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Smart meters and messaging

Task 1.5 in the project “Integrated Renewable Resources and Storage: Operation and Management”

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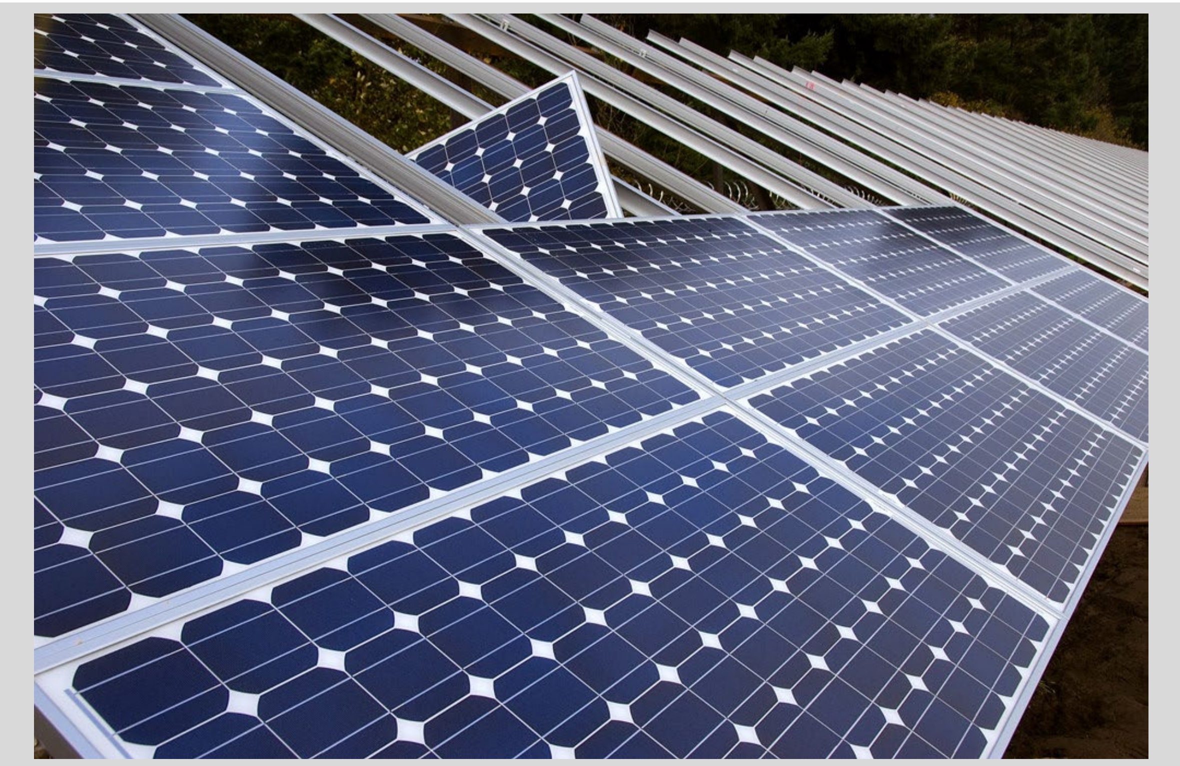
Rapport 7-2022, NORCE Energy and technology



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Summary

Monte Carlo-type simulations based on data from the Skarpnes village have been used to assess the benefits of smart meters for rooftop PV systems. The results show that when installing PV panels on private homes on the south coast of Norway, it is not immediately economically beneficial to also install batteries and smart meters. This will change if the present feed-in tariff is reduced or removed, and it may also change if the load patterns are changed.

Revisjoner/Revisions

Rev.	Date	Author	Checked by	Approved by	Reason for rev.
0.1	12.10.2022	ENOR	JAKO		Draft
1.0	27.10.2022	ENOR			Final version, added discussion on spot price variations and on storage options

Contents

1. Introduction

The present report is part of the project "Integrated Renewable Resources and Storage: Operation and Management", partly financed by the Research Council of Norway as project 285545. More specifically, it is part of task 1.5.:

To develop a tool for data integration, decision making, and messaging based on signals from smart meters for roof top PV systems.

A smart meter is an electronic device that gives practically instantaneous, typically hourly of half-hourly, information on energy consumption and energy production. These meters can also be connected to forecasts on weather and electricity prices. In contrast to when the project proposal was written, such meters are now available, and even mandatory, to the general consumer in Norway. The popularity of electrical cars in Norway has also created a market for smart chargers, see e.g. the solution offered by Haugaland Kraft[1].

It was therefore decided that NORCE's contribution to task 1.5 should be "how integrating information on weather forecasts, electricity prices, and usage predictions influences the energy cost for the building".

As basis for this work, NORCE's work on task 1.6 in the same project was used, as published in 2021[2]. Here, a cleaned data set for a private home on the south coast of Norway from one year is presented, the so-called Skarpnes data. The data set consists of PV production, electric loads, and hot-water loads. The latter is significant since the house has water-borne heating. The main contribution from task 1.6 is however an MILP (Mixed Integer Linear Programming) optimization algorithm that can optimize the operation of the house's energy system. The original house's energy system consists of loads, batteries, a ground source heat pump, a grid connection, and a PV panel for electricity production. For task 1.5 no ground source heat pump was included.

Another data set, the so-called Bergen data, was used for parts of this work. This is daily production from a solar power system supplying electricity to a commercial building in Bergen. The system consists of 368 panels with 101 kWp installed power, and it produced about 70 000 kWh per year. Most of the panels are installed facing east of west. The data is from August 2018 to February 2022, and it has been supplied by Eviny.

The method used for task 1.5 is presented in section 2, while results and discussion follow in section 3, before conclusions are given in section 4. Details on data, methods, and results are given in appendices.

2. Optimal energy use

2.1. Method overview

Three alternatives are compared to consider the benefits of a smart meter:

A. A family installing solar panels. The resulting PV production is used to cover the loads as far as possible, and excess PV production is sold to the utility if possible. Extra loads are covered from the utility.
B. A family installing solar panels and a battery. The system operation is optimized for one year, and this plan is followed as far as possible. Any deviations are handled in a rule-based manner. The battery is dedicated to the PV electricity, so direct energy storage from the grid to the battery is not possible. PV electricity can only be sold to the utility if the current production exceeds the current loads.
C. A family installing solar panels, a battery, and a smart meter. The smart meter allows optimizing for the next day, using the weather forecast and day-ahead electricity prices. Any deviations are handled in the same rule-based manner as in case B, but the deviations in both PV production and loads are significantly smaller. The same limitations for storage and sales of energy applies as in case B.

To compare these alternatives, a Monte Carlo approach was used, where several realisations were tested with variations in PV production and loads. To do so, the data summarized below was used. Details are given in section 2.2.

- PV and load data from Skarpnes for the period 1.5.2015 – 30.4.2016. Details on this data set is given by Nordgård-Hansen et al.[2].
- Nordpool's day-ahead spot prices.
- The net tariff that applied in Agder from April 1st to July 1st 2022.
- The consumer agreement "LOS Solstrøm" as accessed 30.9.2022.
- Standard deviation for predicting hourly PV production for a whole year is assumed to be 116 %, found from the Skarpnes data.
- Standard deviation for one-day-ahead prediction of hourly PV production is assumed to be 20 %, as per the model of Campo-Ávila et al.[3].
- Standard deviation for predicting hourly electricity and hot water loads for a whole year is assumed to be 280 and 1120 W, respectively, found from the Skarpnes data.
- Standard deviation for one-day-ahead prediction for hourly electricity and hot water loads is assumed to scale in the same way as the PV production data, giving 48 and 193 W, respectively.

The comparison is performed as described in section 2.3.

2.2. Data details

2.2.1. Data for loads and PV production

The year of cleaned data from the Skarpnes data set is from May 1st 2015 to April 30th 2016. The Skarpnes house is a near zero-energy building. As explained by Nordgård-Hansen et al.[2], the loads are multiplied by a factor of 1.8 to correspond to the standard heat load demands pr m^2 for a building from 1997 at coastal Southern Norway[4].

2.2.2. Spot prices

Nordpool's day-ahead spot prices for the period 2015 – 2016 is used as basis, to keep any relations that local weather conditions may have caused between loads, PV production and electricity prices. To make the analysis relevant in 2022, synthetic hourly prices for 2020, 2021, and 2022 are generated. To do so, each hourly price from 2015 and 2016 is divided by its respective monthly mean price. For each year, an average day is then defined from all these relative prices. Synthetic hourly prices are then generated for the 2020-2021 and for 2021-2022 by multiplying the average day from the "donor year" by the monthly mean for the "recipient year".

In alternative B, the synthetic prices for the period 2020-2021 is used for optimization. This mimics using last year's prices to optimize next year's operation. An example of the resulting prices is shown in Figure 1, while all prices are shown in Appendix A.

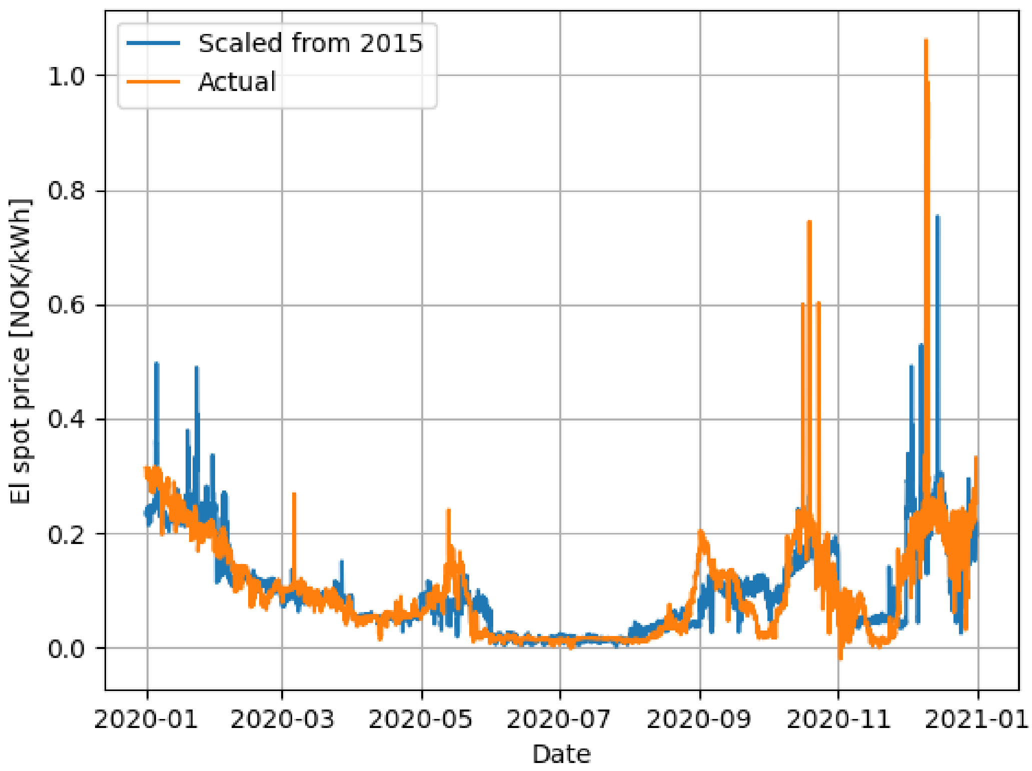

Figure 1. Synthetic el spot prices for 2020, based on details from 2015

2.2.3. Utility prices

The net tariff applied is shown in Figure 2. Capacity tariff was introduced in Norway July 1st 2022. However, the model chosen (a lump sum depending on the average of the power used during the three highest hours from three different days per month) is different from the model chosen for task 1.6 of the present project (a cost per kW applied only to the maximum power used for one hour per month).

NETTLEIE ENERGI ORDINÆR 230 Volts anlegg med hovedsikring tom. 63 Ampere 400 Volts anlegg med hovedsikring tom. 40 Ampere	
Fastledd	318,75 kr/mnd
Energiledd	37,39 øre/kWh
Energiledd sesongdifferensiert	sommer: 34,89 øre/kWh vinter: 38,64 øre kWh

Figure 2. Agder Energi Nett 1.4.2022 – 1.7.2022

The consumer agreement “LOS Solstrøm” is shown in Figure 3. This covers energy prices both as paid by the consumer for utility use, and energy prices received from the consumer for excess PV production.

Strømavtalen for deg som produserer din egen strøm med solceller. Med **LOS solstrøm** kan du selge strøm til oss når du har til overs – og kjøpe av oss ved behov. LOS samarbeider med Otovo – Norges ledende leverandør av solcellepaneler.

Produser din egen fornybare strøm!

LOS

Slik fungerer solstrøm:

- ✓ Du bruker strømmen du selv produserer, men kjøper strøm fra LOS når egen produksjon ikke dekker ditt strømbehov.
- ✓ Produserer du mer enn du bruker, selges den tilbake til oss. Vi kjøper din overskuddsstrøm for det som er til en hver tid gjeldende spotpris.
- ✓ Strømmen du selger tilbake til oss kommer som fratrekk på strømregningen din.
- ✓ Du betaler ikke strømpris eller nettleie for strømmen du selv produserer.
- ✓ Overskuddsstrømmen fra ditt solcelleanlegg blir sendt automatisk ut på strømnettet.
- ✓ Strømmåleren din beregner hvor mye du bruker og produserer.
- ✓ På LOS Min side får du full oversikt og kan følge ditt forbruk og overproduksjon.
- ✓ Tre måneder gratis Fornybar energi (deretter 1,90 kr/dagen). Dersom du ikke ønsker denne garantien - er det bare å gi beskjed til kundesenteret.

✓ **39 kr** Månedspris	✓ **5,95 øre** Påslag per kWh	✓ **Spotpris** per kWh

Figure 3. LOS Solstrøm 30.9.2022

2.2.4. Normalized years

The registered data has resolution one minute. The data is resampled to hourly resolution, using the mean of the values registered for each hour. This is particularly important for the electricity load data, which is very spiky. The data is then converted to relative values by dividing by the monthly mean values. A normalized day is then identified by averaging these relative values. Finally, a normalized year is found as multiplying the hourly values for the normalized day by the monthly averages. The result is a data set where the time series for each day has the same shape, but is scaled differently for each month. Table 1 gives some properties of the normalized year data.

Table 1. Some properties of the normalized year data identified from the Skarpnes data

	PV production	Electricity load	Hot water load
Mean of registered data [W]	811	224	1 080
Mean of normalized year [W]	811	224	1 080
RMS distance from normalized year [W]	810	280	1 120
RMS distance from normalized year relative to monthly mean[1] [%]	116	126	147

The normalized year for the PV production is illustrated in Figure 4. All the normalized data for both PV production and loads are shown in Appendix B, both for the full year and zoomed in to a few days.

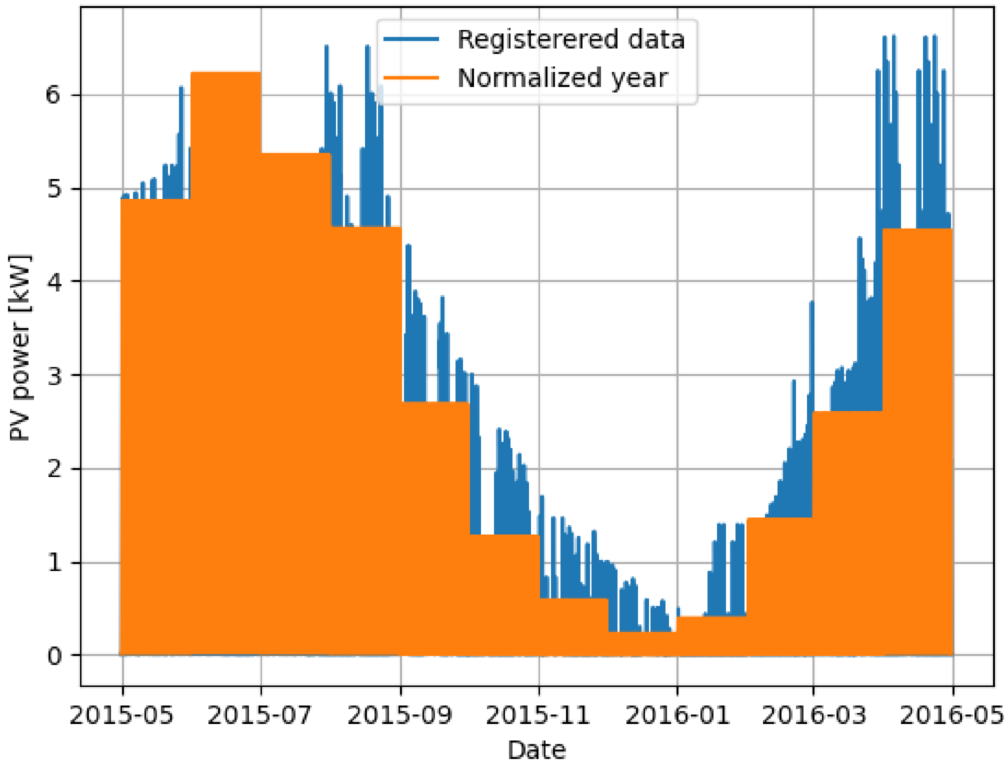

Figure 4. Registered and normalized data for PV production for the full year

[1] `100 * np.sqrt(np.mean(((timeseries['D0'] - normal_year[0])/monthly_mean.values[months, 0])**2))`

2.2.5. PV electricity production uncertainty

Standard deviation for predicting PV production for a whole year can be estimated by different methods:

- The Bergen data contains production data from five years. The average standard deviation in daily PV production is 60 % of the daily mean[2].
- Using the concept of a normalized year, the standard deviation in hourly PV production data from the Skarpnes data can be estimated to 810 W or 116 % of the monthly mean.
- Global irradiation data could also be used to estimate this uncertainty.

