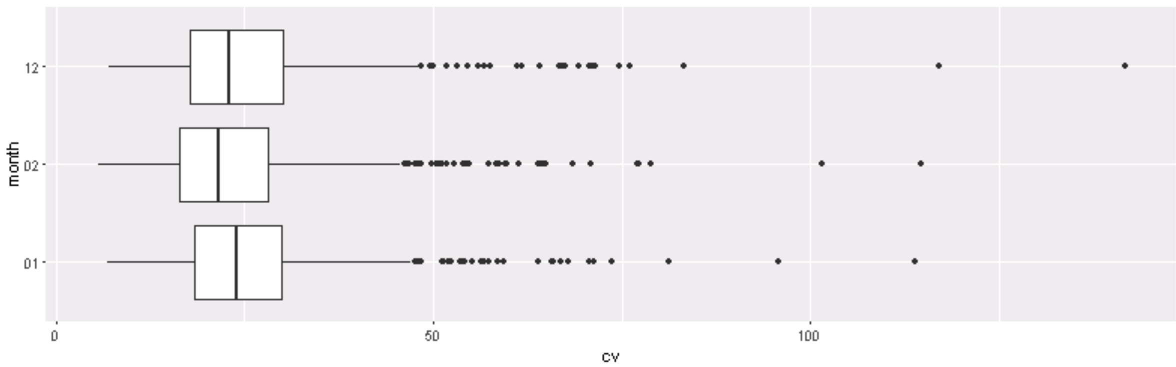

Figure 1. Boxplot of the Coefficient of Variation (CV) for all stores in January (01), February (02) and December (12) – 2016. Vertical line indicates the median.

Table 2. Descriptive statistics for the three stores for January, February and December 2016, including the coefficient of variation (CV).

Store ID	Average kWh	Min kWh	Max kWh	CV	Sum kWh	Area (m²)
2448	103	60	160	18.7	227,208	1,780
2487	76	26	180	44.7	154,870	2,200
2703	151	78	212	17.8	307,298	2,237

P_{inst} = 260 kW_p (STC) or 235 kW_p at operating conditions. Orientation of the building was approximated at α=190° ("south-west"), while modules were oriented at the mentioned α = 180 °, which resulted in some "loss" in module coverage area. In this case, the modules were arranged in 70 strings of 14 modules per string. As for the previous case, 19 inverters of 12 kWac, were defined.

- *Store id 2448*: The modelled system consists of 532 poly-Si modules, integrated on the roof, covering an overall surface of 878 m^2 (98.5 % of the available). Orientation of the building (and, thus, of the modules) was approximated at 164 ° ("south-east"). A total array power P_{inst} = 141 kW_p (STC) or 127 kW_p at operating conditions, was calculated. An arrangement of 38 strings and 14 modules per string and a total 10 inverters of 12 kWac, was suggested.

TRNSYS is a quasi-steady simulation program and was used for making a generic simulation model for a typical food and hardware store. TRNSYS is a transient systems simulation program with a modular structure. The program recognizes a system description language in which the user specifies the components that constitute the system and the manner in which they are connected. The TRNSYS library includes many of the components commonly found in thermal and electrical energy systems, as well as component routines to handle input of weather data or other time-dependent forcing functions and output of simulation results. The modular nature of TRNSYS provides great flexibility, and facilitates the possibility to add mathematical models to the program that are not included in the standard TRNSYS library. Bases on this, it is possible to simulate a variety of different energy systems with TRNSYS, as well as being well suited for detailed analyses of time-dependent systems.

For each individual store, the representative annual load profile was supplied to the TRNSYS model by a text file. An hourly time resolution is used in the model. Two alternatives are available for supplying electricity to each store; local power production from a roof mounted PV system, or purchased electricity from the grid. The peak load tariffs applicable for the various stores were added to the TRNSYS model as indicated by the *Grid cost* symbol. An electricity storage system based on lithium ion batteries is also included in the model. A battery control unit is included in order to utilise the storage system as smart as possible. The control unit takes into account the representative peak load tariffs when deciding to charge or discharge at each timestep.

Results

As it can be seen in Figure 1, the CV varies significantly between the stores, from a minimum CV equal to 21 up to a maximum 141 in December. The idea here is that the potential of shaving peaks is larger among the stores with a large CV value. However, after inspecting the scores and investigating details about the building, we found that the stores with a very large CV value (CV ≥ 70) were typically stores that actually had either undertaken some form of energy efficiency measure, or that had some fault in the metering data. Thus, those stores were discarded from further investigation.

