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

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Motivation

- The availability of hourly energy metering, in particular for electricity consumption, have great potential to contribute to more efficient energy use in buildings
- To reach full potential we need
  - Improved data management
  - Improved analysis to visualize economic possibilities
- We have performed a case study to demonstrate the potential electrical energy costs reductions in commercial buildings.
- Such cost savings are achievable through:
  - peak demand shaving
  - utilizing local PV energy production
  - storage

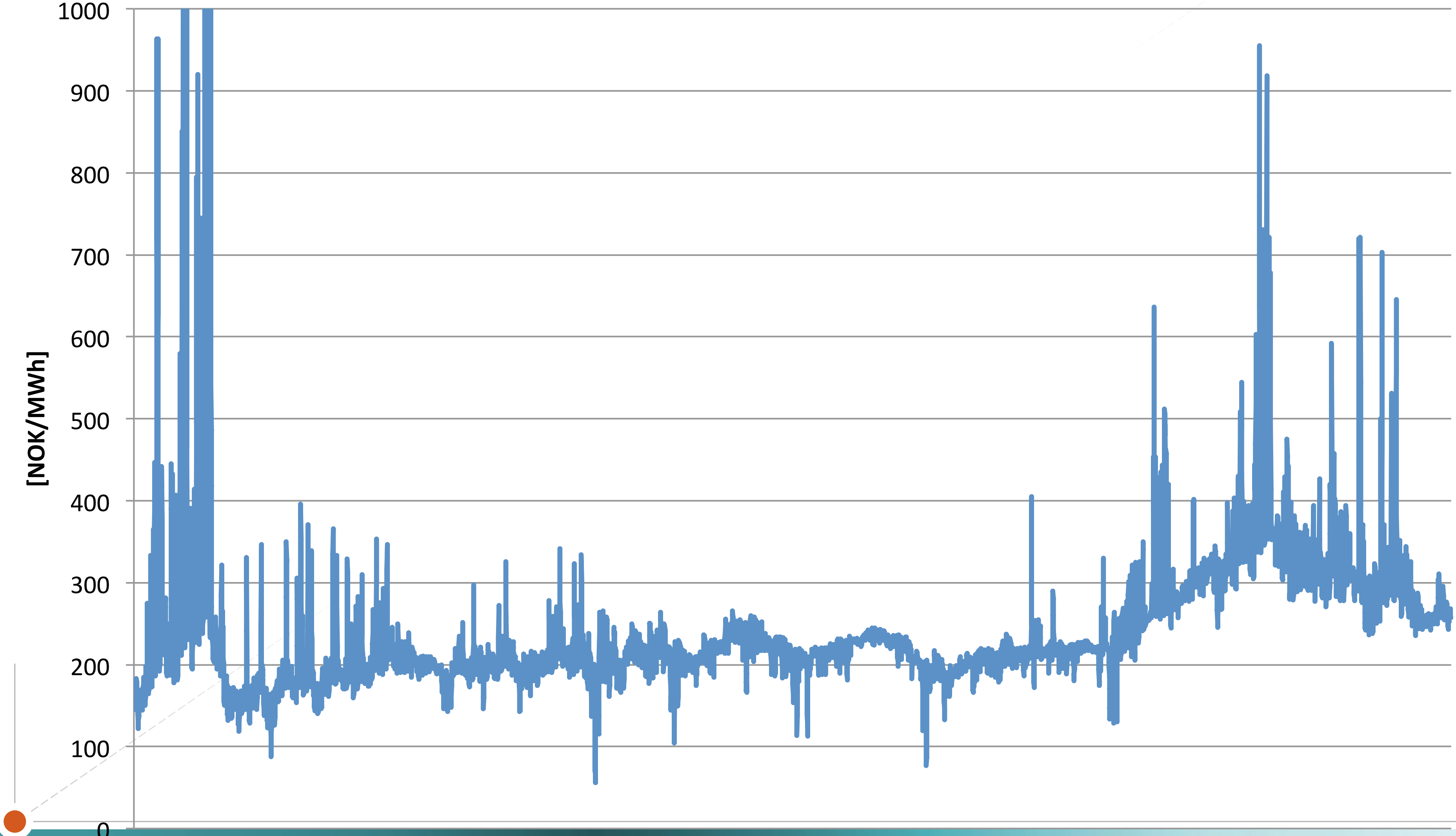
Method

- We analyzed the loadprofile of 600 different stores to identify those with the greatest cost reduction potential.
- The energy consumption is analysed by using the coefficient of variation (CV)
  - The CV value was used to evaluate 600 different stores
- PVsyst was used to determine PV production on an hourly basis.
  - Based on available roof area and local irradiation and climatic conditions
- TRNSYS has been used to look at detailed powerflow and simulation of storage
  - Based on the following information:
    - Results from PVsyst
    - Hourly loadprofiles
    - Effect-tariffs
    - Spotprices

Grid tariffs

Commercial customer: peak-load tariffs	Price	Unit
Fixed charge per installation	340	NOK/month
Peak load charge (Jan-Feb, Dec)	150	NOK/kW/month
Peak load charge (Mar and Nov)	76	NOK/kW/month
Peak load charge (Apr-Oct)	11	NOK/kW/month
Energy charge (Jan-Mar, Nov-Dec)	0.052	NOK/kWh
Energy charge (Apr-Oct)	0.03	NOK/kWh