It is reasonable that the variation in hourly production is larger than the variation in daily production. The value from the normalized year is therefore used in the following, while the value from the Bergen data serves to confirm magnitude of the uncertainty.

Further details on smart meters for PV production forecast, based on the Bergen data, is given in Appendix B.

2.2.6. Load uncertainty

The standard deviation of the load data for a whole year was found from the concept of normalized years. The values are given in Table 1.

2.3. Method details

A Monte Carlo approach was used, where several realisations were tested with variations in PV production and loads. All optimizations were performed using the actual PV production and loads from the Skarpnes data. Then, a number of simulations were run with random deviations from these, assuming normal distributions of the deviations with 0 mean and standard deviations as given in section 2.1.

Details on generating the data sets are given in sections 2.3.1 - 2.3.2, while details specific to the three cases are given in sections 2.3.2 - 2.3.5.

2.3.1. Generating random data for PV electricity production

The PV electricity production varies strongly with time of year. Relative uncertainty is therefore used, rather than a fixed value in W. Deviations were only calculated when the sun was above the horizon, using data from a dedicated website for determining solar altitude[5]. When one of the randomly chosen deviations resulted in a negative PV production, this deviation was swapped with another deviation, positive or less negative, that resulted in a zero or positive PV production for both time stamps. To avoid accumulation of large positive deviations during the winter months, swapping was only allowed within plus/minus 30 days. Any remaining negative deviations were

2

```
np.mean(100*sumdf.groupby(sumdf.index.dayofyear).std()/sumdf.groupby(sumd
f.index.dayofyear).mean())
```

clipped, resulting in a slightly higher average PV electricity production in some of the Monte Carlo realizations than in the starting point.

A sample realisation is illustrated in Figure 5 for a few days, while data for the whole year is shown in Appendix C.

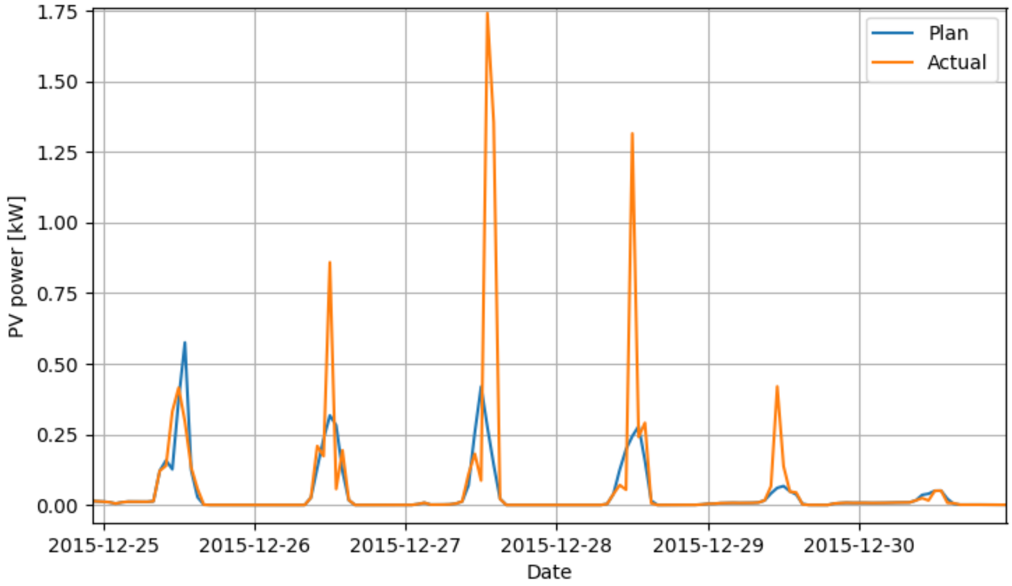

Figure 5. Planned and actual PV electricity production for a few days in December. The former is the true, registered data, while the latter is generated by adding random deviations to this.

2.3.2. Generating random data for loads

Absolute, rather than relative, deviations were used to generate load data, and no limitations were set on the time of day. Otherwise, the same procedure was used as for the PV electricity production. Without the swapping procedure, cases A and B with high uncertainties, resulted in more than 20 % higher loads than case C, which has lower uncertainties.

A sample realisation is illustrated in Figure 6 for a whole year. Samples for both hot water and electricity loads for the full year and for a few days are shown in Appendix C.

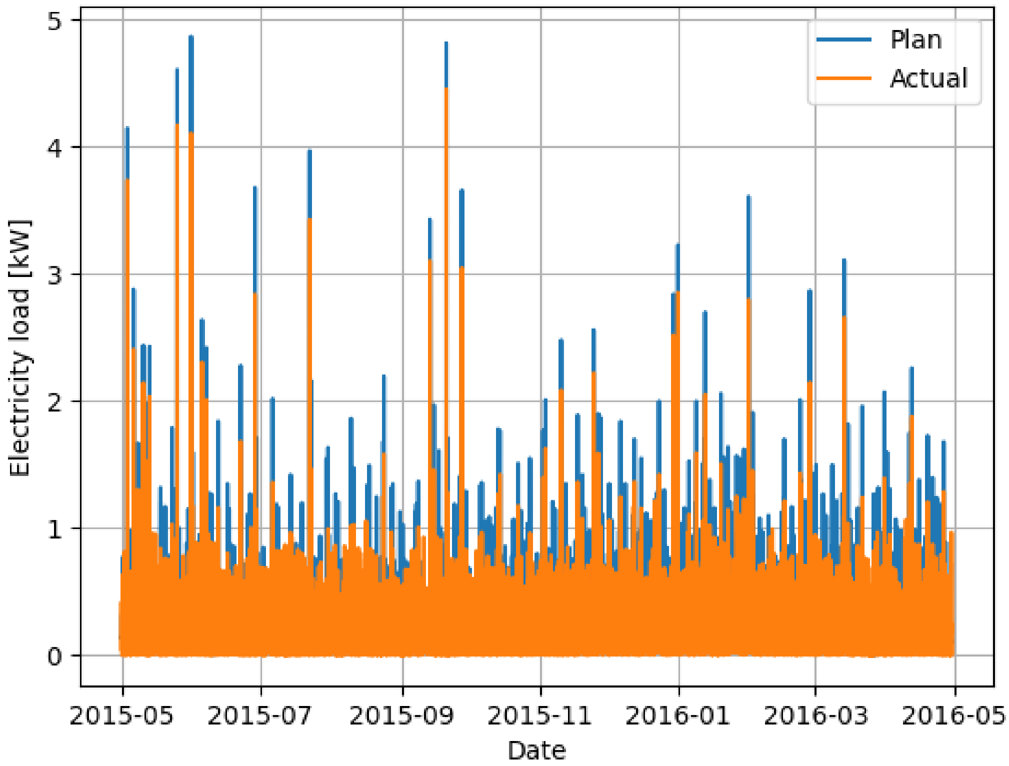

Figure 6. Planned and actual electricity loads for the whole year. The former is the true, registered data, while the latter is generated by adding random deviations to this.

2.3.3. Case A. Solar panels without battery

The simulations were run with the uncertainties given for a whole year in section 2.1 and the synthetic spot prices for 2021 and 2022.

2.3.4. Case B. Solar panels with battery

The simulations were run with the uncertainties given for a whole year in section 2.1. The synthetic spot prices for 2020 and 2021 were used for optimization, while the synthetic spot prices for 2021 and 2022 were used for the realisations.

2.3.5. Case C. Solar panels with battery and smart meter

The simulations were run with the uncertainties given for one-day-ahead predictions in section 2.1. The synthetic spot prices for 2021 and 2022 were used for both optimization and for the realisations.

2.3.6. Rules for handling deviations from the plan

Several kinds of deviations could occur. Some could happen at the same instant, like higher PV production and lower electricity load, and some only at different time steps, like higher and lower PV production. The rules used to handle each kind of deviation are listed in prioritized order below:

- Higher PV production than planned
    - Reduce electricity bought from the grid to cover loads
    - Increase storage to battery
    - Increase PV electricity sale to the grid
- Lower PV production than planned
    - Reduce electricity sale to the grid
    - Reduce storage to battery
    - Reduce use of PV electricity to cover loads
- Lower loads than planned
    - Reduce electricity bought from the grid to cover loads
    - Reduce battery usage
    - Reduce use of PV electricity, and sell any resulting PV electricity excess
- Higher loads than planned
    - Reduce sales of PV electricity and use more PV electricity to cover loads
    - Increase electricity bought from the grid to cover loads
- Resulting battery SOC (state of charge) out of bounds
    - Reduce storage prior to too high SOC
    - Reduce usage prior to too low SOC

3. Results and discussion

3.1. Overview

An overview of the costs for 100 simulations of each of the three cases studied is given in Table 2 and Table 3. Case B was optimized using lower electricity prices than case A and C. If case B is optimized with the same electricity prices as the others, the result would be as for case C.

Table 2. Overview of costs for the three cases studied

Case	Cost [NOK]				
	Optimized	Average	Minimum	Maximum	Standard dev.
A, no battery	16 600	16 600	15 800	17 200	240
B, battery		16 500	15 900	17 100	230
C, battery and smart meter	16 440	16 600	16 470	16 720	46

Table 3. Percent-wise improvement of costs for the three cases studied

Case	Cost reduction from simpler case [%]	
	A, no battery	B, battery
B, battery	0.8	
C, battery and smart meter	0.1	-0.7

These simulations indicate that neither adding a battery nor adding a smart meter gives any significant change in the energy cost for the system.

In the present case, without ground source heat pumps, the cost consists of three terms:

- PV-based profit, i.e. the profit made from selling electricity to the grid
- Time-based cost, i.e. fixed monthly rates for buying electricity from the grid
- Util-based cost, i.e. the cost for buying electricity from the grid

Figure 7 shows how these three parts contribute to the whole for the three cases studied.

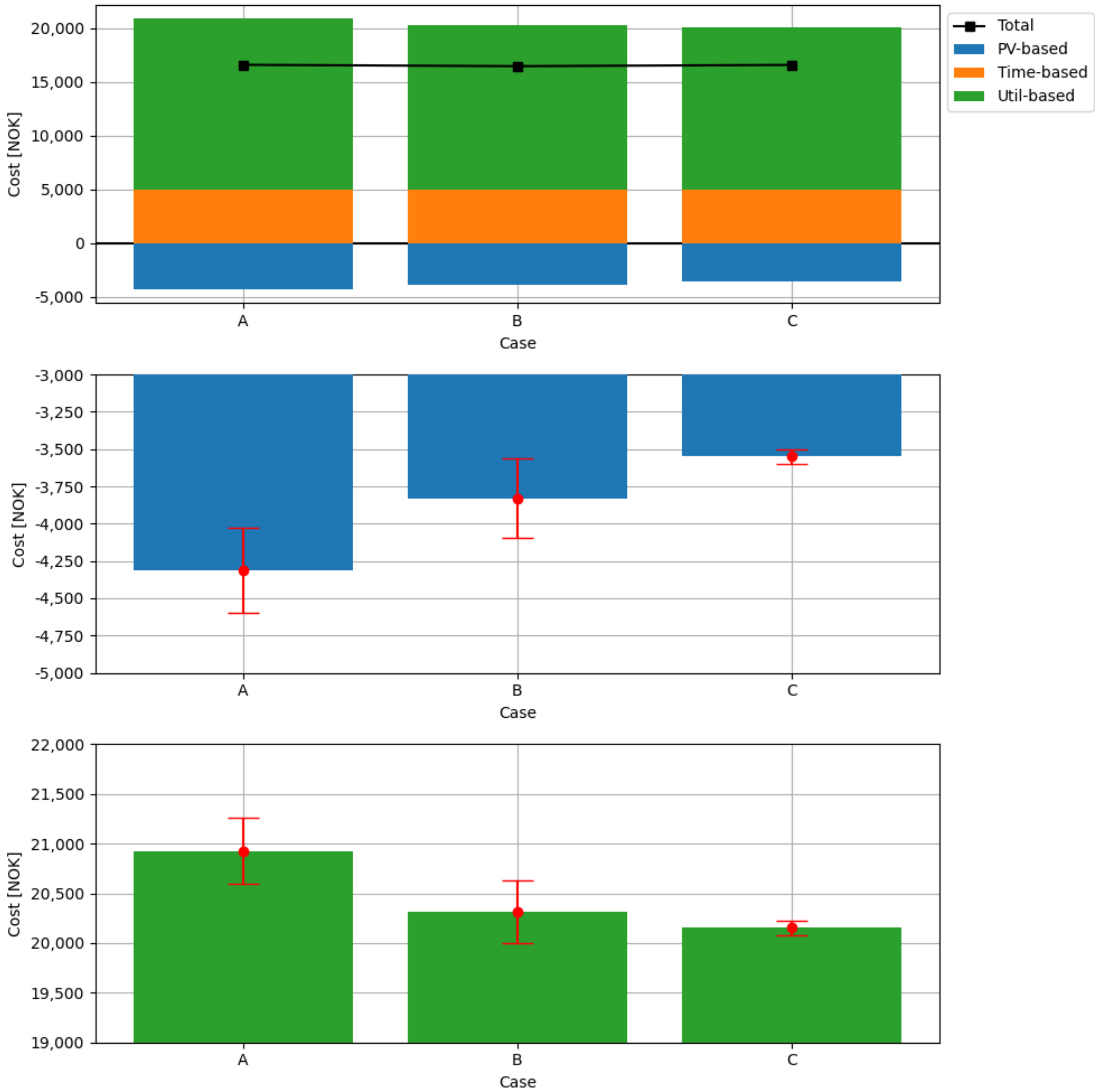

Figure 7. Top: the mean values of the different parts of the cost for the three cases studied plotted together with the total cost. Note the negative PV cost, which is profit from selling PV produced electricity. Middle: The same data, zoomed in on the PV-based cost, with error bars indicating two standard deviations for the PV-based cost. Bottom: The same data, zoomed in on the util-based cost, with error bars indicating two standard deviations for the util-based cost. The time-based cost is constant for all cases.

By far the largest part of the cost is util-based. This is larger for case A than for the other cases, since case A has no battery available and must therefore buy electricity to cover any loads that exceed the current PV electricity production.

It is seen that the PV-based profit is larger for case A than for the other two cases. This is also caused by the lack of a battery, meaning all excess PV production is sold to the grid.

The time-based cost is constant and equal for all cases. It is only included here for completeness.

Finally, it is noted that all error bars are much smaller than the costs themselves. 95 % confidence intervals can be estimated from the mean values plus/minus two standard deviations. Zooming in, as is done in the middle and bottom plots in Figure 7, it is seen that these intervals overlap between cases A and B, but not between A and C.

Both the PV-based profit and the util-based cost are thus significantly higher with neither battery nor smart meter installed than with both. For the prices used in these simulations, these differences balance out, making the net cost independent of the installation of both battery and smart meter.

3.2. Details

In the following, the power flows for three cases are compared for a randomly chosen date, November 20th. This is a day with only minor spot price variations through the day, but where the average price increased from below 0.1 NOK/kWh in 2020 to about 1 NOK/kWh in 2021.

Plots PV electricity production, loads, battery SOC, and spot prices for all three cases are given in Appendix E.

3.2.1. Use of PV electricity production

Note that the planned PV production, used for optimization, is the same in all three cases, while the actual production is the same for cases A and B. For case C, the actual and planned production are closer, meaning the optimal plan can be followed more closely.

As expected, case A results in the most selling of PV produced electricity to the grid (red bars), while cases B and C make use of the battery (green bars). With the close to constant spot prices for this day, the difference between selling the electricity or using the battery to avoid buying electricity later is small.

3.2.2. Covering the electricity loads

As for PV electricity production, the plans used for optimization are identical for all cases, and the actual loads are the same for cases A and B.

For case B, the reduction in electricity load at 9 am results in selling PV production to the grid. The deviation rules used, see section 2.3.6, do not suggest filling up the battery in this situation.

Also for case B, the battery is used from 2 pm, i.e., earlier than planned. This is because the battery is filled more than planned from 12 am.

3.2.3. Covering the hot water loads

As for PV electricity production, the plans used for optimization are identical for all cases, and the actual loads are the same for cases A and B.

Due to changes prior to November 20th, the battery is empty at 9 am for case B. Therefore, electricity must be bought from the grid to cover the hot water load at this time, even though the load at 9 am is significantly smaller than the planned battery use.

3.3. Electricity spot price variations

If the electricity spot prices were low when PV electricity was produced and high when loads occurred, a battery would be useful. Some days, like November 20th, the spot prices were close to constant. Other days, like July 3rd, 2021, actually had the highest synthetic prices when the sun was shining, as shown in Figure 8.