Table 2 presents the descriptive statistics of the energy consumptions, for the three stores that were chosen for further analysis, based on their for CV values, from 2016 for January, February and December (where the highest tariffs occur, as aforementioned). The choice of stores for further analysis was done on the basis of their CV values, the availability of the store owners, and the fact that they had Hafslund as grid operator. None of the stores with the most extreme CV values were chosen. From Table 2 we find that the CV value for the store with ID 2703 is 17.8, while for the stores 2448 and 2487, the CV is 18.7 and 44.7, respectively.

Figure 2 gives the scatter plots of hourly energy consumption for the three stores in January 2016. The plots demonstrate how the scattering of the energy consumption varies between the stores, and we clearly see that store 2487 has larger variation than 2448 and 2703.

For each individual store, three different cases were analysed:

1. Existing system (i.e. only power from grid)
2. Battery storage system combined with power from the grid
3. Battery storage system with power production from PV and electricity purchased from the grid.

For case number 2, power from the grid was used to charge the battery at times when the demand was low. Additionally, the battery was discharged when the power demand exceeded a specific predefined level. For case number 3, power produced from the PV system was first used to cover the load. If the power produced was higher than the demand, excess PV power was used to charge the battery. Similarly for case number 3, power from the grid was used to charge the battery at times with low demand. The local PV production at the three different stores is shown in Figure 3. Specification for the electricity storage system is given in Table 3. Two different battery sizes were used in the simulations, respectively 33 kWh and 66 kWh. For the PV system, two different costs estimates were used. This includes an average cost of NOK 15,000/kWh (PV_avg) and a low cost option of NOK 9,500/kWh (PV_low). The low cost option is based on predicted price reduction of PV systems in 2020 (IRENA, 2016). Two different sets of peak load tariffs were also used in the simulations. One including the current Norwegian tariffs (GT) for the representative grid company, and a future assumed tariff with twice the costs of today (2GT).

The annual electricity supply pattern for three different stores is presented in Figure 4. The *Battery* configuration is identical to case number 2 described above, whereas the *Battery + PV* configuration is identical to case number 3. The annual electricity supply to case number 1 is almost identical to case number 2, and is therefore not included in the figure. For store 2448, the electricity production from the PV system covers 14 % of the load. For store 2487, 29 % of the load is covered by electricity produced locally, whereas for store 2703 it is 18 %.

Figure 5 illustrates a typical electricity supply pattern for store 2487 for a week in April. As seen in the figure, in the five first hours of the day electricity from the grid is used to cover the load. In the next two hours, the load is covered by a combination of electricity produced locally and purchased electricity. In hour number 8, which coincides with the peak demand for that day, the battery is discharged in order to reduce the power from the grid. In the next two hours, the load is lower, and the battery is charged. In hour number 11, the local electricity production is higher than the demand, but since the battery is fully charged (not shown in the figure), some of the produced electricity is curtailed. Since the battery control system does not have perfect foresight, such an adverse situation can arise. From hour number 12, a combination of electricity produced locally and purchased electricity is used to cover the load. In the last five hours of the day, only purchased electricity is used to cover the load.

Figure 6 illustrates a typical electricity supply pattern for store 2487 for a day in June. As seen in the Figure, in the first four hours of the day electricity from the grid is used to cover the load. In addition, the battery is also charged in the two first hours. In the next two hours, the load is covered by a combination of electricity produced locally and purchased electricity. In hour number 8, the battery is discharged in order to reduce the power from the grid. This does not happen in hour number 9 since the demand drops below a predefined threshold value. In the next seven hours, the load is covered by a combination of electricity produced locally, purchased electricity and elec-

