A novel smart grid architecture that facilitates high RES penetration through innovative markets towards efficient interaction between advanced electricity grid management and intelligent stakeholders

H2020-GA-863876

Pilot demonstration testing results and project assessment

Deliverable D7.3

Document Information

Scheduled delivery	30.09.2022
Actual delivery	30.09.2022
Version	Final
Responsible Partner	AIT

Dissemination Level

PU Public

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Acknowledgements

The research leading to these results has received funding from the EC Framework Programme HORIZON2020/2014-2020 under grant agreement n° 863876.

Glossary of Acronyms

Project management terminology

Acronym	Definition
HLUC	High Level Use Case
WP	Work Package
UCS	Use Case Scenario

Technical terminology

Acronym	Definition
AC	Alternating Current
AHU	Air Handling Units
ANN	Artificial Neural Network
API	Application Programming Interface
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
ATP	Automated Trading Platform
BEMS	Building Energy Management Systems
BESS	Battery Energy Storage System
BMS	Building Management System
CES	Centralised Energy Storage
CHIL	Controller Hardware-In-the-Loop
CHP	Combined Heat and Power
DA	Day-Ahead
DC	Direct Current
DER	Distributed Energy Resource
DES	Distributed Energy Storage
DLFM	Distribution Level Flexibility Market
DN	Distribution Network
DR	Demand Response
DSO/TSO	Distribution/Transmission System Operator
EM	Energy Market
ENC	Energy Centre
ES	Energy Service
ESP	Energy Service Provider
ESS	Energy Storage System
EV	Electric Vehicle
FCU	Fan Coil Unit
HIL	Hardware-In-the-Loop
ICT	Information and Communication Technology
IDE	Integrated Development Environment
IoT	Internet of Things
KPI	Key Performance Indicator
LSTM	Long Short-Term Memory

LV	Low Voltage
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Squared Error
MO	Market Operator
MV	Medium Voltage
OPF	Optimal Power Flow
PCC	Point of Common Coupling
PV	Photovoltaic
RES	Renewable Energy Sources
RI	Research Infrastructure
R/P/I-DLFM	Reactive/Proactive/Interactive Distribution Level Flexibility Market
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
RM	Reserve Market
S/W	Software
TN	Transmission Network
TRL	Technology Readiness Level
VAV	Variable Air Volume
VS	Validation Scenario
WVK	Wärmeverbundkraftwerk (CHP)

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Document History

This deliverable includes the research output of task 7.3.

Table 1: Document History Summary

Revision Date	File version	Summary of Changes
21/04/2022	V0.1	Draft ToC circulated among all consortium partners
28/08/2022	V0.2	First round of inputs for the second validation strand
09/09/2022	V0.3	First round of inputs for the first validation strand
23/09/2022	V0.4	Second round of inputs for the first validation strand
28/09/2022	V0.5	Second round of inputs for the second validation strand
28/09/2022	V0.6	Draft submitted for review
30/09/2022	V0.7	Integration of review results

Executive Summary

In order to validate the methods and tools developed in FLEXGRID, three validation strands were developed in the FLEXGRID project: (i) Automated Energy Flexibility Aggregation, (ii) Evaluating Forecasting Methods for DSO Services, and (iii) Evaluating Advanced Market Clearing Algorithms and x-DLFM Architectures. This deliverable presents the implementation and the results from tests done of the first two validation strands. The first validation strand focuses on validating aggregator's services and was carried out as pilot tests at UCY's campus. This strand studies how the FLEXGRID methods can be used for optimal aggregation of flexibility for various business cases. The second validation strand focuses on FLEXGRID's services directed towards DSOs and how these can be optimally provided by ESPs. This strand was carried out as a pilot using bnNETZE's test system in and around the city of Freiburg, Germany. Here, the goal was to study how the advanced forecasting methods and the collaboration possibilities between the DSO and ESPs developed in FLEXGRID can be used by the DSO for peak-shaving business case (cf. chapter 2 of D8.3).

The two UCSs, that have been demonstrated in the UCY pilot were focused on managing the generated FlexRequest from the market and then respond with a FlexOffer. Apart from the UCY campus (Microgrid) that took part in FLEXGRID solution, the PV Technology Laboratory PVTL (Nanogrid) has also participated. Regarding the UCY microgrid (that considers a centralized BEMS architecture), most of the DR event tests and results were successful. Regarding the PVTL, the IoT/OpenHAB solution is suitable for all types of end-users, due to its interoperability and with the usage of the open-source platform OpenHAB, all electrical loads are easily controlled and monitored.

The second validation strand implemented at bnNETZE's pilot site focused on showing how the real operation of the test site is controlled by FLEXGRID ATP and its algorithms and contributes to the bnNETZE's "peak shaving" business case for the entire distribution grid. In spite of problems to operate the test site such as connectivity problems with prosumers and the system limitations due to the summer season, it must be stated that the test operation in the end fulfilled the expectations. Firstly, it was possible to realize an actual test period over more than three weeks with real prosumers and a large-scale battery – both controllable by bnNETZE and monitored on different platforms. Furthermore, all relevant scenarios can be found in the results of the tests and give a proof to the working principle of the approach regarding the business case of peak shaving.

In total, the tests have shown that the FLEXGRID solutions have a great potential in supporting real-life challenges and integration of real-life legacy systems with FLEXGRID ATP is promising towards replicating and scaling up to other pilot sites in the future.

1 Introduction

1.1 Purpose of the document

The goal of FLEXGRID is to facilitate energy sector stakeholders, such as Distribution System Operators (DSO), Transmission System Operators (TSO), Energy Service Providers (ESP) and aggregators of Renewable Energy Sources (RES) and FlexAssets to: *i)* easily and effectively create advanced Energy Services (ESs), *ii)* interact in a dynamic and efficient way with their environment (i.e. electricity grid) and the remaining of the stakeholders, and *iii)* automate and optimize the planning and the operation of their ESs. In this way, FLEXGRID envisages secure, sustainable, competitive, and affordable ESs. In particular, the main objectives set by FLEXGRID are:

- An Automated Trading Platform (ATP) able to provide as a service the composition and the operation of energy markets
- Automated planning and optimal operation of DSO's/TSO's Energy Services
- Automated Planning and optimal operation of ESP's Business Models (assets and policy)

These objectives will be fulfilled by the development of a service oriented smart grid architecture that offers energy stakeholders several tools equipped with advanced mathematical models and algorithms. These tools will be used for internally optimizing the planning and the operation of the ESs, participating in real time markets of future smart grids, and interacting through markets with other stakeholders in order to meet the highly demanding objectives of future smart grids. Furthermore, it is the idea of FLEXGRID that its software (S/W) platform will be able to host a variety of actors, including: (i) DSOs/TSOs that want to effectively plan and operate their electricity grid towards low-cost and high-quality ESs (distribution and transmission services), (ii) progressive ESPs (utilities) that want to provide more advanced ESs and achieve an attractive trade-off between their risks, their profits and the quality of services they deliver, and (iii) aggregators of RES and FlexAssets that need to address the high volatility and uncertainty of renewables, and offer more competitive ESs (i.e. enhancing the RES "dispatchability" and thus be able to participate in equal terms in the EU energy markets).

In order to validate the methods and tools developed in FLEXGRID, three validation strands were developed in the FLEXGRID project: (i) Automated Energy Flexibility Aggregation, (ii) Evaluating Forecasting Methods for DSO Services, and (iii) Evaluating Advanced Market Clearing Algorithms and x-DLFM Architectures. More detailed information about each validation strand can be found in D7.1 [FleD71].

This deliverable presents the implementation and the results from tests done of the first two validation strands. The first validation strand focuses on validating aggregator's services and have been carried out as pilot tests at UCY's campus grid at TRL 5. This strand studies how the FLEXGRID methods can be used for optimal aggregation of flexibility for different business cases.

The second validation strand focuses on FLEXGRID's services directed towards DSOs and how these can be optimally provided by ESPs. This strand has also been carried out as a real-life pilot using bnNETZE's test system in and around the city of Freiburg, Germany at TRL 5. Here, the goal is to study how the advanced forecasting methods and the collaboration possibilities between the DSO and ESPs developed in FLEXGRID can be used by the DSO for "peak-shaving" business case (see more details about this business case in chapter 2 of D8.3 [FleD83]).