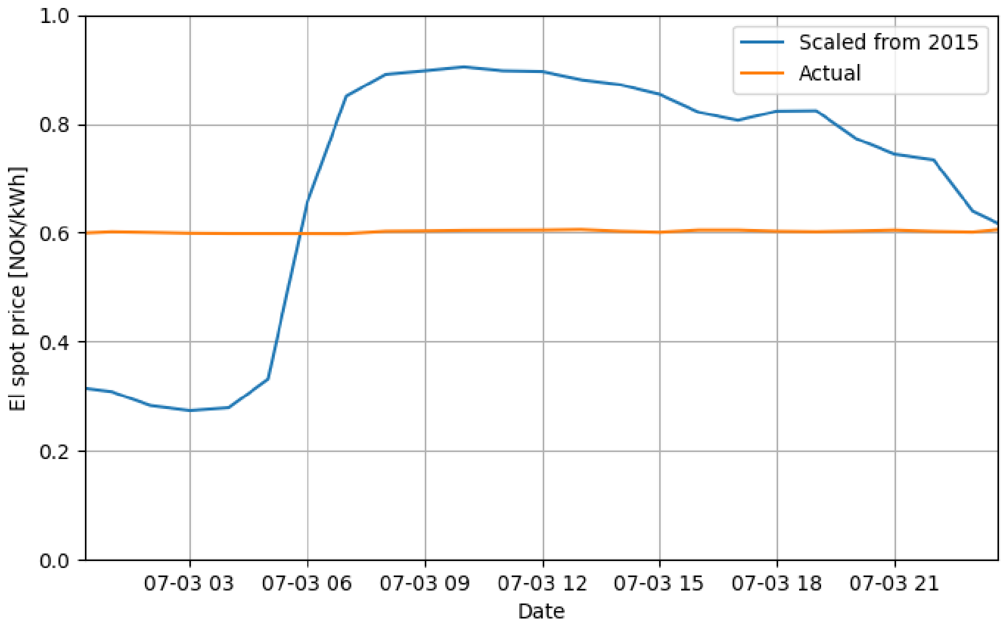

Figure 8. Electricity spot prices for July 3rd, 2021

January 21st had highest synthetic electricity spot prices when the sun was *not* shining, as seen by comparing Figure 9 and Figure 10. The different handling of this situation in cases A and C are shown in Figure 10 - Figure 13.

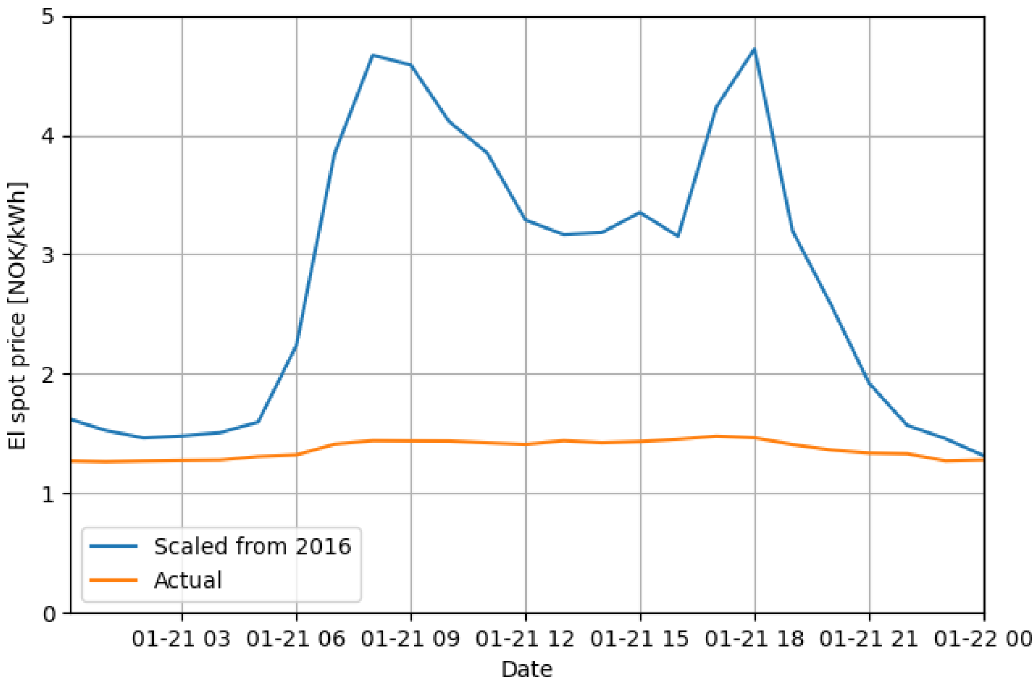

Figure 9. Electricity spot prices for January 21st, 2022

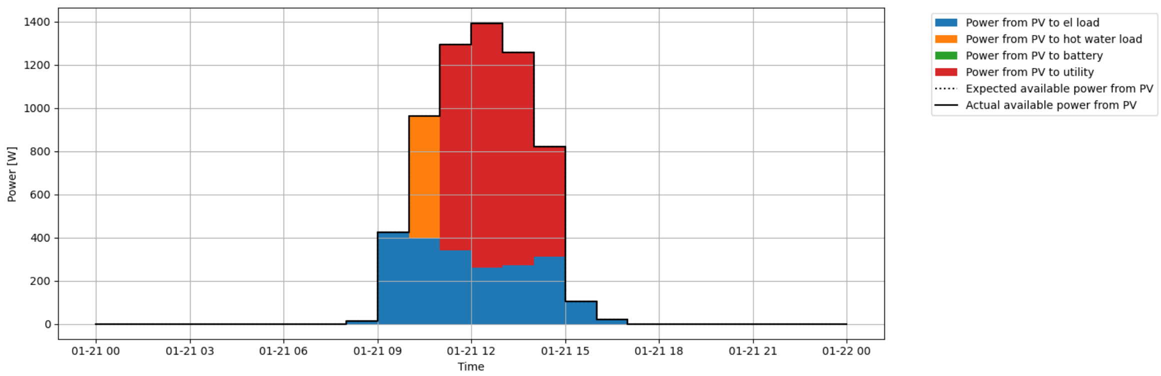

Figure 10. Optimized use of PV production January 21st in case A, no battery

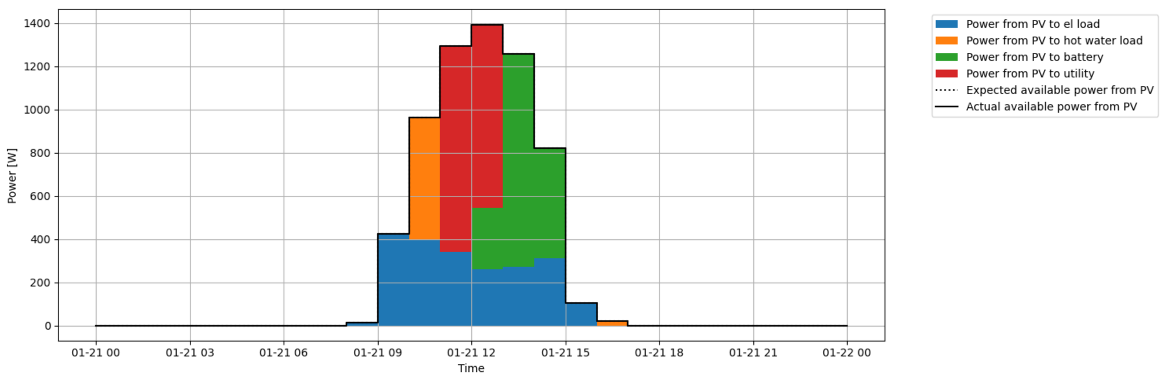

Figure 11. Optimized use of PV production January 21st in case C, battery and smart meter

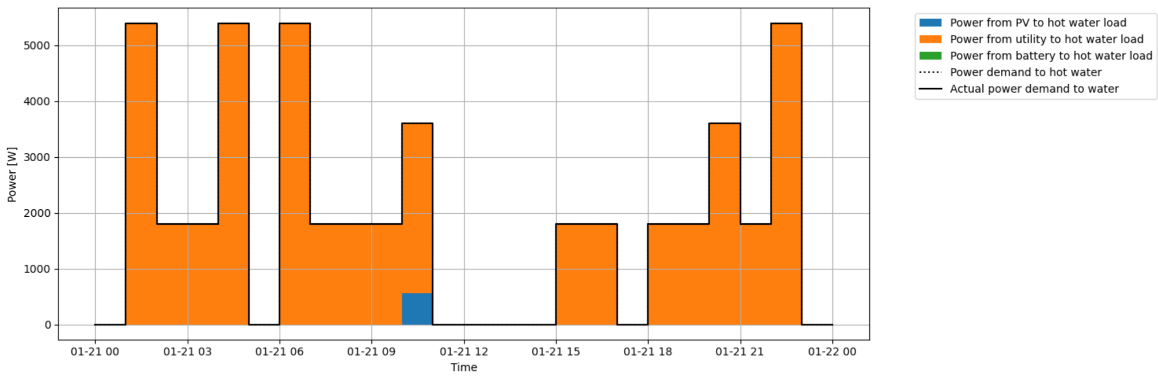

Figure 12. Optimized coverage of the hot water load January 21st in case A, no battery

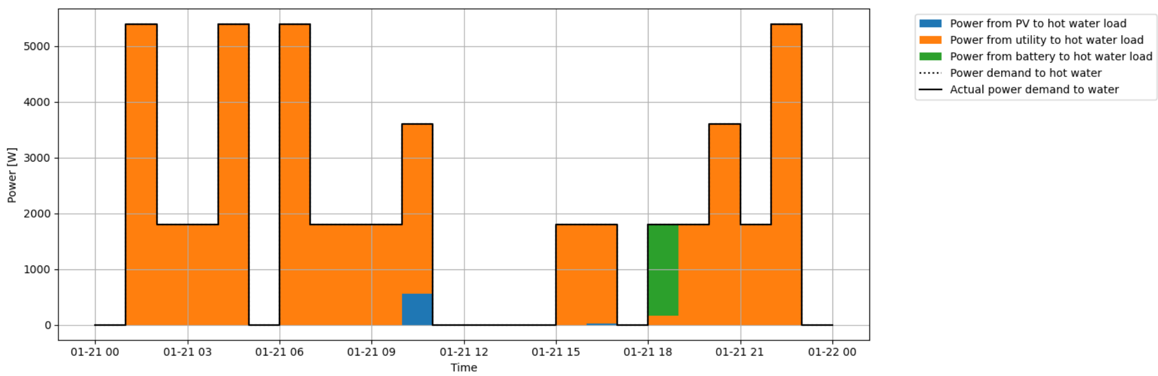

Figure 13. Optimized coverage of the hot water load January 21st in case C, battery and smart meter

By comparing cases A and C in Figure 10 - Figure 13 it is seen that it is economically beneficial to store energy in the battery from noon to avoid buying expensive electricity at 6 pm. This feature of having to sell electricity at a low price, just to buy the same amount later at a higher price, is called capture cost. The fact that the battery and smart meter do not result in a benefit for the year as a whole, indicates that the capture cost is small, i.e., that few days have a price profile as seen in Figure 9.

To quantify the potential for cost savings by optimizing the use of PV produced electricity, the standard deviation of the spot price for each day was calculated. Only the hours when the sun was above the horizon were considered. A large price variation indicates that it could be beneficial to store energy for later user, rather than selling it when it is produced. A summary of the results is shown in Table 4, where the variation is grouped in small, medium, and large. A significant change is seen between 2020 – 2021 and 2021 – 2022. On the other hand, the price synthetization did not have a strong influence on the average daily spot price variation.

Table 4. The number of days with various magnitude of daily spot price variation during the time when the sun was above the horizon. Small variation is defined as standard deviation less than 0.2 NOK/kWh, medium variation as between 0.2 NOK/kWh and 1.0 NOK/kWh, and large variation as standard deviation above 1.0 NOK/kWh

Period	Price source	Days with spot price variation of magnitude		
		Small	Medium	Large
1.5.2020 – 30.4.2021	Actual	275	90	0
1.5.2020 – 30.4.2021	Synthesized	264	101	0
1.5.2021 – 30.4.2022	Actual	6	332	27
1.5.2021 – 30.4.2022	Synthesized	9	326	30

The results in Table 4 indicate a potential for cost savings by storing PV produced electricity. To look deeper into this, the daily correlation coefficient between the PV electricity production and the synthesized el spot price for 1.5.2021 – 30.4.2022 was calculated, again using only the hours when the sun was above the horizon. A summary of the results is shown in Figure 14. It is seen that far more days have a positive correlation than have a negative correlation. It is also seen that the most common correlation coefficient value is between 0.6 and 0.8. In other words, with the data set used here, the el spot price is usually high when the PV electricity production is high. Consequently, as long as the PV produced electricity can be sold at spot price, big savings cannot be expected from selling this electricity at another time than when it was produced.

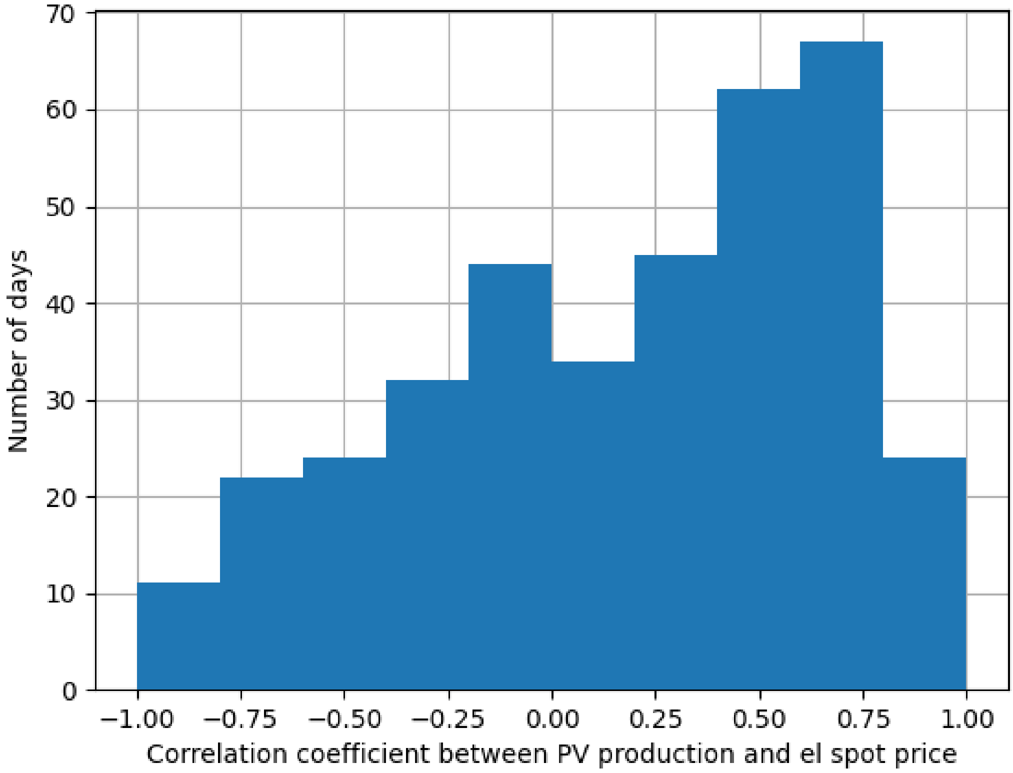

Figure 14. Daily correlation coefficients between PV production and synthesized el spot price for the period 1.5.2021 – 30.4.2022

3.4. Storage options

As mentioned in section 2.1, the simulations presented here assume that PV electricity can only be sold to the utility if the current production exceeds the current loads. An alternative interpretation of the “LOS Solstrøm” agreement is that energy stored in a battery can be used to cover some of the current loads, so PV electricity can be sold if it exceeds the remaining, net loads. Optimizing cases B and C for this interpretation gave only minute differences from the original optimizations. In the present model, energy cannot be stored directly from the utility to the battery. Consequently, this battery usage only allows a time shift in when PV produced electricity is sold to the utility. As discussed in section 3.3, the el spot price is often high when the PV electricity production is high. When there is a small energy loss related to charging and discharging of the battery, such shifting is clearly not very beneficial.

As mentioned in the introduction, the model used here was developed for an energy system with geothermal energy storage. This storage was available from the utility, while the battery was reserved for PV electricity usage. Allowing energy storage directly from the utility to a battery would clearly reduce operational costs, since there are significant variations in the el spot price each day, as shown in Table 4. However, further discussion of such usage is outside the scope of the present task, which has smart meters for rooftop PV systems as focus.

Even though the daily spot price variation does not encourage short-term storage of PV electricity, the sunshine hours in Norway are very few when the loads are high, in winter. Consequently, seasonal storage may be cost-efficient, in particular if the feed-in tariff is lower than used in the present simulations. Since the focus of the present task is smart meters, which are not required for optimal use of *seasonal* energy storage, this topic is not discussed further.

3.5. Generalization

The present simulations have considered data from one specific house, using prices for one particular region for one particular time period. An important question is therefore if and how the results can be generalized. In the following, each of the factors mentioned are discussed in more detail.

3.5.1. Load and PV electricity production data

As discussed earlier, the capture cost is small for the scenarios simulated here. Higher loads during times with no PV electricity production would favour batteries and smart meters. It would therefore be interesting to do similar simulations for other cases, using either typical data sets or actual measurements from other parts of Norway or e.g., from India.

3.5.2. Prices

That the utility company pays the customer for produced electricity is called feed-in tariff. As discussed previously in this project[2], this is a political instrument, designed to encourage installation of PV panels. If the feed-in tariff is removed or reduced, the benefit of batteries and smart meters will increase significantly.

The analyses presented here are based on utility prices on the south coast of Norway during the period 1.5.2020 – 30.4.2022. The period was chosen to be relevant at the time of writing this, in October 2022. As illustrated in Appendix A, this is a period when the average spot price increased dramatically, from below 0.02 NOK/kWh in July 2020 to 2-2.5 NOK/KWh in April 2022. The error introduced by using last year’s prices to optimize the system operation is therefore high, compared to times and places with more predictable electricity prices. Looking into the future, an increased reliance on uncontrollable renewable energy sources is planned in Europe. Combined with a possible growth of energy-intensive industry in Norway, this indicates that the present situation, with high and varying spot prices, may very well be representative for the next few years.

4. Conclusions

Simulations on data from the Skarpnes village have shown that when installing PV panels on private homes on the south coast of Norway, it is not immediately economically beneficial to also install batteries and smart meters. This will change if the present feed-in tariff is reduced or removed, and it may also change if the load patterns are changed.