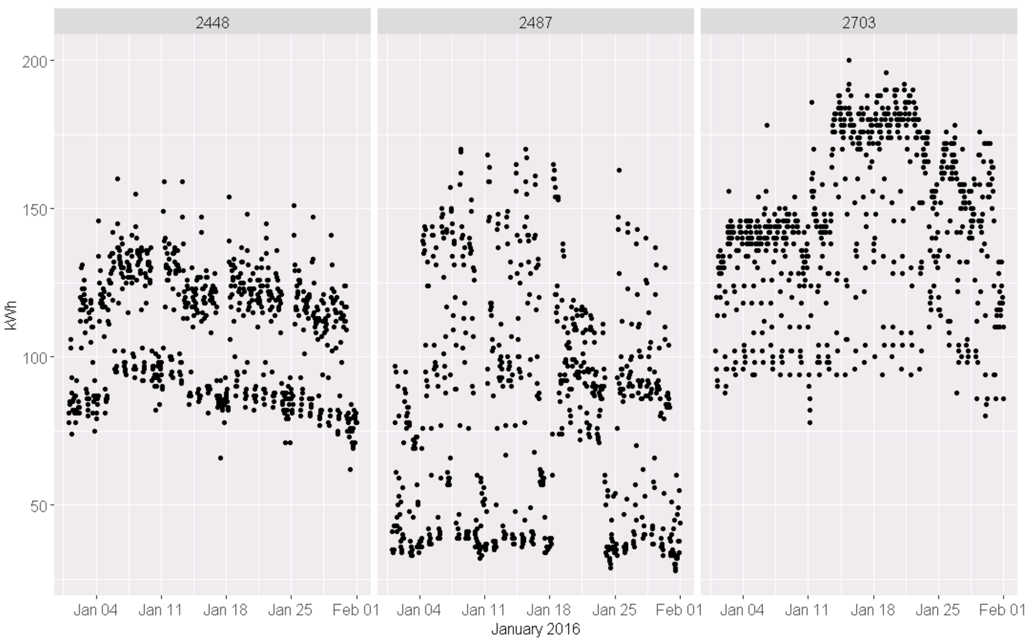

Figure 2. Hourly load profiles for stores 2448, 2487 and 2703 for January 2016.

tricity from the battery. The battery reaches is minimum state of charge in hour number 16, so it is therefore not possible to discharge the battery anymore that day. As seen, the battery is charged again in the last two hours of the day.

Two additional examples for store 2487 are demonstrated below. Figure 7 illustrates the electricity supply pattern for a typical day in October. As seen for the period between 7 and 8 in the morning, the peak demand is around 150 kW for the selected day. By using a combination of electricity produced locally and discharging of the battery, the peak power from the grid is reduced to 90 kW for this day. The other example (Figure 8) shows how the peak demand is reduced from above 160 kW to 120 kW for a typical day in January.

Figure 9 gives a summary of the payback time for the various system configurations. The payback period is the time required for the amount invested in an asset to be repaid by the net cash outflow generated by the asset, or as in this case, the amount saved each year due to investments in an electricity storage sys-

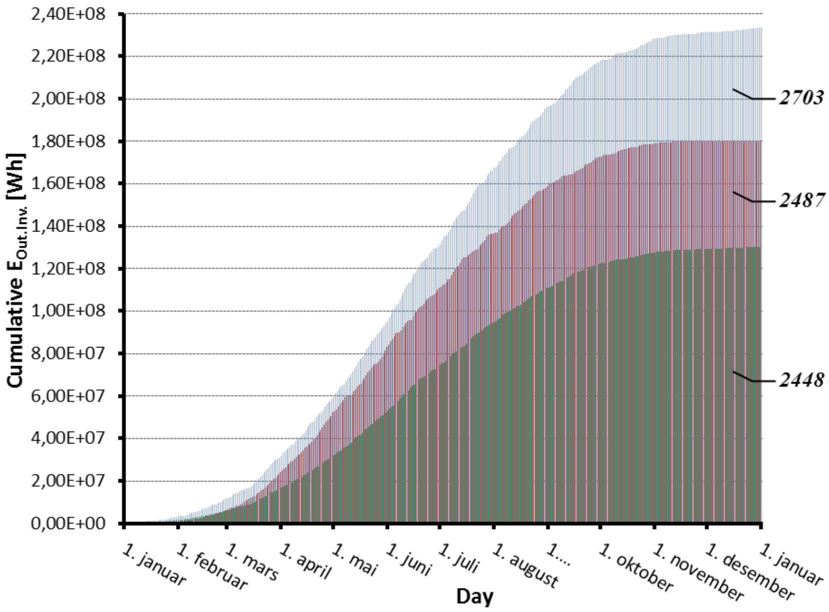

Figure 3. Cumulative PV energy yield, as calculated from the PVsyst simulations for the cases of: (a) 2703, (b) 2487, (c) 2448.