1.2 Scope of the document

The FLEXGRID validations are done in WP7, which has three main tasks focusing on the pilot demonstration plan (Task 7.1), development of the testing platforms and validation activities (Task 7.2), and execution and evaluation of the pilot tests (Task 7.3). This deliverable covers the results from both Task 7.2 and Task 7.3, but focuses on the experiments and tests that were developed and executed for the real-life pilot validation strands. The results from the laboratory tests (i.e. TRL 4) are presented in D7.2 [FleD72].

1.3 Structure of the document

This document is structured as follows: Section 1.4 describes the methodology used for the validations in the FLEXGRID project. In Section 2, the experiments for the "Automated Energy Flexibility Aggregation" strand are presented. This is followed by the experiments "Evaluating Forecasting Methods for DSO Services" in Section 3. The document is concluded with the recommendations for the future in Section 4.

1.4 Validation Methodology

All validation strands in FLEXGRID follow the same validation methodology. It is based on the ERIGrid Holistic Validation Methodology [Bla16], which is described in more detail below and illustrated in Figure 1.

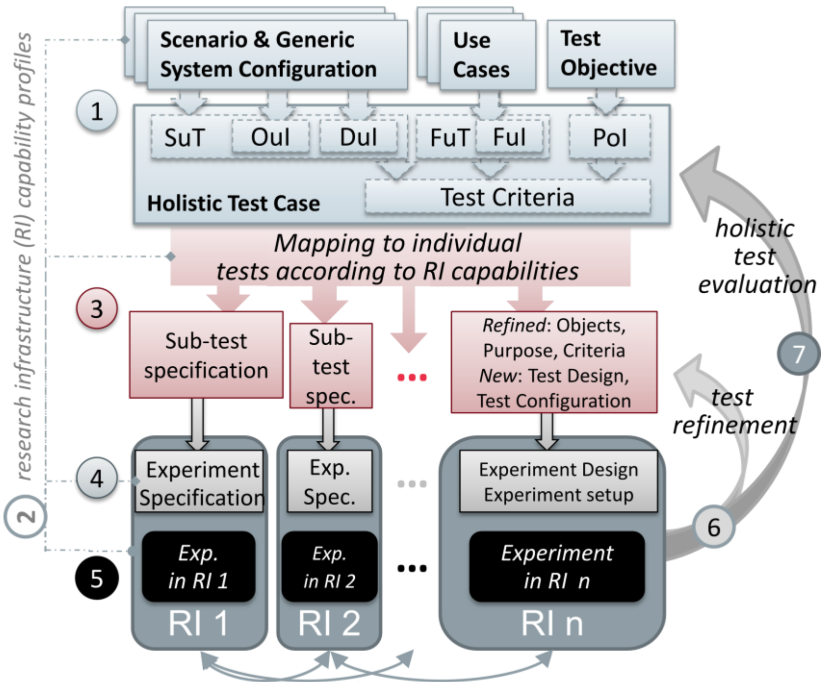

Figure 1: Overview of the ERIGrid validation approach for power systems [Bla16]

1.4.1 The ERIGrid holistic validation methodology applied to FLEXGRID

In the H2020 ERIGrid project [ERI21], a formalized method for testing power system applications was developed, depicted in Figure 1. In a nutshell, the approach is divided into multiple layers, starting with the definition of test cases, which are then broken down into more detailed experiment specifications and in the end mapped to pilot or testing infrastructure where the tests are executed. More information about the ERIGrid approach can be found in D7.1 [FleD71] and [Bla16].

Based on the ERIGrid method, a slightly adapted validation methodology was defined for the work in FLEXGRID, in order to plan, specify, configure and execute several proof-of-concept laboratory and real-life pilot validations. It is illustrated in Figure 2 and is described by the following steps:

1. *Scenario Description*: In the first phase, different Validation Scenarios (VS) descriptions were collected based on the FLEXGRID UCS from WP2.
2. *RI Capabilities Profiling*: The second step is carried out in parallel with Step 1. Here, the infrastructure provided in each of the validation strands is analysed and a profile is made of what can be tested using this architecture.
3. *Mapping*: The mapping step is used to map the identified VS from Step 1 with the RI profiles from Step 2. The most important result from this step is a feasibility check that the scenarios can actually be implemented in the relevant RI.
4. *Experiment Specification*: Following the mapping detailed experiments are specified based on each VS. Each VS may result in many experiments. The main goal with this step is to make sure that all aspects of a VS is covered.
5. *Experiments*: Here, the experiments are carried out using the specified equipment.
6. *Analysis*: For each experiment that is carried out, results are collected and analysed. As indicated in Figure 2, an iterative process between steps 3, 4, 5, and 6 is possible and in most cases likely.
7. *Results*: The final step is to combine the results from each carried out experiment. The outcome of this step is the final result of the VS from Step 1.

Steps 1, 2, and 3 were covered in D7.1 [FleD71]. This deliverable focuses on the final steps from Step 4 to Step 7 for the two pilot validation strands. The experiments for the third validation are covered in D7.2.

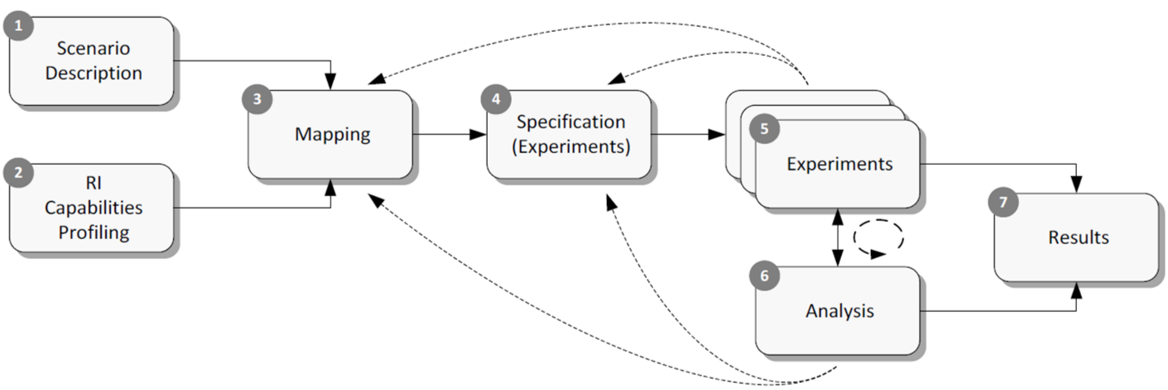

Figure 2: Validation methodology for the validation strands in FLEXGRID.

2 Automated Energy Flexibility Aggregation – UCY Pilot Evaluation

2.1 Pilot Overview/Environment

A comprehensive description of the UCY campus has been presented in D7.1 [FleD71], which includes all the details about the UCY's target and scope, the validation scenarios, the initial validation plan, and finally the pilot environment and setup plan. Essentially, the UCY campus is a quite unique pilot site due to its heterogeneity of the buildings, the number and capacity of intermittent generation, its centralised cooling and heating district-level energy management systems and the ability of controlling most of them remotely and directly via different communication protocols. The two UCSs, that have been demonstrated in the UCY pilot, were focused on managing the generated FlexRequest from the market (cf. UCS 4.1 called "Manage a FlexRequest") and then respond with a FlexOffer (cf. UCS 4.3 called "Create an aggregated FlexOffer"). The whole university operates as a microgrid with a hierarchical architecture with cutting-edge technological systems (for more details see D7.1 [FleD71]), to be able to control, monitor and exploit the flexibility potential of the UCY campus.

The first milestone that was necessary to be achieved was the establishment of the baseline load consumption of the assets that have been participating, to evaluate the DR events and exploit the flexibility that has been provided. The following figures (Figure 3 - Figure 6) show the average monthly energy profiles of the chiller units currently installed at the UCY campus. These energy profiles represent the pilot environment, that was presented in D7.1 [FleD71]. In the figures below, we can see that the energy consumption of the 8 chillers is maximized during summer months (and also during working hours), while in winter the energy consumption is lower.