5. References

1. Nå kan du lade bilen smart i Mitt Hjem. *Haugaland Kraft* https://hkraft.no/elbillader/smart-lading/.
2. Nordgård-Hansen, E., Kishor, N., Midttømme, K., Risinggard, V. & Kocbach, J. Case study on optimal design and operation of detached house energy system: Solar, battery, and ground source heat pump. *Applied Energy* **308**, (2021).
3. del Campo-Ávila, J., Takilalte, A., Bifet, A. & Mora-López, L. Binding data mining and expert knowledge for one-day-ahead prediction of hourly global solar radiation. *Expert Systems with Applications* **167**, 114147 (2021).
4. *Brødrene Dahls Varmebok, Kapittel 1 Energi- og effektberegning [The Dahl brothers' book of heating, Chapter 1 Calculation of energy and power]*. https://varmefaktor.no/assets/files/Kapittel1.pdf (2018).
5. Sustainable By Design :: sunposition. http://susdesign.com/sunposition/.
6. JRC Photovoltaic Geographical Information System (PVGIS) - European Commission. https://re.jrc.ec.europa.eu/pvg_tools/en/tools.html#PVP.

Appendix A. Synthetic electricity prices

Synthetic electricity prices are shown in Figure 15 - Figure 18.

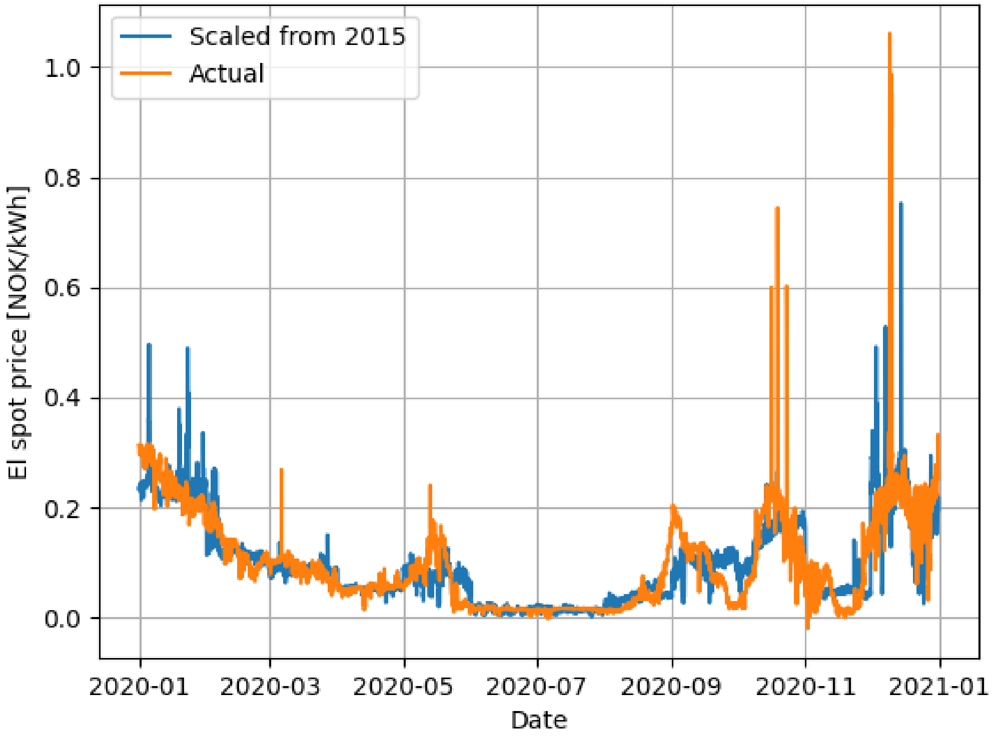

Figure 15. Synthetic el spot prices for 2020, based on details from 2015

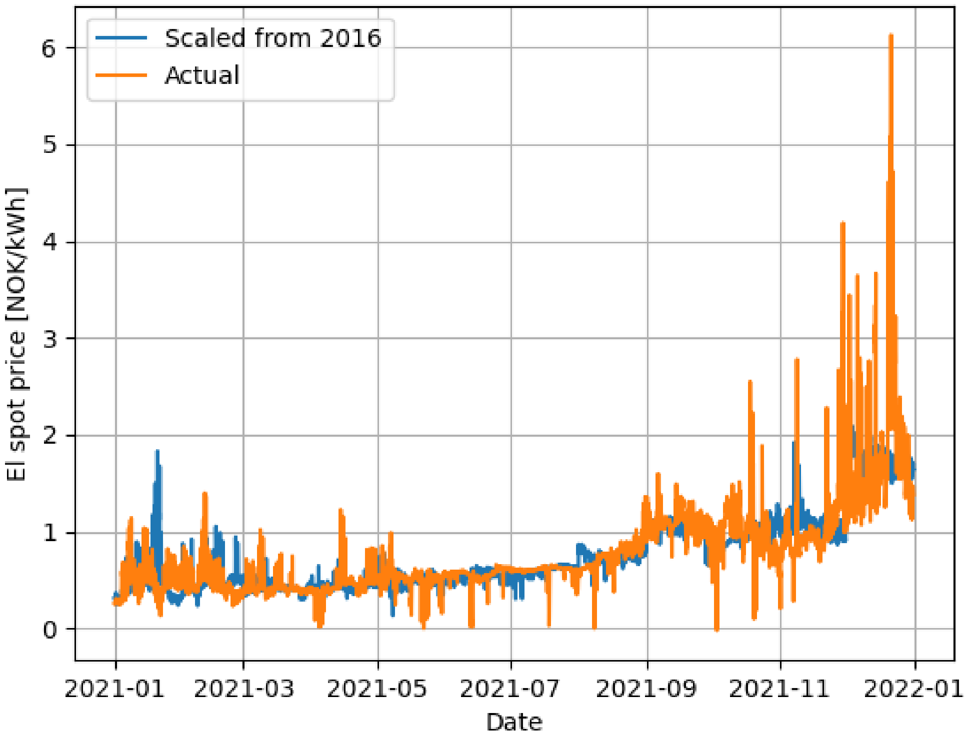

Figure 16. Synthetic el spot prices for 2021, based on details from 2016

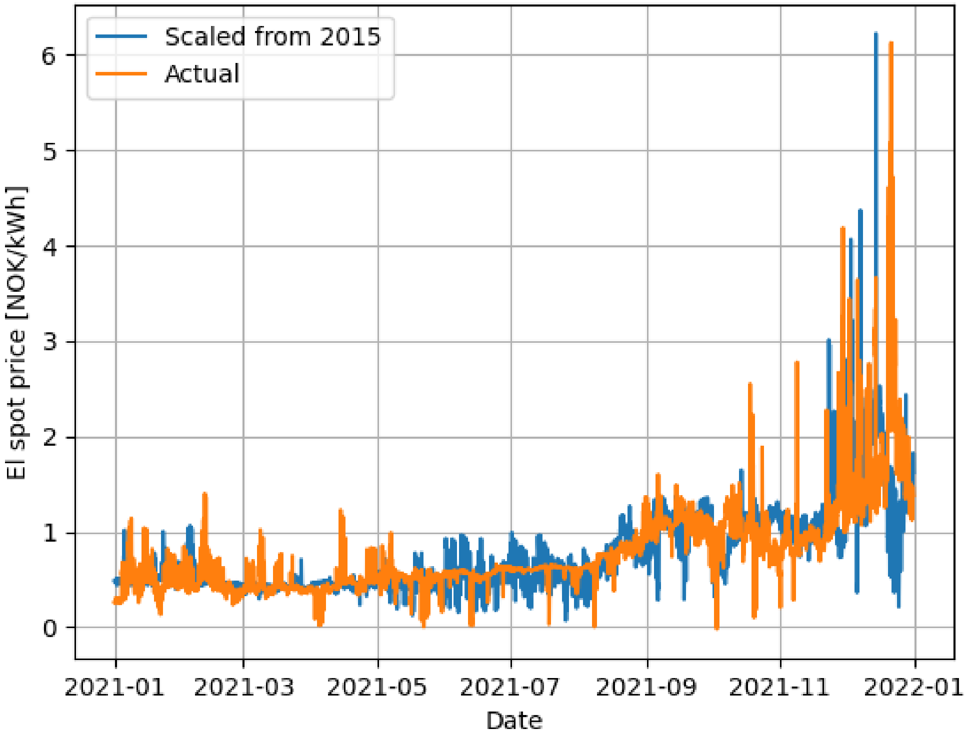

Figure 17. Synthetic el spot prices for 2021, based on details from 2015

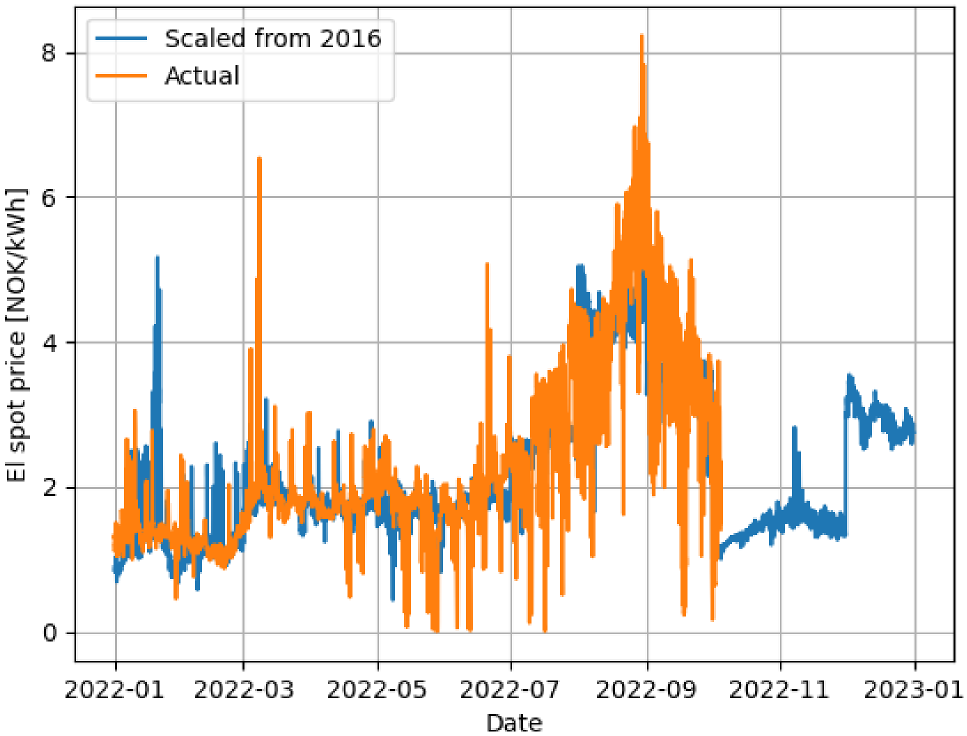

Figure 18. Synthetic el spot prices for 2022, based on details from 2016

Appendix B. Normalized PV production and loads

Registered and normalized data for PV production and loads are shown in Figure 19 - Figure 24.

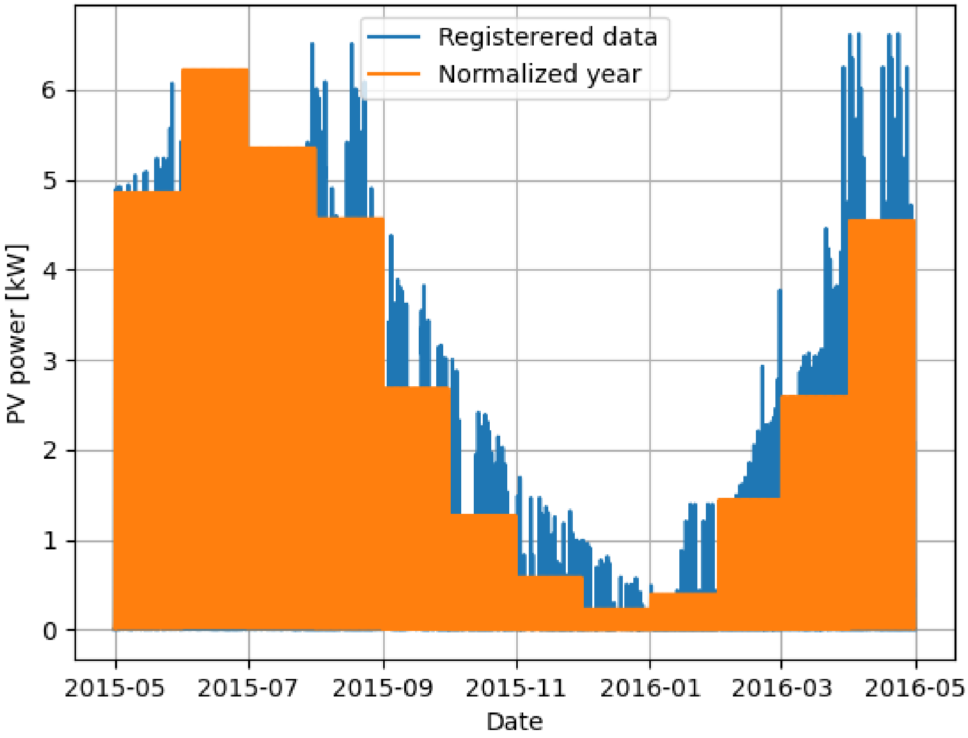

Figure 19. Registered and normalized data for PV production for the full year

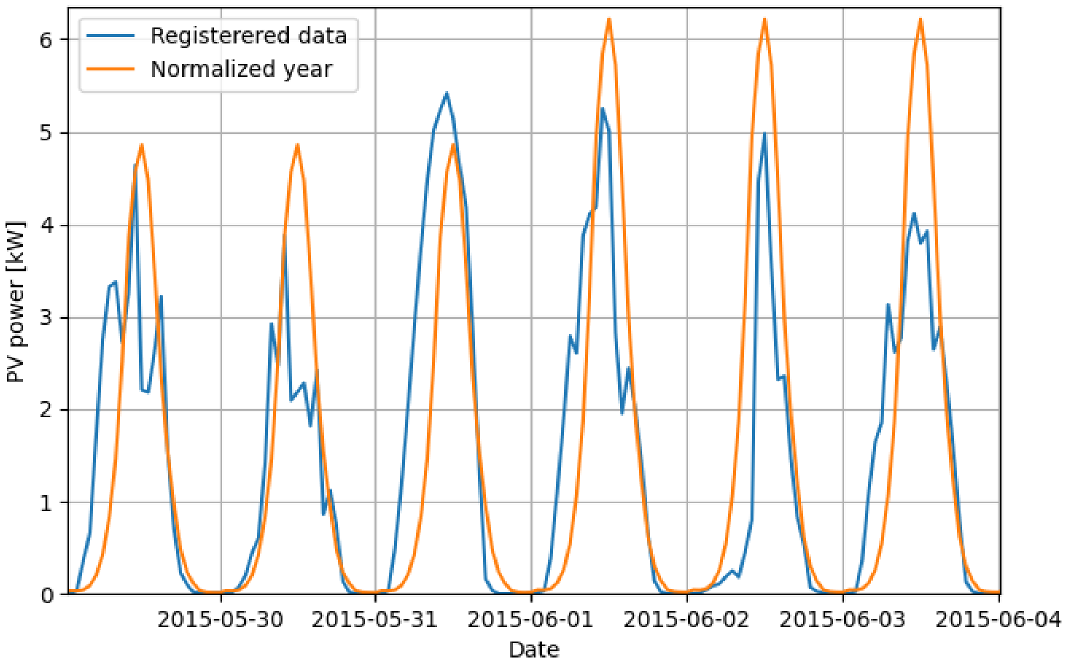

Figure 20. Registered and normalized data for PV production for a few days

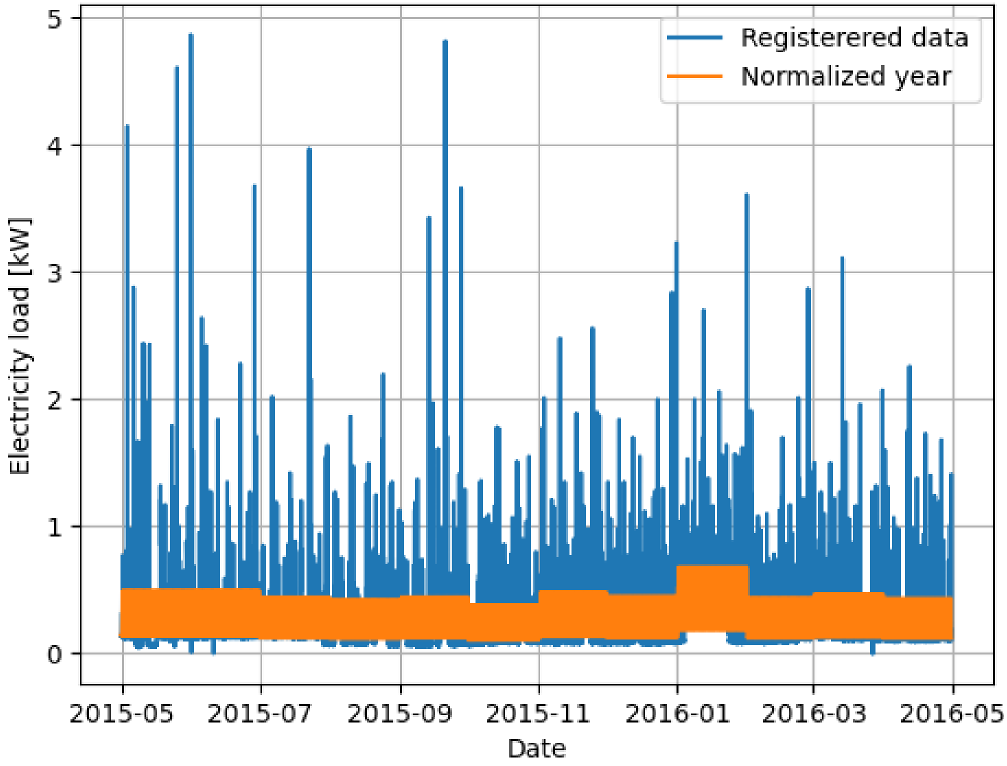

Figure 21. Registered and normalized data for electricity loads for the full year