Table 3. Battery specifications.

Current battery cost (B) [NOK/kWh]	Optimistic battery cost (0.5B) [NOK/kWh]	Battery efficiency [–]	State of charge (low) [–]
6,440	**3,220**	**0.9**	**0.2**

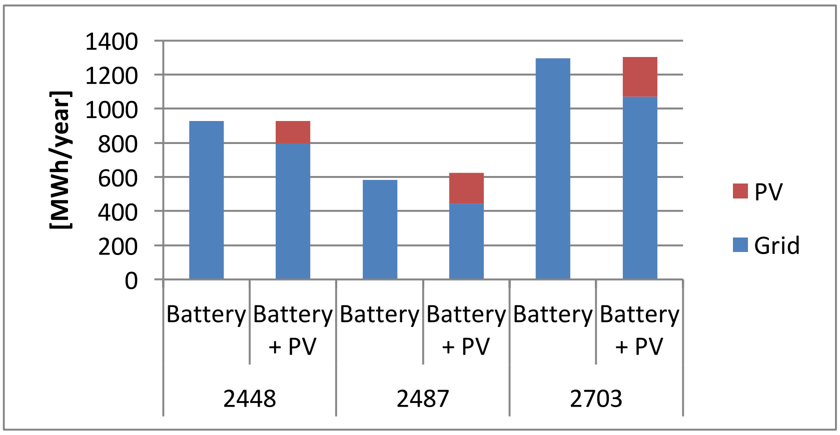

Figure 4. Annual electricity supply pattern for three different stores (2448, 2487, and 2703).

tem and a PV system. It is a simple way to evaluate the risk associated with a proposed project. A system which yields a very short payback period is typically a profitable one, whereas a system which cannot be paid back over the lifetime of the system is a poor investment. In Figure 9, a value of 25 years means that the payback time is 25 or higher. It is assumed that the battery system can be cycled for 15 years, which is a somewhat optimistic assumption.

With today's prices, only one system configuration with a 33 kWh battery and no PV system gives a payback period of less than 15 years (store 2448). However, if the battery price drops (0.5B) or the peak-load tariffs increase (2GT), several of the system configurations become profitable. A store with a high CV value (see Table 2), like store 2487, is much more likely to profit from investments in an electricity storage system. Stores with low CV values, like 2703, does not show the same profitability as stores with high values. For the PV system, a technological lifetime of 25 years is assumed. As seen in the figure, three of the configurations with PV systems had payback times of less than 25 years. It is assumed that during year 16, all system configurations with PV systems must reinvest in a new battery storage system.

Further, while the cost savings might not be as high as expected, this is likely to change in the relatively near feature, as the cost of PV systems and batteries keep declining. Since 2007, the cost of Lithium ion batteries has declined by 8 % annually, and the trend is expected to continue (Nykvist and Nilsson 2015). Also, tariffs can be designed to favour peak shaving as it is a measure that can defer network upgrades (Saldarriaga 2013). Both reduced battery cost and a potential increase