Spotpriser 2016 (NO1)



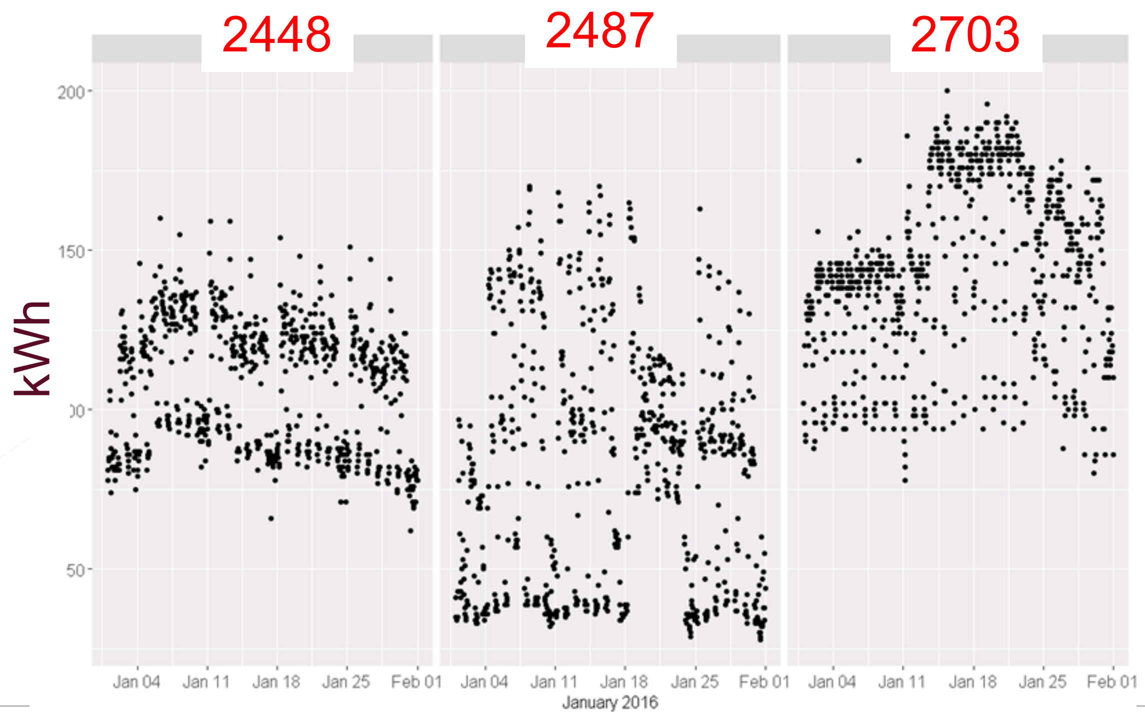
Selecting the stores with the highest cost saving potential

- 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):

$$CV = \sigma / \mu$$

Statistics for three selected stores with high and intermediate *CV* for the winter months

Store ID	*Average KWh*	*Min KWh*	*Max KWh*	*CV*	*Sum KWh*	*Area (m2)*
2448	103	60	160	18,7	227 208	1780
2487	76	26	180	44,7	154 870	2200
2703	151	78	212	17,8	307 298	2237



Analysis

- For each individual store, three different cases were analysed:
  - Existing system (i.e. only power from grid)
  - Battery storage system combined with power from the grid
  - Battery storage system with power production from PV and electricity purchased from the grid