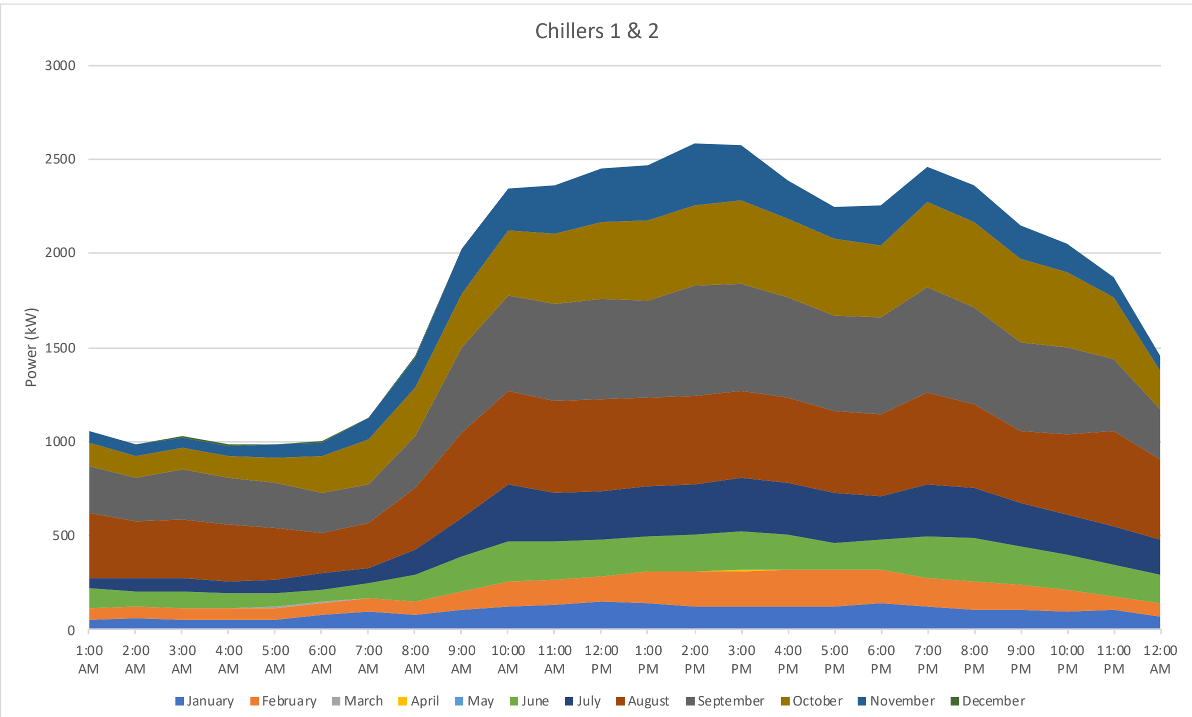

Figure 3: Average Load Profile of the chiller units 1 & 2 installed at UCY.

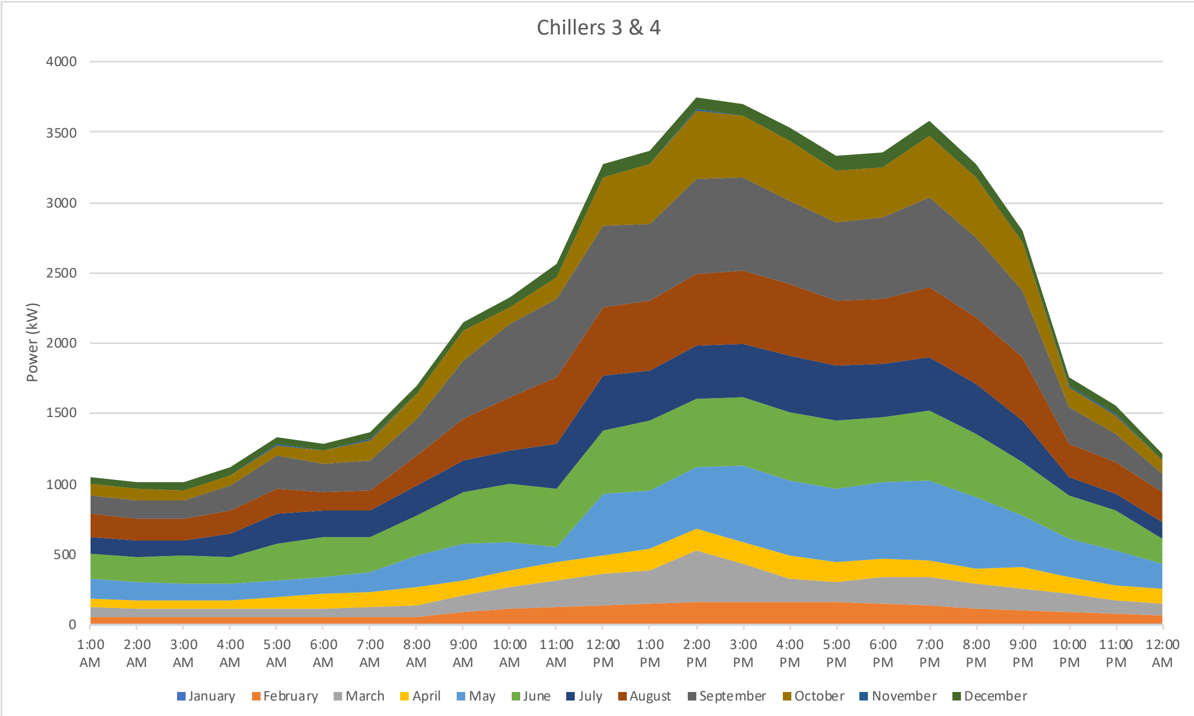

Figure 4: Average Load Profile of the chiller units 3 & 4 installed at UCY.

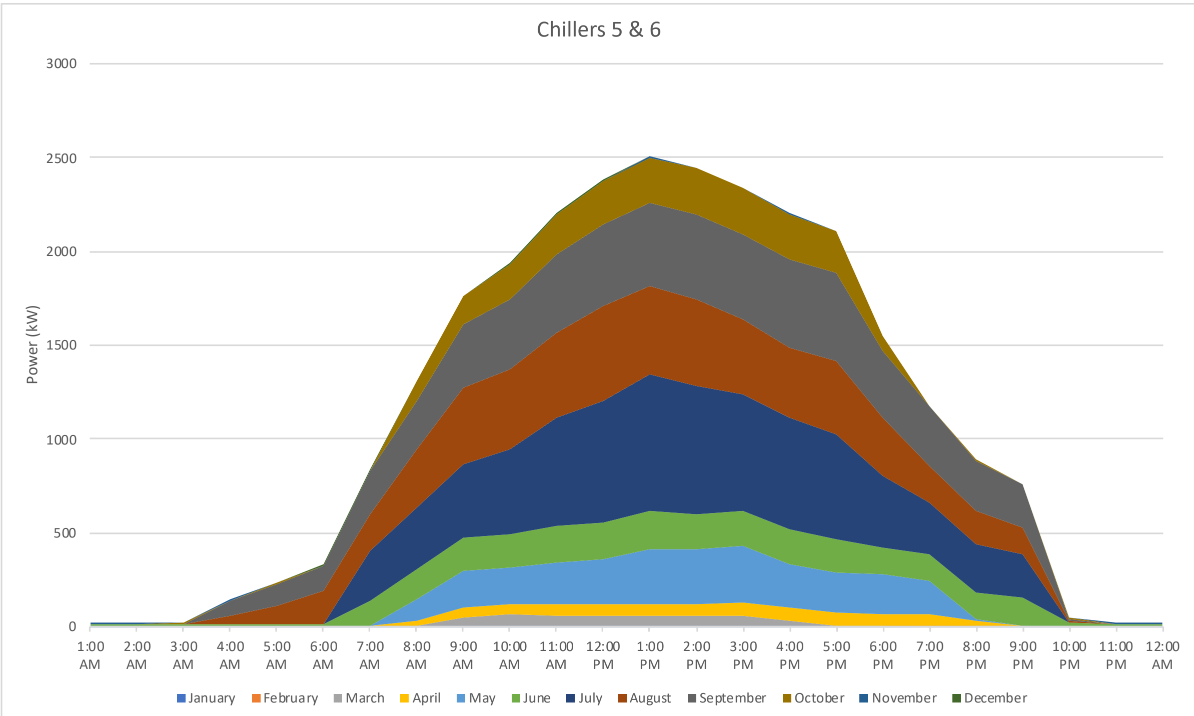

Figure 5: Average Load Profile of the chiller units 5 & 6 installed at UCY.