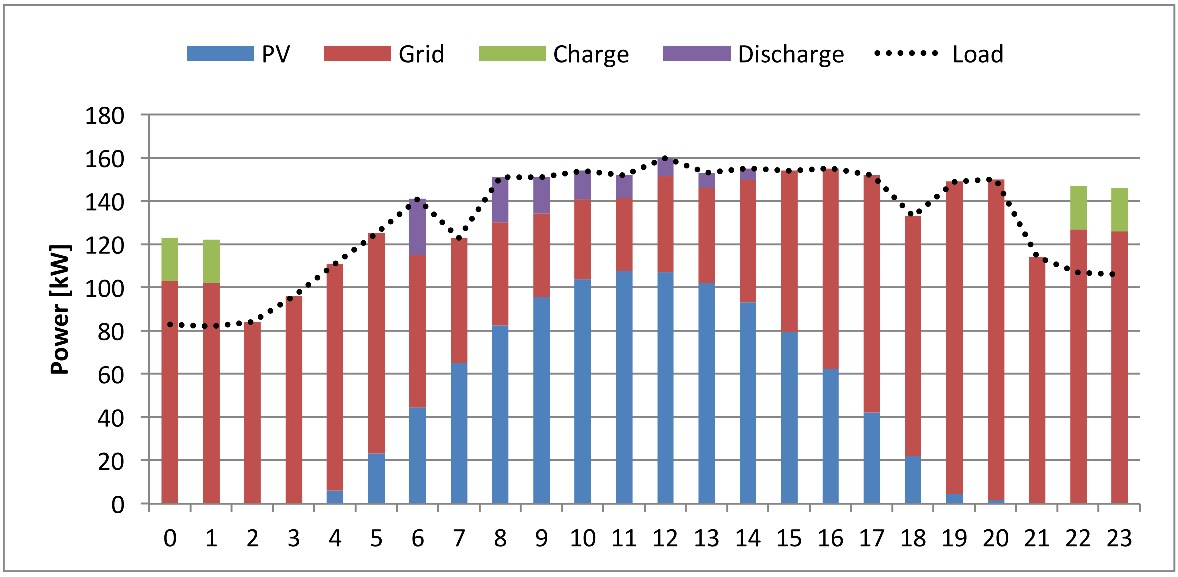

Figure 5. Electricity supply pattern for store 2487 for a typical day in April.

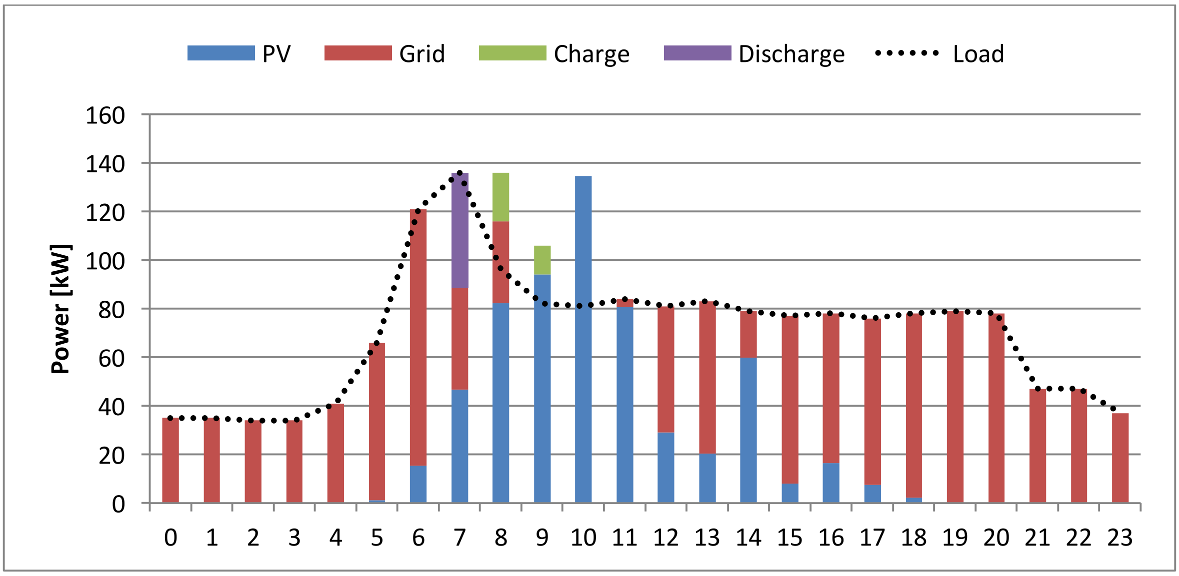

Figure 6. Electricity supply pattern for store 2487 for a typical day in June.

of peak-load tariffs are included in the payback time analysis. However, expected price reductions for PV systems are currently not taken into account, as the two scenarios included are the average and low end of actual installations prices in Norway in 2016. Other potential cost efficiency measures that are not currently included in the analysis are to give value to the ancillary grid support services that batteries and inverters can offer to the Distribution System Operator (DSO) in order to improve the reliability of the electrical grid. Also, for retailers with both refrigerated and frozen goods, outage protection may be a large additional value.

In the next stage of this project we are developing predictive models that will be used to predict the peaks, and further be used in-store to switch to battery use in the hours where the predicted peaks are. This could improve the cost savings considerably. Future research should also investigate benchmarking tools for hourly data. For example, Ferreira (2009) demonstrates how to calculate different load factor indices used on half hourly data to detect when the average energy load is far from the peaks. Using this method, we find a strong correlation (-0.86) between the load indices and the CV value, but further work is needed to establish a more general relation between the two methods.