Cumulative PV-production

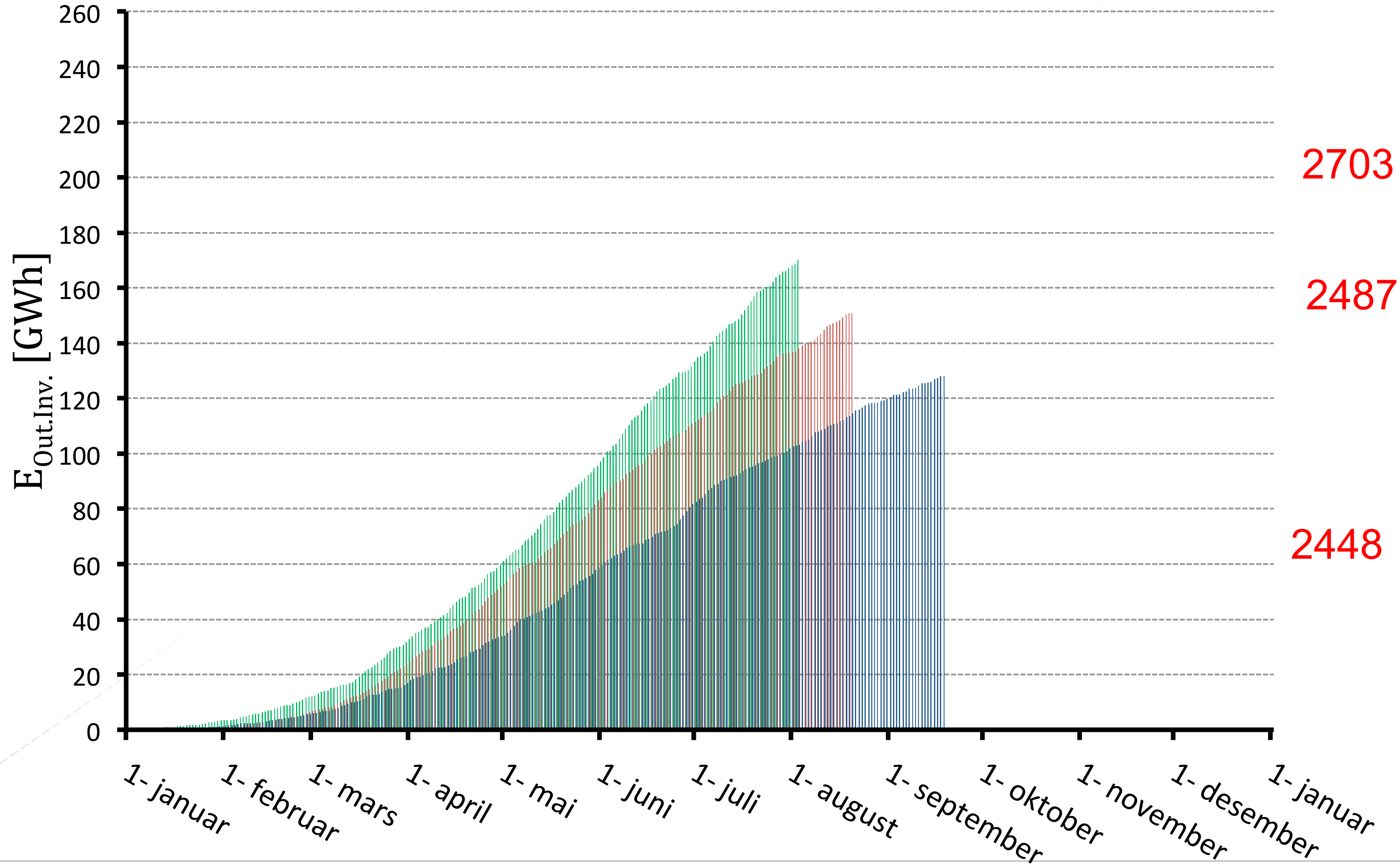


Table 1: Irradiation data, balance and main results for the system of Scenario 1.

	GlobHor kWh/m²	T Amb °C	GlobInc kWh/m²	GlobEff kWh/m²	EArray MWh	E_Grid MWh	EffArrR %	EffSysR %
January	10.6	-1.83	13.8	12.6	1.71	1.62	14.08	13.32
February	27.2	-2.31	33.8	31.4	4.43	4.29	14.92	14.43
March	70.6	0.11	80.4	76.0	10.59	10.32	15.01	14.63
April	111.0	5.71	119.7	114.2	15.54	15.16	14.79	14.43
May	161.6	11.05	168.4	161.4	21.32	20.82	14.42	14.08
June	172.4	14.69	176.7	169.7	21.91	21.37	14.13	13.77
July	168.1	17.21	174.3	167.3	21.37	20.84	13.97	13.62
August	129.7	16.22	137.1	131.0	17.05	16.63	14.17	13.82
September	80.9	11.67	90.4	85.7	11.43	11.13	14.40	14.03
October	37.0	6.49	44.0	41.0	5.59	5.41	14.48	14.01
November	12.2	2.59	14.6	13.5	1.80			
December	6.7	-1.09	9.5	8.4	1.13			
Year	988.0	6.76	1062.8	1012.3	133.87	1		

Legends:				
	GlobHor	Horizontal global irradiation	EArray	Effe
	T Amb	Ambient Temperature	E_Grid	Ene
	GlobInc	Global incident in coll. plane	EffArrR	Effic
	GlobEff	Effective Global, corr. for IAM and shadings	EffSysR	Effic

- Hourly production values
- Based on local irradiation and climatic conditions
- Modelled on the actual roof orientation and inclinations