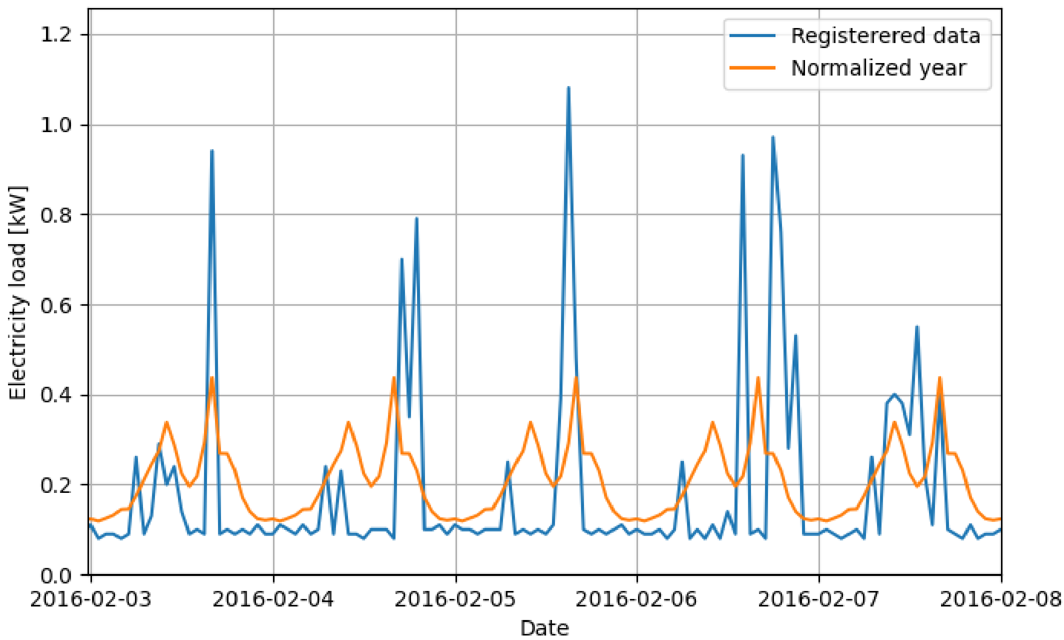

Figure 22. Registered and normalized data for electricity loads for a few days

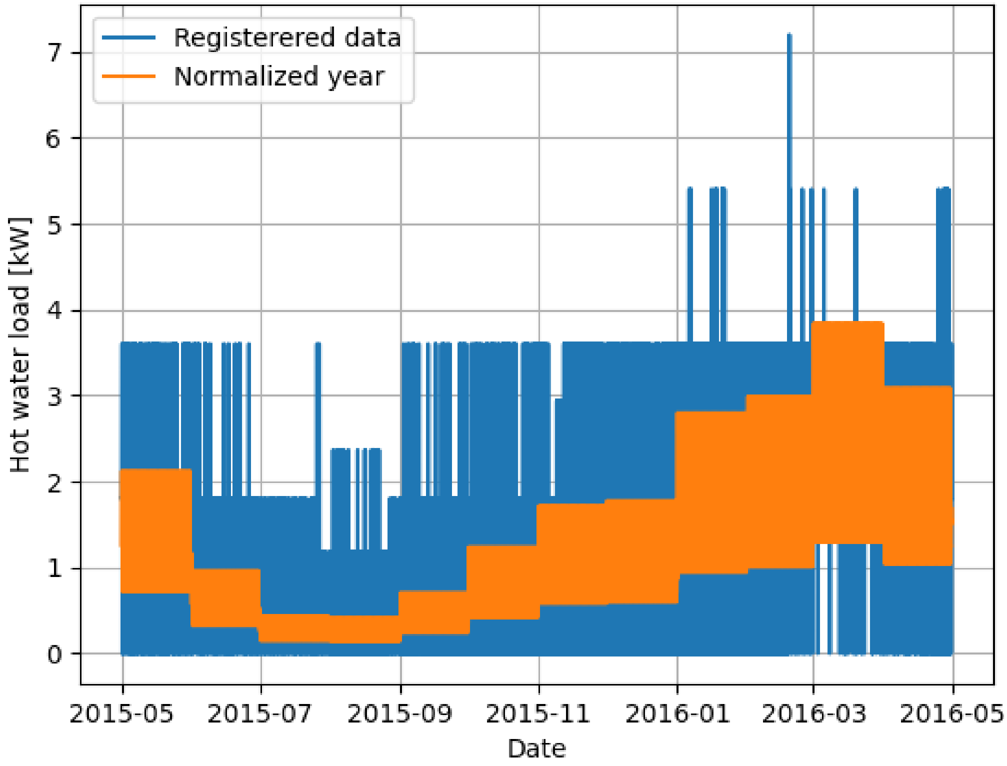

Figure 23. Registered and normalized data for hot water loads for the full year

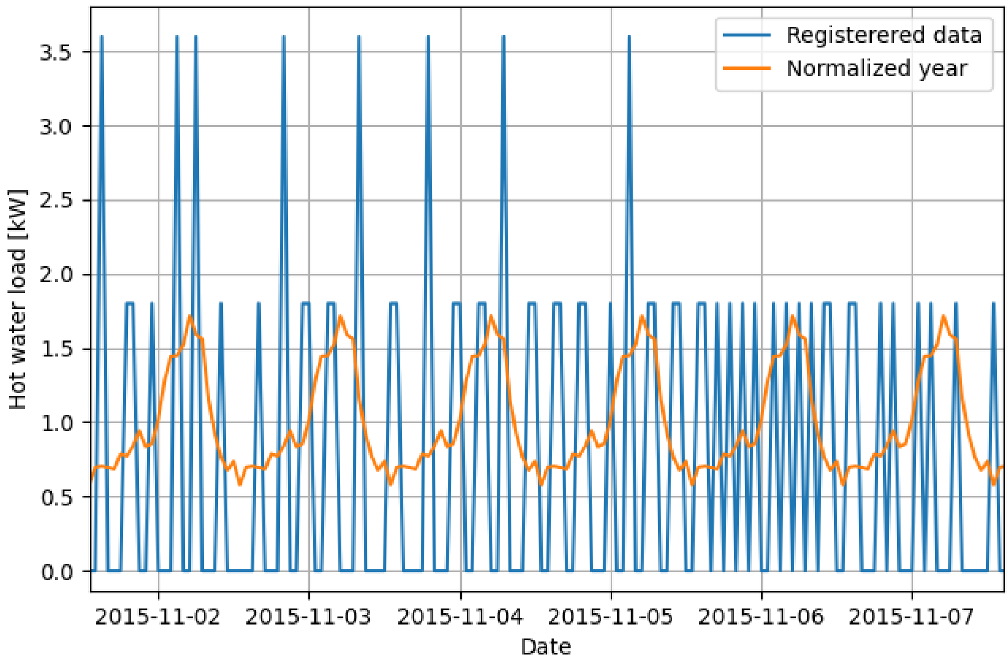

Figure 24. Registered and normalized data for hot water loads for a few days

Appendix C. PV production forecast

The Bergen data set is not from a system with smart meters, and the data set only has daily resolution. Consequently, it was interesting to investigate to what degree a smart meter is required to give forecasts for PV electricity production.

D.1. Forecast without smart meters

Place, date, and time are static information, readily available anywhere. Using this to predict PV electricity production serves as a baseline for evaluating smart meter methods.

The following is known:

- The transfer function from light falling on a horizontal plane on the ground with irradiation I_h, to light falling on a PV panel at any angle with irradiation I_{panel}, is given in equation (1),

$$I_{panel} = \frac{(\cos(90° - \phi) \cdot \cos(\alpha - \gamma)) + (\sin(90° - \phi) \cdot \tan(\theta))}{\tan(\theta)} \cdot I_h \qquad (1)$$

  where

  - ϕ is the panel's inclination, where 0° is a flat plane, e.g., mounted on a flat roof, and 90° is a vertical panel, e.g., mounted on a wall
  - α is the azimuth of the incoming light, i.e., the angle between due north and the projection of the incoming light beam on the ground. Incoming light from the east thus has α=90°
  - γ is the orientation of the PV panel, i.e., the angle between due north and the projection of a normal to the panel on the ground. A west-facing PV panel thus has γ=270°
  - θ is the solar altitude, where any value below 0° indicates that the sun is below the horizon. In practice, a minimum angle of 3.5° is used

  Negative values for I_{panel} indicates that light hits the panel from behind.

- The solar angles altitude and azimuth as a function of position, date, and time. These can e.g. be obtained from the web site of Sustainable By Design[5]
- Typical incoming radiation as a function of position, date, and time. These can e.g. be obtained from the web site PVGIS[6]

  Global incoming radiation consists of direct radiation and diffuse radiation. Diffuse radiation is light spread by the atmosphere, clouds, etc., as well as light diffusely reflected by the ground. As exemplified in Figure 25, diffuse irradiance (orange line) can be of the same magnitude as direct irradiance (blue line).

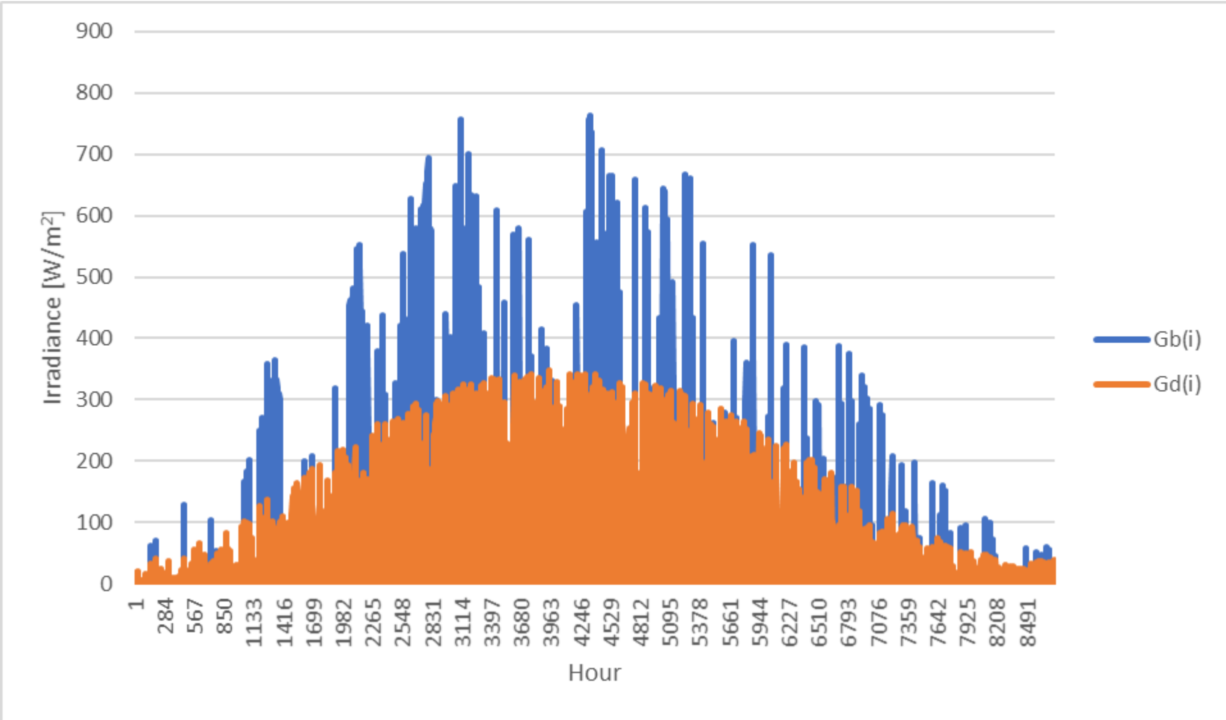

Figure 25. Solar irradiance on an eastwards oriented solar panel with 40° slope Bergen in 2005[6]

Figure 26 shows the daily PV energy production from the Bergen data as blue dots, taken as the maximum value registered for each day of the year during the period the data is from, i.e., August 2018 to February 2022. In the same plot, a monthly estimate of the irradiance hitting the panels is shown as red stars. This estimate is found as the monthly average of the daily direct irradiance hitting a horizontal plane in Bergen from PVGIS[6], combined with equation (1). In equation (1) it is assumed that half the panels are oriented eastward and the other half westward, all with slope 40°. It is seen that the overall shape of curve is well described by this simple estimate. However, the production was often lower than predicted from the estimate. Also, the fit is less good in May – September than for the other months.

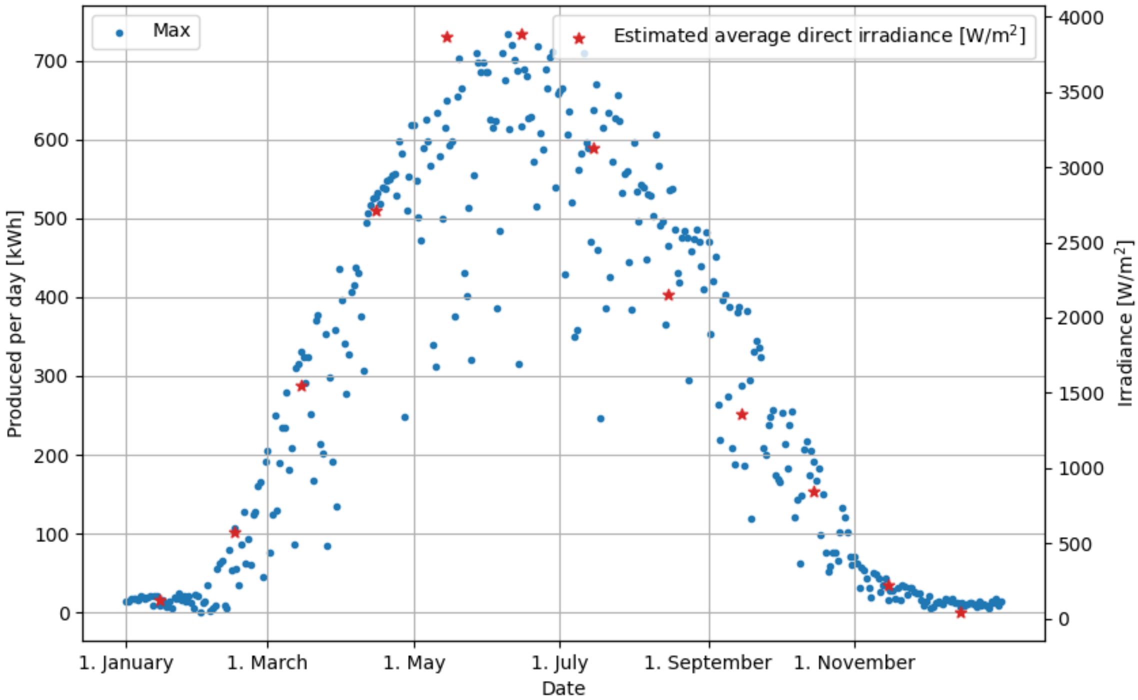

Figure 26. Daily PV energy production as the maximum value registered in the period 2018 – 2022 in the Bergen data, plotted together with average direct irradiation per month estimated from average direct irradiation per month from PVGIS[6] and equation (1), assuming half the panels being oriented eastward and the other half westward, all with slope 40°.

Consequently, place, date, and time can only give rough estimates of the maximum PV electricity production that can be expected.

D.2. Forecast with smart meters

The model of Campo-Ávila et al[3] was found after a brief, simple literature search. They combined expert knowledge, data-driven modelling, and weather forecasts to make one-day-ahead predictions of hourly global solar radiation. Doing so, they found a relative root mean square error of prediction of less than 20 %.

Figure 27 shows the PV production for each of the inverters in the Bergen data, plotted against the sum of registered global irradiation on east- and west-oriented planes at slope 40° from PVGIS[6]. Note that the PVGIS measurements are not available after 31.12.2020. A clear correlation is seen, and as expected, the different inverters exhibit different proportionality constants. Statistical properties of these correlations are given in Table 5.

