

STORY

added value of STORage in distribution sYstems

Deliverable 3.5 Report on performance evaluation of control



Revision 1
 Preparation date ..2019-10-31 (m54)
 Due date2019-10-31 (m54)
 Lead contractor.... VTT
 Dissemination level PU

Authors:

Francesco Reda VTT	John Harrison B9
Hassam ur Rehman VTT	David Surplus B9
Rinat Abdurafikov VTT	Marjan Jerele EG
Timo Korvola VTT	Raquel Garde CEN
Timo Laakko VTT	Gabriel Garcia CEN
Andrej F. Gubina UL	Alicia Kalms CEN
Jernej Zupančič UL	Ana Goncalves Soares
Nicolas Hassid ACT	VITO
Arnout Aertgeerts ACT	Jef Verbeeck VITO
Leen Peeters THINK	Johan Van Bael VITO





STORY

Table of contents

1	PUBLISHABLE EXECUTIVE SUMMARY.....	5
2	DEMO1	1
2.1	DEMO1: PART A, DEMONSTRATION OF CONTROLS FOR THE NZEB BUILDING OUD-HEVERLEE, BELGIUM	1
2.1.1	<i>Introduction</i>	1
2.1.2	<i>Performance and evaluation of demo</i>	2
3	DEMO1	11
3.1	DEMO1: PART B, DEMONSTRATION OF CONTROLS FOR THE OTHER BUILDINGS IN OUD-HEVERLEE	11
3.1.1	<i>Introduction</i>	11
3.1.2	<i>Performance and evaluation of demo</i>	11
4	DEMO2.....	19
4.1	DEMO2: DEMONSTRATION AT RESIDENTIAL NEIGHBORHOOD SCALE OUD-HEVERLEE, BELGIUM	19
4.1.1	<i>Introduction</i>	19
4.1.2	<i>Performance and evaluation of demo</i>	19
5	DEMO3.....	23
5.1	DEMO3: DEMONSTRATION OF SMALL SCALE BATTERY TO REDUCE PEAK POWER NAVARRA, SPAIN	23
5.1.1	<i>Introduction</i>	23
5.1.2	<i>Performance and evaluation of demo</i>	23
6	DEMO4.....	33
6.1	DEMO4: DEMONSTRATION IN RESIDENTIAL DISTRICT - LECALÉ, NORTHERN IRELAND (UK)	33
6.1.1	<i>Introduction</i>	33
6.1.2	<i>Performance and evaluation of demo</i>	34
7	DEMO5.....	35
7.1	DEMO5: DEMONSTRATION OF FLEXIBLE AND ROBUST USE OF MEDIUM SCALE BATTERY - SLOVENIA.....	35
7.1.1	<i>Introduction</i>	35
7.1.2	<i>Performance and evaluation of demo</i>	36
7.1.3	<i>Operation of the storage unit</i>	41
8	DEMO6.....	45
8.1	DEMO6: DEMONSTRATION OF ROLL OUT OF PRIVATE MULTI-ENERGY GRID IN INDUSTRIAL ZONE OLEN, BELGIUM 45	
8.1.1	<i>Introduction</i>	45
8.1.2	<i>Performance and evaluation of demo</i>	46
9	CONCLUSIONS	48
10	ACRONYMS AND TERMS.....	48
11	REFERENCES.....	48

Disclaimer

The information in this document is provided without guarantee or warranty, that the content fits for any particular purpose. The user thereof uses the information at its sole risk and liability.
The documents reflects only the author's views and the Community is not liable for any use that may be made of the information contained therein.



1 Publishable executive summary

In deliverable 3.4. Streamlined control algorithm for storage integration are developed and discussed. These control algorithms are developed and simulated in various climatic conditions of Ireland, Belgium, Spain and Slovenia. This document i.e. deliverable 3.5. contains the simulation based performance evaluation of the control algorithms developed for different demos and the demonstration sites monitored results after using the proposed novel control algorithms. Due to different components, demand, storage, production and locations of the demos, no single control algorithm is developed. Each demo has proposed a different approach to tackle the need. The concept is to utilize the storage and reduce the grid exchange and operation costs of the renewables and storages integrated with the demos.

- **Demo1: Demonstration at residential building scale- Oud-Heverlee, Belgium**
 - **Demo1: Control for the NZEB building**

The performance analysis has been developed by VTT with the support of THINK, which provided the model of the building, system components technical data, site information and assistance on local regulations.

- **Demo1: Control for the other buildings in Oud-Heverlee**

The performance analysis has been developed by ACT, Two use cases have been pursued are Minimize grid exchange. & Dynamic pricing.

- **Demo2: Demonstration at residential neighbourhood scale-Oud-Heverlee, Belgium**
ACT has performed the analysis of the control algorithms.

- **Demo3: Demonstration of small scale battery to reduce peak power- Navarra, Spain**
CENER, supported by EXCAL that provided information about the factory energy loads and local regulatory framework, have performed the analysis of the control algorithms.

- **Demo4: Demonstration in residential district- Lecale, Northern Ireland (UK);**
B9 performed the analysis of the control algorithms for this demo.

- **Demo5: Demonstration of flexible and robust use of medium scale battery- Slovenia;**
UL, supported by VTT (as regard the creation of the simulation model for testing the control) and EG (as regard requirement and instrumental data of the network), have performed the analysis of the control algorithms.

- **Demo6: Demonstration of roll out of private multi-energy grid in industrial zone Olen, Belgium**

VTT has developed a simulation platform that includes the models of the systems involved in the pilot plant for drawing initial conclusion on the performance of the system and initiating the control algorithm creation. To ensure proper operation, advanced control strategies have been evaluated by VITO.

Overall, it is found model predictive control and forecasting can improve the performance of the energy systems and promote better utilization of renewables. These algorithms are site specific



STORY

and can be affected by various parameters such as weather or energy price. Moreover, there can be many technical challenges that has to be addressed before using such control algorithms at a commercial level.



2 DEMO1

2.1 Demo1: Part A, Demonstration of controls for the NZEB building Oud-Heverlee, Belgium

2.1.1 Introduction

The demonstration is located in the Oud-Heverlee in Belgium as shown in Figure 1. The main components of the energy systems are electricity and heat generation systems (PV/T and vacuum collector), storages (batteries, short-term and seasonal storage) and ground source on heat pump. The building is highly insulated to reduce the heat demand. The building's foundations are thermally activated and used as a shallow geothermal system. The excess heat in the summer produced by solar is stored in the seasonal storages and excess electricity produced by solar can be stored in the battery or exported to the grid. The excess electricity produced when exported to the grid gives zero feed-in tariff therefore; there is no motivation to sell excess electricity to the grid.



Figure 1: A photo of the demonstration site: the residential building, large array of PV/T panels, three evacuated tube solar collectors and access to underground seasonal heat storages [1]

The main characteristics of equipment and energy storages are summarized in Table 1.



STORY

Table 1 - Main technical characteristics of equipment installed at Demo 1 [2].

System	Main characteristic
PV/T system	10 kW _p ,/ 24.3 kW
Vac. collectors system	3.8 kW
Seasonal heat storage	2 x 12 m ³
Short-term heat storage	2 x 0.2 m ³
Heat pump	1.53 kW / 5.8 kW
Reservoir	42 m ³
Shallow geothermal	312 m ³ of activated soil
Battery (SoC 30-100%)	32.2 kWh

The control algorithm is developed by VTT with the help of THINK that provided the model of the building, the technical data of the components, location data and local regulations. The control algorithm aim is to focus on:

- Increase renewable energy usage by maximizing the use of renewable energy onsite
- Minimize the export of excess electricity to the grid, due to no economic benefits.

The model predictive control algorithm is developed to achieve following goals:

- Peak shaving, the energy demand over certain limit will be provided via energy storage.
- Demand side management (peak shifting), shifting the electrical vehicle load to a convenient time.
- Smart supply scheduling, daily predictive identification of energy supply based on energy cost and weather data.
- Energy schedule prediction (time shifting), shifting energy source production considering the price and weather forecast.

A more detailed explanation on the controls algorithms and simulations are described in deliverable 3.4.

2.1.2 Performance and evaluation of demo

Due to complexity of the model and relatively long computation time with MPC, its performance is studied using three selected weeks of a year, which are defined as seven consecutive days having the highest, lowest and median daily average dry-bulb temperature of outdoor air. The yearly weather profile used for constructing the temperature profiles of correspondingly the warmest, the coldest and median temperature weeks is presented on Figure 2 ; the selected weeks are marked with colors red, blue and green.





STORY

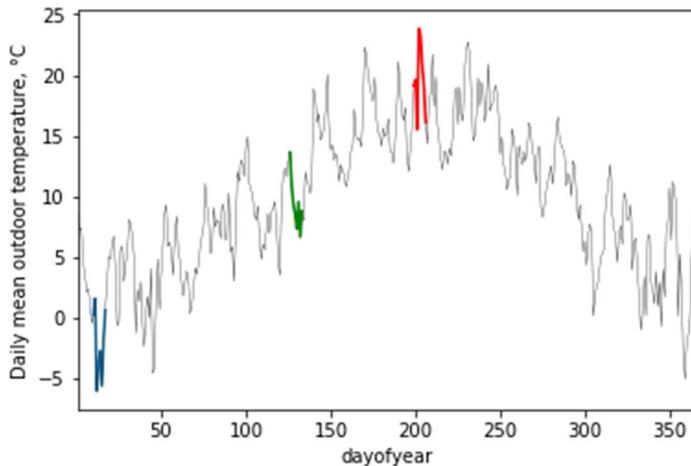


Figure 2: Outdoor air temperature during selected test weeks

The costs calculated from the results of the simulations under the rule based and model predictive controls (MPC) are shown in Table 2. In Table 2, the numbers in the parentheses are the total direct costs of purchased electricity whereas those outside parentheses are corrected for the difference in stored electricity and heat at the end of corresponding test week. The differences in stored energy between MPC and rule-based control are also shown.

Table 2: Operation energy costs of the system controlled by the two control systems during test weeks and differences in energy content of storages at the end of test weeks [2].

Test week	Total cost, €		Difference in stored electricity, kWh	Difference in stored heat, kWh
	Rule-based	MPC		
The coldest	6.44	4.39 (4.69)	7.49	-34.7
The warmest	0.01	0.70 (0.31)	0.61	-108.7
Median temperature	0.01	1.24 (0.65)	2.74	-184.4

It is observed in Table 2 that at the end of all the three test weeks, use of model-predictive control (MPC) resulted in a higher energy content in the battery compared to the case when the system is operated using the rule-based control. In the case of stored heat, the result is opposite.

The energy content of the battery is directly observable and the price used for valuation of stored electricity is the night electricity tariff. Heat storage values are calculated by taking the differences of total enthalpy of water stored in the tanks and the heat capacity of activated ground and the average temperature. The prices used for valuation of stored heat are set as fractions of the price of stored electricity. The information about the differences in final states of storages and used prices of stored heat is presented in Table 3. The value of energy content in the shallow geothermal storage is also shown in the Table 3.



STORY

Table 3: The differences in content of energy storages, applied prices for valuation of the energy content and resulting corrections to total costs [2]

Test week	Energy storage	Difference in stored energy, kWh	Value of energy as fraction of price of stored electricity (0.05988 €/kWh)	Correction, €
The coldest	Battery	7.5	1.0	0.45
	Swimming pool	-56.3	0.1	-0.34
	Seasonal tanks	17.5	0.2	0.21
	DHW tank	-3.2	0.1	-0.02
	Space heating tank	-0.6	0.1	0.00
	Geothermal	0.4	0.1	0.00
	Total	-34.7	-	0.30
The warmest	Battery	0.6	1.0	0.04
	Swimming pool	-146.7	0.1	-0.88
	Seasonal tanks	40.0	0.2	0.48
	DHW tank	-4.5	0.1	-0.03
	Space heating tank	2.0	0.0	0.00
	Geothermal	-0.1	0.1	0.00
	Total	-108.7	-	-0.39
Median temperature	Battery	2.7	1.0	0.16
	Swimming pool	-239.2	0.1	-1.43
	Seasonal tanks	61.7	0.2	0.74
	DHW tank	-9.5	0.1	-0.06
	Space heating tank	0.0	0.0	0.00
	Geothermal	-0.2	0.1	0.00
	Total	-184.4	-	-0.59

The results presented in Table 2 suggest that the best performance of model-predictive control system compared to the rule-based one, both with and without corrections for the final states in heat storages, is achieved in the coldest week. During the warmer weeks, there is significant on-site electricity generation by the PV/T system. The system is able to store the excess electricity in sufficient amounts to almost entirely cover electrical loads, including operation of heat pump. This is exactly what happens with rule-based control and can be seen by negative net exchange with electrical grid in Table 4.





STORY

Table 4: Interaction of the system with electrical grid when controlled by the two control systems during test weeks [2].

Test week	Imported energy, kWh		Net exchange, kWh	
	Rule-based	MPC	Rule-based	MPC
The coldest	95.3	75.5	95.2	75.5
The warmest	0.1	4.8	-127.8	-110.1
Median temperature	0.2	10.3	-116.5	-119.1

On-site energy fraction (OEF) and on-site energy matching (OEM) give a more comprehensive picture of the system performance under the two control approaches[3]. The OEF evaluates the portion of final energy consumption covered by the produced on-site renewable energy. OEM evaluates the portion of the produced on-site renewable energy directly consumed. These indicators have been stated as:

$$OEF_e = \frac{\int_{t_1}^{t_2} \text{Min}[G_{elec}(t) - ES_{on}(t); L_{elec}(t)]dt}{\int_{t_1}^{t_2} [L_{elec}(t)]dt}, \quad 0 \leq OEF_e \leq 1$$

$$OEM_e = \frac{\int_{t_1}^{t_2} \text{Min}[G_{elec}(t); L_{elec}(t) + ES_{on}(t)]dt}{\int_{t_1}^{t_2} [G_{elec}(t)]dt}, \quad 0 \leq OEM_e \leq 1$$

where dt is the differential time step, G_{elec} is the on-site electricity generation, L_{elec} is the total electrical loads, and ES_{on} is the electric power to the battery (negative when flow is from the battery).

The following three figures (Figure 3, Figure 4 and Figure 5) show the consumption of electricity from the electrical grid and the values of daily indices of on-site energy fraction and matching for electricity, OEF_e and OEM_e , respectively. The indices are calculated from the data having one-minute time resolution and for this reason the values of indices may differ from the expected from hourly presentation of electricity consumption from the grid.



STORY

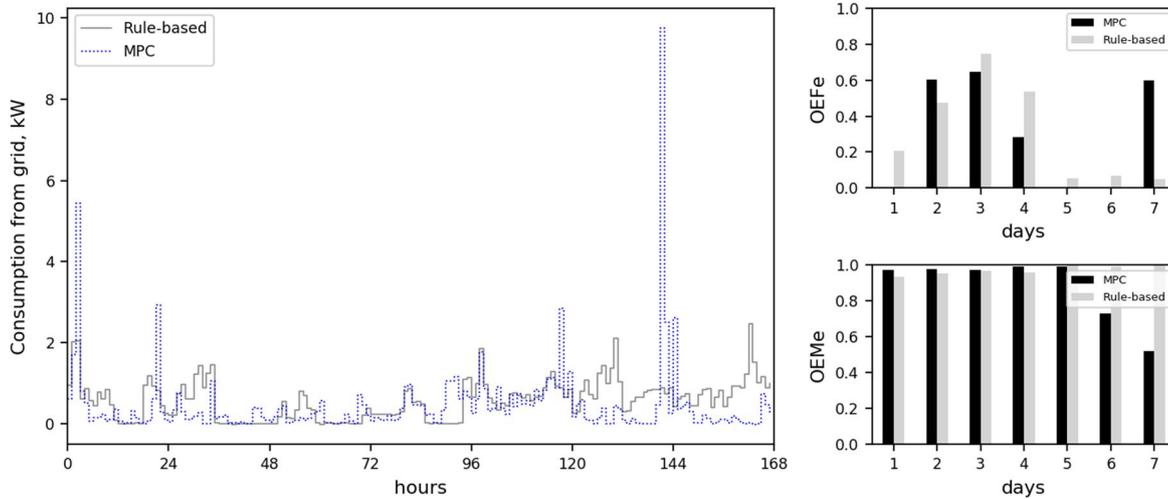


Figure 3: Electricity consumption from the grid and daily on-site energy indices during the coldest week [2]

During the coldest week (Figure 3), the model-predictive control is charging the battery during the night and as a result consumes less electricity from grid during the day when the electricity price is higher. This affects the values of OEF_e index on days 1, 5 and 6 in MPC that is mainly due to the absence of generation during winters.

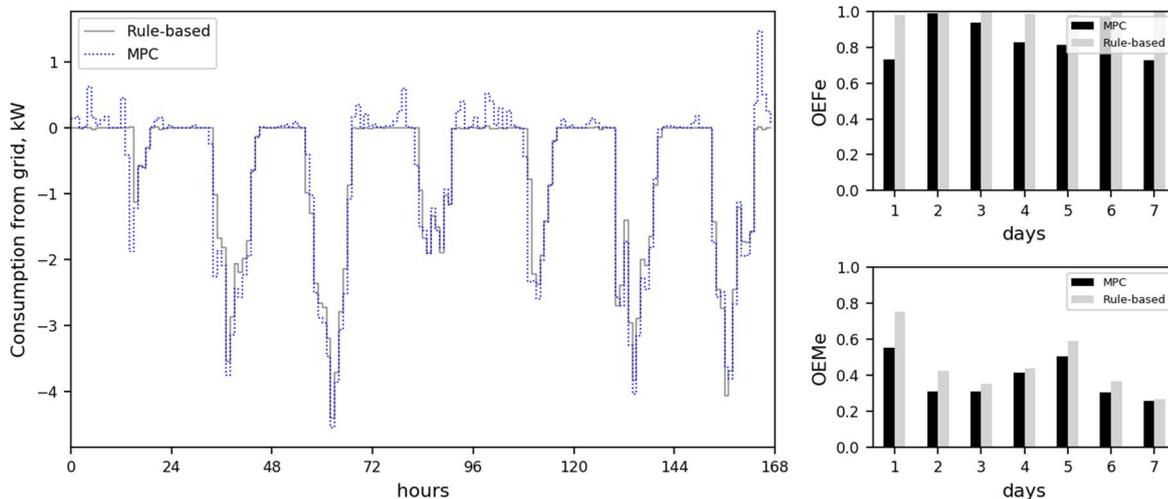


Figure 4: Electricity consumption from the grid and daily on-site energy indices during the median temperature week [2]

During both warmer weeks in Figure 4 and Figure 5, due to the excess on-site electricity generation, the values of OEF_e are relatively high for both systems and the values of OEM_e are relatively low. Low values of on-site energy matching index is explained by feeding the surplus electricity that cannot be entirely stored in the battery to the grid.