Conclusions

The coefficient of variation (CV) is a useful statistical method to analyse the scattering of the energy consumption for commercial buildings when hourly consumption data is available. Knowledge of whether recent energy efficiency measures have

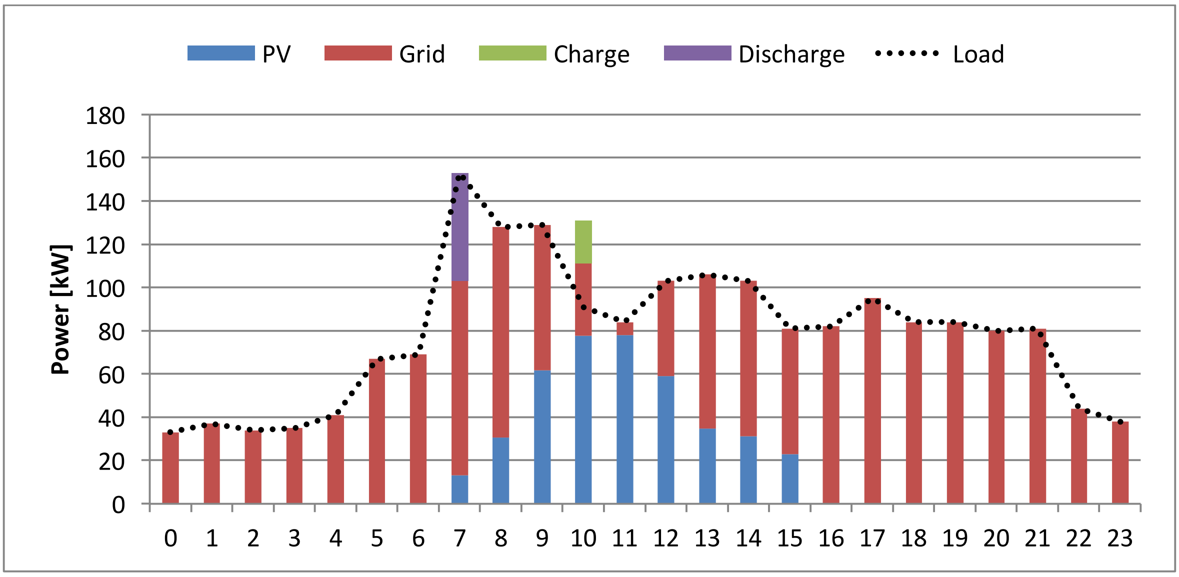

Figure 7. Electricity supply pattern for store 2487 for a typical day in October.