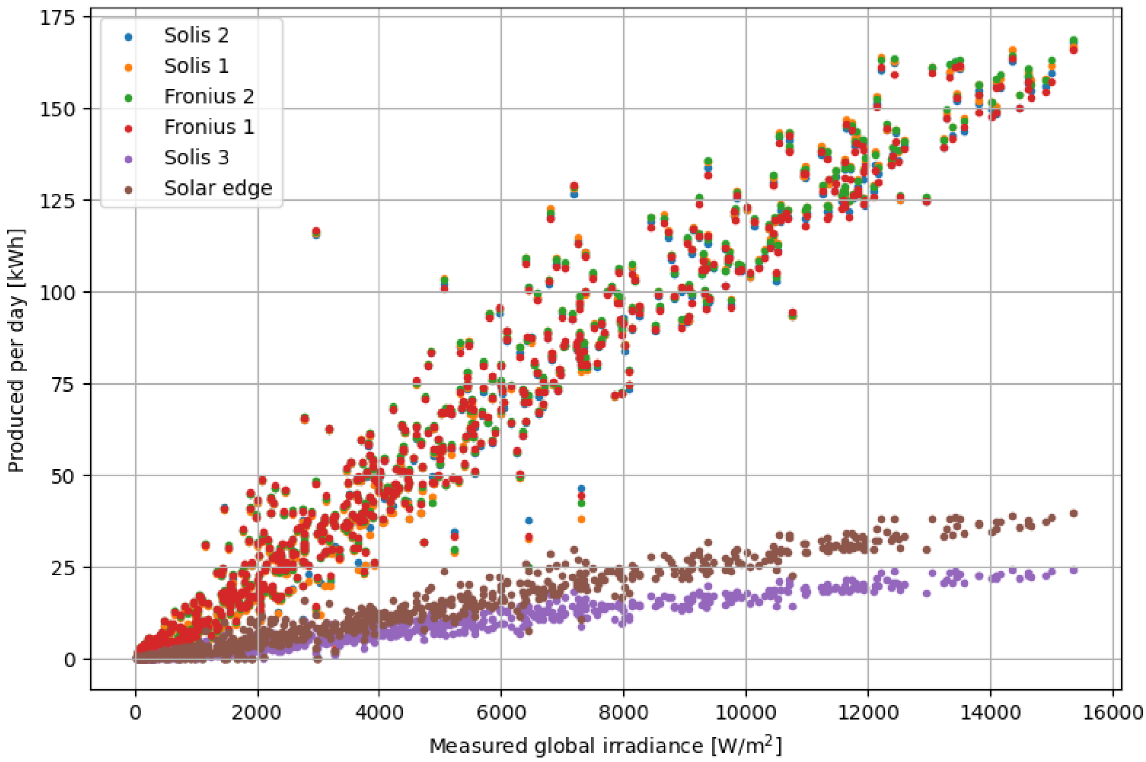

Figure 27. PV production from the Bergen data and measured global irradiance from 2018 – 2020. The global irradiance is the sum of irradiance hitting east- and west-oriented panels at slope 40° taken from PVGIS[6].

Table 5. Statistical properties of linear regression on the data in Figure 27

Inverter	R^2	RMSEC [kWh]
Solis 2	0.95	10
Solis 1	0.95	10
Fronius 2	0.95	10
Fronius 1	0.95	10
Solis 3	0.95	1.5
Solar edge	0.96	2.3

From Figure 27 and Table 5 it is seen that global irradiance can be used to estimate PV electricity production with high accuracy. The global irradiation values can either be forecast directly, or they can be predicted from weather forecasts, e.g. by the model of Campo-Ávila et al[3]. A calibration period is required before the PV production can be predicted directly.

Appendix D. Randomly generated data for PV electricity production and loads

Sample realisations are illustrated in Figure 28 - Figure 33.

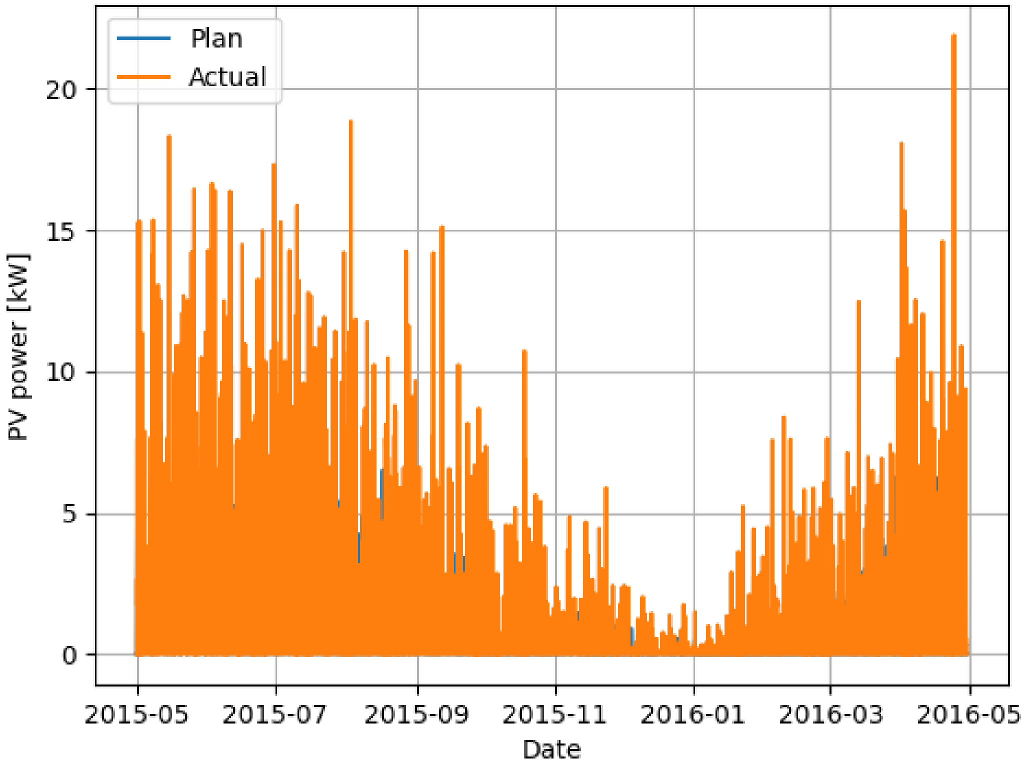

Figure 28. Planned and actual PV electricity production for the whole year. The former is the true, registered data, while the latter is generated by adding random deviations to this.

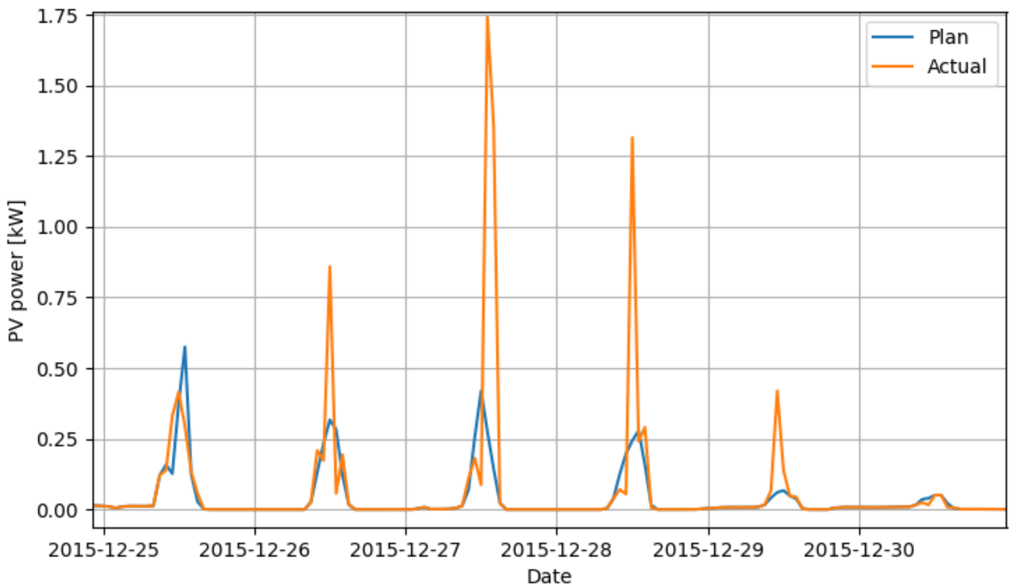

Figure 29. Planned and actual PV electricity production for a few days in December. The former is the true, registered data, while the latter is generated by adding random deviations to this.

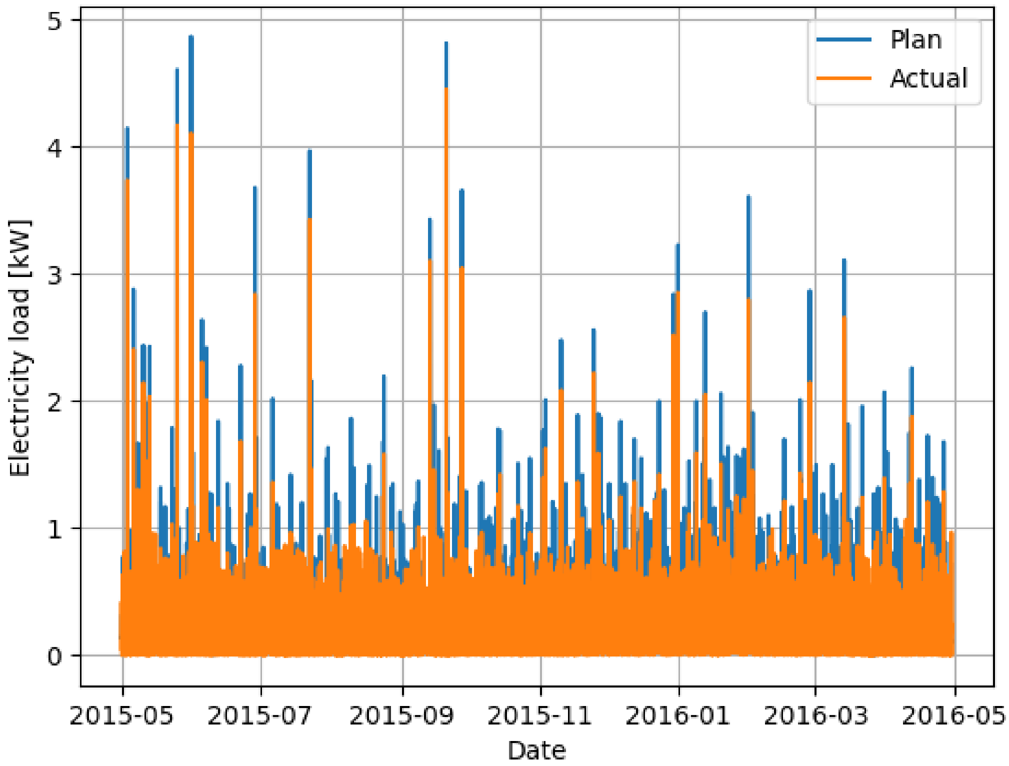

Figure 30. Planned and actual electricity loads for the whole year. The former is the true, registered data, while the latter is generated by adding random deviations to this.

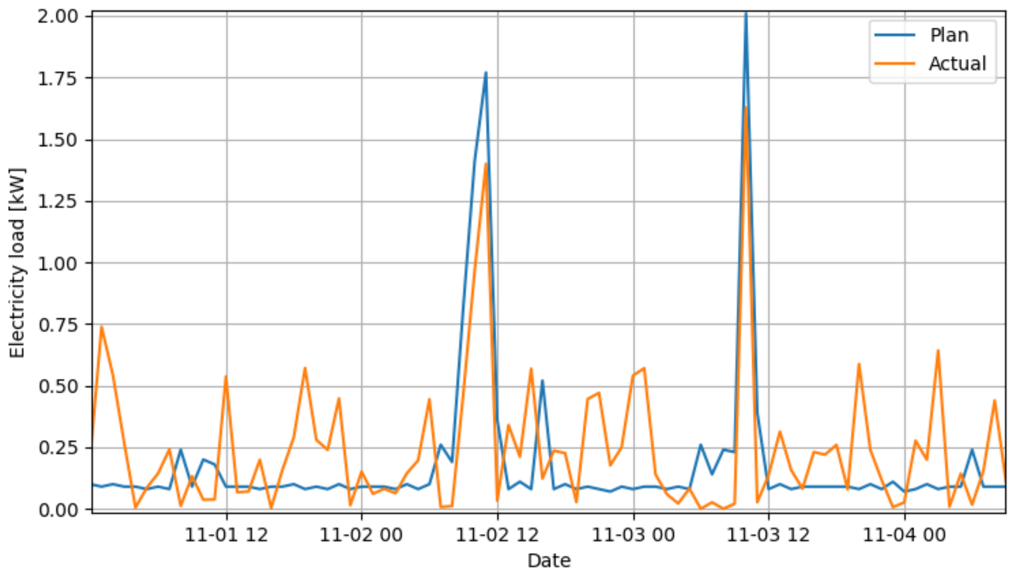

Figure 31. Planned and actual electricity loads for a few days in November. The former is the true, registered data, while the latter is generated by adding random deviations to this.

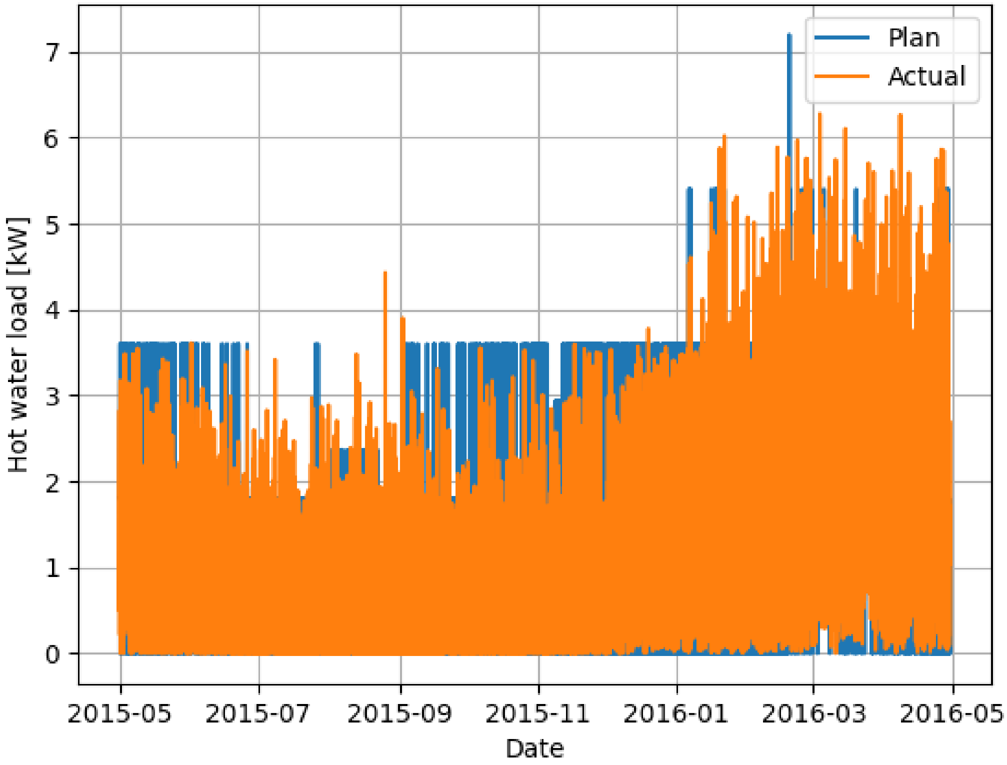

Figure 32. Planned and actual hot water loads for the whole year. The former is the true, registered data, while the latter is generated by adding random deviations to this.

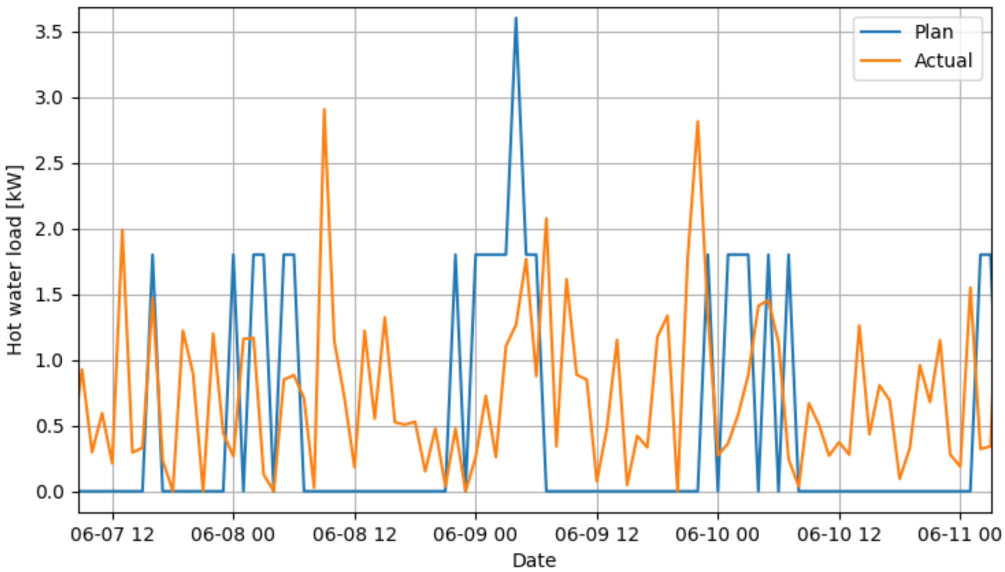

Figure 33. Planned and actual hot water loads for a few days in June. The former is the true, registered data, while the latter is generated by adding random deviations to this.

Appendix E. Result details

E.1. Use of PV electricity production

Examples of the use of PV electricity generation for the three cases for November 20th are shown in Figure 34 - Figure 36.