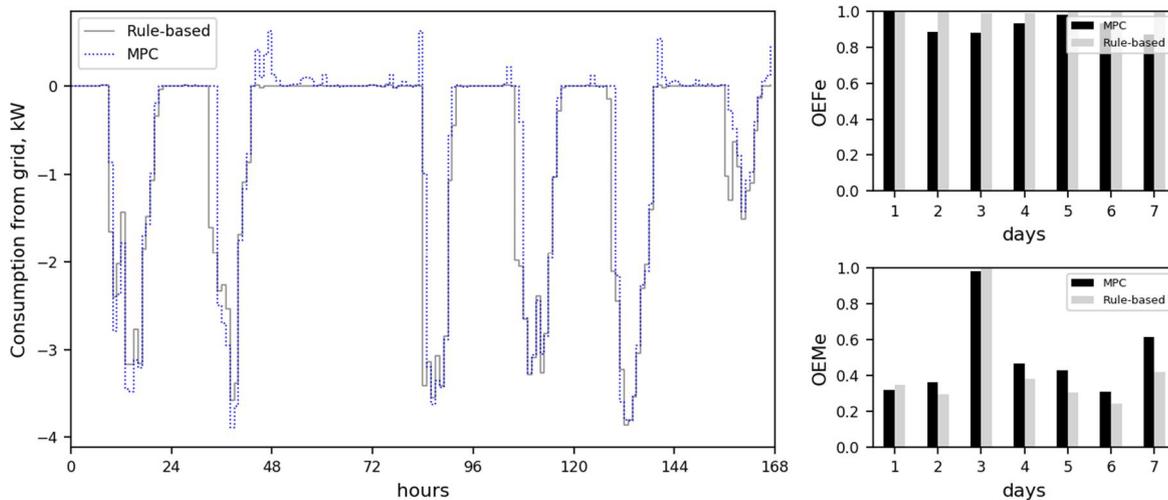


Figure 5: Electricity consumption from the grid and daily on-site energy indices during the warmest week [2]

It should also be noticed that the observed surplus of electricity-produced onsite is intended for charging an electrical vehicle. Charging and discharging the vehicle would most certainly improve the results of model-predictive control system. However, at this time we did not have sufficient data about the vehicle, which is thus completely absent from the models.

2.1.2.1 The effects of curtailment in PV production

Machine learning is applied to evaluate the effects of curtailment in PV production and, to correct the timespans from the measured data where PV production may be curtailed. The corrected data is then used for MPC as input. In order to properly train and create the machine-learning model, only the input data segments where curtailment cannot occur have been used. This has ensured that the PV production estimations, done by the trained machine-learning model, do not consider potential periods where curtailment could have occurred.

In order to detect PV curtailment periods (see Figure 6) the following conditions are considered:

- Full house battery (SoC data values corresponding to 100%) and
- PV production value is greater than measured electricity load.

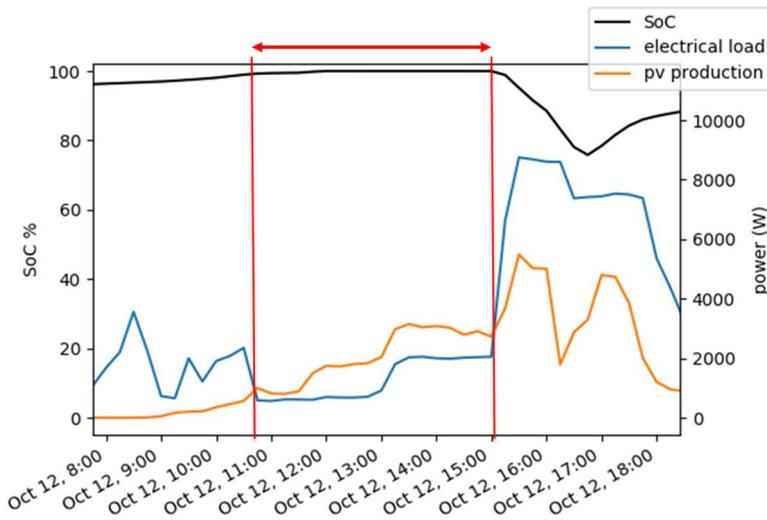


Figure 6: A time segment where curtailment may occur

To summarize, the analysis of the potential curtailment of PV production consists of three steps:

1. Train the machine-learning model using only the time segments where PV production curtailment cannot occur;
2. Use the machine-learning model to estimate the non-curtailed PV production, and generate the estimated PV production data;
3. Compute the volume of PV produced energy curtailed as the difference between machine learning model generated PV production data and the PV production measured data.

Figure 7 shows shows the difference between machine learning models generated PV production data (curtailment fixed) and the PV production measured data (original) considering a single day.

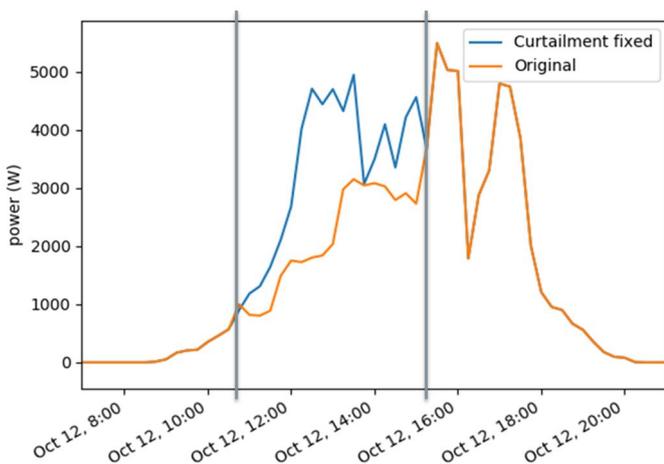


Figure 7: Measured PV production curve (original) and the machine learning generated PV production curve



STORY

In this example, input measured data from a full year period (considering only the periods, when curtailments do not occur) is used to train and evaluate the machine-learning model. The accuracy of the machine-learning model depends much on the data used to train the model. In this certain case, the mean absolute error of the predicted values by the trained model is approximately 0.03 (i.e., 3% of the maximum value).

Then, the trained machine-learning model is used to fix the curtailed PV data values. By using the predicted PV production values, the effects of curtailment is approximately 179 kWh/year, while the yearly measured PV production is 8195 kWh based on the measured input data. Therefore, after the correction, the PV production in this case is approximately 8374 kWh.

2.1.2.2 Comparison of the proposed control systems of electrical system

The NZEB electric system consisted of PV/T panels, a power grid connection, a stationary battery and two electric vehicles as well as other household loads that we considered uncontrollable. For details, see the description of the NZEB electric system described in Deliverable 3.4.

Table 5 summarizes the outcomes of one-year control using the two models - one with fixed charging power and another with varying charging power of the electric vehicles. The assumed fixed charging powers of the two electric vehicles are 3.5 and 7.0 kW. In addition, the table shows the results obtained using identified actual behavior data. The same table provides a sensitivity analysis with respect to different sizes of the battery electricity storage system (BESS) and the PV/T system. The sizes of installed equipment are 10 kWp of solar (PV/T) panels and 32.2 kWh of effective energy storage.

The total identified consumption of the two electric vehicles amounted to 3567 kWh and other uncontrollable consumption - 13009 kWh. The electricity price used in the calculation of the costs are the local electricity rates: 0.2899 €/kWh during the night and 0.3079 €/kWh during the day.

Table 5: Performance of studied models for control of electrical system of NZEB

PV, kWp	BESS, kWh	scenario	Energy from Grid, kWh	Curtailed Energy, kWh	Annual Energy Cost, €	PV, kWh
20	64.4	varying	5408.1	4549.5	1594.7	16390.2
		fixed	5467.0	4545.4	1614.4	16390.2
	32.2	varying	5606.1	4791.8	1653.2	16390.2
	64.4	actual	5613.1	4570.7	1653.4	16390.2
	32.2	fixed	5705.9	4827.7	1686.1	16390.2
		actual	5976.8	4998.1	1760.3	16390.2
	16.1	varying	6044.0	5309.7	1782.5	16390.2
		fixed	6234.3	5456.3	1844.7	16390.2
		actual	6766.3	5929.8	1994.7	16390.2





STORY

PV, kWp	BESS, kWh	scenario	Energy from Grid, kWh	Curtailed Energy, kWh	Annual Energy Cost, €	PV, kWh
10	64.4	varying	8843.8	97.4	2613.3	8195.1
	32.2	varying	8919.7	181.0	2636.4	8195.1
	64.4	fixed	8937.6	89.7	2637.2	8195.1
		actual	8958.6	91.0	2652.7	8195.1
	32.2	fixed	9023.3	181.5	2663.3	8195.1
	16.1	varying	9019.0	298.2	2667.0	8195.1
20	0	varying	9009.0	8803.0	2670.6	16390.2
10	32.2	actual	9037.7	184.0	2678.3	8195.1
	16.1	fixed	9130.7	308.6	2696.6	8195.1
		actual	9174.8	345.4	2721.6	8195.1
20	0	fixed	9410.2	9224.5	2808.4	16390.2
		actual	10453.1	10267.4	3104.0	16390.2
10	0	varying	10897.1	2507.9	3233.4	8195.1
		fixed	11236.8	2856.1	3366.4	8195.1
		actual	11717.1	3336.3	3492.3	8195.1
5	32.2	varying	12552.7	0.0	3727.0	4097.5
	64.4	varying	12552.7	0.0	3727.0	4097.5
	16.1	varying	12552.7	0.0	3727.0	4097.5
	32.2	fixed	12605.9	0.0	3740.8	4097.5
	64.4	fixed	12606.0	0.0	3740.8	4097.5
	16.1	fixed	12603.0	0.0	3740.8	4097.5
		actual	12596.4	0.0	3762.5	4097.5
	32.2	actual	12596.4	0.0	3762.5	4097.5
	64.4	actual	12596.4	0.0	3762.5	4097.5
	0	varying	12974.0	493.7	3856.8	4097.5
		fixed	13150.1	671.7	3927.6	4097.5
		actual	13265.8	787.5	3968.6	4097.5

The results suggest that existing battery is over dimensioned: for the PV/T system of the same size, halving or doubling the battery size leads to a maximum of 2 percent change in the annual energy costs. More significant annual energy cost savings appear to be possible when increasing the size of the PV system. For example, the results suggest that doubling the PV size would result in ca. 34 percent reduction in the annual energy cost. The results show that with larger solar power installations, curtailment of significant amounts of PV output may prove economically justified with the existing electricity pricing scheme, with zero price for exported electricity.



3 DEMO1

3.1 Demo1: Part B, Demonstration of controls for the other buildings in Oud-Heverlee

3.1.1 Introduction

The demo 1 is about the residential demonstration in Oud-Heverlee, Belgium. There are multiple houses with electricity production using photovoltaics, heat production using heat pumps and gas burners and fuel cells along with battery storages.

A model predictive control (MPC) algorithm is developed by *Actility* based on the mixed integer linear models of the controllable systems. The concept to use MPC is to show the benefits of the storage integration in buildings. It is done by demand-side management and peak shaving.

The control algorithm is developed to perform demand-side management and peak shaving by two methods: 1) using dynamic pricing and 2) minimizing the grid exchange.

In order to use such concept for the buildings and neighborhoods a simulation model is built in Python, Java and ThingPark Energy. The details of the controls algorithm are described in deliverable 3.4. Four-simulation period are considered to access the performance of the MPC algorithm. The simulation periods, methods, parameters and weather profiles are also defined in the deliverable 3.4. demo and control descriptions

3.1.2 Performance and evaluation of demo

The following Table 6: shows the buildings in the neighborhood. Particularly, the building indicated with color (numbers 1, 4 and 7) are part of this section. All these houses are heated by an electric consuming or producing source that can be scheduled by the advanced control (Model Predictive Control) to optimize a defined Use case.

Table 6:: Buildings studied for simulation and the available energy and storage sources

Number	House number	Battery	Heating	Electricity Production
1	143	-	Heat pump	-
2	133	-	Fuel cell	Fuel cell
3		-	Gas-fired burner	-
4	137	Battery possible	Heat pump	10 kWp PV
5		-	Gas-fired burner	-
6		-	Gas-fired burner	-
7	131	Battery possible	Heat pump	-
8		-	Gas-fired burner	3 kWp PV
9		-	Gas-fired burner	-
10		-	Gas-fired burner	-
11		-	Gas-fired burner	-
12	140	Battery possible	Heat pump	11 kWp PV

The simulation results are described in this chapter. For each scenario the key performance indicators (KPI) are discussed

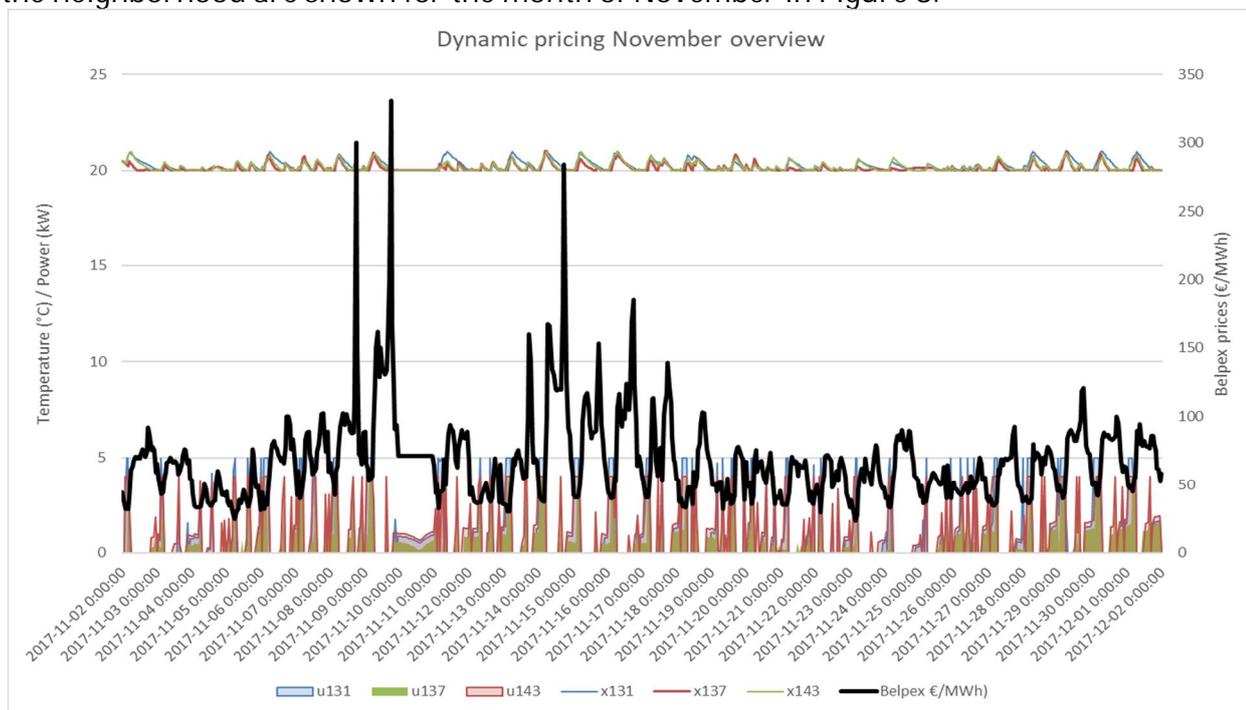
Following convention is used to discuss the results and figures.

- $u_{\langle component \rangle}$ refers to the power consumed by a flexible system. If the component is a single number, this represents a building heated by a heat pump. In all other cases, the suffix describes the flexible component. This variable is always expressed in kW.
- $x_{\langle component \rangle}$ refers to the state of the flexible system and follows the same suffix rules as for u . The state of the system is equal to a temperature in the building models, expressed in °C and an energy capacity volume, expressed in kWh, for both the boiler and battery models.

3.1.2.1 Dynamic pricing

The aim of this control is to reduce the energy cost of the flexible component while considering the thermal comfort of the buildings. The buildings are pre-heated when the energy prices are low, while heating is delayed as much as possible during high-energy prices hours.