Normalized productions (per installed kWp): Nominal power 141 kWp

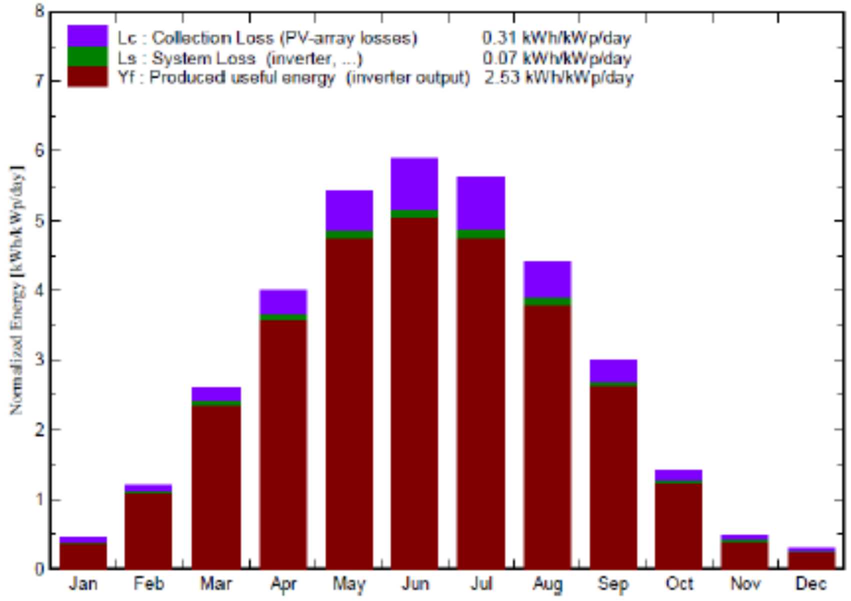
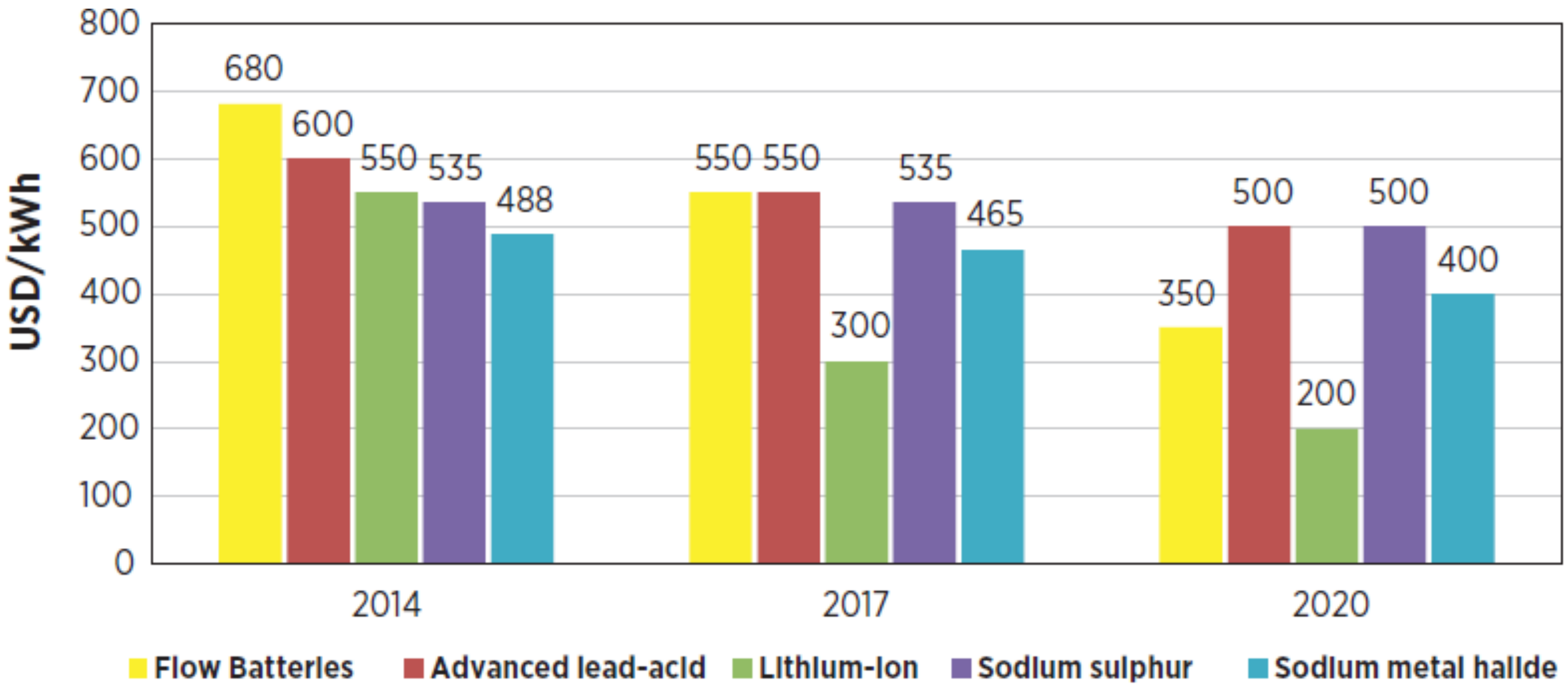


Fig. 4: Normalized PV production for the PV system defined of Scenario 1.