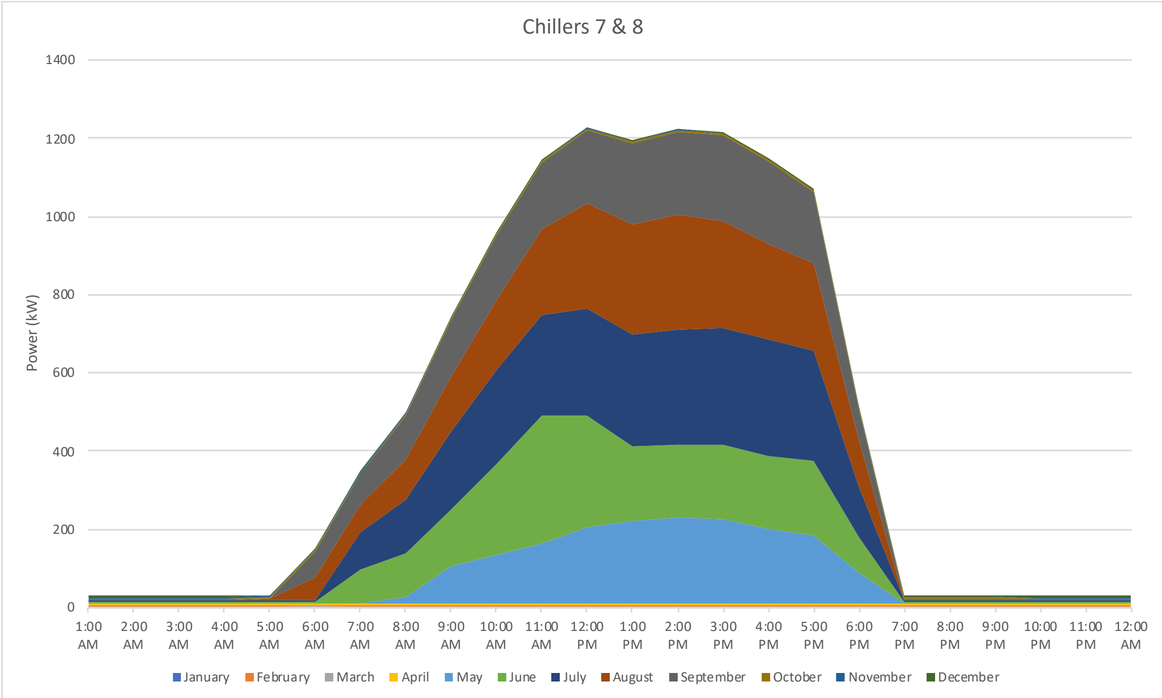

Figure 6: Average Load Profile of the chiller units 7 & 8 installed at UCY.

Figure 7 illustrates the outdoor average temperature levels per month for the UCY campus. These levels ranged from 10° to 45° C over the year.

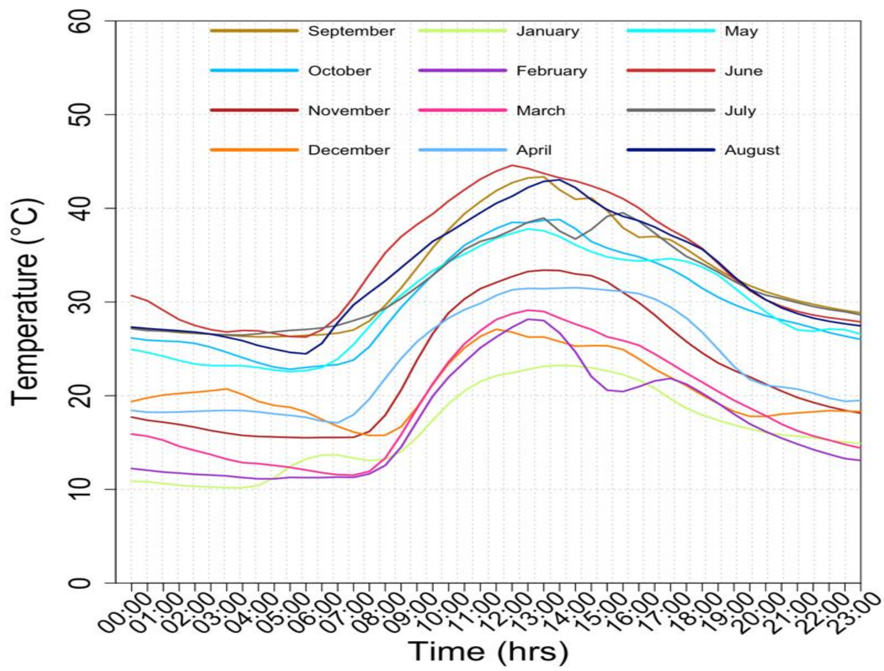

Figure 7: Average Temperature levels per month.

As described in D7.1 [FleD71], the BEMSs of the campus' buildings are controlled by an upper layer control platform that is capable of altering the cooling operation modes for each floor of the buildings. Essentially, the control points of the Air Handling Units (AHU) are shown in the figure below. However, their positions do not exactly represent the control area. Text boxes with air handling unit names are coloured accordingly to their operational regime. By clicking on the text boxes, the operator can manually choose the operating regime for each air handling unit, see Figure 8.

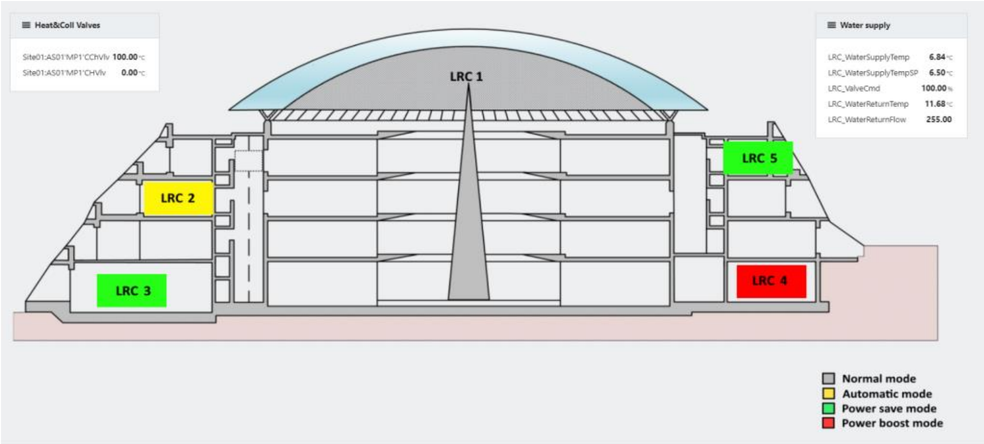

Figure 8: Internal spaces of UCY library building.

Operational regimes (or else modes) can also be changed automatically in accordance with the predefined schedules or via the developed API with the Aggregator. The Air Handling Units control two different systems; the Variable Air Volume (VAV) and the Fan Coil Unit (FCU). The VAV system enables energy-efficient HVAC system distribution by optimizing the amount and temperature of distributed air, and the FCU system that uses chilled water to transfer heat from indoors to outdoors. From the four operation modes ("Normal", "Automatic", "Power Save" and "Power Boost"), we mainly used the Power Save mode (for the whole building) to reduce the electricity consumption of the UCY campus, which results in reduced environmental pollution and CO2 emissions and less cost of the electricity bill.

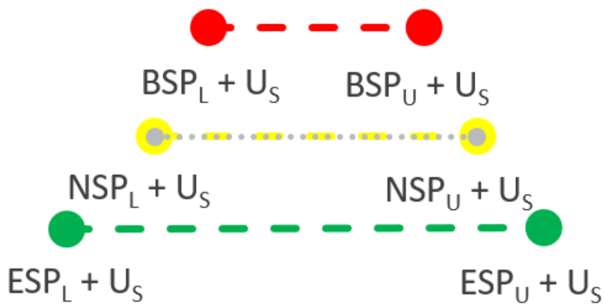

Figure 9: Temperature mode setpoints with the User Input for the air handling units.