The energy price, energy consumption of the heat pumps and indoor air temperature of buildings in the neighborhood are shown for the month of November in Figure 8.



u131 = Power consumption of the heat pump heating building 131

u137 = Power consumption of the heat pump heating building 137

u143 = Power consumption of the heat pump heating building 143

x131 = Indoor temperature of building 131

x137 = Indoor temperature building 137

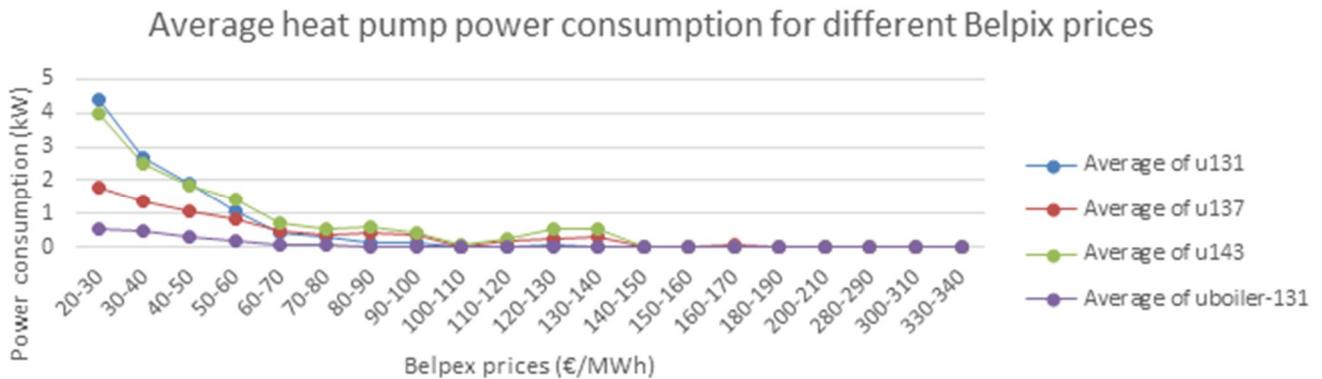
x143 = Indoor temperature building 143

Figure 8: Buildings energy consumption, indoor air temperature and energy price during November



STORY

Another figure shows that the energy consumption of the components shifted towards the low energy price hours. Figure 9 shows the average power consumption of the heat pumps in the buildings during the month of November. The power consumption of the heat pumps are high during low energy price and low during high-energy price.



u131 = Power consumption of the heat pump heating building 131

u137 = Power consumption of the heat pump heating building 137

u143 = Power consumption of the heat pump heating building 143

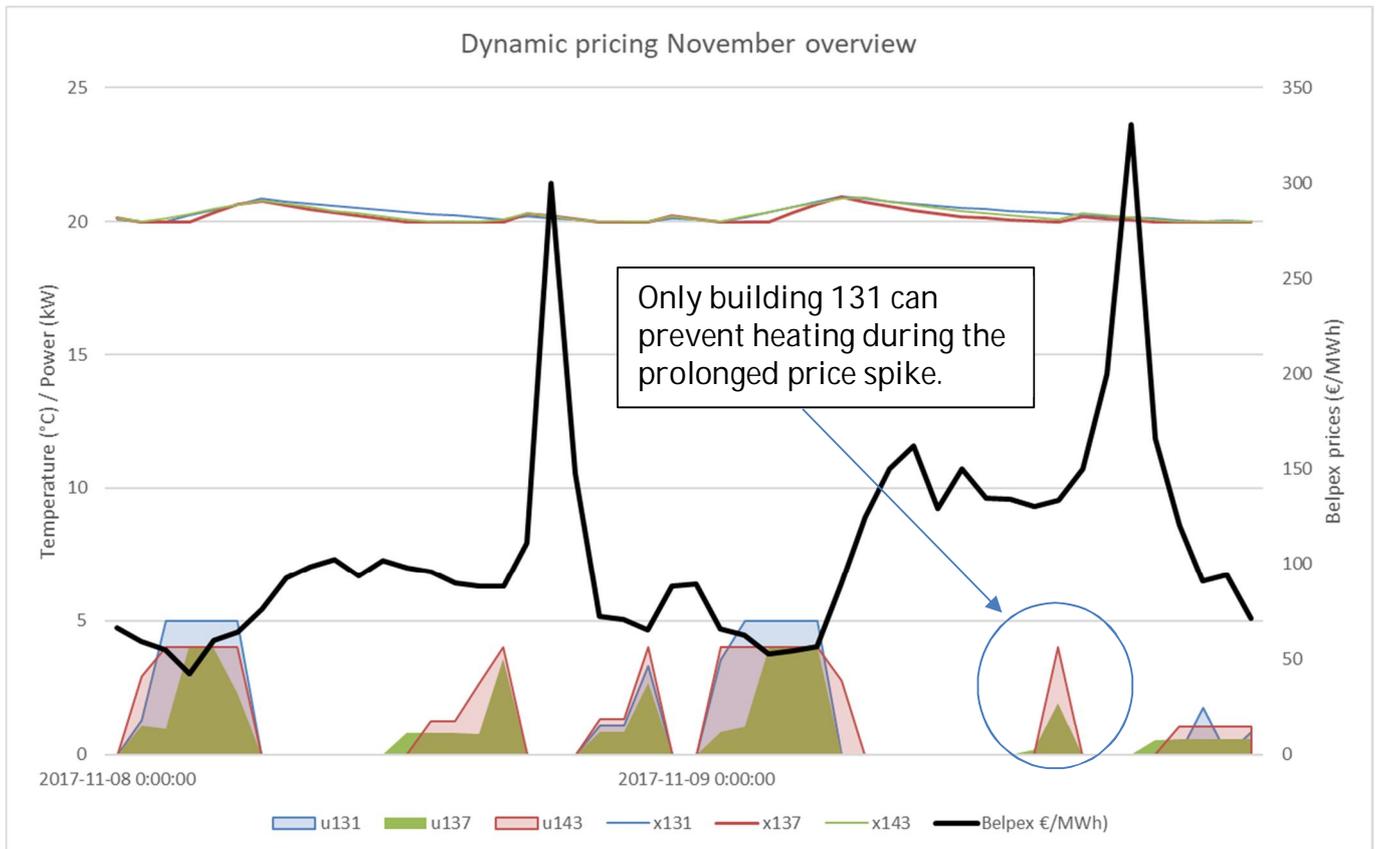
uboiler-131 = Power consumption of the heat pump heating the DHW storage tank in building 131

Figure 9: Average heat pump power consumption for different energy prices in November.

Similarly, another Figure 10 shows that during the high-energy price hours, the power consumption is low for the heat pumps, and during the low energy price hours, the power consumption is high. Moreover, the buildings with the hot water tanks and boiler control is able to shift the energy use for more than 12 hours, when the energy prices are higher than 80 €/MWh. Building 131 has the higher thermal mass and it is able to preheat the building during low energy price hours, allowing to shift the heat pump operation during high energy price hours.



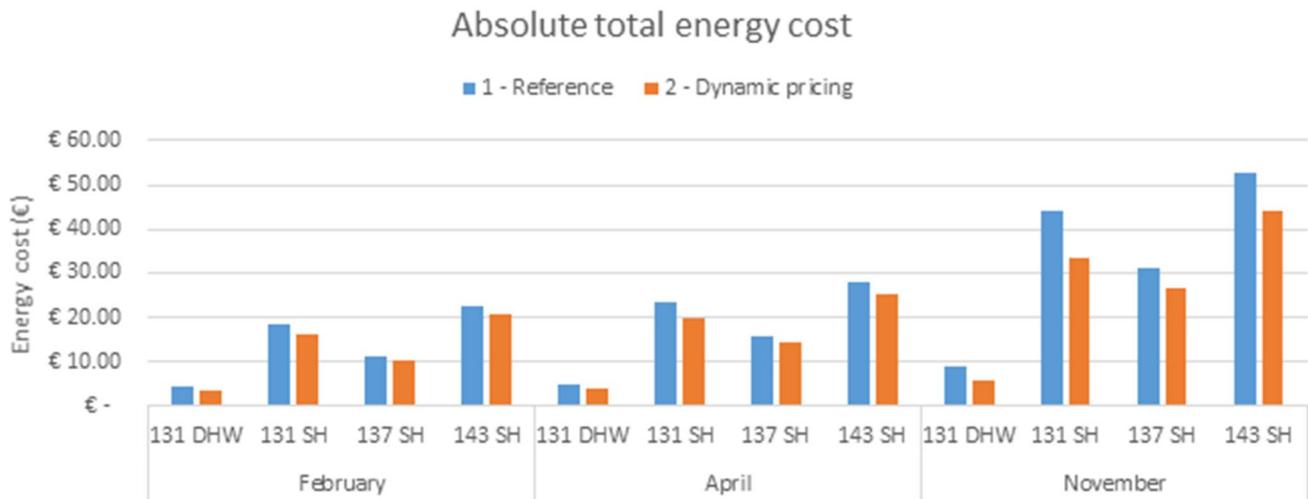
STORY



- u131 = Power consumption of the heat pump heating building 131
- u137 = Power consumption of the heat pump heating building 137
- u143 = Power consumption of the heat pump heating building 143
- x131 = Indoor temperature of building 131
- x137 = Indoor temperature building 137
- x143 = Indoor temperature building 143

Figure 10: Energy consumption profiles for buildings during varying energy price

When the dynamic pricing controller is compared against the reference scenario. It is observed that on an average 20% energy costs can be saved and can go up to 30% for the boiler during November as shown in Figure 11.



131 DHW = Flexible system consisting of a heat pump and a hot water storage tank in building 131

131 SH = Flexible system consisting of a heat pump and building 131

137 SH = Flexible system consisting of a heat pump and building 137

143 SH = Flexible system consisting of a heat pump and building 143

Neighborhood = Small neighborhood consisting of all components in the buildings 131, 137, 143 and 133

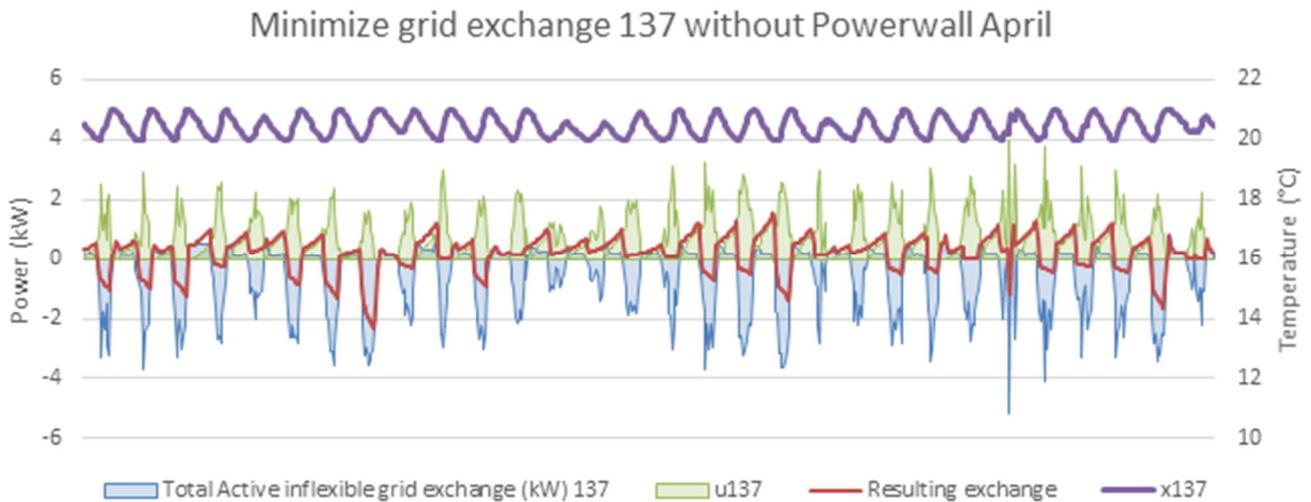
Figure 11: Energy costs comparison for the reference case and the dynamic pricing control case

3.1.2.2 Minimizing grid exchange for building 137

The minimize grid exchange use case focuses on minimizing the impact of the electrical consumption and production of a house or a neighborhood on the rest of the distribution grid. As this is a local problem, tariff schemes to incentivize this are hard to design and even harder to implement. The objective of this scenario is to minimize the exchange of power of the building 137 with the grid during a single hour. Two cases are formulated for the simulations, one with Tesla Powerwall battery and one without it. Figure 12 shows an overview of the flexible component (heat pump) without the Powerwall battery in April. Without the batteries, the flexibility of the house is used to its maximum potential, using heat pump. The heat pump consumption is delayed as much as possible to cut the largest peaks from the solar production. Note that the predictive nature of the MPC algorithm allows waiting for the moment on which the PV production is previewed to be maximal and ensure this injection peak is reduced.



STORY

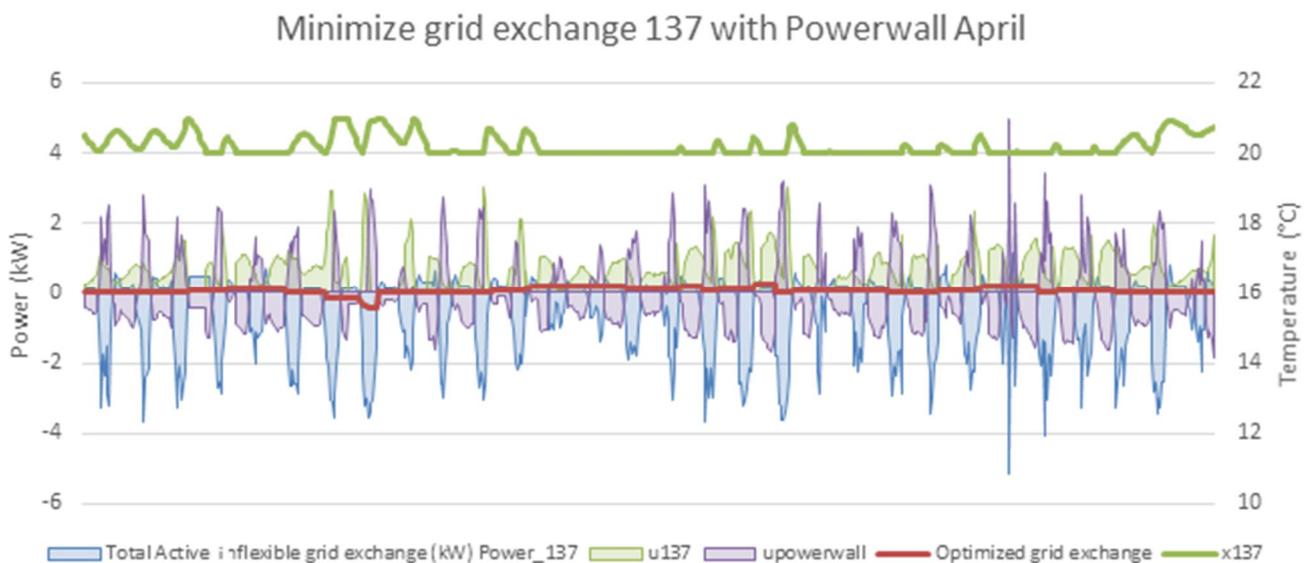


u137 = Power consumption of the heat pump heating building 137
 x137 = Inside temperature building 137

Figure 12: Overview of the month of April's flexible components (heat pump) without Powerwall battery

Figure 13 shows the flexible components (heat pump and Powerwall battery) behavior together in April.

Figure 13 shows that batteries could reduce the grid exchange to minimum or almost zero for each hour. The Powerwall battery has a large power capacity of 5 kW. The heat pump is used to shave the largest solar peaks but is mostly powered by the battery in a constant manner.



u137 = Power consumption of the heat pump heating building 137
 upowerwall = Power consumption or production of the Powerwall installed in building 137
 x137 = Inside temperature building 137

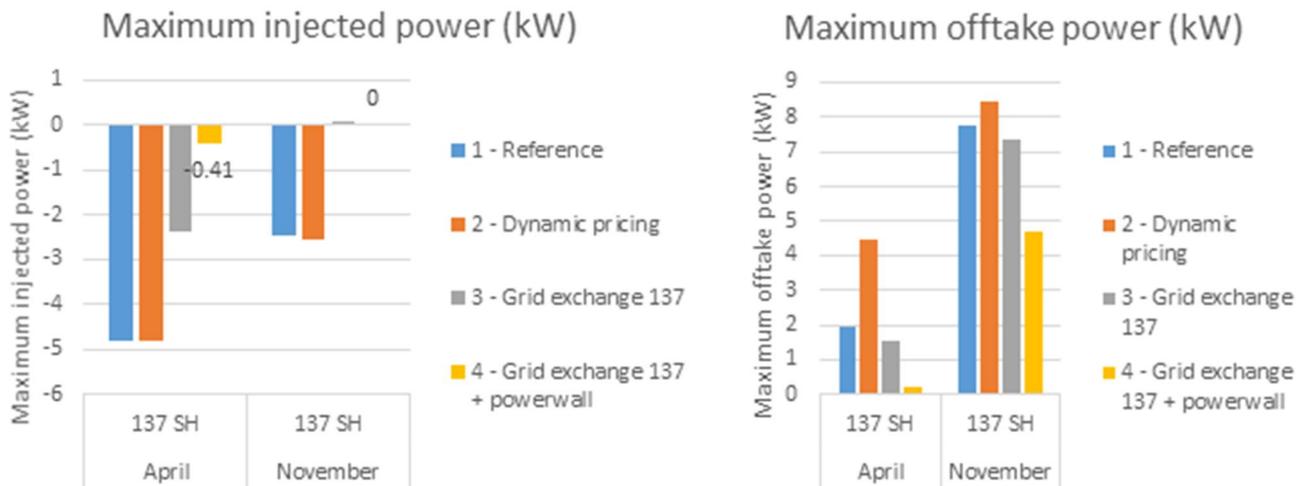
Figure 13: Overview of the month of April's flexible components (heat pump and Powerwall) together





STORY

Figure 14 shows that the injected power in April can be reduced by half by using MPC and can completely consume all energy injected on the grid in November by controlling the heat pump. By adding the battery, the building can almost nullify the grid exchange on an hourly basis during some months. The increase in the maximum offtake in April for the dynamic pricing case is due to the utilization of heat pump during high prices when solar energy is not available.



131 DHW = Flexible system consisting of a heat pump and a hot water storage tank in building 131
 131 SH = Flexible system consisting of a heat pump and building 131
 137 SH = Flexible system consisting of a heat pump and building 137
 143 SH = Flexible system consisting of a heat pump and building 143
 Neighborhood = Small neighborhood consisting of all components in the buildings 131, 137, 143 and 133

Figure 14: Maximum injected power and maximum offtake power during April and November

The difference in the results between April and November can be shown in Figure 15. Figure 15 shows the non-flexible grid exchange that happens during these months. In April there is more solar production compared to November. Therefore, November has large offtake peaks compared to April. During November, the batteries and heat pump must take the power from the grid when solar production is low.



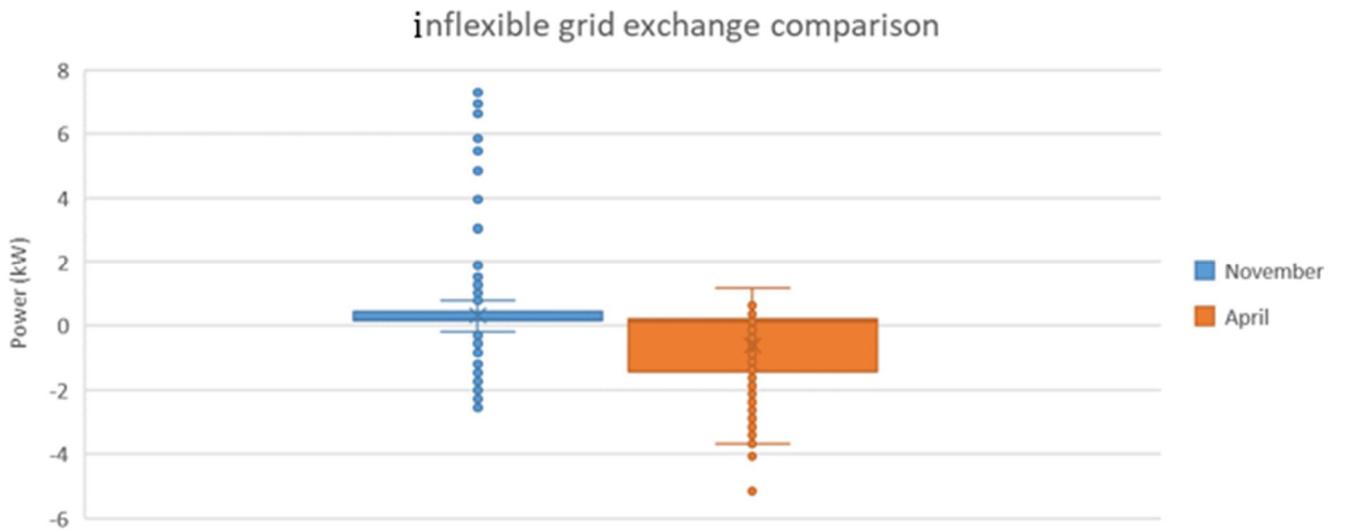
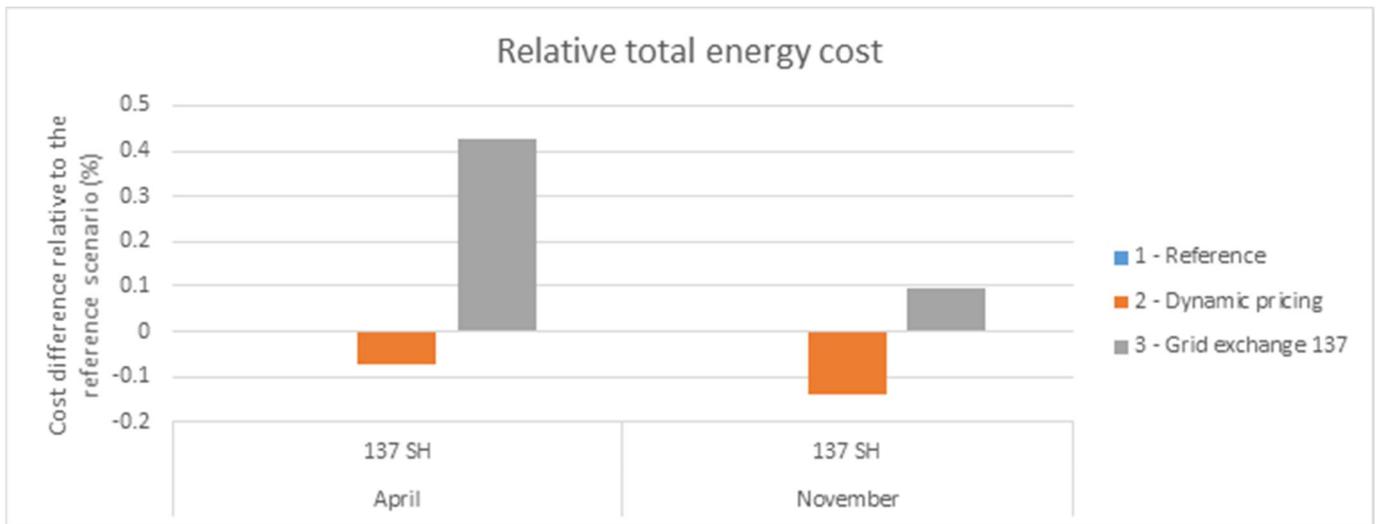


Figure 15: Inflexible grid exchange during April and November

Figure 16 shows the relative cost difference of the reference, dynamic pricing and grid exchange control scenario. It is important to note that no attention is made on the energy pricing when trying to avoid the grid exchange. When using grid exchange control, the cost difference relative to the reference scenario could reach up to 40% increase in the energy cost as shown in Figure 16.