Battery specifications

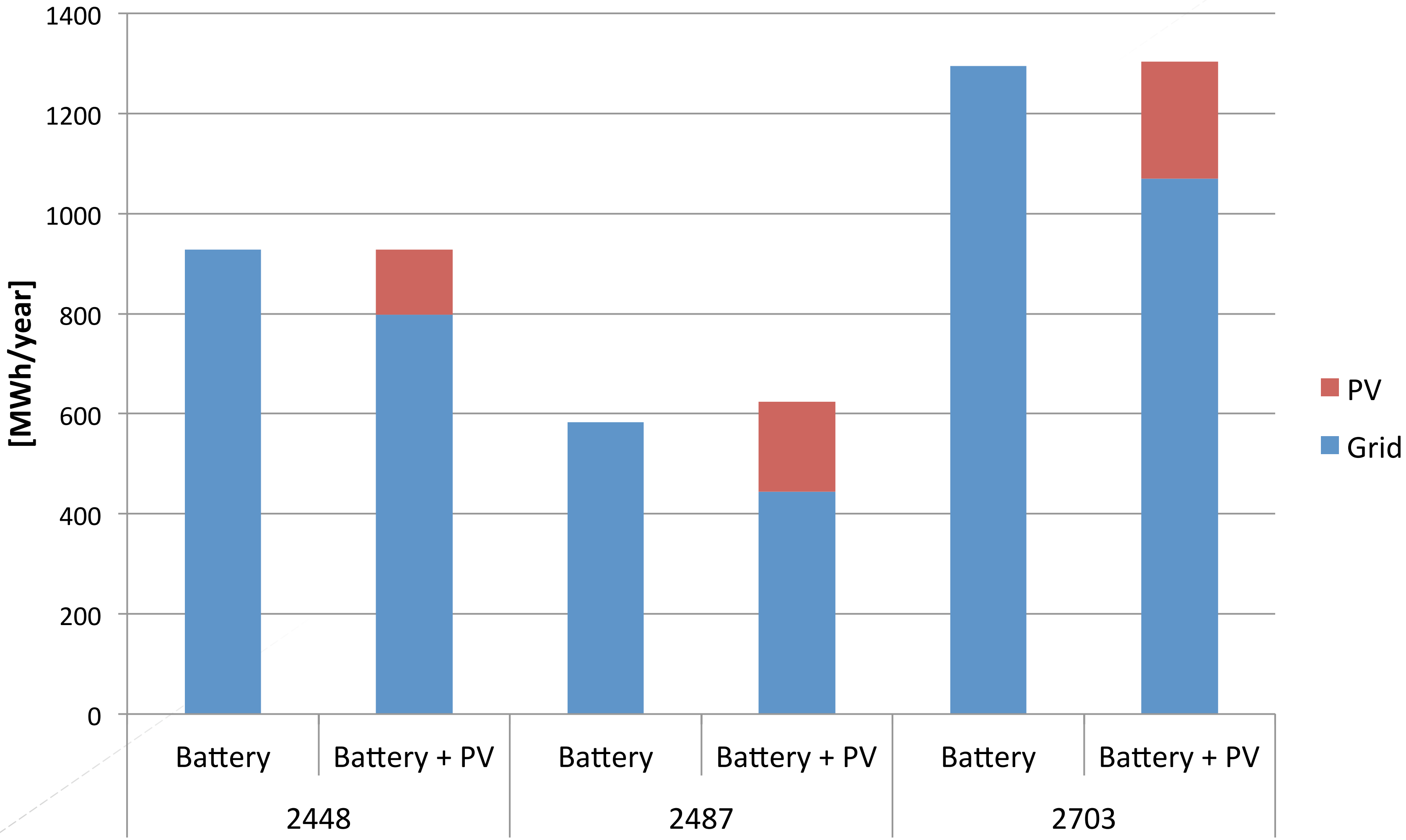
Current battery cost [US$/kWh]	Optimistic battery cost [US$//kWh]	Battery efficiency [-]	State of charge (low) [-]
776	388	0.9	0.2