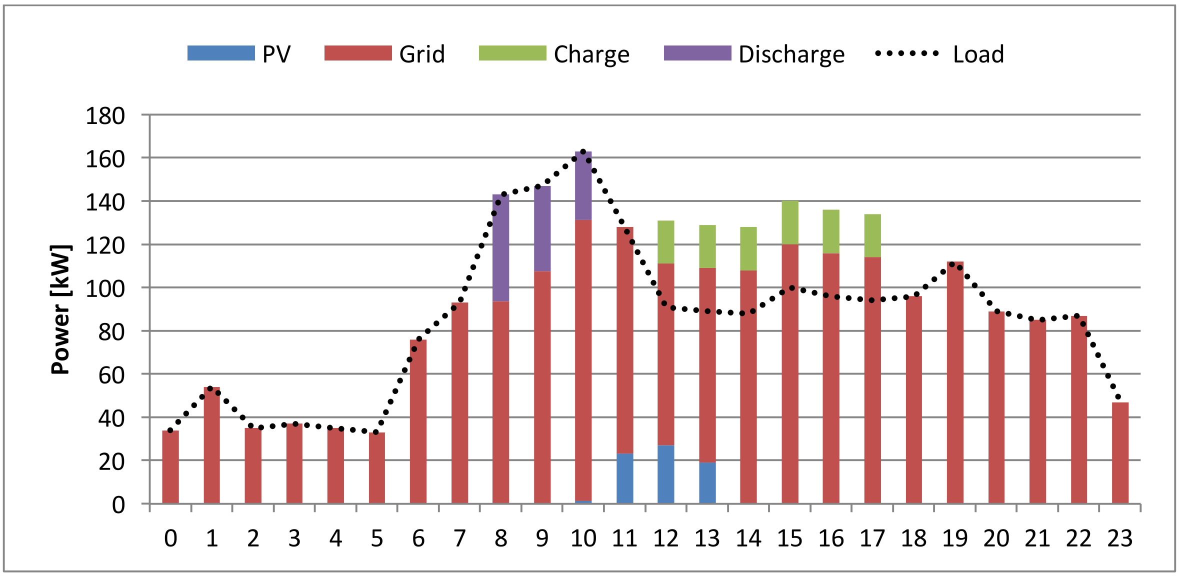

Figure 8. Electricity supply pattern for store 2487 for a typical day in January.

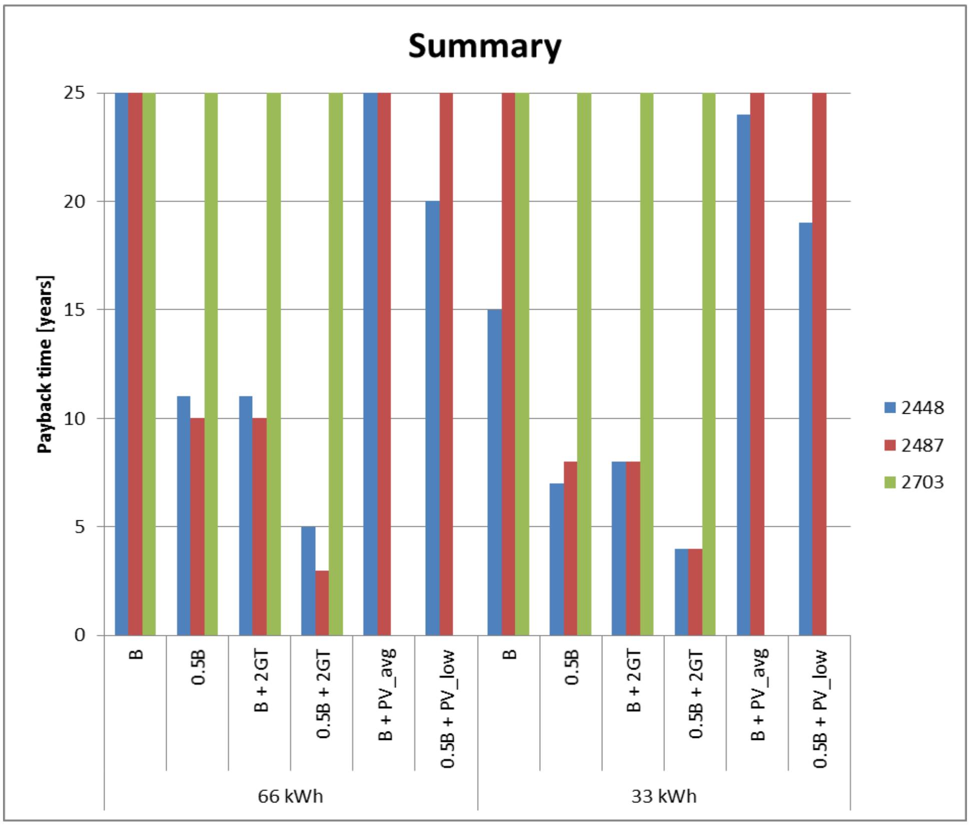

Figure 9. Payback time calculations for the various system configuration.

been undertaken is currently needed in order to identify actual scattering in energy consumption. Due to the peak load tariffs, buildings with a high CV will have the greatest potential for reducing energy costs by shaving the peak loads. Three stores with intermediate to high CV values are chosen to model energy costs for three scenarios a) grid, b) grid and battery, and c) grid, battery and PV. The analysis show that the economic gain from installing PV and battery storage system in Norway today is still very small, even for the stores with high variation in energy consumption. Store 248, with the largest CV, may benefit from an optimally sized battery today, while a PV and storage solution is not economically viable with current costs and tariffs. However, given the steady cost decline for battery and PV technology, such systems are likely to be a favourable option in the near future. Also, improved data mining methods to rank stores with potential for savings (large variation), combined with statistical models to switch to battery and/or PV at predicted peaks could further improve the economic gain.

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