- 131 DHW = Flexible system consisting of a heat pump and a hot water storage tank in building 131
- 131 SH = Flexible system consisting of a heat pump and building 131
- 137 SH = Flexible system consisting of a heat pump and building 137
- 143 SH = Flexible system consisting of a heat pump and building 143
- Neighborhood = Small neighborhood consisting of all components in the buildings 131, 137, 143 and 133

Figure 16: Relative energy cost difference between the reference case, dynamic pricing case and minimizing grid exchange case



4 DEMO2

4.1 DEMO2: Demonstration at residential neighborhood scale Oud-Heverlee, Belgium

4.1.1 Introduction

Figure 17 shows the neighborhood demonstration location in Belgium. Buildings 131 and 143 and their flexible components are added to the objective to minimize the neighborhood grid exchange. Furthermore, building 133 is added which has an almost constant electricity production produced by the fuel cell installed. The control algorithm developed in this demo is same as in Demo1 and explained in deliverable 3.4.



Figure 17: Neighborhood in Belgium under study for STORY [1]

4.1.2 Performance and evaluation of demo

In this case buildings 131 and building 143 (their flexible components, like heat pump, boilers and battery) are used as an example to study the impact of using the controller that can minimize the grid exchange of the neighbor. Moreover, building 133, which has a fuel cell and can produce electricity

at a constant amount, is also added to the study. Figure 18 shows that the MPC can effectively control the grid exchange of the neighborhood using different flexibility sources of the buildings.

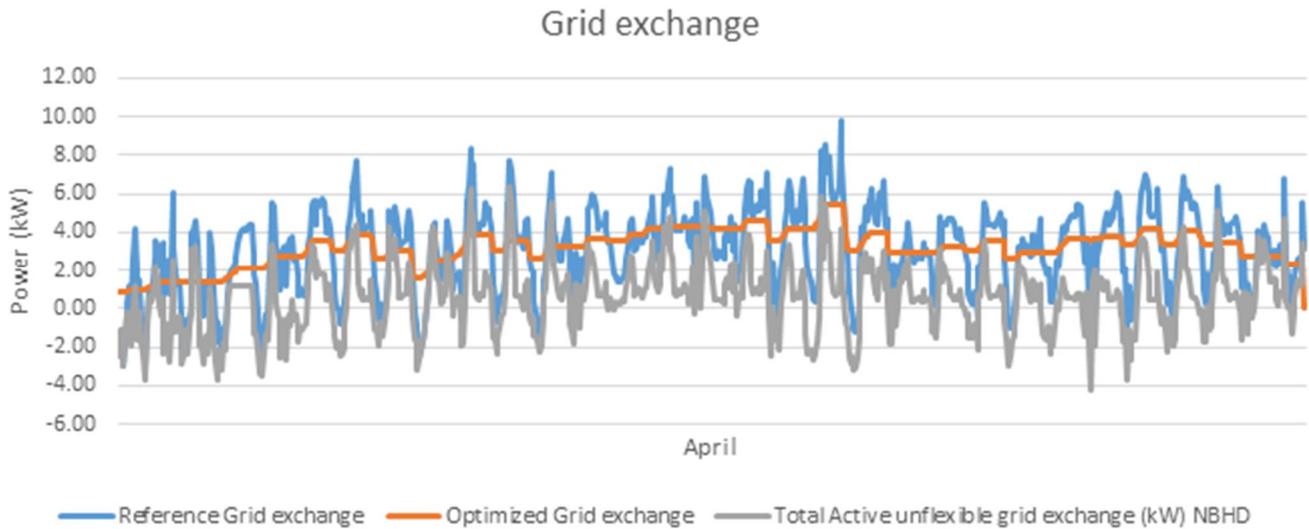


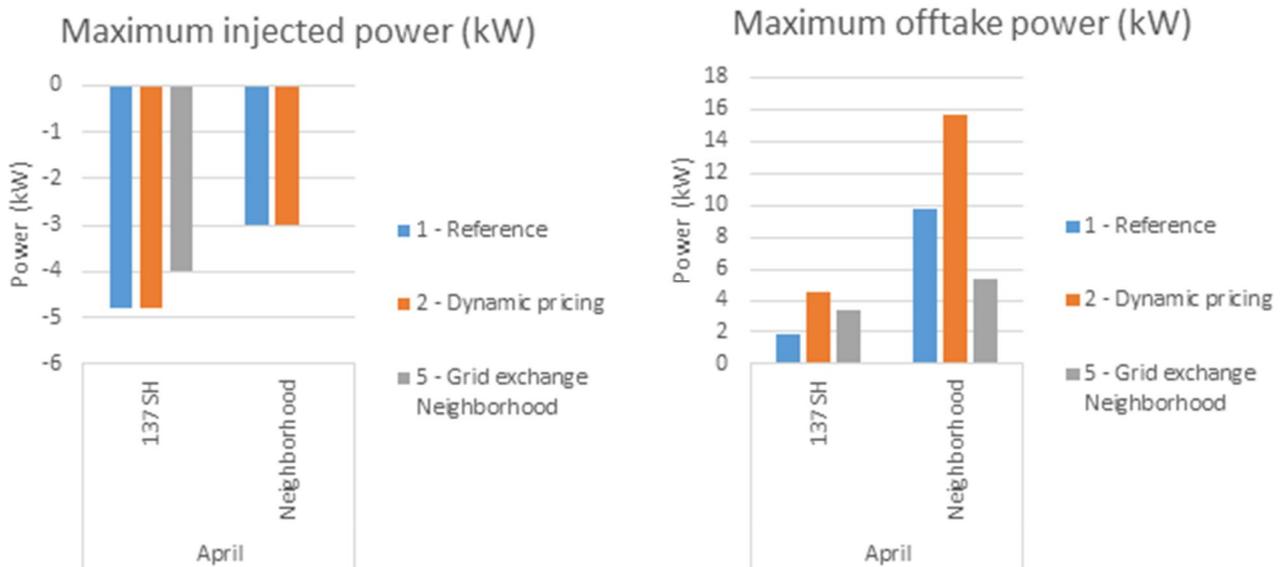
Figure 18: Grid exchange of the neighborhood in April.

Figure 19 shows that neighborhood can almost nullify the injection of the PV and fuel cell production into the grid by utilizing and scheduling the heat pumps, batteries and boilers. The maximum injected power is reduced by half as shown in Figure 19. This shows that by sharing or utilizing the neighborhood, the grid interaction can be minimized. Note that the joint objective for the neighborhood does not imply an improvement on the house level as well. For example, the maximum offtake of house 137 increases while that of the neighborhood decreases significantly. Another interesting result is the maximum offtake for the dynamic pricing objective. As every flexible component reacts in this scenario on the same price level, the consumption of the different components is heavily synchronized and results in three times the maximum offtake compared to the optimized grid exchange.

The MPC can take the dynamics of the houses, battery, and boiler into account and schedules the consumption based on the real-time operational limits. Therefore, it is hard to attribute the contribution of each component to a certain event.



STORY



131 DHW = Flexible system consisting of a heat pump and a hot water storage tank in building 131
 131 SH = Flexible system consisting of a heat pump and building 131
 137 SH = Flexible system consisting of a heat pump and building 137
 143 SH = Flexible system consisting of a heat pump and building 143
 Neighborhood = Small neighborhood consisting of all components in the buildings 131, 137, 143 and 133

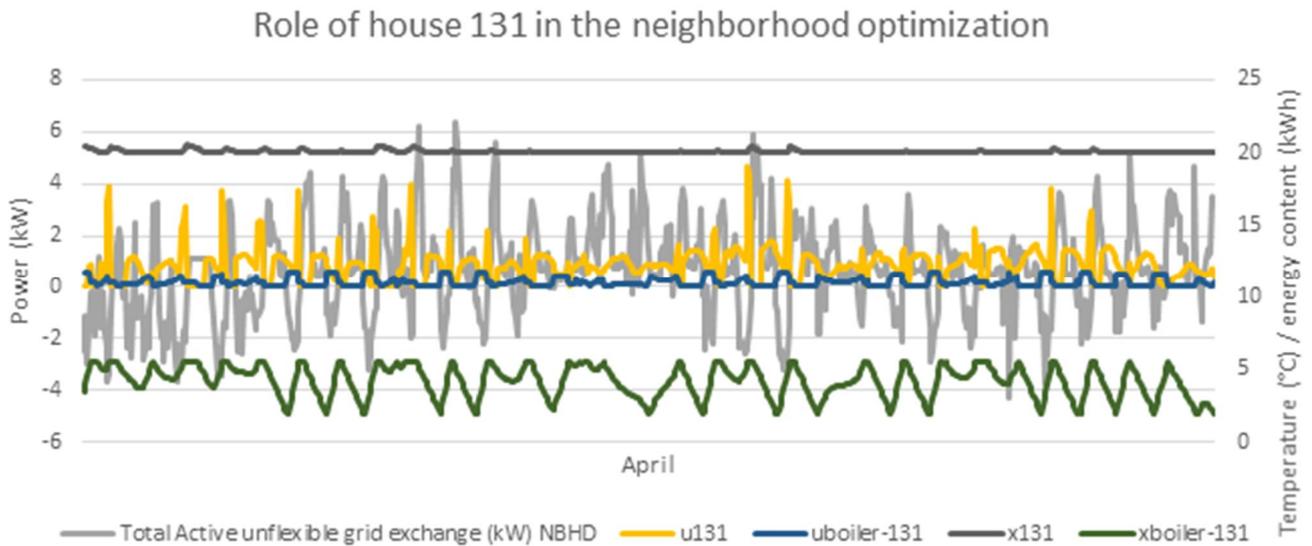
Figure 19: Maximum injected power and maximum offtake power of the building 137 and neighborhood

Figure 20 shows the importance of the flexible components in house 131 to minimize the grid exchange. The heat pump (u131) is mostly used to minimize the largest injection peaks while during the rest of the time the heat pump tries to keep the temperature close to the lower comfort limit to minimize the offtake. The boiler is kept within reasonable comfort boundaries and is never started together with the heat pump.





STORY



u131 = Power consumption of the heat pump heating building 131

u131-boiler = Power consumption of the heat pump heating the DHW storage tank in building 131

x131 = Inside temperature of building 131

xboiler-131 = Energy content in the boiler above the comfort boundary

Figure 20: Building 131 role in the neighborhood optimization



5 DEMO3

5.1 DEMO3: Demonstration of small scale battery to reduce peak power Navarra, Spain

5.1.1 Introduction

The demonstrator plant in Spain is located in Marcilla (Navarra, Spain) and belongs to STORY and EXKAL S.A. that provides technical advice to the Navarre Company GREEN RENOVABLES. The aim of this demonstration is to manage the Lithium-ion batteries integrated with the photovoltaics in order to reduce the peak demand of the factory as shown in Figure 21. The peak consumption of the factory is around 200-250 kW depending on the day. The factory has a photovoltaic installed on the roof, with a peak capacity of 112.7 kWp. The Lithium-ion batteries has a capacity of 180 kWh, with the corresponding convertor.

The concept in this DEMO3 is to reduce the peak power demand of the factory. This would allow reducing the contracted power from grid by utilizing photovoltaics and batteries in an efficient way. The detailed control strategy, methods, hardware, software and simulation parameters are described in detail in deliverable 3.4.



Figure 21: Photovoltaic and Lithium-ion batteries installed at Navarra, Spain demonstration site for STORY [1]

5.1.2 Performance and evaluation of demo

The system is designed and implemented on the simulation platform on a RT-LAB and the control algorithm control the operation set points build on JAVA.

Several cases are designed on the tested simulation plant system to identify the benefits of using storage and smart energy management system.

5.1.2.1 Case study 1

Figure 22 shows the basic management simulated results, when applied on the system. The fully charged battery, 100% is discharged and charged based on the balance between PV production and demand of the factory. Figure 22 shows the total active power and SOC of the Li-battery during a week in November 2015.

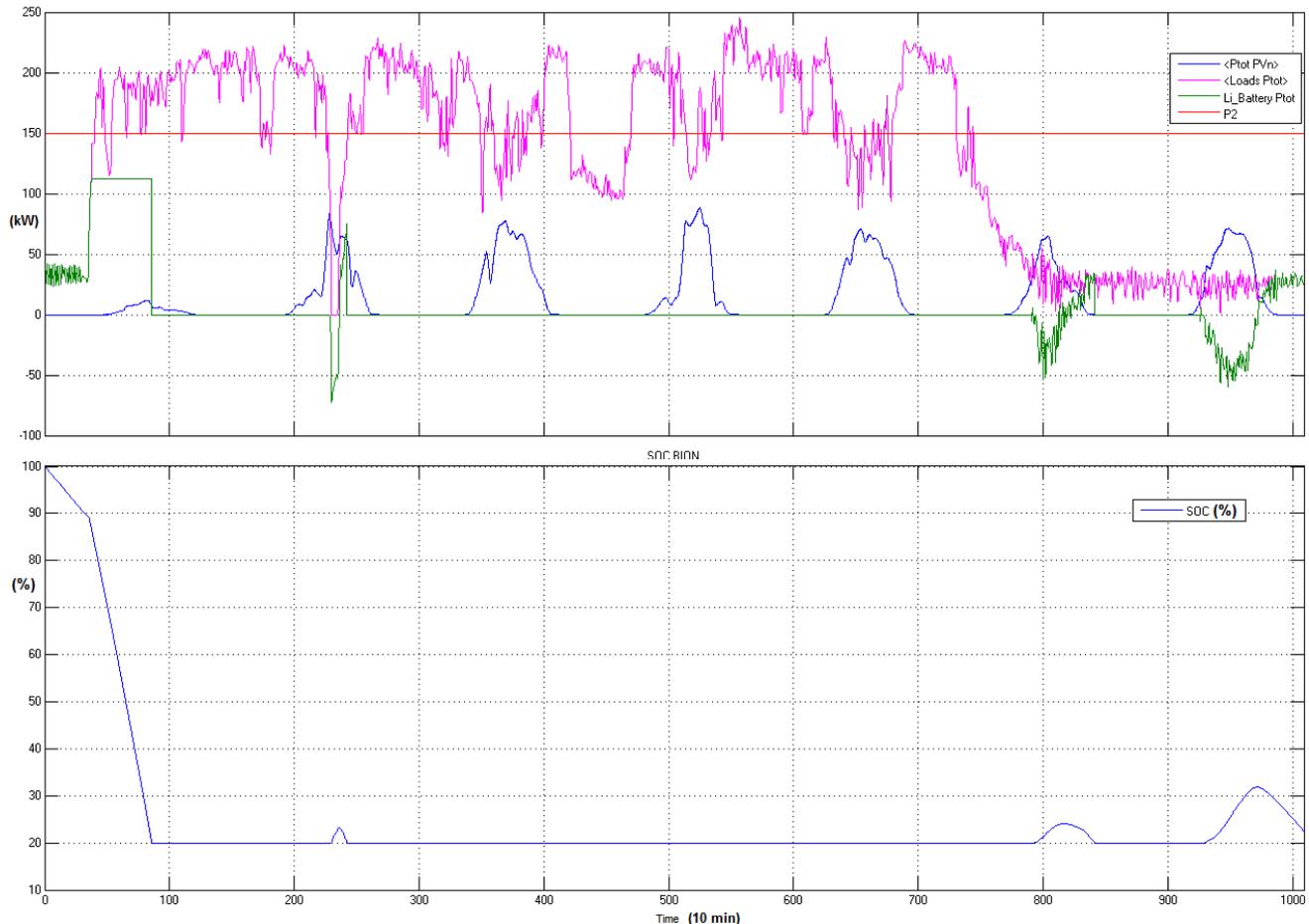


Figure 22: Power (PV generation, Load, Battery and P2) and SOC evolution (26th October-1st November 2015) of case study 1

The weather data is shown in Figure 23 for the year. The Figure 23 a) shows the solar irradiation and b) shows the monthly average ambient temperature.