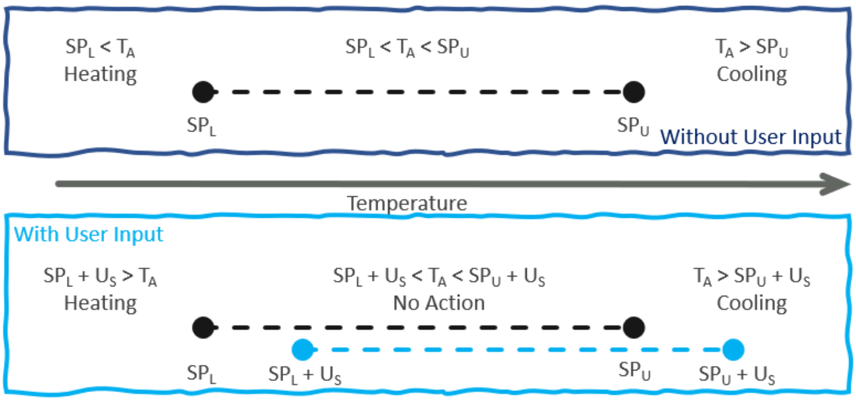

Figure 10: Temperature setpoints for the air handling units with and without the User Input.

The acronyms in Figure 9 and Figure 10 are as follow:

- SP_L stands for Lower Bound Setpoint (Heating): The letters N (normal), B (boost), P (power save), A (automatic) in front of the SP_L (e.g., NSP_L) classify the temperature mode that is currently active;
- SP_U stands for Upper Bound Setpoint (Cooling): The letters N (normal), B(boost), P (power save) and A (automatic) in front of the SP_U (e.g., NSP_U) classify the temperature mode that is currently active;
- T_A stands for Actual Temperature;
- U_S stands for User Setting: The User Input [± 0,3 °C] needs to be taken into consideration because it can affect the operation of the air handling units, which means that the results of the DR events depend on the user engagement. The reason why the DR events cannot be 100% explicitly controllable, is because the end-user has the freedom to change the temperature up to ± 3 °C of the defined setpoints.

Essentially, the setpoints are set by the building operator (manager), which represent the normal operation of the building and define the accepted indoor temperatures for the buildings. When the power save mode is selected, the lowest setpoint decreases and the higher increases, resulting to a wider range of accepted indoor temperatures, so that the chillers will stay at 'sleep' mode for a longer period of time, deducting energy consumption. The exact opposite happens when we set the temperature mode into boost mode, where the setpoints' range gets narrowed. The chillers will operate more often to maintain the preferable indoor temperature of the building and this results to more energy consumption. This is a rarer case, when the DSO will send a DR signal commanding more energy consumption for a certain period of time. Another case is when the FlexRequest price per unit is very high, because the DSO faces an imminent congestion and thus the DSO is willing to pay at a more (euros per flexibility unit) expensive price for procuring flexibility.

Apart from the 3 out of 17 tertiary buildings of the UCY campus (Microgrid) that took part in FLEXGRID solution, the PV Technology Laboratory PVTL (Nanogrid) has also participated.

The PVTL Nanogrid acts as a testbed and a subset of the UCY campus. Within its premises there are PV systems, Battery Energy Storage Systems (BESS), smart meters, electrical loads associated to its offices, an electronic Chroma load and an Electric Vehicle (EV) charging station. Six zones (009 – 014) are used as offices for the researchers working within, an in-door testing facility (004), a conference room (001), a storeroom (008) and a cabinet for the BESS (015). The indicated zones can be seen in the architectural design in Figure 11.

Within zones 009 – 014, one can find typical appliances associated with user comfort at the workplace, such as AC units, dimmable lighting, as well as the portable computers and laptops that are used by the researchers. The conference room (001) has a projector for presentation and a kitchen attached to it.

The PV panels that are shown in Figure 12 are installed mainly for testing purposes. For this reason, the total number of PV modules is constantly changing, with the average installed capacity being around 50 kWp. Moreover, there is a modern PV inverter, often referred to as 'smart' inverter, which is an embedded system that includes functions for monitoring and control of main functionalities.

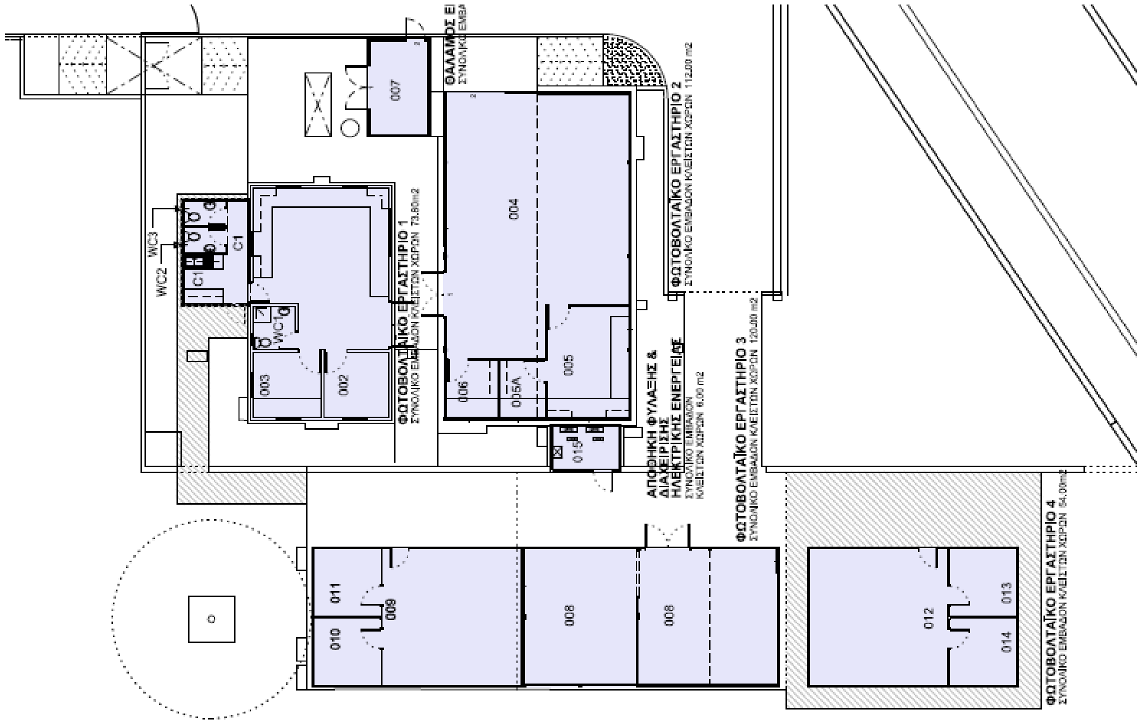

Figure 11: UCY PV Technology Laboratory architectural design.

The monitored variables of the PV inverter are usually related to the electric parameters or characteristics of the inverter and the PV array (e.g., power, current and voltage in both the DC and AC side, or frequency, among others). The control functionalities usually refer to set points for real or reactive power with respect to the total inverter's capacity, or smart control algorithms for real (active) or reactive power as a function of the PV penetration, local voltage and frequency readings in the location where the inverter is connected to the local electricity network.

Figure 12: Top view of PVTL.

2.2 Microgrid Demand Response Events – Reduce energy consumption

2.2.1 Experiment Description

In order to test the demand response capability of the UCY Microgrid, the concept shown in Figure 13 was used. The flowchart shows the interaction with the FLEXGRID ATP and how the results from this platform are translated and adopted by the Microgrid.