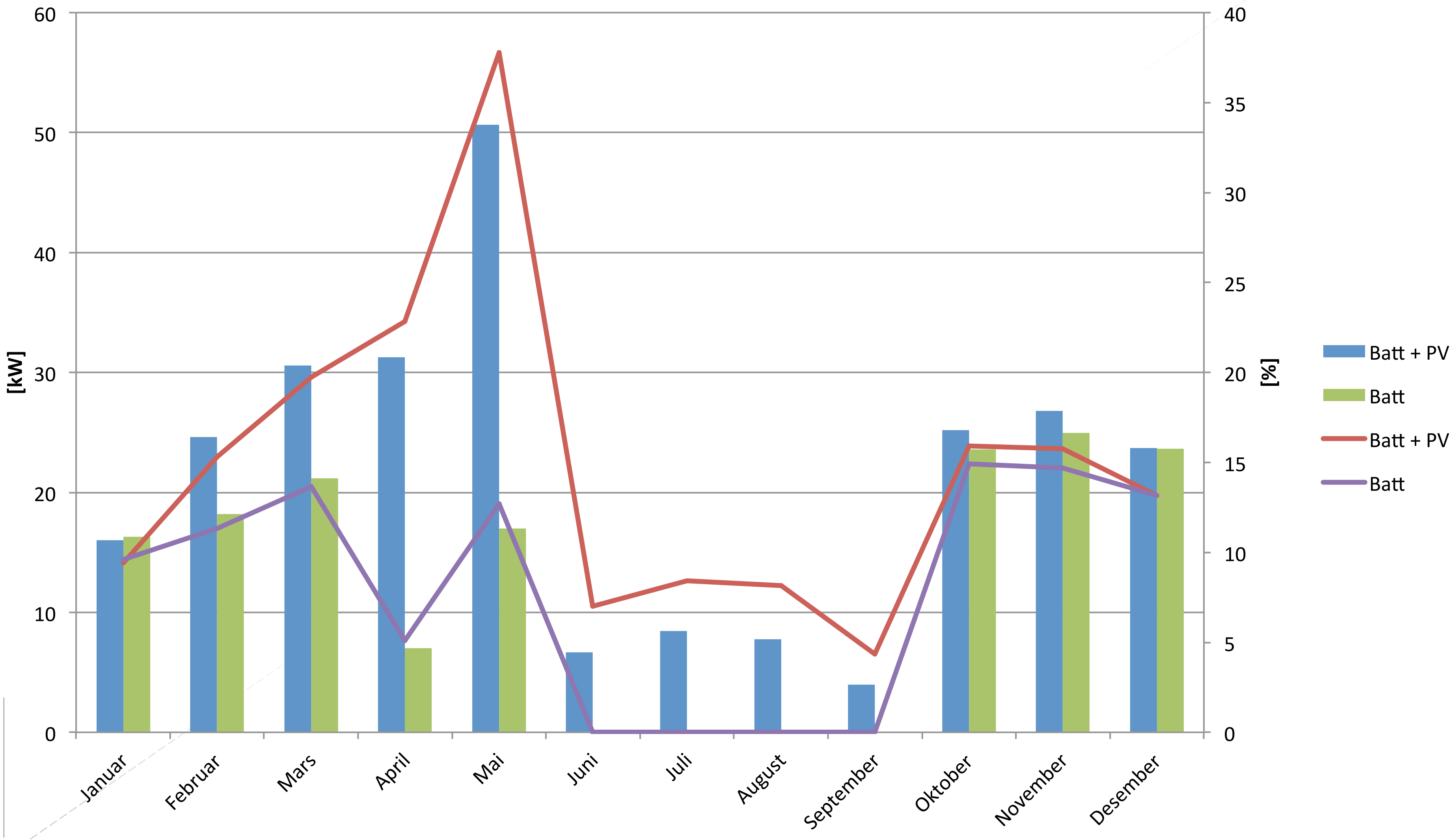
From: Irena 2015

PV price assumptions

Yearly grid supply and production



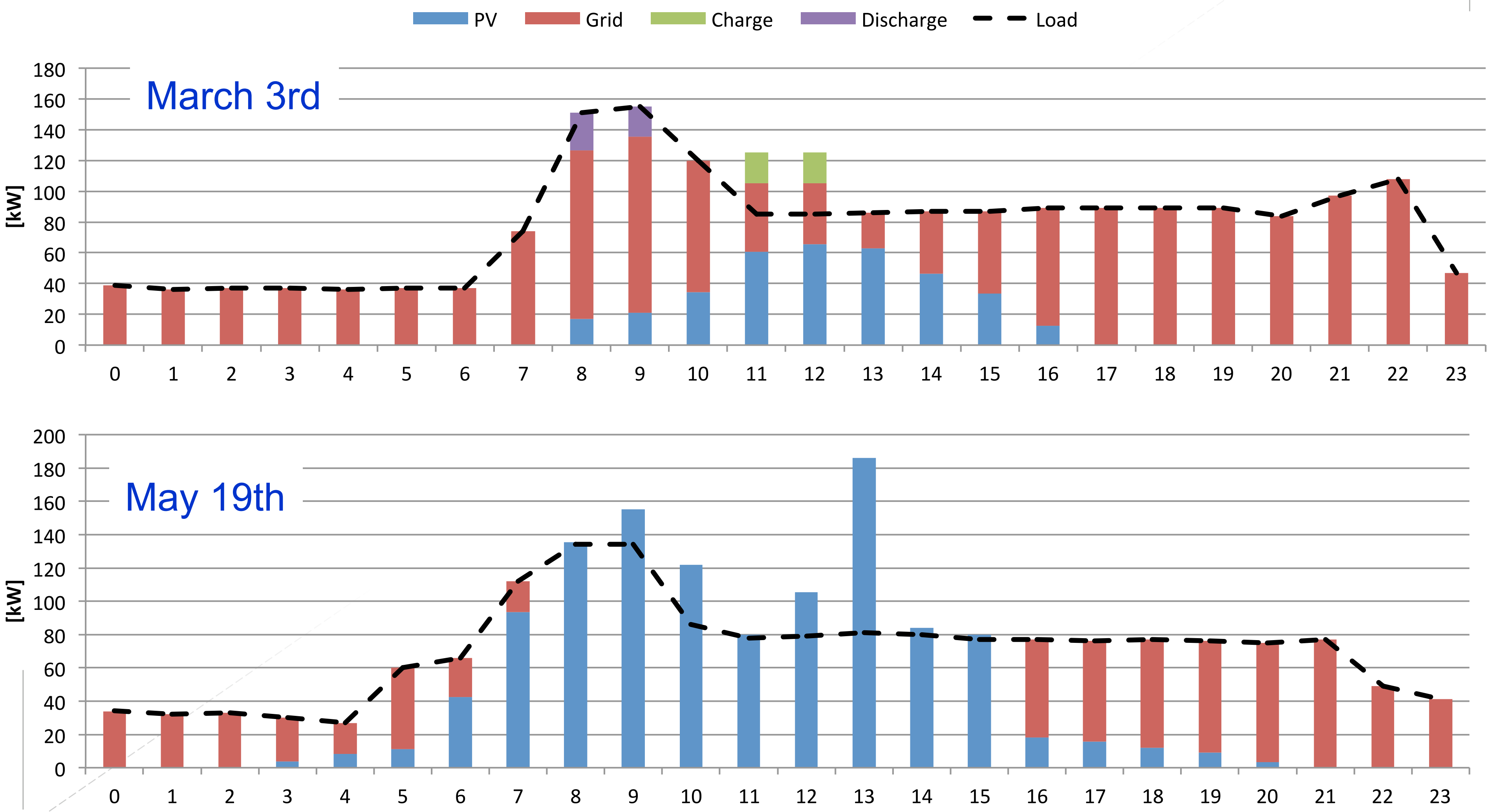
Store 2487: Reductions in grid effect



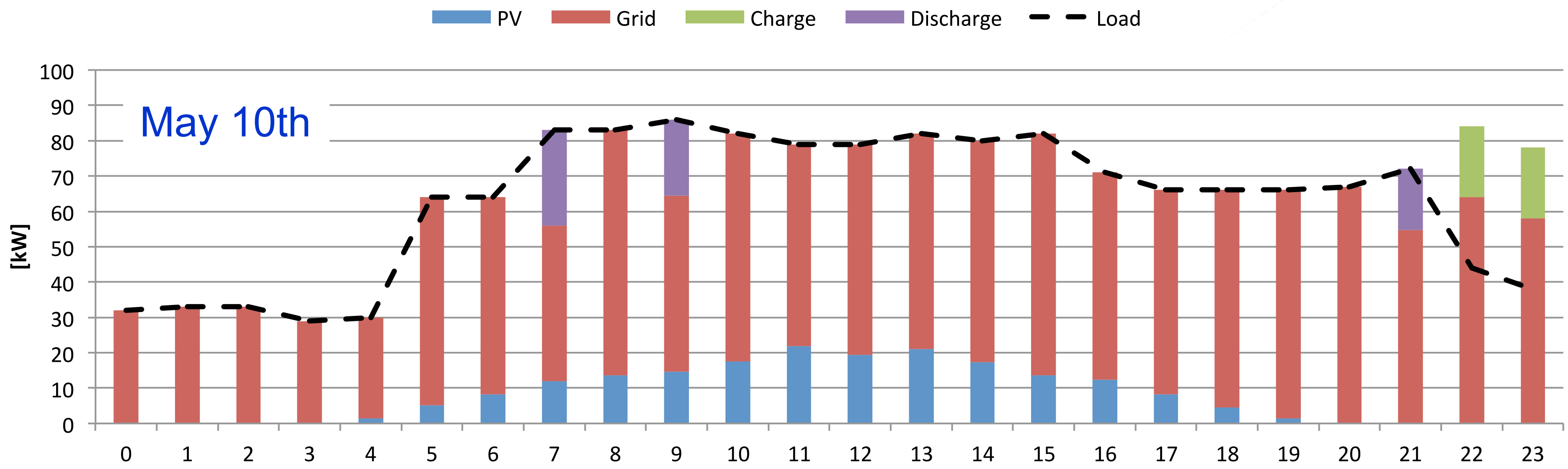
Store 2487: Powerflow

Battery-strategy
Use: (Load – PV) >= 130 kW

Charge: Load <= 110 kW
(20 kW or PV_surpluss)