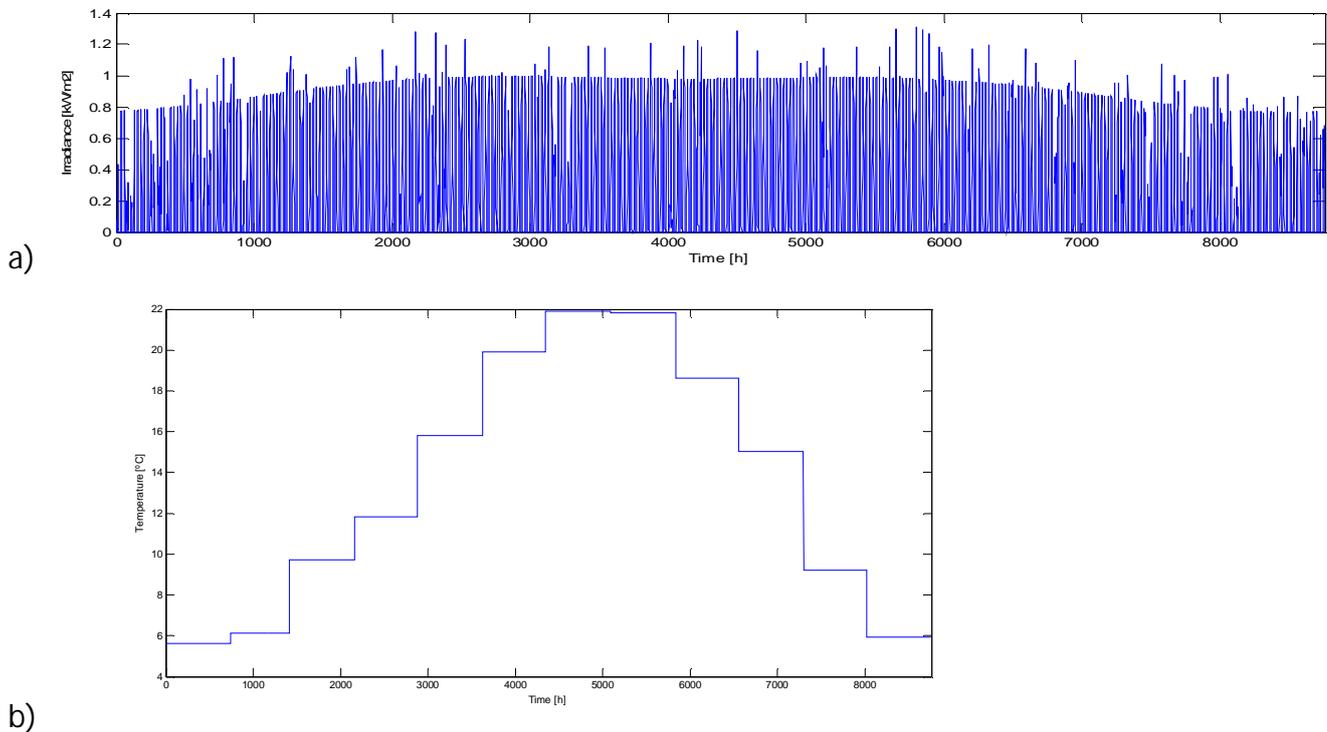


Figure 23: Meteorological data of one synthetic year: a) Radiance (W/m^2), b) Monthly Average Ambient Temperature ($^{\circ}C$)

Regulation only allows charging the battery with the PV energy produced locally, and excess of PV energy cannot be fed into the grid. The factory does not operate during weekends thus; the PV energy produced is stored in the battery and used as soon as is needed with the aim of reducing the demand charge. The stored energy generally can only cover the energy needs at the beginning of the week thus; the battery usually is discharged on Mondays.

In the following results, accelerated simulations are presented. In this case, one hour in real life equals to one seconds in the simulation. Over 365×24 real-life hours of data, 8760 points are collected. Data interpolation is applied to plot the results. In addition, reduction of the computational step time of the integrator solver is applied in order to compute in-between results.

The results collected over one year are presented by representative months and weeks shown in the figures as follow. Figure 24 and Figure 25 show the PV production, load and SOC of the batteries during the months of January and July respectively.

- Month: January

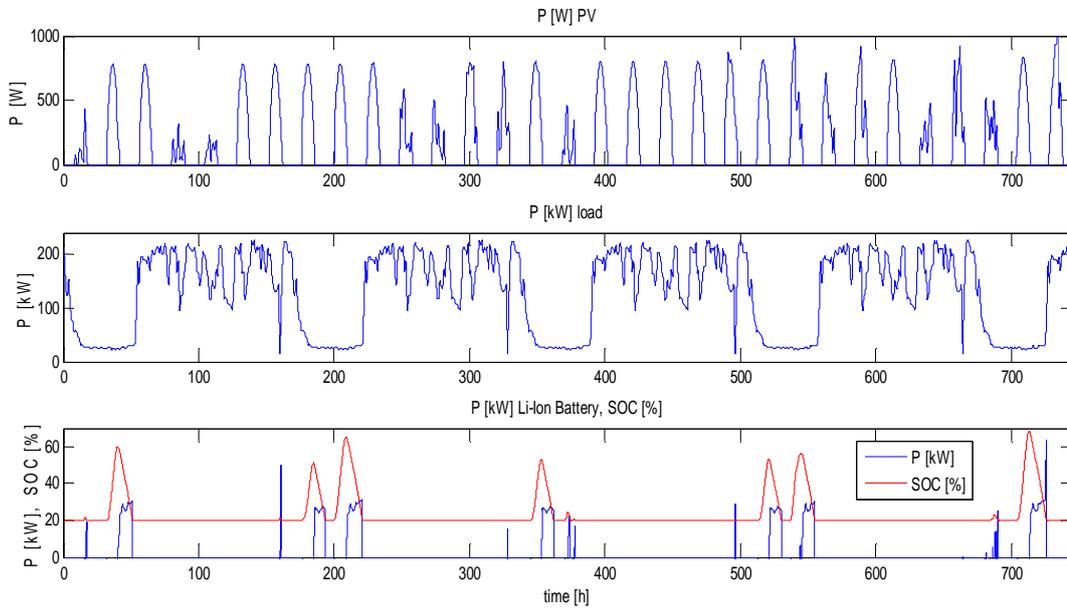


Figure 24: January: results of PV power, loads and Li-Battery active power and SOC

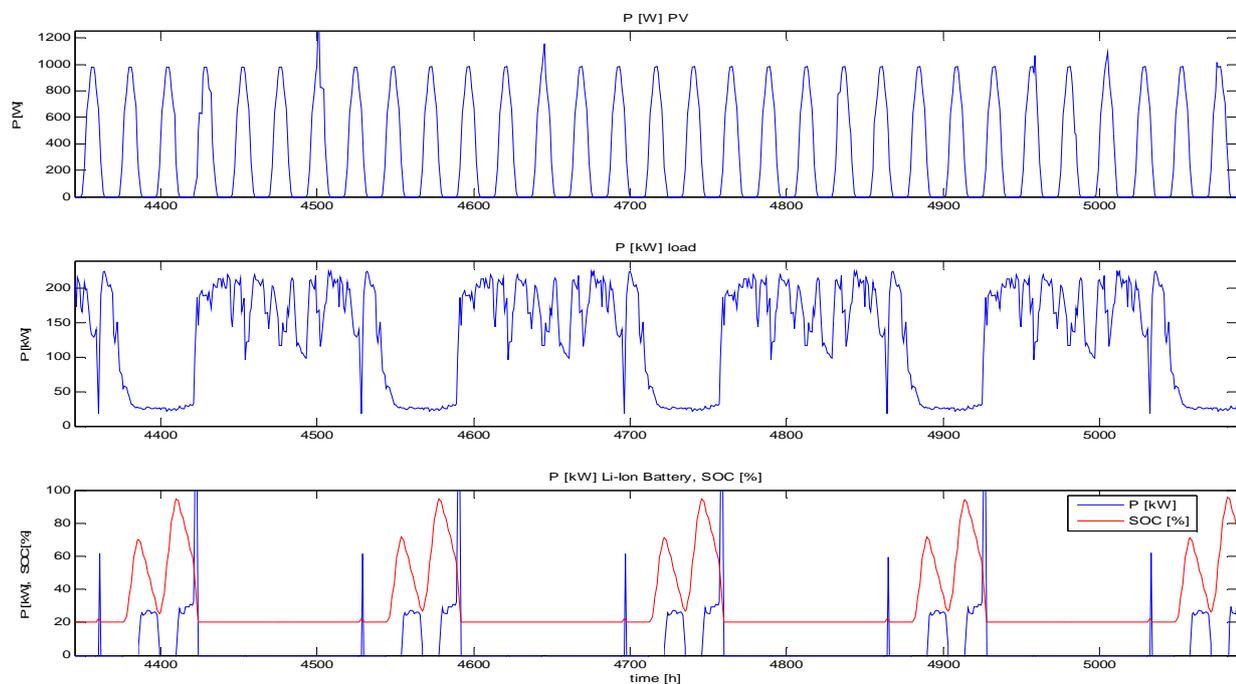


Figure 25: July: results of PV power, loads and Li-Battery active power and SOC

In Figure 26 the evolution of SOC is showed for the second week of July.

- Week: second week of July

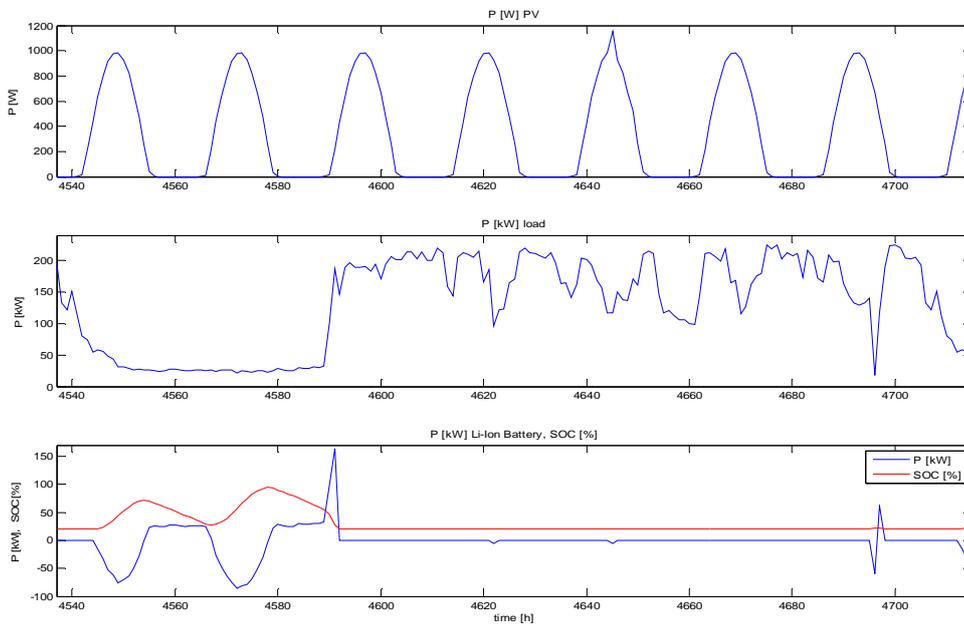


Figure 26: Second week of July: results of PV power, loads and Li-Battery active power and SOC

Figure 27 shows the annual results computed for the equivalent demand in 2015. The upper part of the figure shows the annual PV power production, the middle figure shows the power load over one year and the lower figure shows the operation of the battery (power and SOC).

- Annual

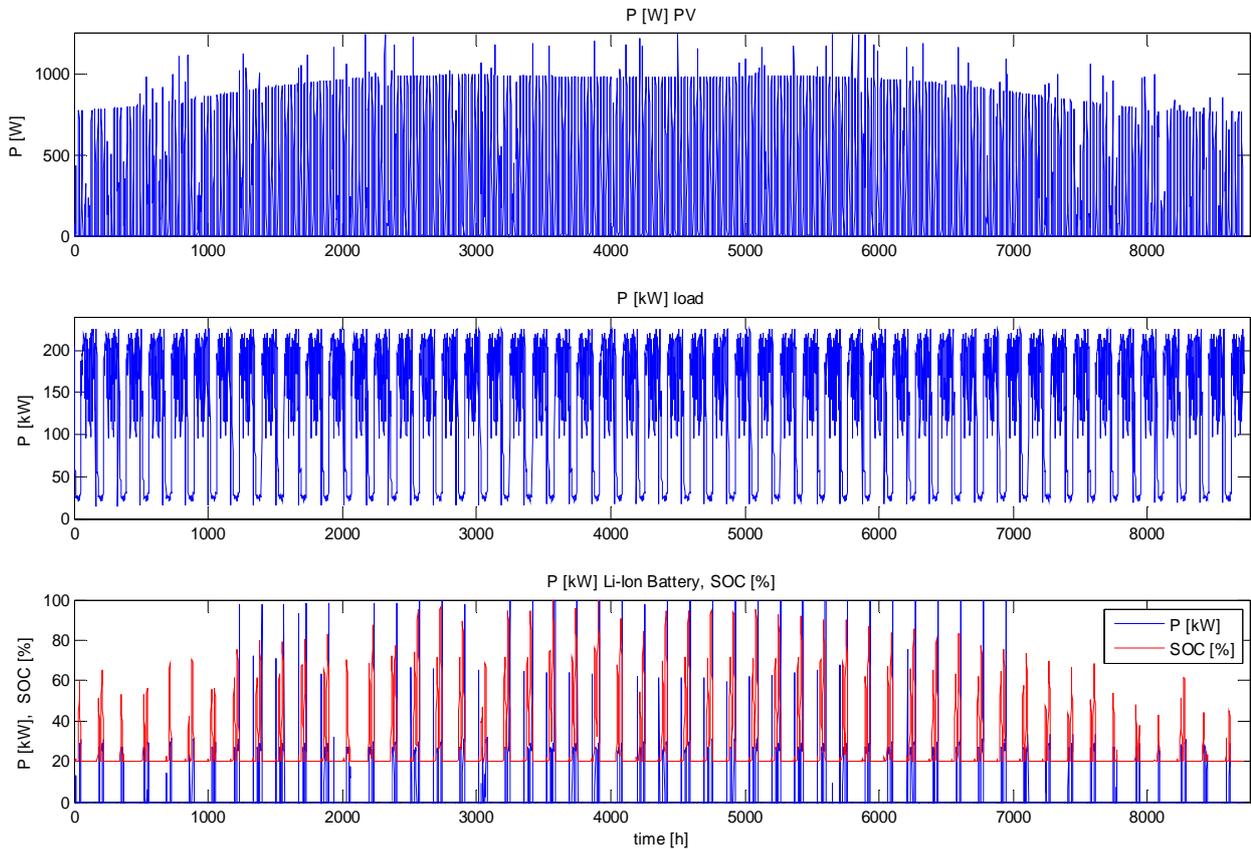


Figure 27: Annual results of PV power, loads and Li-Battery active power and SOC

In Figure 28 the analysis of the overall data are resumed reporting the maximum variation of SOC per month of the Li-Battery assuming generation and demand. To summarize, the maximum variation of SOC corresponds to July (59.75 %), and the poorest case happens in December (31.68 %) and January (31.77 %).



STORY

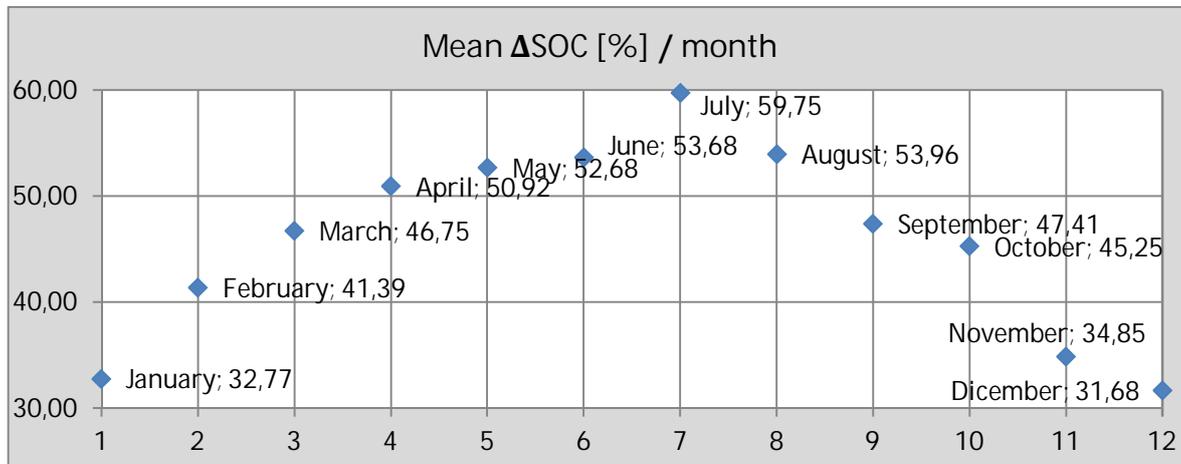


Figure 28: Analysis of the mean SOC [percentage] computed for each month of one year

5.1.2.2 Case study 2

New energy management systems (EMS) is developed by CENER that includes the forecasts of renewable generation and power demand in the standalone hybrid renewable energy systems and grid-connected hybrid renewable systems with storage. The aim of the project is to optimize the plant's operation cost. The goal of this specific control strategy is the reduction of the peak power demand through peak shaving with the minimal cost while giving priority to renewable energy source. Moreover, the commitment methodology applied in this strategy is designed to control the Li-Battery charge and discharge processes. The Li-Battery acts as a buffer for shaving the consumption in peak demand hours, as well as compensate the deviations of renewable generation and demand forecast from real generation and consumptions.

Two scenarios are created based on the working shifts and load demand profiles, based on the regulation in force in 2015 in which the Li-Battery is unable to store energy from the grid during the more convenient billing period.

- Case study 2: Scenario (i)- 3 working shifts

In this scenario with three working shifts, the advantage of the control strategy is tested without considering possible deviation from the forecasting. In this scenario the approximation between the real data and model are achieved. The set points are computed each 10 minutes of real time in accelerated mode during one week of simulation from 26th of September to 1st October 2015.

Starting from a complete charged Li-Battery (SOC=100%), the Li-Battery power set point value is established calculating the amount of power that the battery has to serve in order to avoid that a maximum power value (cut power) can be exceeded. The cut power of each period is calculated at the beginning of the month using the renewable generation and the demand profile predicted for the first seven days. If the cut power of any period is exceeded, the value of this new peak demand is set as cut power for this period.



STORY

The strategy aims to keep the peak demand of each period under the values of their cut power, giving a special priority to cover overconsumptions by the battery in the more expensive periods of the day. The cut power values computed for each different tariff periods, according to the economic tariff of the factory are presented in

Table 7.

The computation for the first case is made based on the loads of a week in 2015, when three working shifts take place from Monday to Friday. The demand curves of the plant and the SOC evolution of the Li-Battery along the registered week are shown in Figure 29. In this graphic, it can be observed that the demand profile predicted (pink curve) excess the cut power (purple curve) in some periods, being needed the use of the energy stored in the Li-battery to keep the demand under the cut power values.