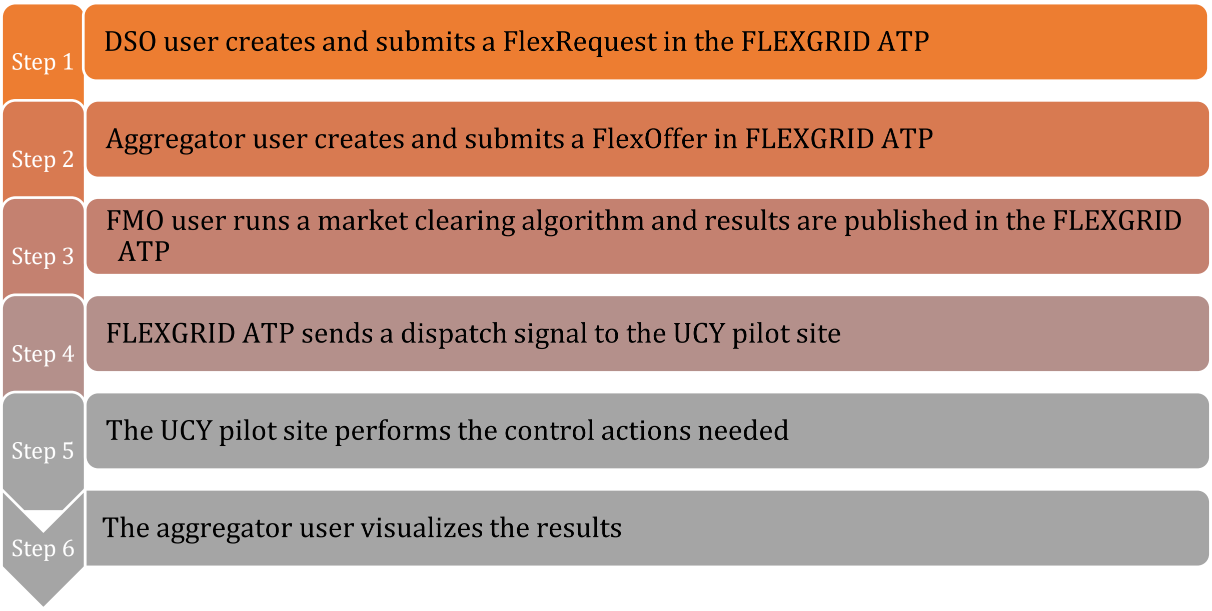

Figure 13: Flowchart for dispatching the DR events signals at Microgrid of UCY pilot site.

2.2.2 Experiment Setup

As described in D7.1 [FleD71], the UCY campus cooling and heating system is centralised and controlled by the BEMSs with the aforementioned temperature modes that change the temperatures' operational regimes (setpoints). However, in order to be able to control the entire system remotely and directly, a backend communication between our developed INEis platform with the BEMSs has been established and represents the upper layer control platform. With this experimental setup, the building manager/operator is capable to modify either manually or automatically the setpoints based on the provided FlexRequest. Figure 14 shows the change from Normal Mode to all available modes for each floor separately.

The changes for activating the DR event based on the DSO/Aggregator FlexRequest, will alter the energy drawn from the grid (see Figure 15) and then by the results evaluation process, the DR event will be either successful or not.

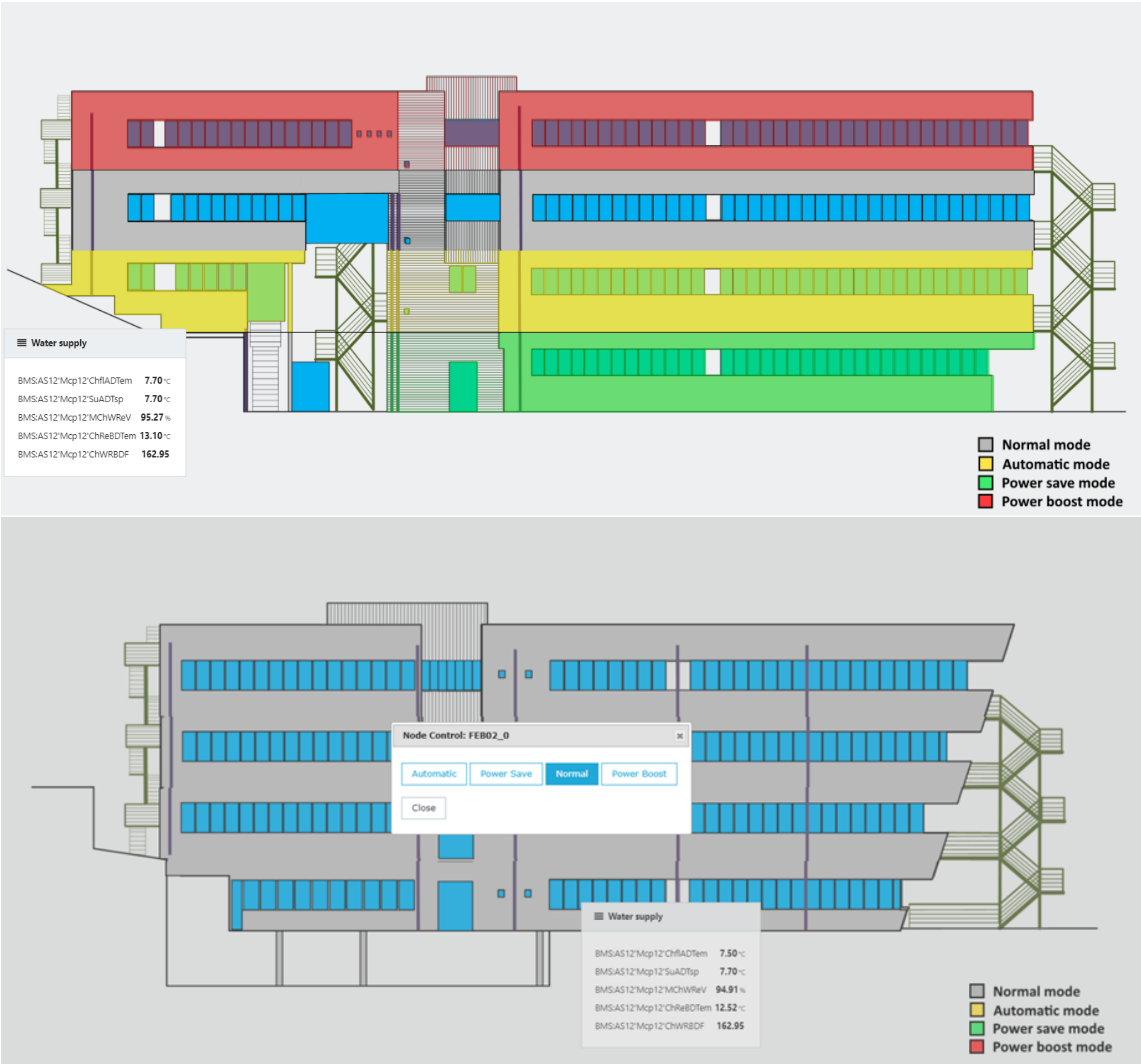

Figure 14: Control of operating modes of the cooling system in a building of a connected BEMS.

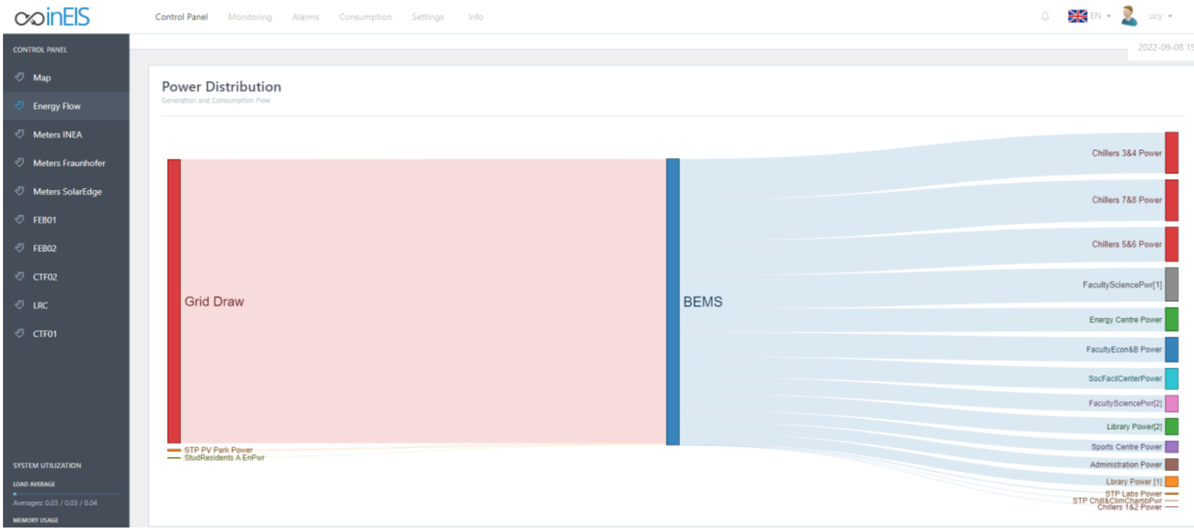

Figure 15: Energy drawn from the grid and its distribution among the campus resources.