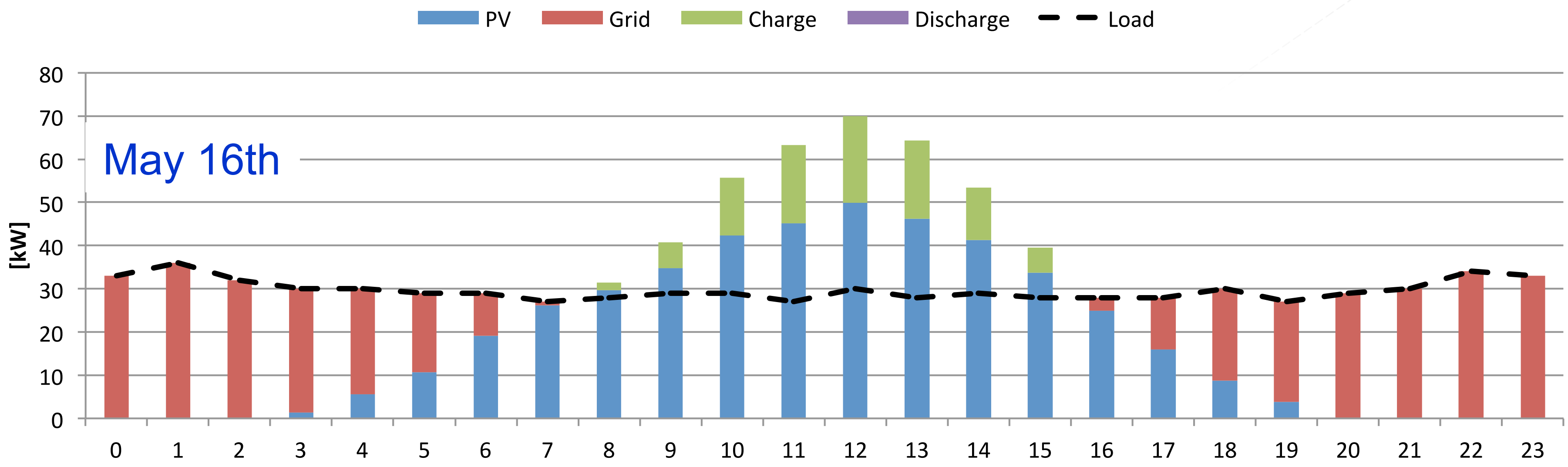
Store 2487: Powerflow



Battery-strategy

Jan, Feb, Dec:	Use:	(Load – PV) >= 130 kW
	Charge:	Load <= 110 kW
	(20 kW eller PV_surpluss)	
March:	Use:	(Load – PV) >= 100 kW
	Charge:	Load <= 80 kW
	(20 kW eller PV_surpluss)	
April - Sep:	Use:	(Load – PV) >= 70 kW
	Charge:	Load <= 50 kW
	(20 kW eller PV_surpluss)	