Table 7: Values of power cut applied in case study 2, (i)

P Cut (kW)		
Valley	Flat	Peak
221	213	205

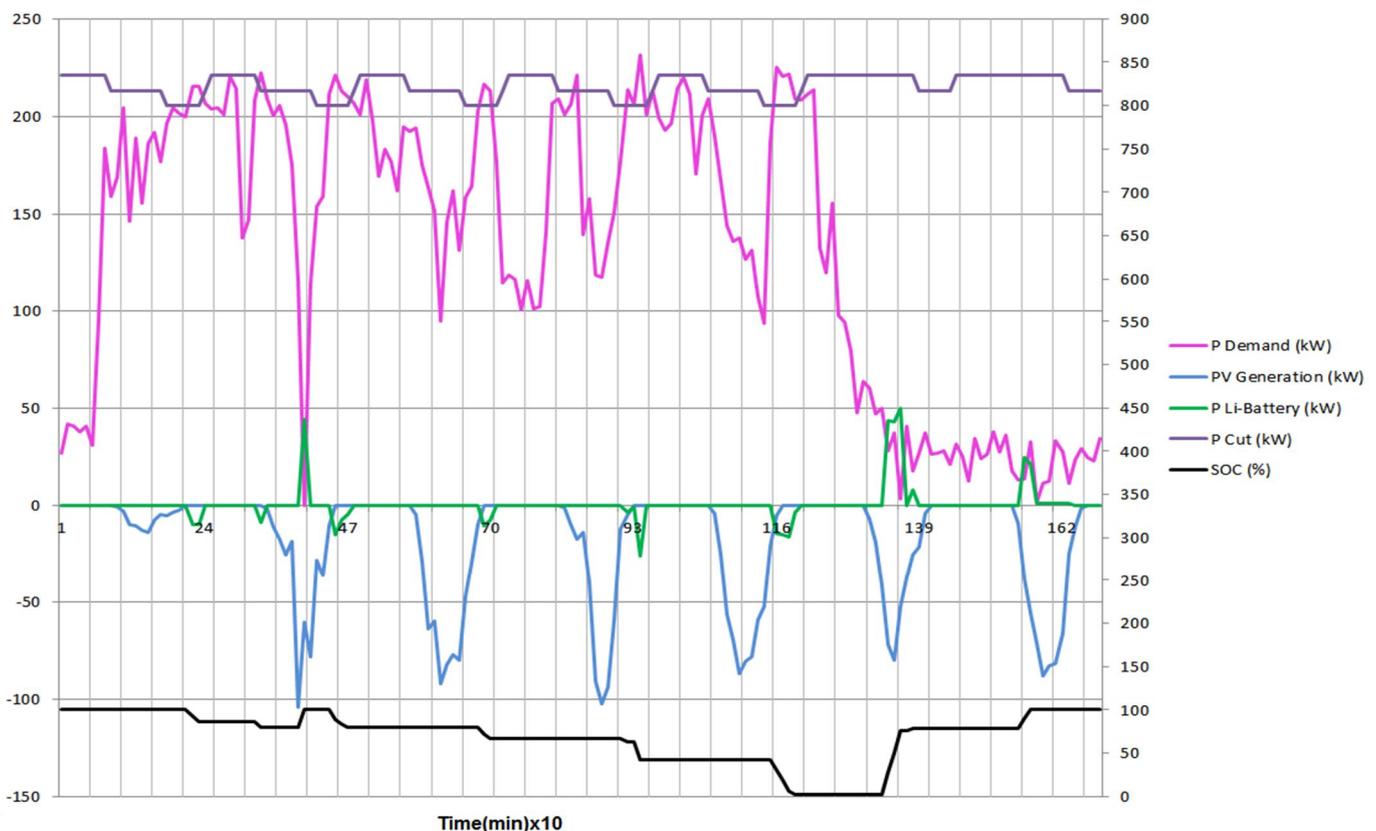


Figure 29: Power (primary Y-axis) and SOC evolution (secondary Y-axis) (26th October-1st November 2015) of case study 2, (i)

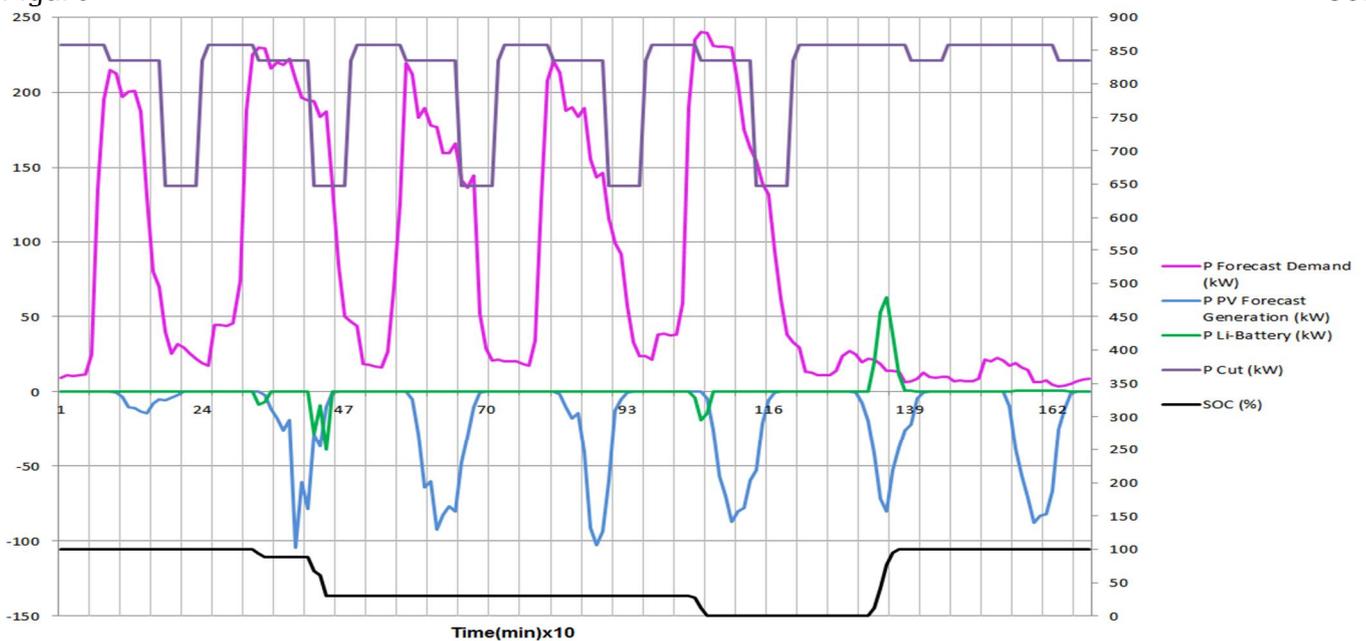




STORY

- Case study 2: Scenario (ii)- 2 working shifts

In the second scenario, two working shifts take place from Monday to Friday over 2013. In this scenario, simulations are obtained by applying the management that is predicting at the same time the demand and the forecasting. In addition, the set points are computed each 10 minutes of real time in accelerated mode during one week of simulation; from 28th September to the 3rd October 2013. The neuronal network is trained with 2013 available registered data. The results of active power demand, PV generation, power active and SOC of Li-Battery evolution over time are presented in Figure 30.



In this figure, the cut power values, that have been obtained as explained in the 1) case, are showed in violet. Besides, the cut power values at each different tariff period are resumed in Table 8. The results show that the energy stored increased by 5.7 % compared to the scenario (i), therefore the required power from the grid is decreased in the same percentage. Although the PV generation is around one third lower than the power demand, the battery is able to charge completely during the weekend.

Table 8: Values of power cut applied in case study 2 (ii)

P Cut (kW)		
Valley	Flat	Peak
231	221	138



STORY

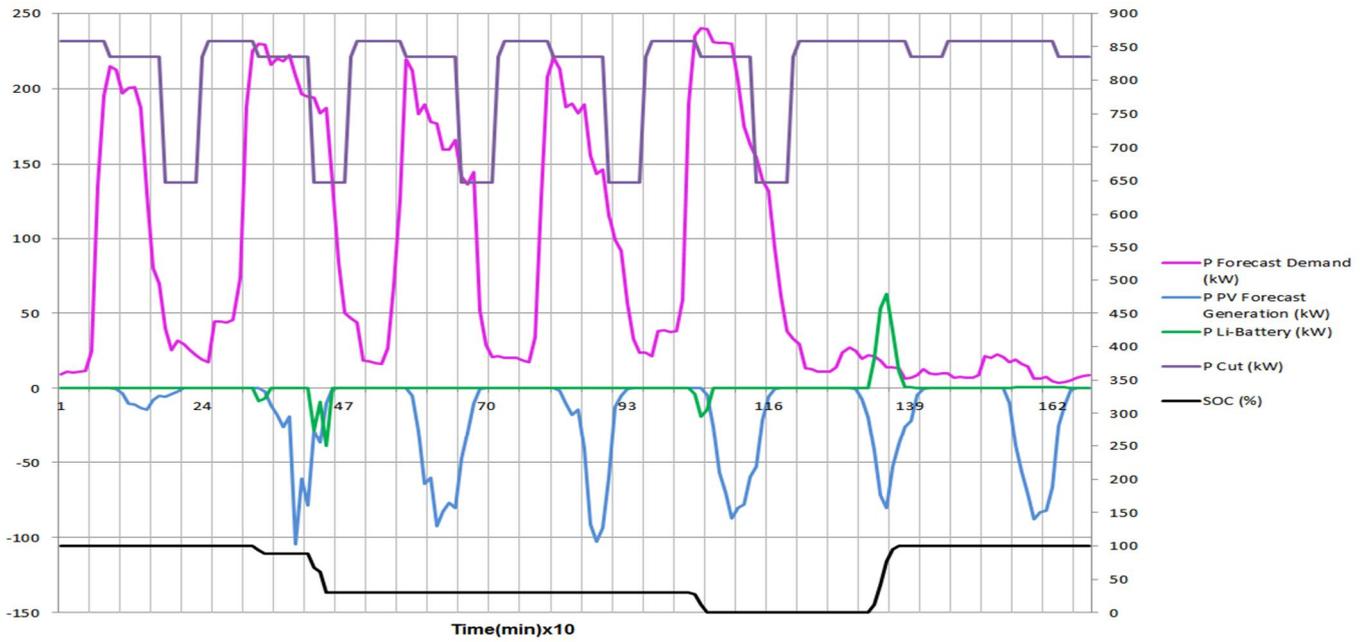


Figure 30: Power (primary Y-axis) and SOC evolution (secondary Y-axis) (28th October-3rd November 2013) of case study 2 (ii)



6 DEMO4

6.1 DEMO4: Demonstration in residential district - Lecale, Northern Ireland (UK)

6.1.1 Introduction

Figure 31 shows the layout of the district and how different energy generation and storage components are arranged. This demo shows the development of the compressed air storage integrated with the national electrical grid. The idea is to reduce the curtailment of the renewable energy generation (tidal and wind energy) in the district.

The case study in this project is to operate the system in a way such that three different benefits or revenues can be generated through this system.

- 1) Arbitrage - Buying electricity in the nighttime, when it is cheap and selling it during the daytime when it is high.
- 2) Load on demand - Balance load service to avoid curtailment of the wind turbines.
- 3) Generation on demand - provide electricity to the district when needed, to avoid overloading of the 33/11 kV substation in the conventional direction.

The objective of the demo is to create a control algorithm that will allow the renewable energy generation to operate even when there is a need to curtail them due no demand and over production. The detail information about the control algorithm and other parameters are discussed in detail in deliverable 3.4.

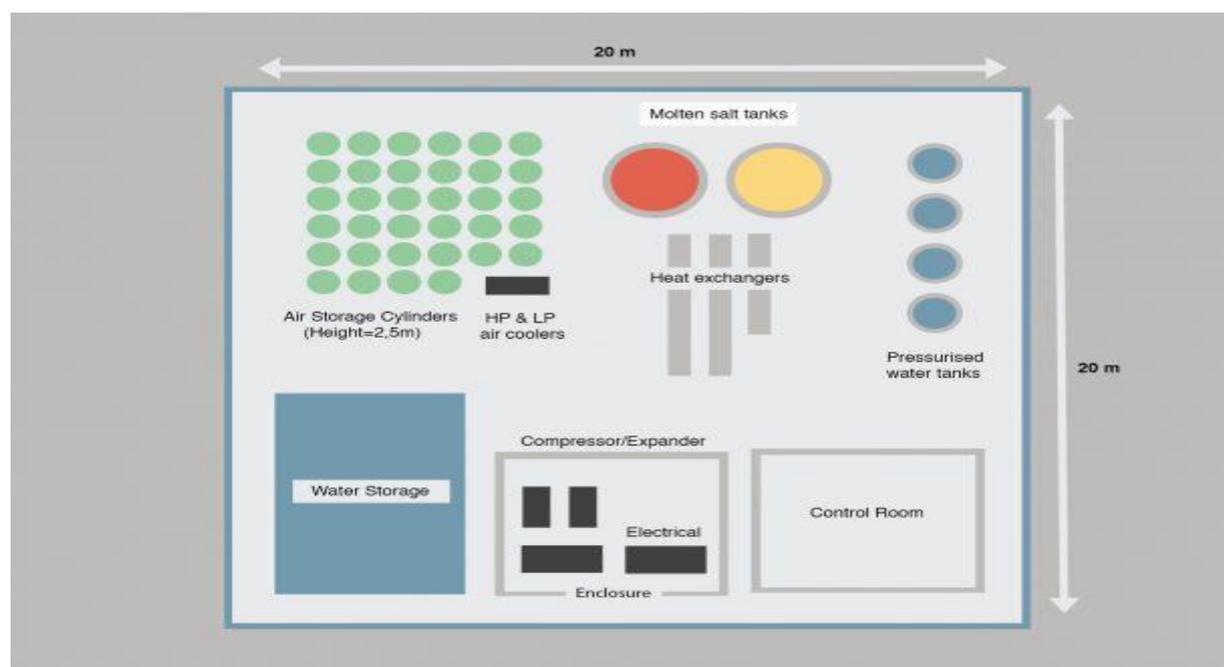


Figure 31: The illustration of the district and energy components layout [1]

6.1.2 Performance and evaluation of demo

Table 9 shows the profits during the months when the system is tested for the whole year. By simulating the novel control algorithm of shifting the generation, using Day Ahead Scheduler and predictive controller the yearly profits increased. The arbitrage schedule, load on demand and generate on demand controls along with the simulation files are discussed in deliverable 3.4.

Table 9: Monthly and yearly profits using simulation

Month	Profit	Yearly_Profit	Gen_Shift_Profit	Yearly_Profit
January	5411.65	52020.01	5318.52	53003.73
February	5243.51		5472.31	
March	3920.65		4144.61	
April	3402.59		3418.52	
May	3725.68		3576.14	
June	3805.01		3667.99	
July	3794.46		3648.19	
August	3753.90		3660.77	
September	4164.03		4426.27	
October	5048.88		5327.85	
November	4693.28		4993.02	
December	5056.38		5349.55	

It is found that the revenues of the system can change from season to season. The controller is able to generate more profits when there is seasonal transition such as during autumn and winter. Whereas during spring and summer the profits are least.

7 DEMO5

7.1 DEMO5: Demonstration of flexible and robust use of medium scale battery - Slovenia

7.1.1 Introduction

A small-scale medium sized storage unit is built, that contains battery bank of 170 kW (450 kWh) for the demonstration of flexibility. This battery bank will operate with 1x 400 kVA OLTC MV/LV transformer station of Elektro Gorenjska supplying Suha village residential grid. While the second demo site is proposed to be, Elektro Gorenjska headquarters in Kranj. From 2018 onwards, the first demo site is in operation. The demonstration site 1, Suha village is shown in Figure 32.

The Suha village has seven PV power station as shown in Figure 32. There is 210 kWp of installed PV production in the LV grid. The goals of this demonstration is to:

- Easy integration of PV, grid and batteries
- Control and battery management
- Control of battery integration with PV and grid
- Maximize the efficiency of the decentralized energy systems
- Support PV production
- Impact on efficiency and payback period of the system
- High degree of self sufficiency
- Peak demand control within the daily load profile
- Reduction of line congestion

The detailed control strategy and integration of the PV, batteries and grid transformer is described in deliverable 3.4.

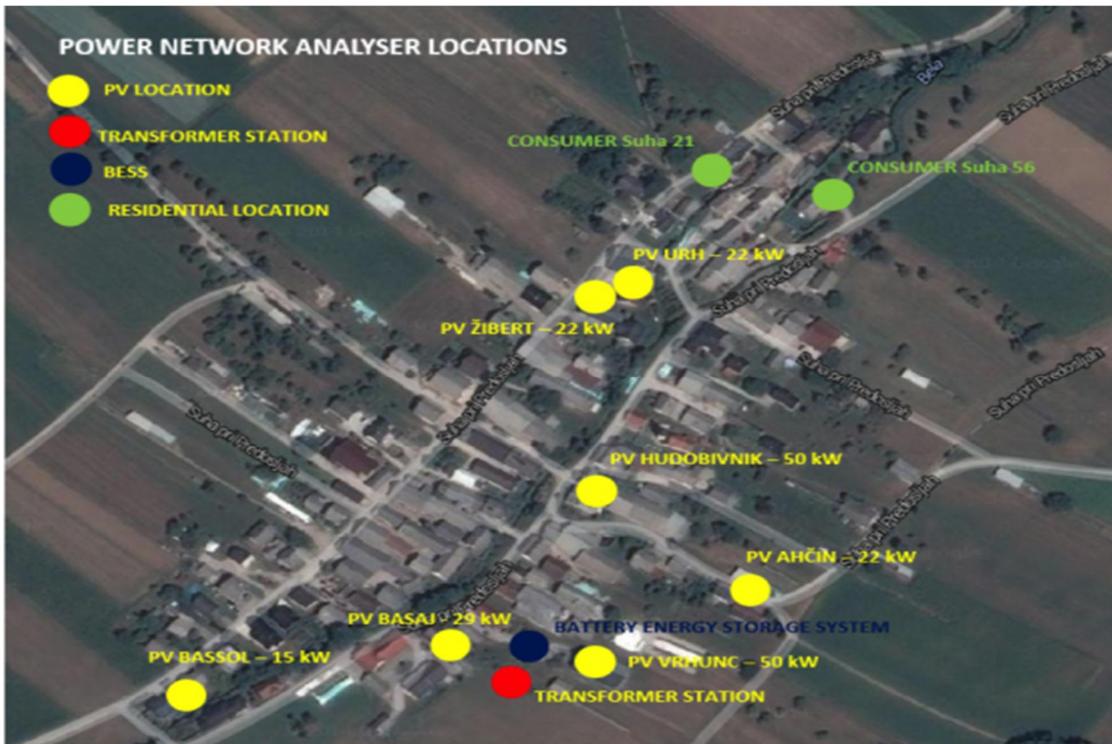


Figure 32: Demo5 demonstration site [1]

7.1.2 Performance and evaluation of demo

The solar radiation data generated from the Slovenian weather agency ARSO during 2016 and during 2017 is shown in Figure 34 and Figure 34 respectively.