2.2.3 Performed Tests and Results

For the Microgrid of the UCY pilot, all events were downward flexibility DR events (i.e. curtailment of energy consumption) and the presented data is an aggregation of all involved buildings. The total energy saving for the following three DR events is 1302 kWh, which corresponds to an average energy consumption reduction of 29.16%. The saved energy corresponds to €761.77 cost reduction and according the European Environment Agency (EEA), the CO_2 impact for Cyprus is 0.623kg CO_2/kWh, so with the UCY DR events we achieved 811.146 kgCO_2 reduction [Eur22].

The first DR event that is presented in Figure 16, was five "power-save" DSO requests for the UCY Microgrid of 500 kWh, with each signal set for a minimum of 100 kWh. The DR event was successful, resulting to an energy reduction of 630 kWh (or an average energy reduction of 30%). The event lasted for five hours (5h) and the buildings participated were the Faculty of Economics & Business, Library and Administration buildings.

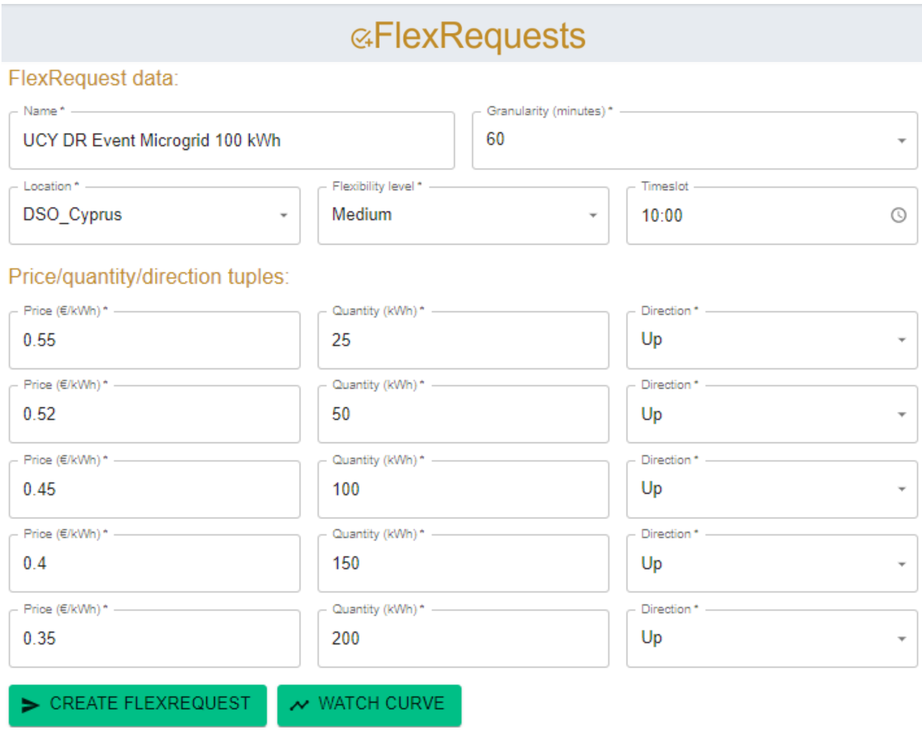

Figure 16: Indicative ATP screenshot for creating a FlexRequest for UCY Microgrid.

Figure 16, Figure 18, and Figure 20 show the Flexibility Requests, the Flexibility Offers and the Market Clearing respectively (Flexibility level: Medium and granularity: 60) with the corresponding prices for 10:00, which relate to the UCY pilot, while Figure 17 and Figure 19 show the corresponding curves.

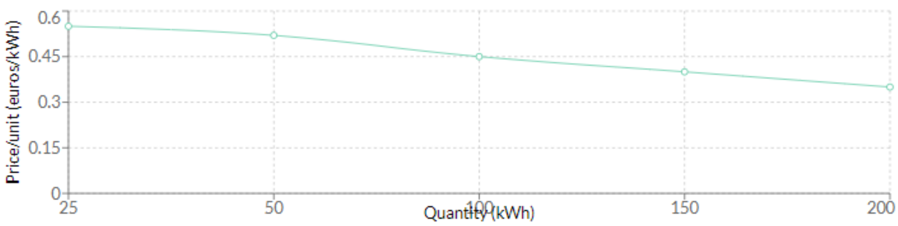

Figure 17: FlexRequest prices (EUR/kWh)/Medium Level.

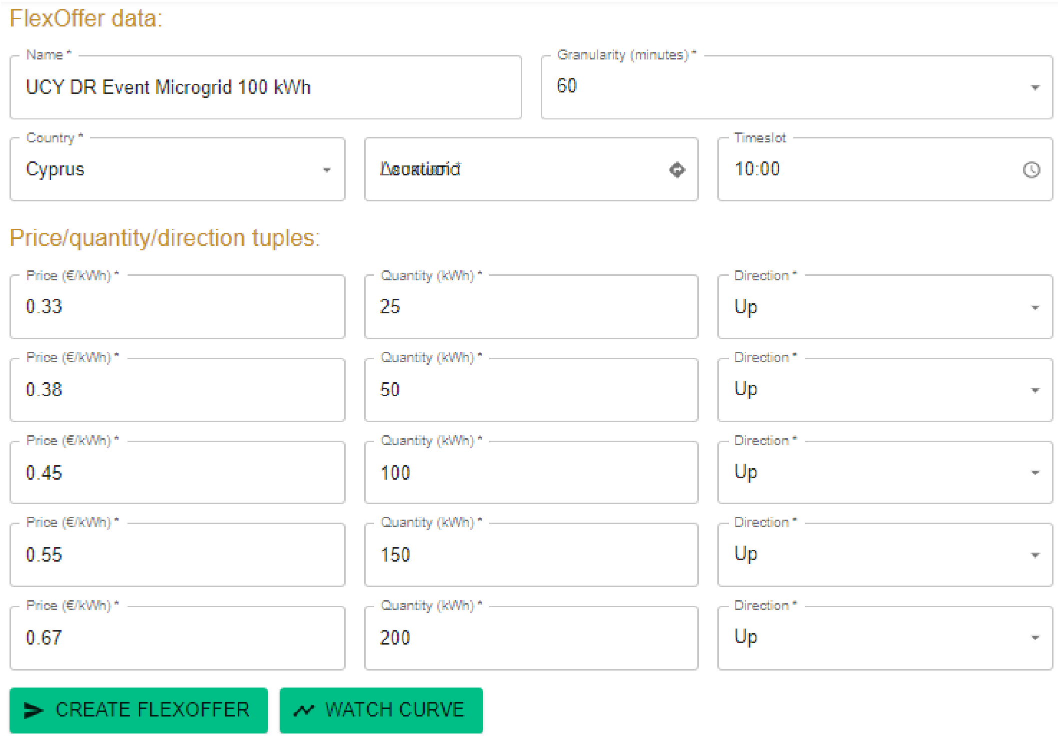

Figure 18: Indicative ATP screenshot for creating a FlexOffer for UCY Microgrid.

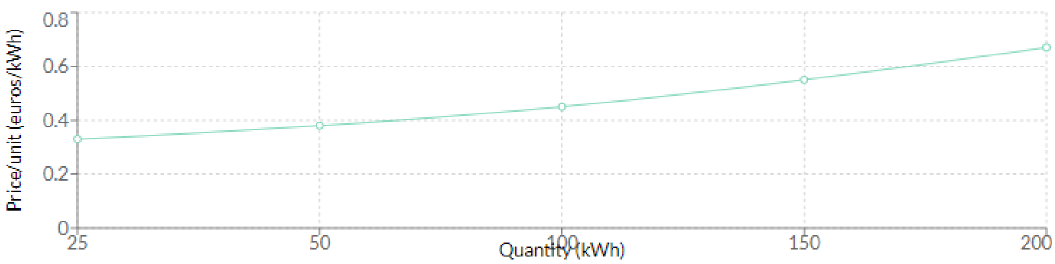

Figure 19:FlexOffer prices (EUR/kWh)/Medium Level.