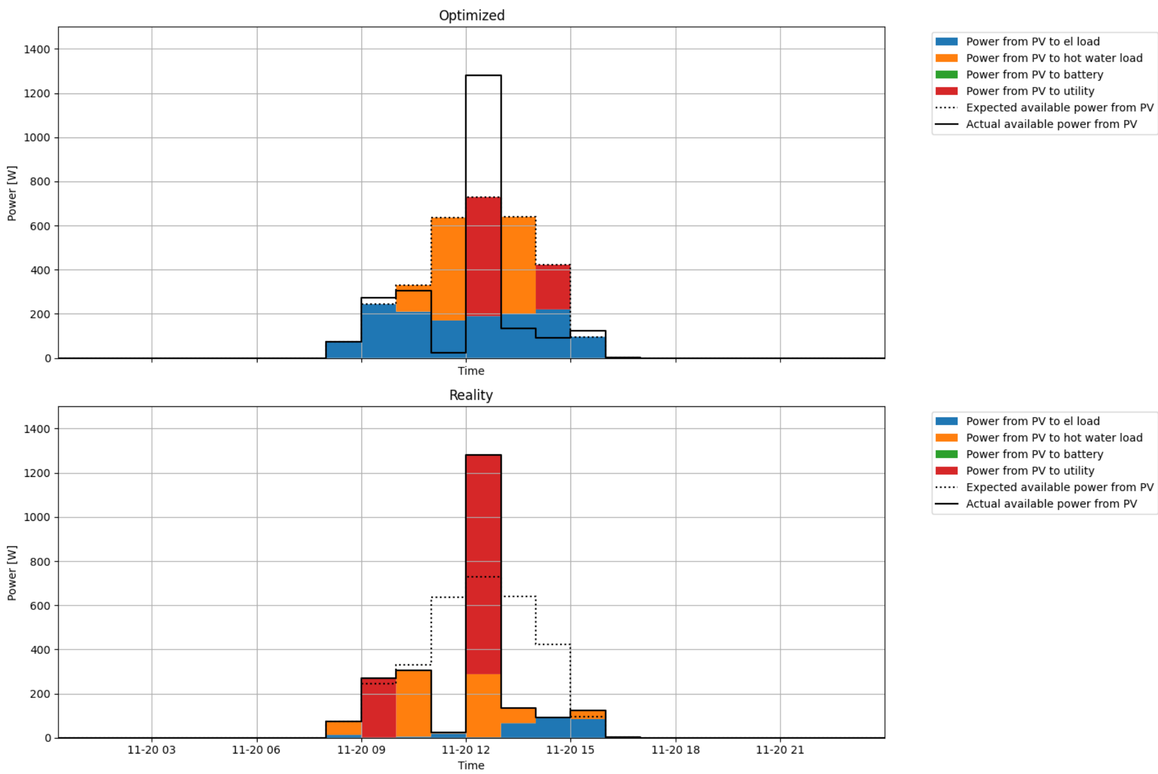

Figure 34. Optimized (top) and actual (bottom) use of PV production in case A, no battery

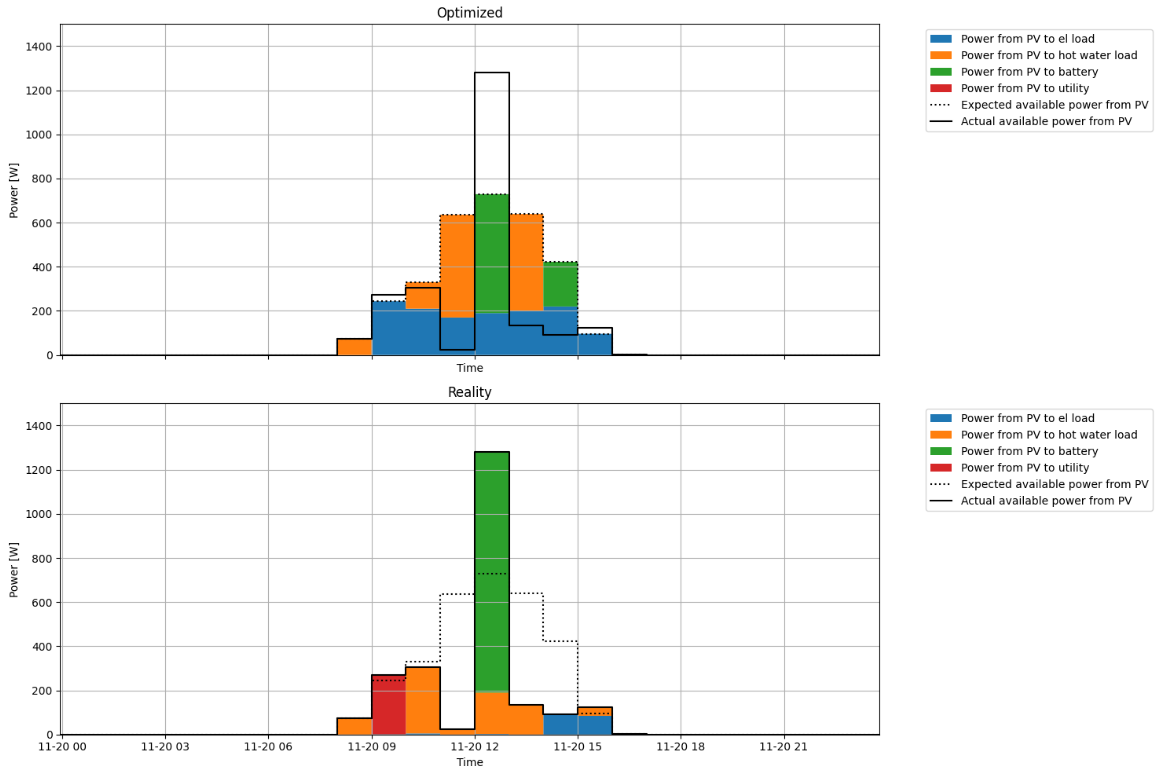

Figure 35. Optimized (top) and actual (bottom) use of PV production in case B, battery

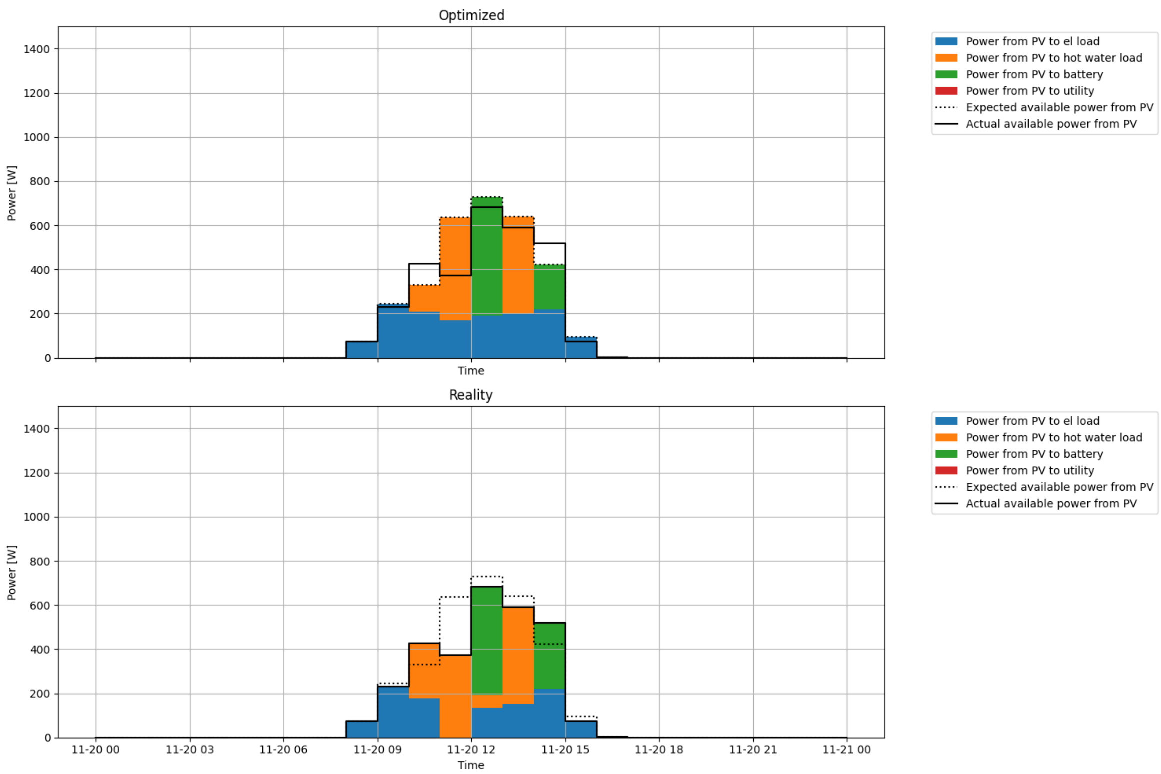

Figure 36. Optimized (top) and actual (bottom) use of PV production in case C, battery and smart meter

E.2. Covering of electricity loads

Examples of the use how the electricity loads are covered for the three cases for November 20th are shown in Figure 37 - Figure 39.

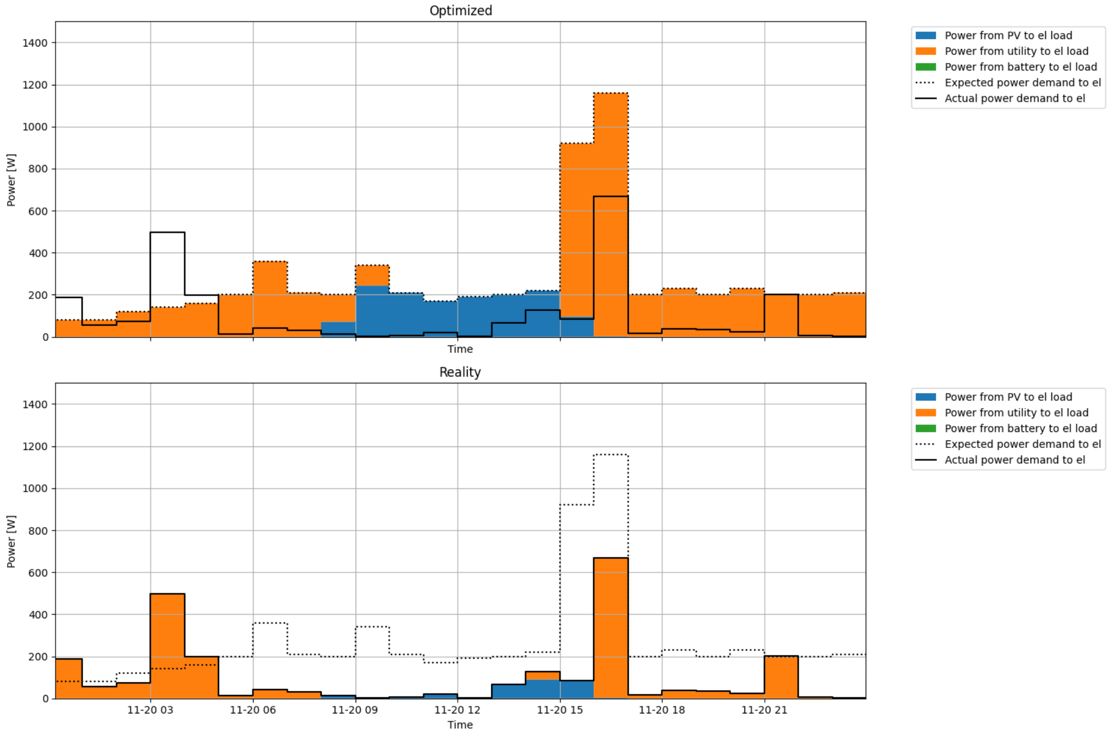

Figure 37. Optimized (top) and actual (bottom) coverage of the electricity load in case A, no battery

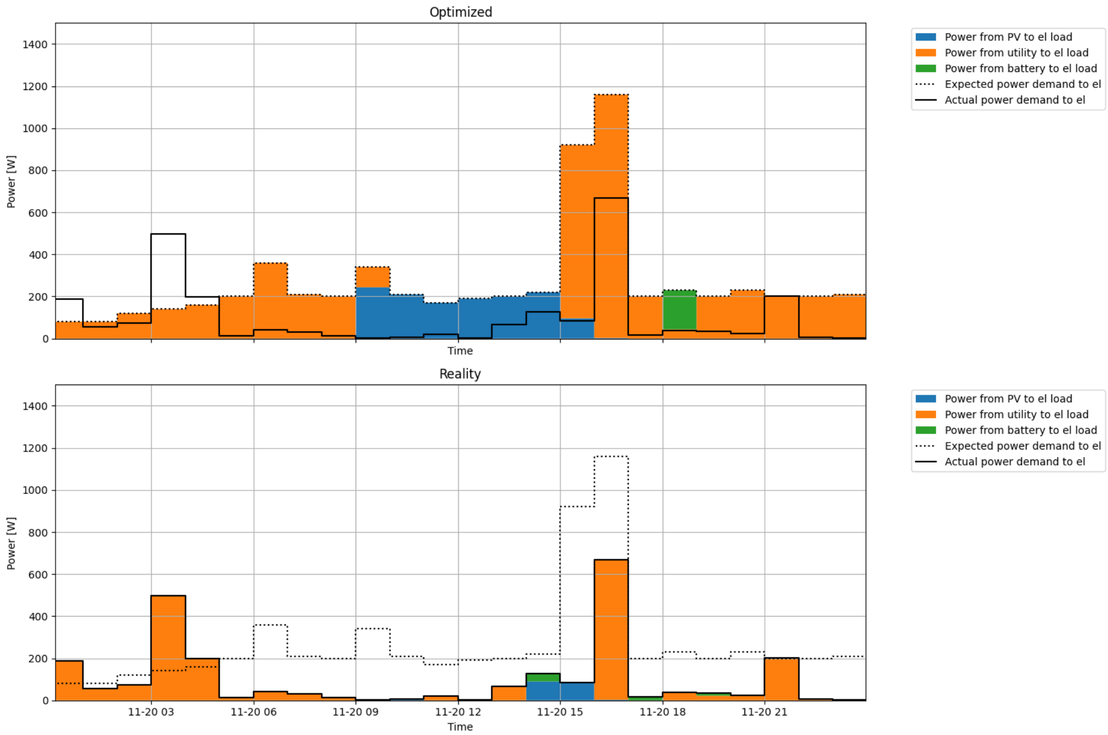

Figure 38. Optimized (top) and actual (bottom) coverage of the electricity load in case B, battery

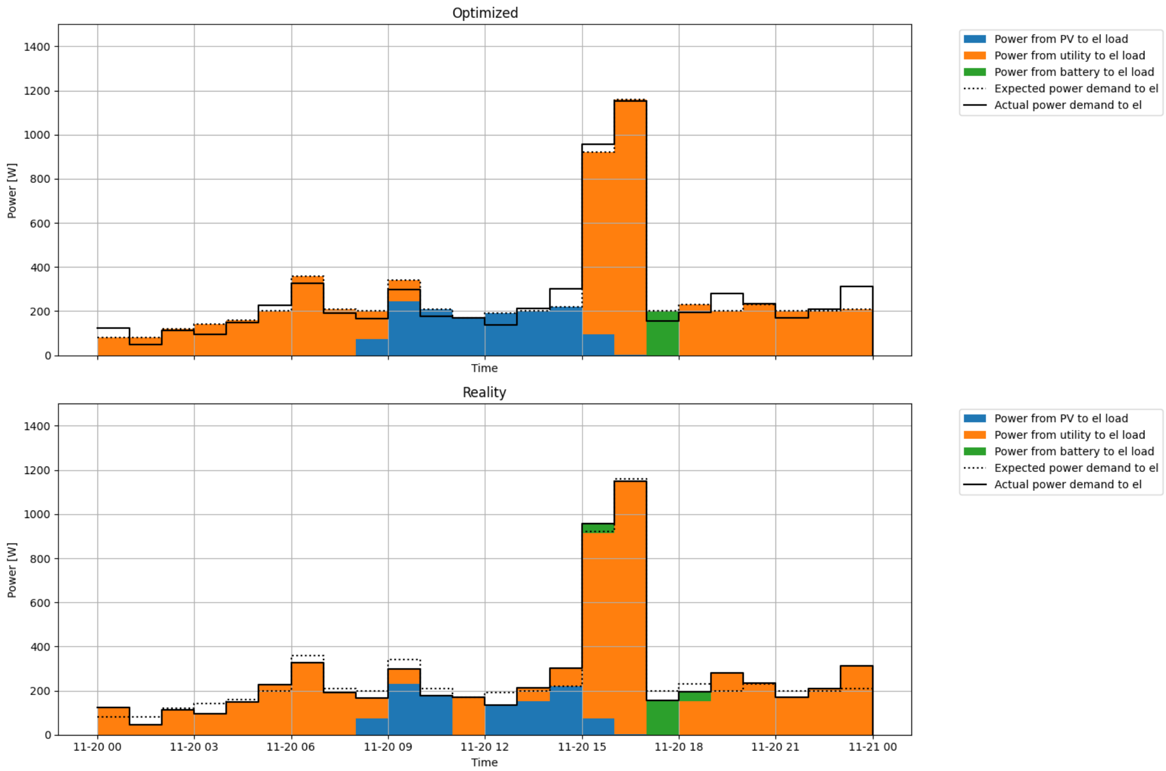

Figure 39. Optimized (top) and actual (bottom) coverage of the electricity load in case C, battery and smart meter

E.3. Covering of hot water loads

Examples of the use how the electricity loads are covered for the three cases for November 20th are shown in Figure 40 - Figure 42.