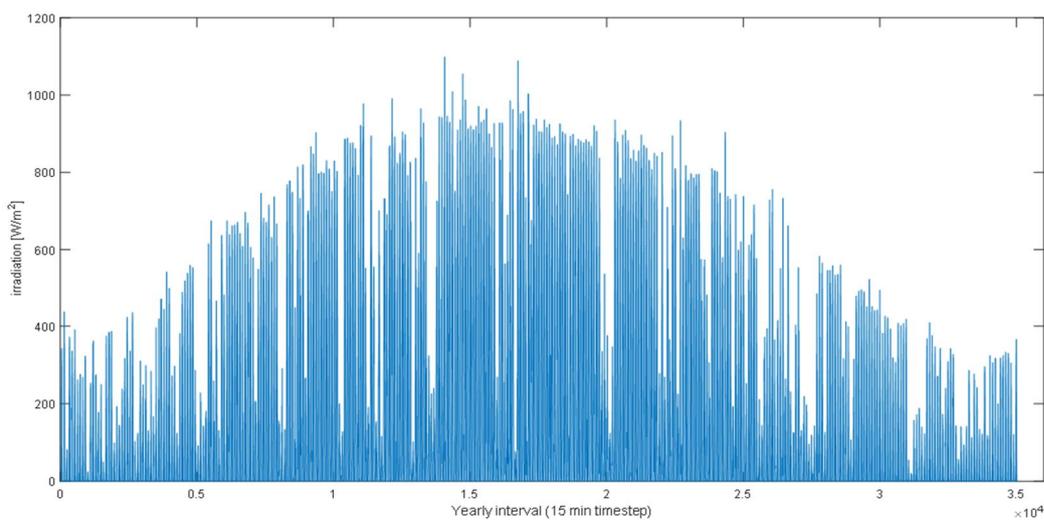


Figure 33: Solar irradiation level in 2016

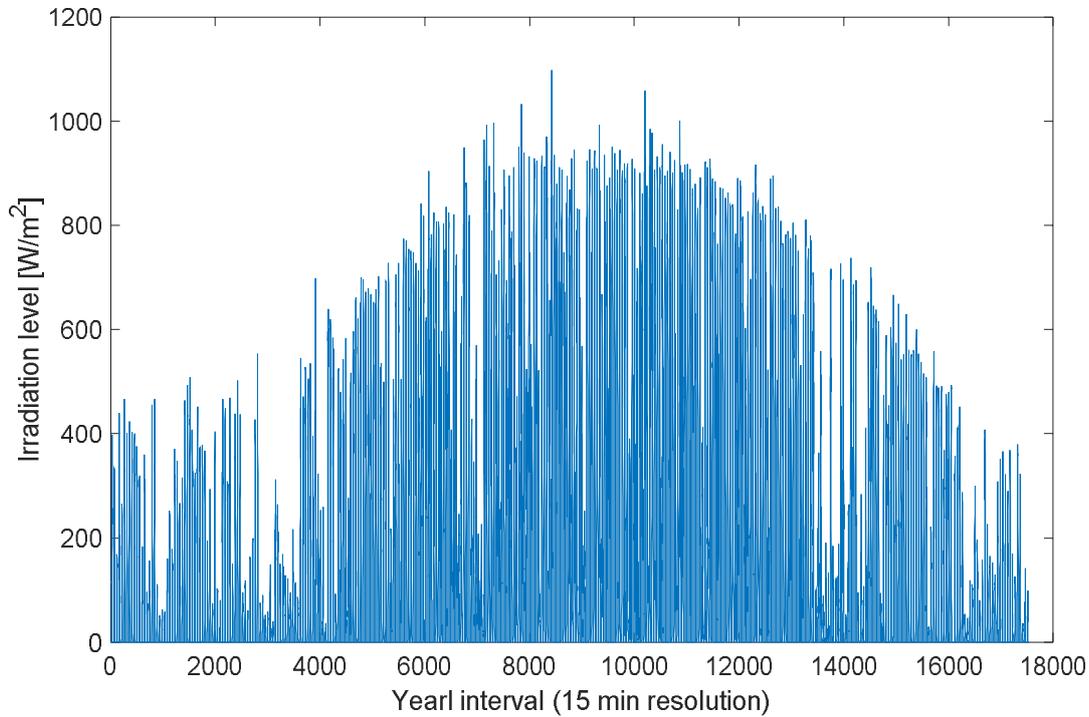


Figure 34: Solar irradiation level in 2017

Yearly measurements of the transformer active power flows for 2016 and for 2017 are shown in Figure 35.

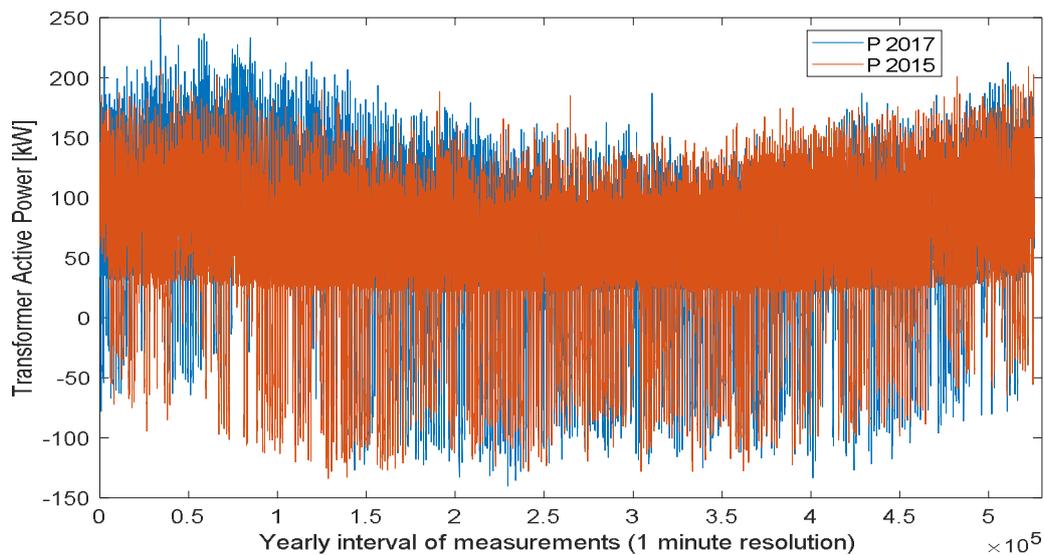


Figure 35: Active power flows in 2016 and 2017 comparison

Based on the solar irradiation data and transformer measurements for 2017 new database is created. It presents expansion from 16 available profiles to yearly database of 360 transformer profiles seen in Figure 36. Based on the received solar irradiation forecast, a most similar day in the database is selected with method of least square root deviation from the forecasted profile. Transformer profile database now allows more accurate selection of the profile and thus better-expected storage operation.

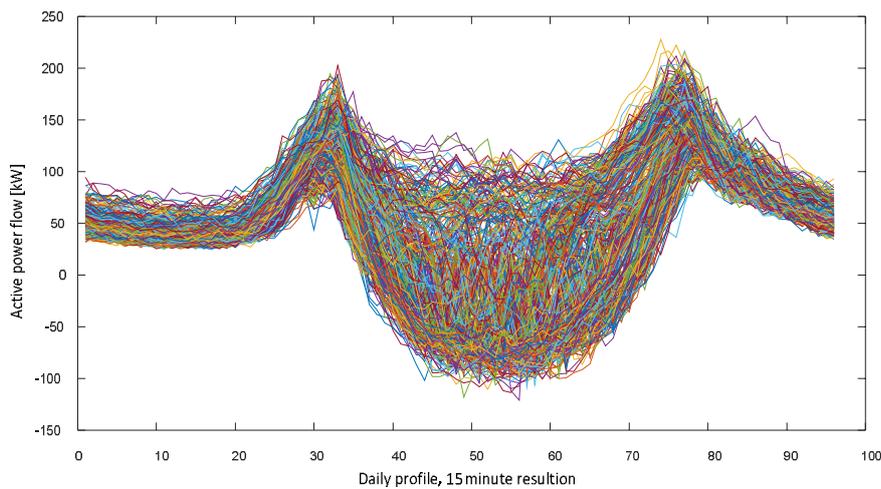


Figure 36: Yearly profile database of active power flows

7.1.2.1 Peak demand algorithm updates

In initial algorithm, based on solar forecast, one of the 16 stored profiles are selected for daily calculation. Daily thresholds are calculated based on SOC measurement; expect transformer power flows and storage operation. In the iterative process, maximal threshold levels are defined based on the storage limitations. In Figure 37 calculations are shown. These threshold levels are then applied in real time control and updated once per day at midnight. From discussion with the DSO and result, analysis algorithm is updated.

In updated version of algorithm, based on the received forecast, one of the 360 daily profiles are selected and it presented better fitting daily profile curve. Any process such as averaging or smoothing of the curve does not affect selected curve and thus it responded better to expected daily irradiation curve. As a result, forecasted transformer profiles are selected via more sophisticated method, and hourly deviations from ideal curve is easily matched and taken into account.

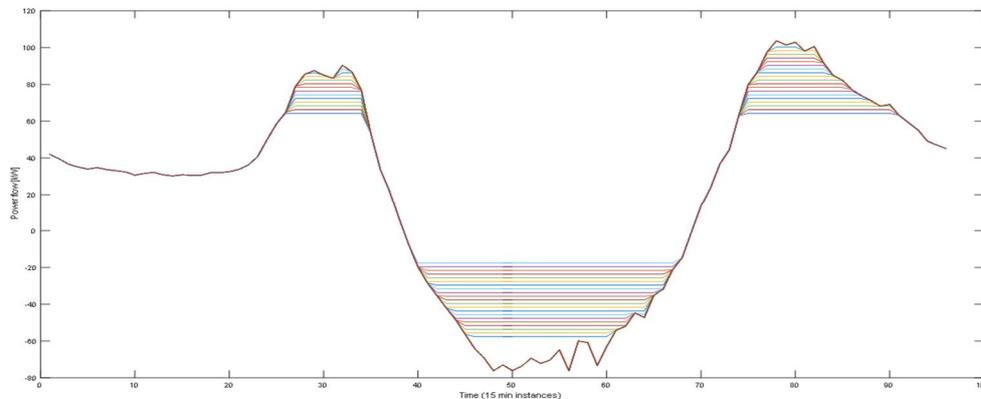


Figure 37: Initial iterative threshold process

- Forecast interval of 36 hours

After initial 24-hour forecast interval, 36-hour forecast is used. Based on this longer period, daily profiles are determined at midnight for coming day and day ahead. This brought additional calculation factors into the algorithm. Based on the expected solar energy in following day, morning discharge is calculated. This discharge allowed storage unit to charge from PV production surplus of energy during the day. Before the evening peak, storage is full or at least sufficiently charged from PV and reallocated SOC in the storage. Based on the expected evening peak, and day ahead profile, thresholds for evening discharge are calculated. In addition to this threshold levels, operation levels for day ahead are calculated as well.

- Addition of night charging

The batteries are also charged during the nighttime, in addition to PV charging capability during low radiation days. This allowed charging the batteries at full capacity for the daily morning peaks.

Two different scenarios are observed in Figure 38 and in Figure 39. The blue color represent the expected transformer power flow and the yellow color represent the state of charge (SOC) of the battery. The thresholds are calculated for each peak and resulting operation in orange line. If PV generation is expected to be surplus, the morning peak is shaved with the storage discharge and the discharged battery is charged with the PV generation.

In Figure 39, no PV production surplus is expected, and storage is recharged to low state of charge level. Almost no storage energy is available that day, and storage is charged during the night to allow operation of the storage in following day.

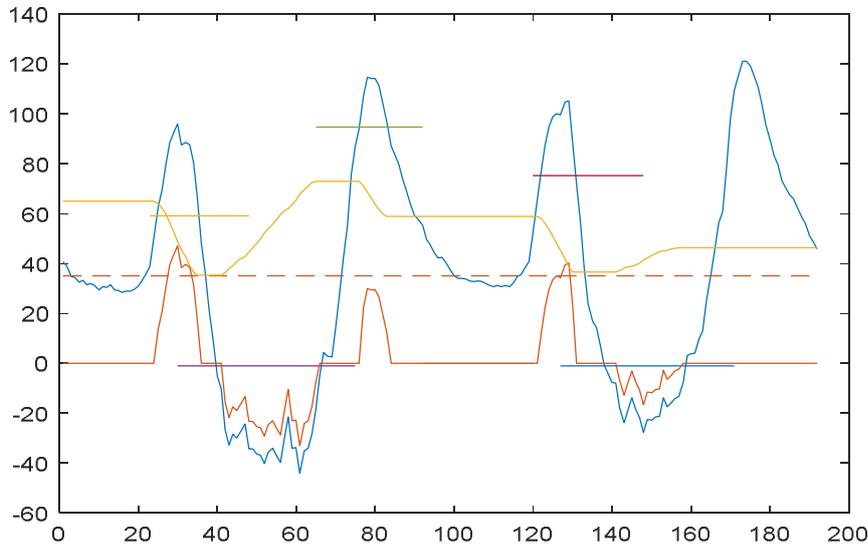


Figure 38: Threshold levels for 2 days with expected PV surplus

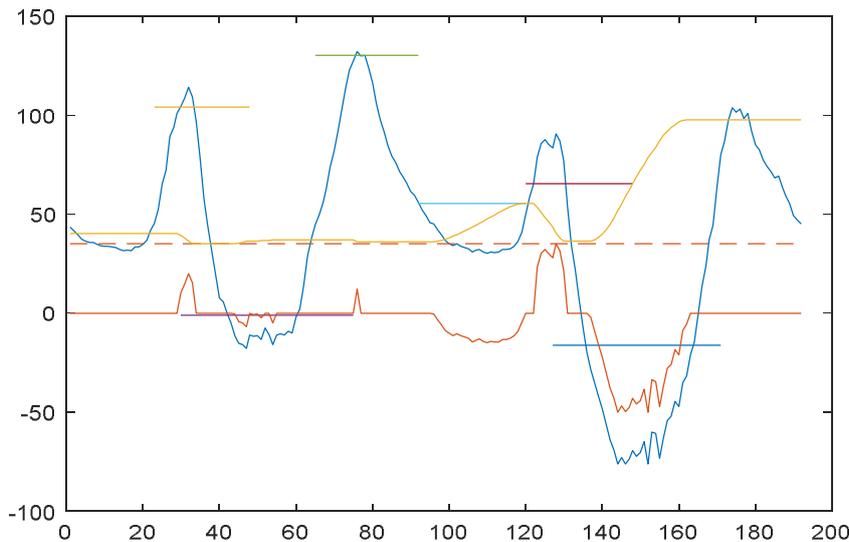


Figure 39: Storage operation on days with low PV production and high charge

- 6-hour update of weather forecast

Due to deviation between weather forecast and actual weather condition, update frequency is increased. Accurate solar irradiation forecast is crucial for precise storage operation. With weather forecast being available every 6 hours, 6 hours update of forecast and transformer profile is introduced. Threshold calculation is now activated at midnight, six in the morning and 5 in the afternoon. These three time instances are proven most beneficial for the algorithm calculation. Midnight calculation served as back up of the threshold values that are updated for morning discharge at 6:00 in the morning when new forecast is received. At five in the afternoon, new forecast

is considered when calculating evening discharge levels. All three activation of algorithm calculation provided threshold calculations for two days ahead that are stored as a backup up value until next activation. New received forecast provided better fitting of the forecasted and actual data, while more frequent calculations with update SOC levels brought additional potential to the storage operation.

- AC power factor and hourly updates

Newly discovered impact of AC power consumption had to be implemented in the algorithm as well. Power consumption directly influenced storage operation since the storage consumption from the grid point of view is not equal on the battery cell point of measuring. It is reduced for the AC consumption and resulting storage operation yielded slower charging process and faster discharging process of the unit. Additionally, SOC parameter of the storage is considered as well. Due to the deviation between forecast an actual profile of active power through transformer. Storage did not charge discharge to calculated level in situations with less accurate forecast. With hourly recalculation of the threshold levels, we mitigated this impact. Storage calculates each hour, based on the SOC measurement, how much can charge, or discharge based on the expected profile.

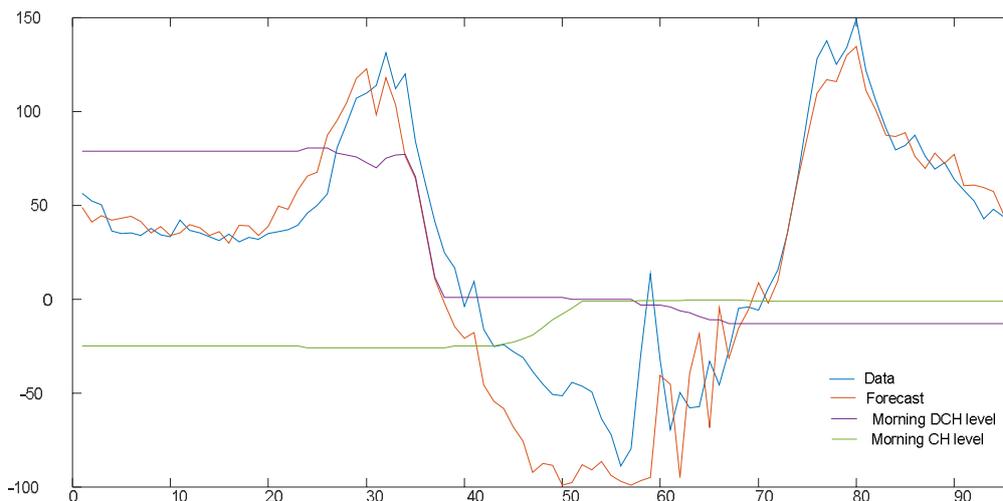


Figure 40: Hourly updates of the thresholds

Figure 40 visualizes hourly updates of the threshold calculations. When SOC deviation from planned levels occur. Algorithm adjusts the charge and discharge levels based on the forecasted profile and actual SOC measurements. With this action, the system can monitor what is the actual SOC level in the system and how deviation of the real power flow profile from forecasted one can be mitigated to some extent.

7.1.3 Operation of the storage unit

After the updated algorithm are implemented, storage is operating with final version of the algorithm, described in previous subchapter. All the system parameters are monitored within EG



STORY

SCADA system, and BESS is remotely controlled from their headquarters building. On Figure 41 we see SCADA visualization of storage operation. In the lower part, we see algorithm calculations, based on the received solar forecast. On the upper part, we see real measurement of the transformer power flow. We see that real measurement (green line, upper graph) deviates from the forecasted profile (green line, lower part). As a result, the application of thresholds for charging and discharging brings deviations in SoC graphs as well. With hourly recalibration of the thresholds based on real SoC reading, the system receives new set points and follows the charging and discharging goals more efficiently.