Store 2487: Powerflow



Battery-strategy

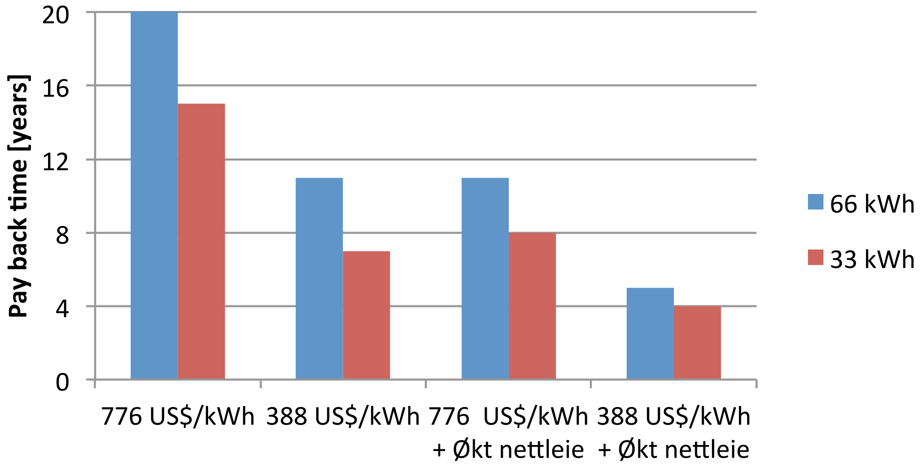
Jan, Feb, Dec: Use: (Load – PV) >= 130 kW
Charge: Load <= 110 kW
(20 kW eller PV_surpluss)

March: Use: (Load – PV) >= 100 kW
Charge: Load <= 80 kW
(20 kW eller PV_surpluss)

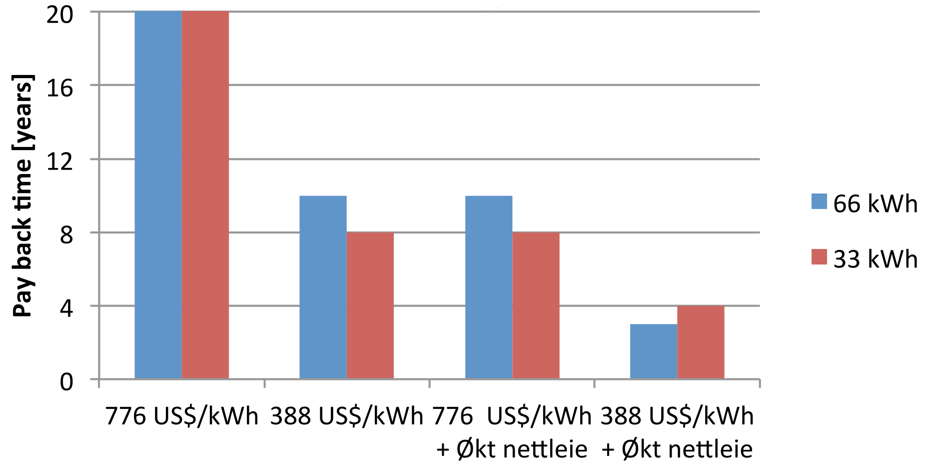
April - Sep: Use: (Load – PV) >= 50 kW
Charge: If surpluss from PV
(PV_surpluss)

Payback time

2448

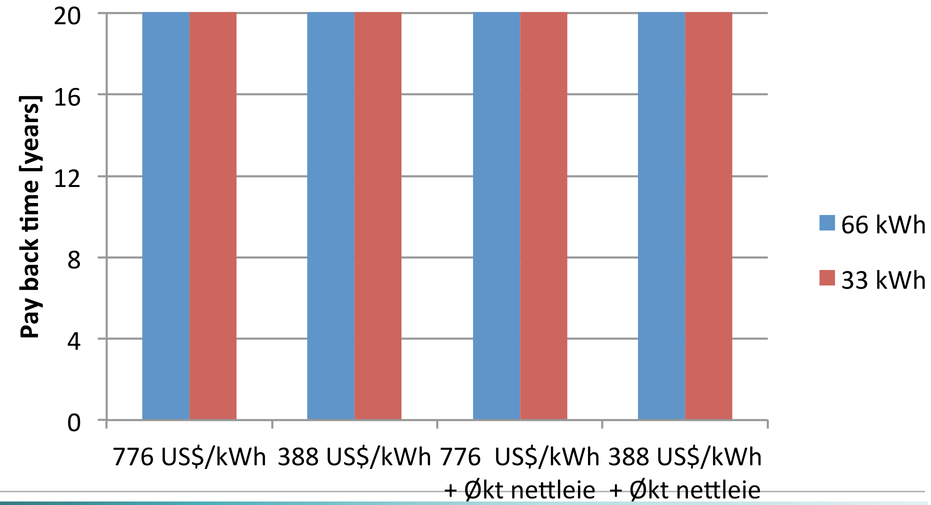


2487



≈ 66 kWh battery

2703



Summary

- The coefficient of variation (CV) is a useful statistical method to analyse the dispersion of energy consumption in commercial buildings
  - (there is a need to sort out buildings that has recently carried through energy efficiency measures!)
- High peak load tariffs will give high saving potential for buildings with high CV values, though peak load shaving
- Three buildings of intermediate to high CV values were analysed in detail:
  - Three scenarios: a) grid, b) grid and battery, og c) grid, battery and PV
  - Commercial buildings with high CV values may profit from optimized battery systems already today.
  - Expected increases in peak load tariffs and reductions in battery and PV prices will increase the relevance of such systems.
- More advanced battery strategy is identified as key to achieve the most cost optimal solutions
- Further work includes implementing machine learning strategies for load predictions and battery strategies, in addition to PV forecasting.

Thank you for the attention!

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