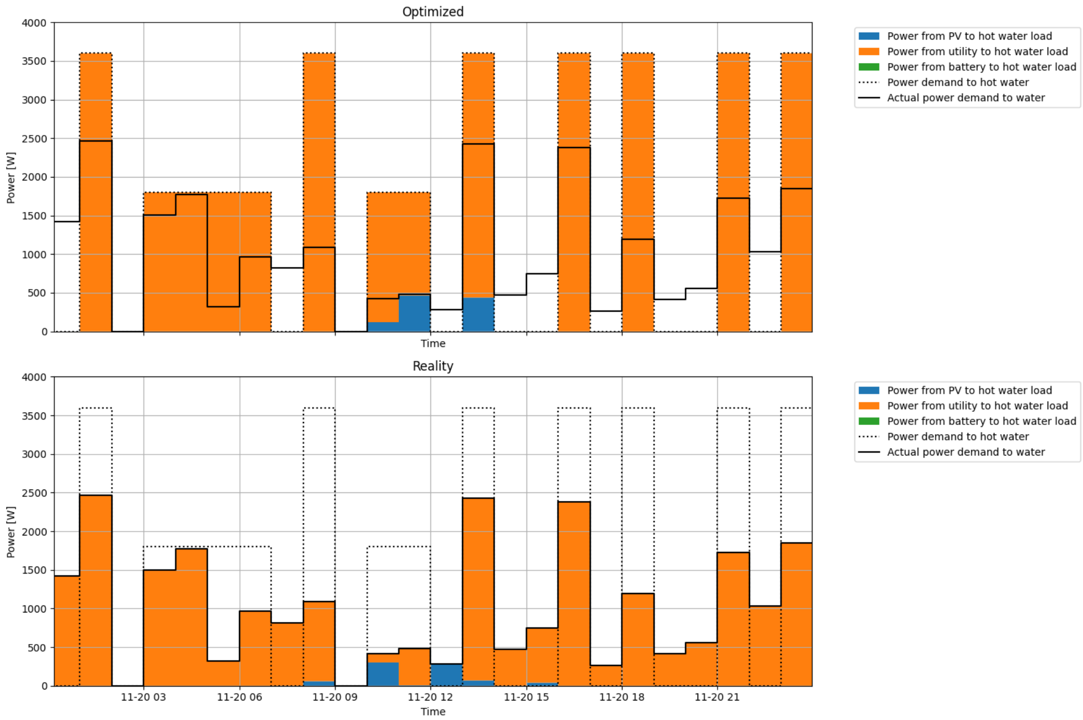

Figure 40. Optimized (top) and actual (bottom) coverage of the hot water load in case A, no battery

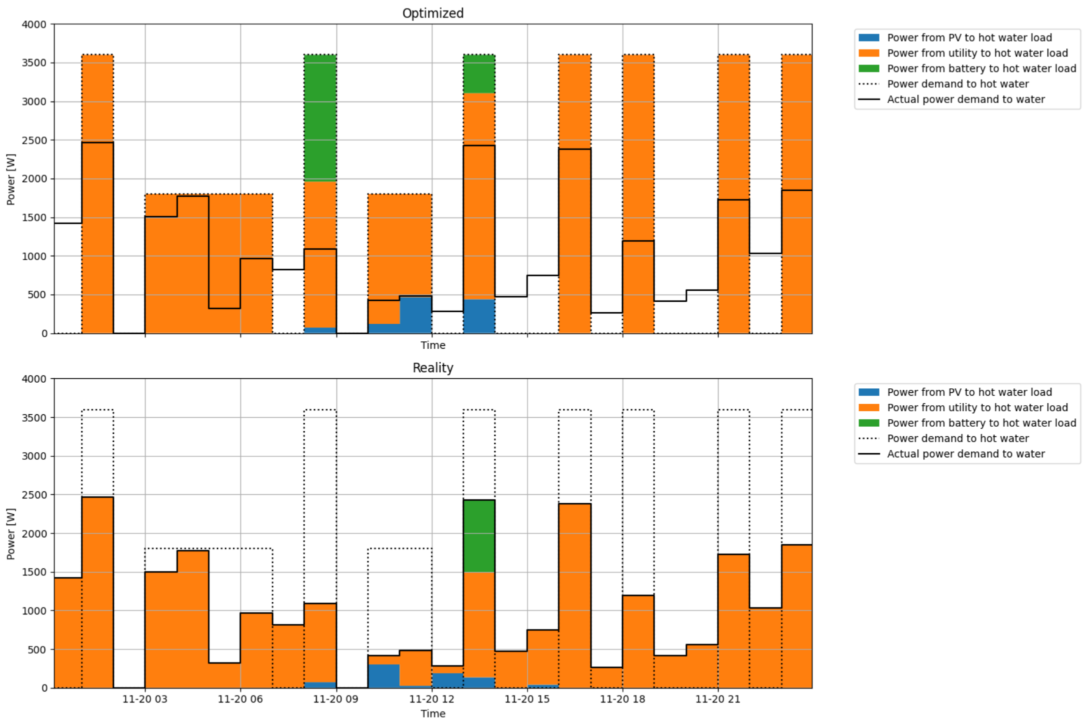

Figure 41. Optimized (top) and actual (bottom) coverage of the hot water load in case B, battery

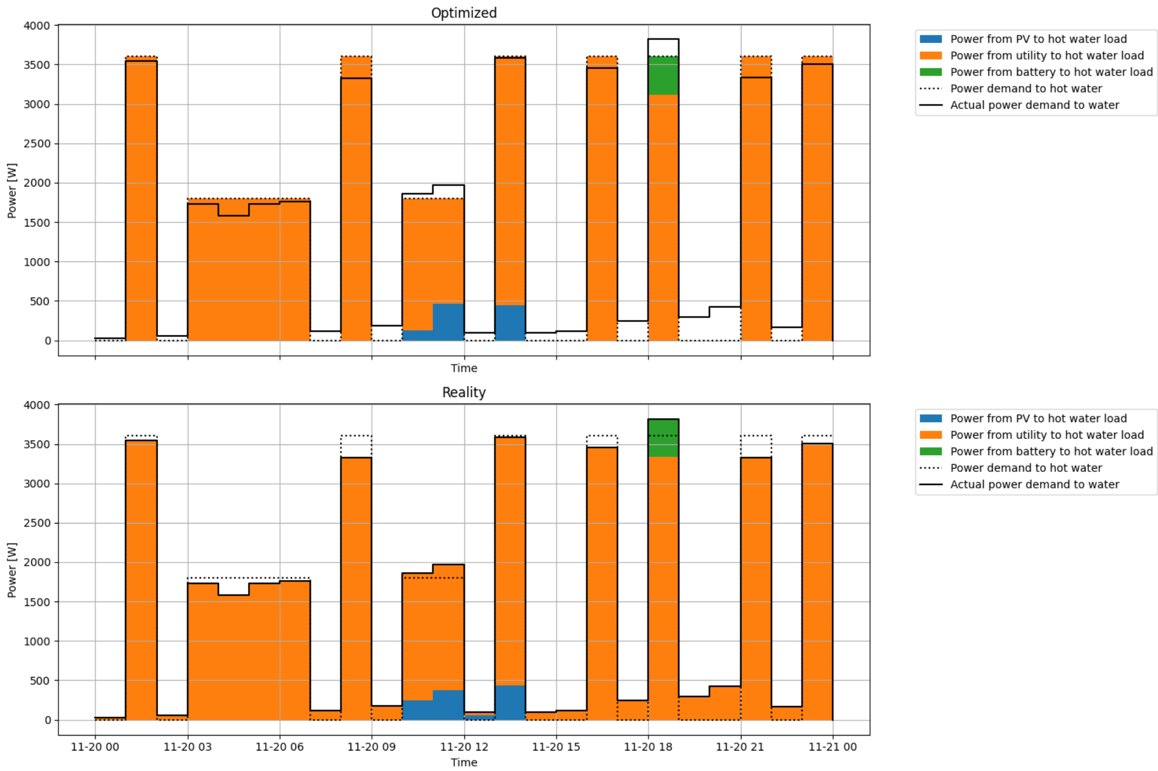

Figure 42. Optimized (top) and actual (bottom) coverage of the hot water load in case C, battery and smart meter

E.4. Battery SOC

Examples of the battery SOC for the two cases with battery for November 20th are shown in Figure 43 - Figure 44.

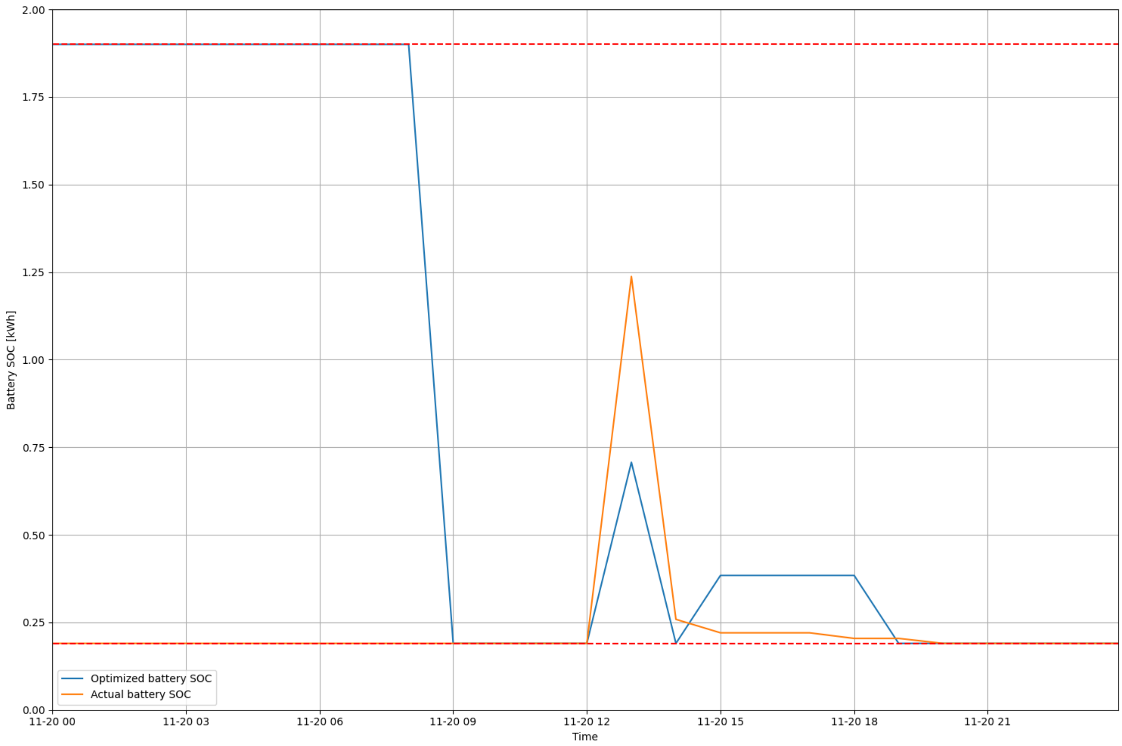

Figure 43. Optimized (top) and actual (bottom) battery SOC in case B, battery

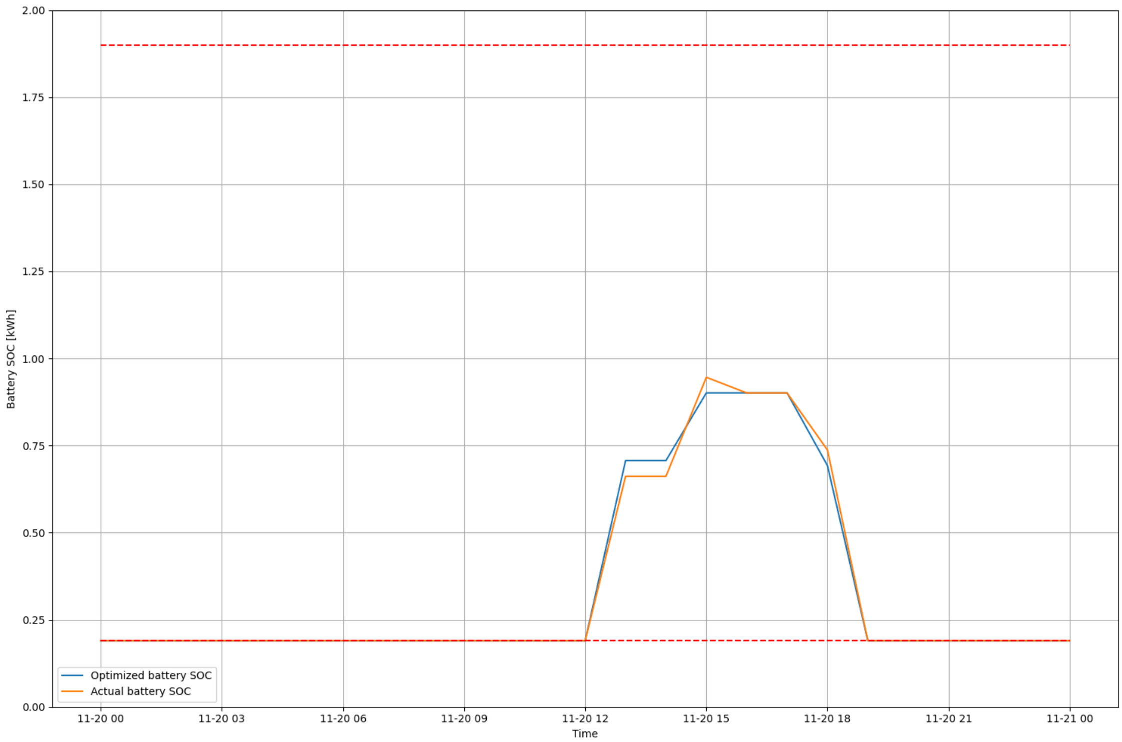

Figure 44. Optimized (top) and actual (bottom) battery SOC in case C, battery and smart meter

E.5. Spot prices

The electricity spot prices used for November 20th are shown in Figure 45 and Figure 46.

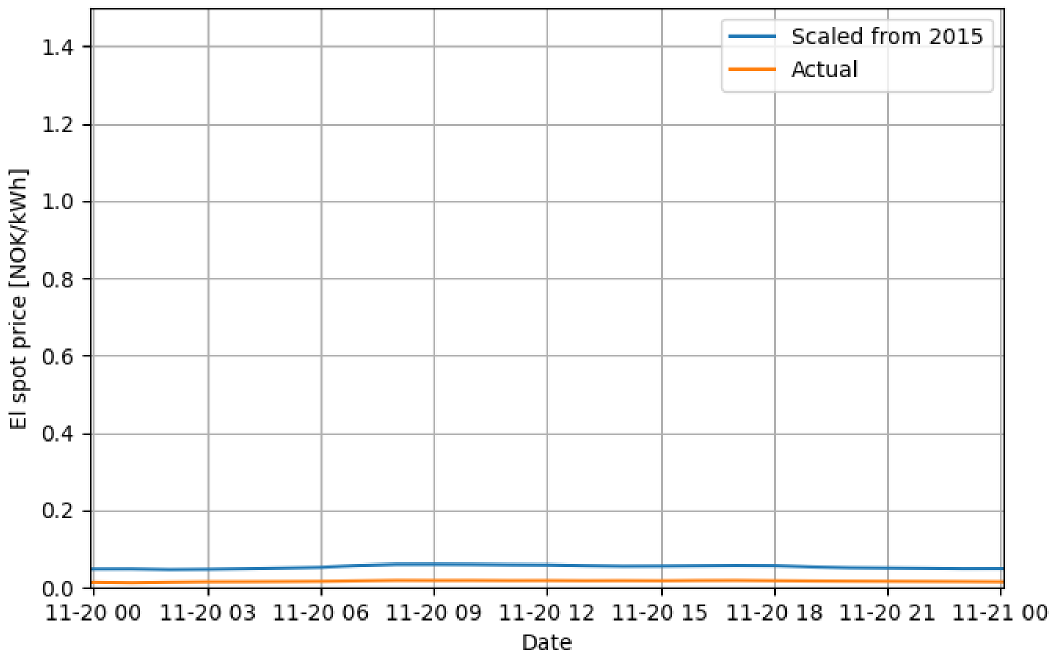

Figure 45. Electricity spot prices for November 20th, 2020

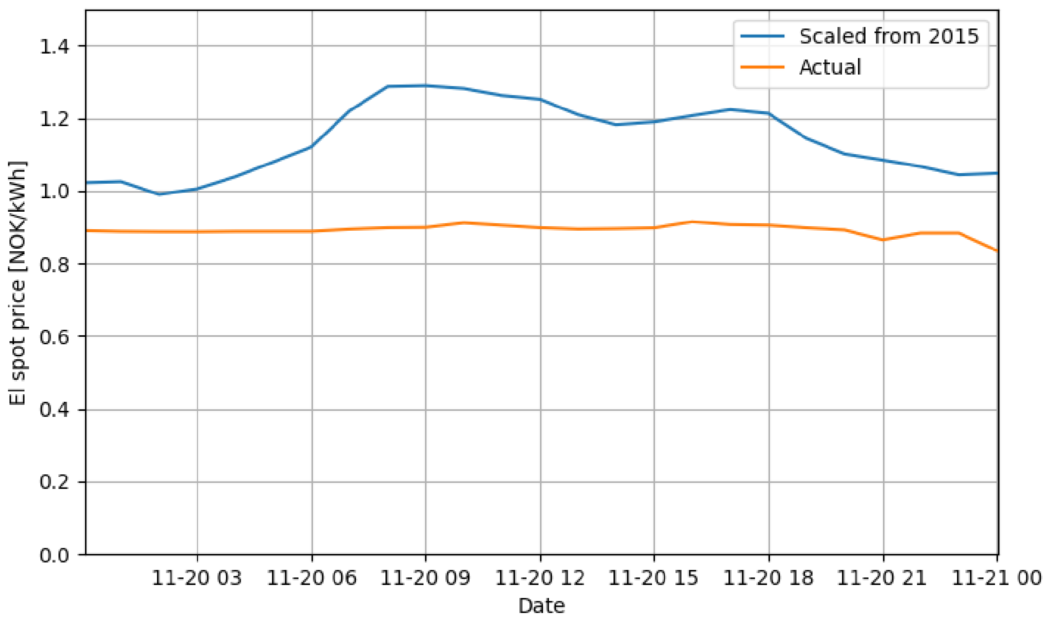

Figure 46. Electricity spot prices for November 20th, 2021