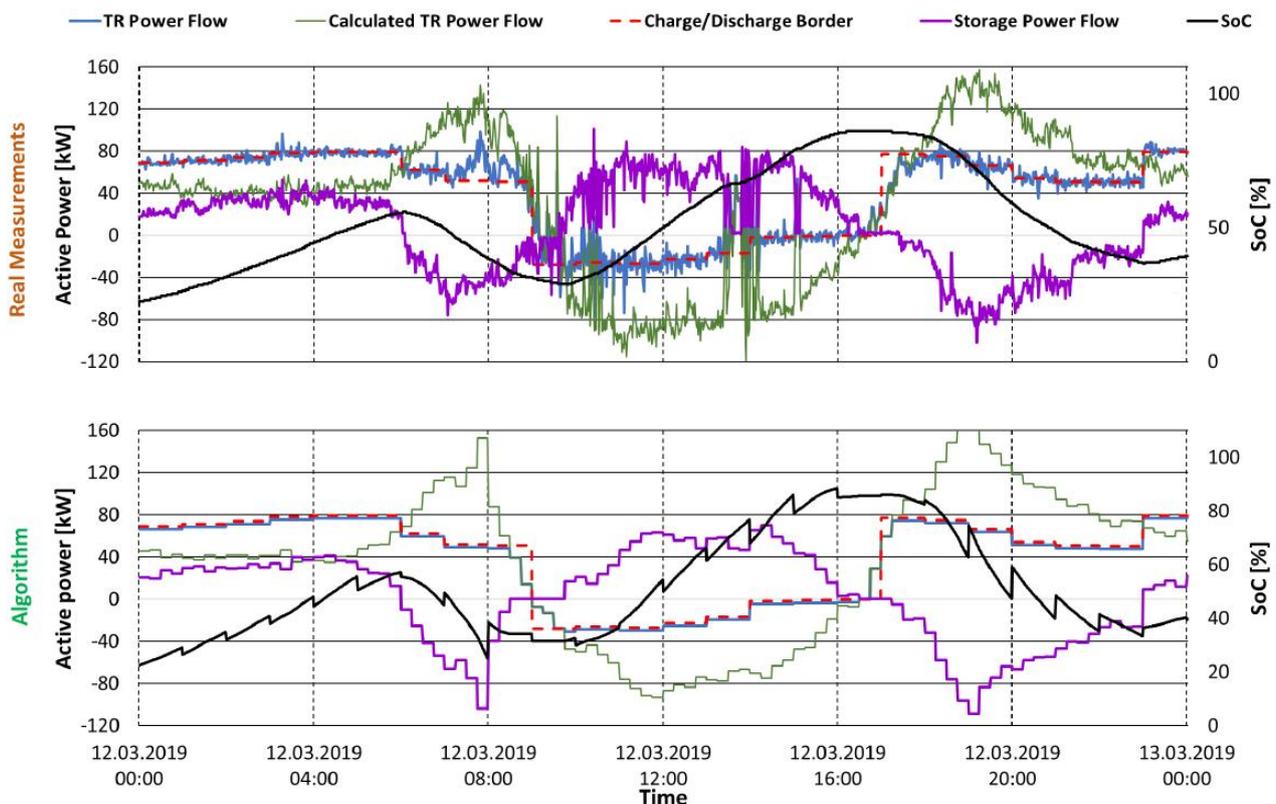


Figure 41: SCADA interface: comparison of algorithm calculation and real-time control of the BESS

On Figure 42 we see the reduction of power flows through the transformer due to the storage operation. BESS unit, successfully reduces morning and evening peak demand intervals. It charges during the day, with the PV produced energy, in case of little PV production it also utilizes night charging in interval from 2300 to 600 in the morning, when the consumption and energy prices are low.



STORY

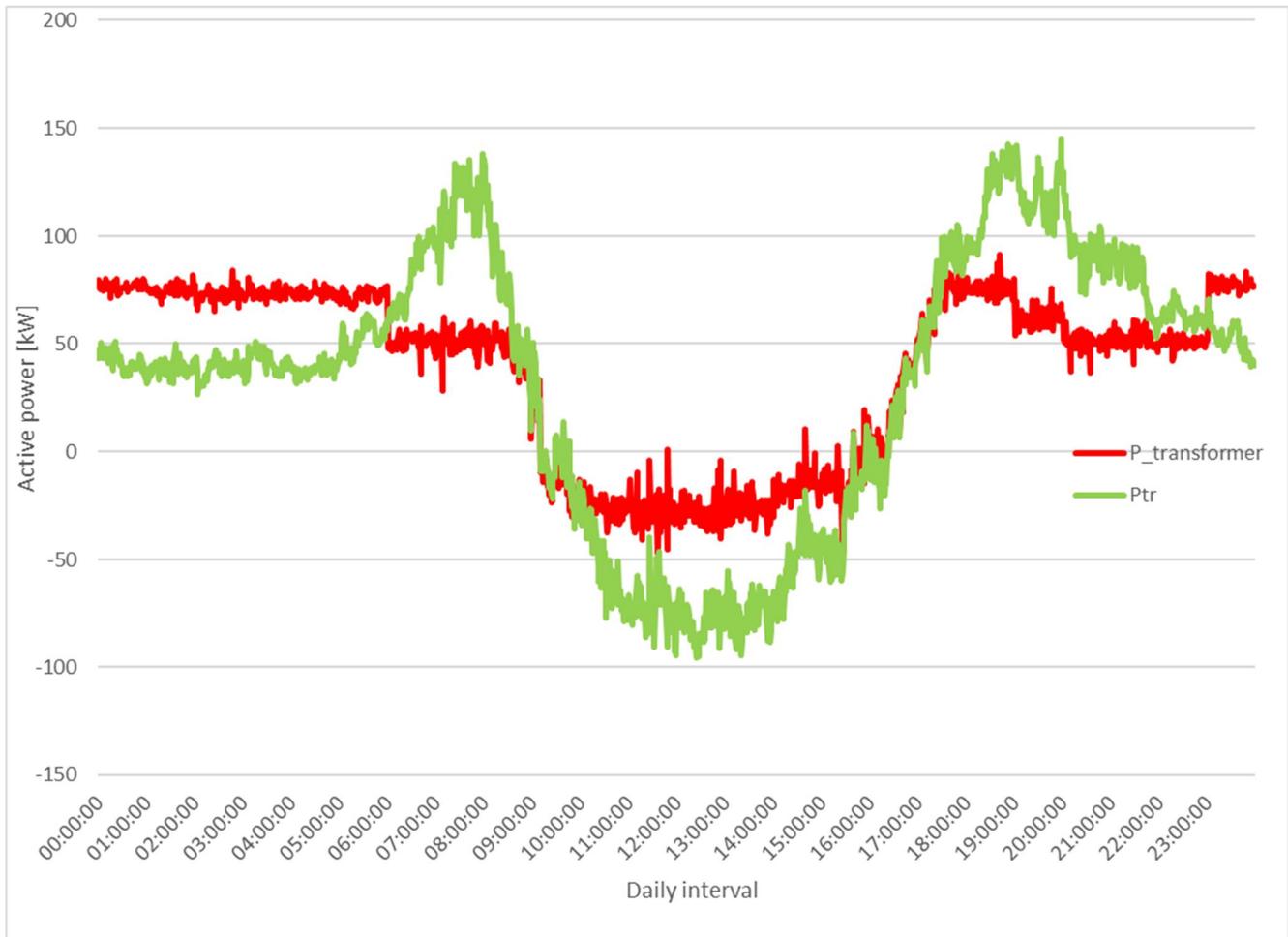


Figure 42: Transformer power flow comparison of active power (green line: original power flow, red line: resulting power flow)

For the presented day on the figure above, the KPI evaluation is also performed. Seven KPIs are presented below to see the benefits of storage implementation.

Table 10: KPI evaluation for 27.2. 2019

K2	Increased self consumption	SCL	60.64%
K2	Increased self sufficiency	SSL	33.33%
K3	Change of peak to average demand ratio	dPARdemand	- 46.48%
K4	Relative peak power change	dRPP	- 36.83%
K5	Grid (transformer) losses change	dEloss	- 37.89%
K6	Grid energy consumption change	dEgrid	-20.56%
K9	Full cycle equivalents of storage	FCE	69.34%
K11	Storage efficiency	ϵ storage	68.54%



STORY

In the Table 10, we see how BESS impacted the network situation. It increased consumption of the network produced energy for 60.64%, while self sufficiency level is increased for 33% compared to original state of the network. With resulting lower power flows through the transformer, peak power rate is reduced for 36.83 % and peak to average ratio is reduced for 46.5%. This means that transformer is more smoothly loaded through the interval with lower peak levels, which means less stress for the network elements. Energy delivered from the grid is reduced for 20.6% on the account of BESS unit. During this day, storage made 69.3 % of full cycle equivalent, which means it utilized almost 70% of installed capacity. Since it cannot fully discharge to 0% SoC or charge to 100% SoC this info presents how much of the capacity is used or made available during this day. The storage efficiency factor we see how much of the stored energy we are able to discharge back to the network. The 68.54% efficiency of the system may seem low at first glance, but it has to be considered that within this calculation also the AC power cabinet consumption is covered as well. Ac unit is taking care of BESS unit condition and it is supplied from the BESS charging and discharging energy.



8 DEMO6

8.1 DEMO6: Demonstration of roll out of private multi-energy grid in industrial zone Olen, Belgium

8.1.1 Introduction

A small and medium scale factory known as Beneens in Mol, Belgium is used as a demonstration site to implement a multi-energy grid at the factory level as shown in Figure 43. The factory is located near joinery that produces large amount of waste wood. The wood factory requires electricity and heat for processing. Therefore, the waste wood can be used to produce heat that can be utilized in the factory and in the neighboring factories through multi-temperature heating grid.

The organic Rankine cycle (ORC) is used at the site to produce electricity by utilizing low temperature heat produced in the 1.6 MW waste wood boiler on site. Two thermal energy storages 20 m³ and 50 m³ operating at two different temperature levels are also integrated to provide the flexibility in the energy system, to decouple heat and electricity and to increase the efficiency of the ORC. To ensure proper operation, advanced control strategies are required and have been developed by VITO and implemented by Beneens. The control strategies also require accurate knowledge on the state-of-charge (SOC) of the thermal storage units. These methods have also been developed by VITO.

The goal of this demonstrator is to show the increased efficiency of the ORC realized by the intelligent use of thermal storage. The approach is to determine the SOC of the thermal storage units, so that peak power demand can be met by ORC, in addition, local batteries can be used to reduce congestion. Lastly, the local heating demand of the locality can be met by two thermal storage tanks operating at two temperature levels. The control strategies and algorithms are discussed in detail in the deliverable 3.4.



Figure 43: Demonstration site of multi energy grid in industrial area in Belgium [1]

8.1.2 Performance and evaluation of demo

The demo is online and monitored since September 2016. However, there are still some technical issues in the installation that are being investigated.

One of the main issues is that the boiler is not able to provide maximum heat energy of 1.6 MW. Instead, it is only able to provide 850 kW. Investigations are carried out the maximum power that can be reached as a function of the supply temperature. Due to this low heat energy, output from the boiler the ORC is not able to work properly. The ORC shaft sealing has broken several times due to many load/unload cycles. It is also suggested to change the ORC working fluid.

Figure 44 shows the performance of the boiler. It shows the maximum heat energy output from the boiler is around 850 kW.

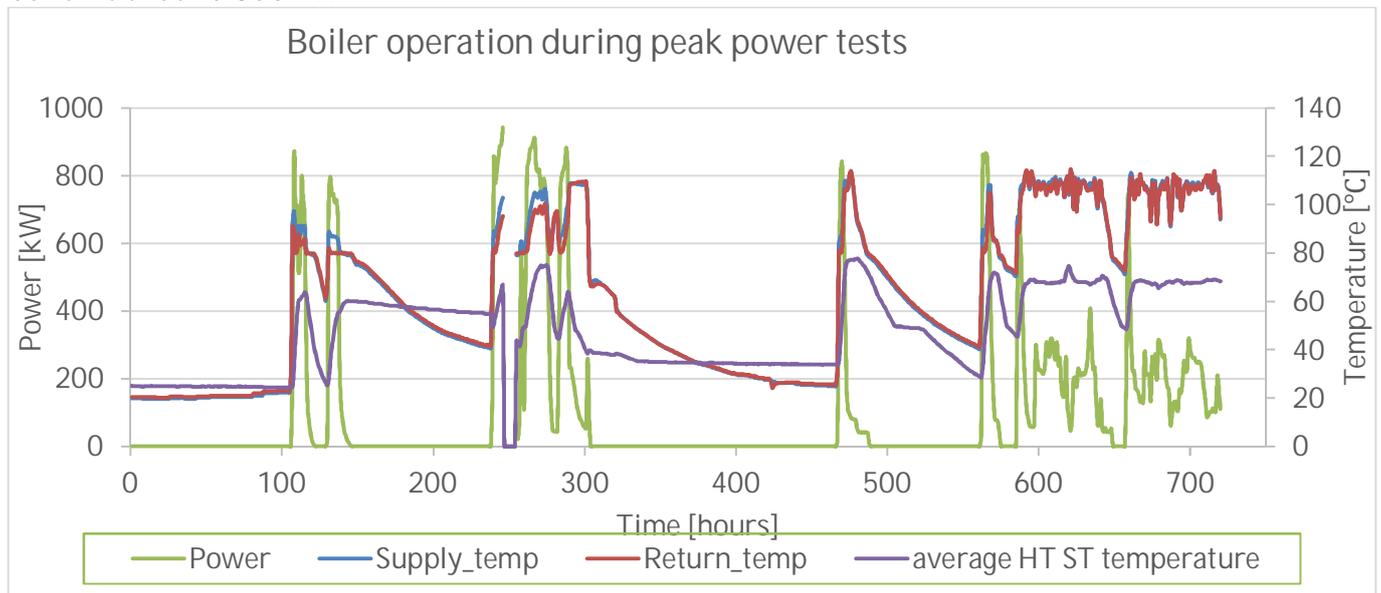


Figure 44: Boiler performance during peak power tests

The data collected so far shows that power output of the wood boiler is not stable and produces below 1000 kW of heat energy. Due to this reason, the ORC is not able to operate efficiently.

Figure 45 shows the energy balance of the plant. The red bar shows the energy produced by the boiler, green bar shows the energy consumed by the ORC and blue bar shows the energy consumed by the high temperature circuit. It is observed that in December 2017 and January 2018, the heat consumption exceeds the production that is not possible. This issue is due to the faulty energy meter that is maintained now.

The issue with the ORC operation is also observed in the Figure 45. From August 2017, onwards the energy production by ORC has decreased and limited heat offtake by the ORC since December 2017.



STORY

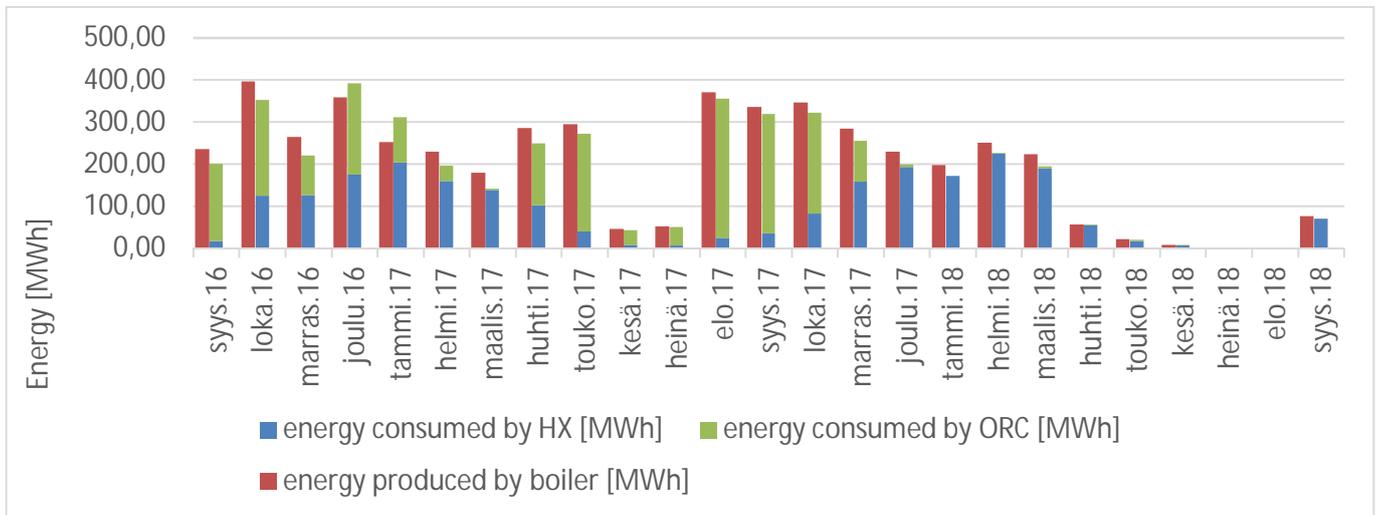


Figure 45: Energy balance of the Beneens installation



9 Conclusions

The deliverable contains the simulation results of the different demonstrations of STORY. The controls algorithms are developed to address the utilization of renewable energy sources and storages in a cost effective way.

It is found that the control algorithms have to be developed based on the site specific needs, local legislations, weather conditions, energy and storage components. It is not possible to build a standard or single control algorithm that can meet all the demands and conditions. The control algorithms are sensitive to the load, generation, costs and technical features of the energy and storage component. Therefore, lesson learned from this study is to build advanced algorithms based on the needs and requirements of the specific plant or site.

The technical issues, demand profiles, electricity costs and other parameters has to be thoroughly investigated before using advanced model predictive controls. As such, controls are sensitive to all the above-mentioned parameters.

10 Acronyms and terms

EMS	Energy management systems
LV	Low voltage
MPC	Model predictive control
MV	Medium voltage
OEF	Onsite energy fraction
OEM	Onsite energy matching
ORC	Organic Rankine cycle
PV	Photovoltaic
PV/T	Photovoltaic thermal
RP	Report
SOC	State of charge
WP	Work package

11 References

- [1] "Home - STORY." [Online]. Available: <http://horizon2020-story.eu/>. [Accessed: 15-Oct-2019].
- [2] T. Korvola, R. Abdurafikov, and F. Reda, "Control strategies for a residential property with solar building, thermal and electricity storages," 2018.
- [3] S. Cao, A. Hasan, and K. Sirén, "On-site energy matching indices for buildings with energy conversion, storage and hybrid grid connections," *Energy Build.*, vol. 64, pp. 423–438, 2013.