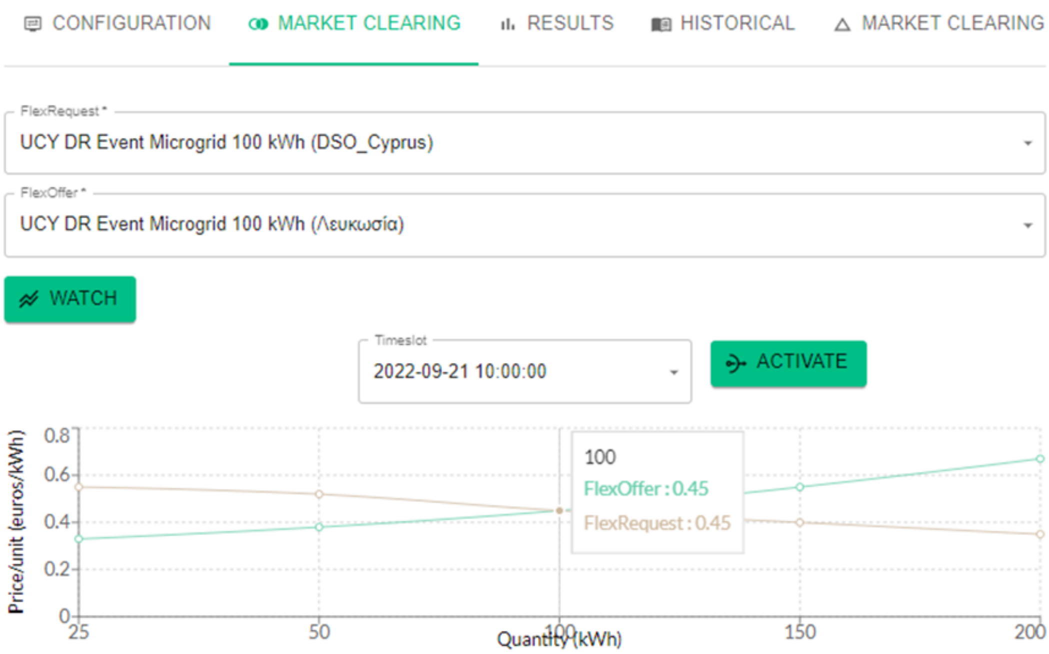

Figure 20: Market Clearing Results (matched at 0.45 €/kWh for 100 kWh) shown in the ATP.

The same procedure was followed for the consecutive 4 DR FlexReqeusts and FlexOffers that led to the successful DR event that is presented in Figure 21 below.

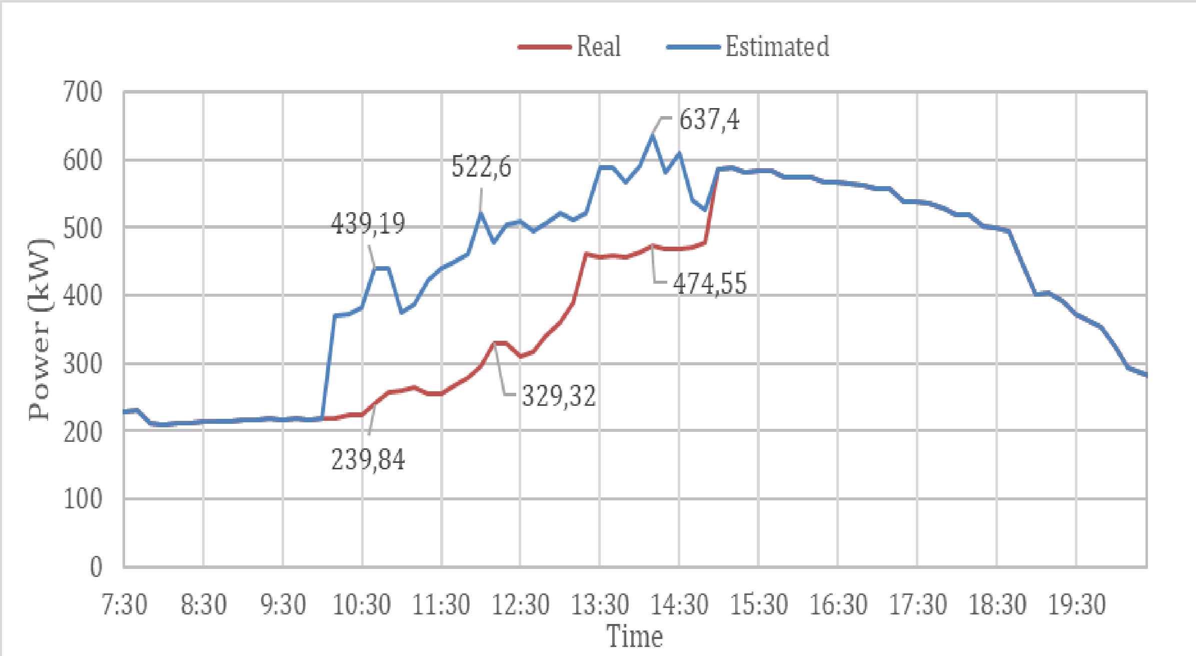

Figure 21: DR Event Results at UCY Microgrid for 500 kWh.

The second DR event that is presented in Figure 22, was a “power save” DSO request for the UCY Microgrid of 100 kWh (minimum). The DR event, that occurred for an hour at the Faculty of Economics & Business and Administration buildings, resulted to an energy reduction of 88 kWh (or an average energy reduction of 25%). That classifies this DR event as unsuccessful.

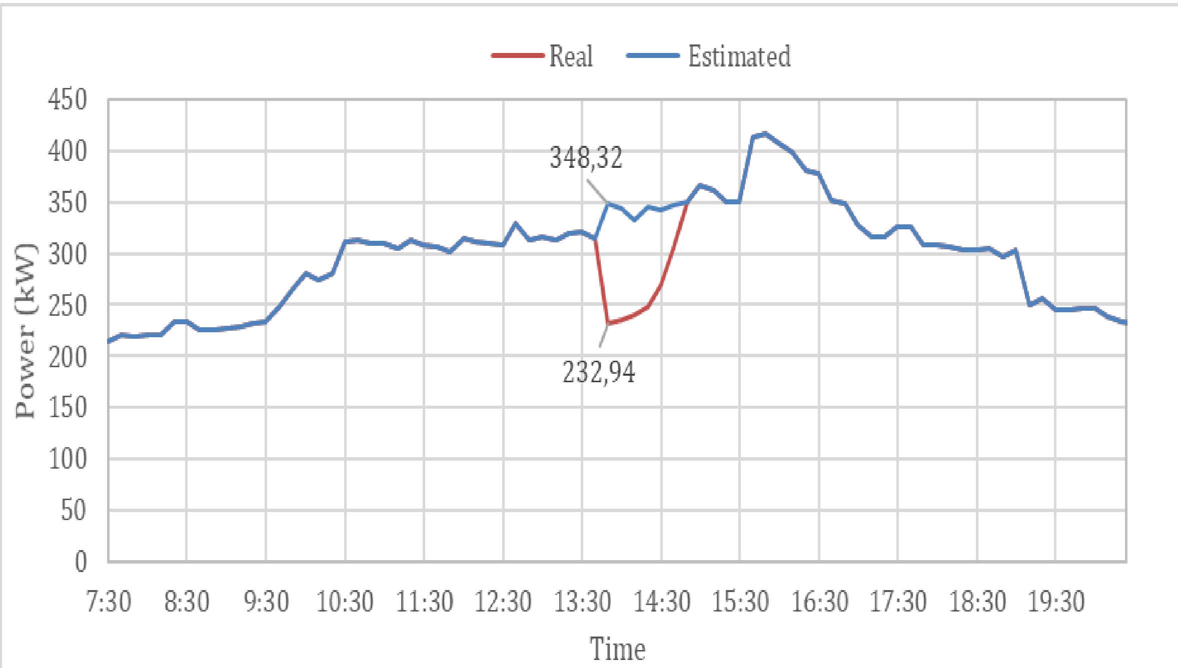

Figure 22: DR Event Results at UCY Microgrid for 100 kWh.

The reason why the DR event in Figure 22 was not successful is due to the fact that the end users' input was against the DR event. As it is mentioned in section 2.1 and in D7.1 [FleD71], the end user can modify the current setpoint (the one that was set by the building operator, in this case power save) with ± 3 °C. The DR event occurred during Summer at 13:45 – 14:45, with approximate outdoor temperature 35 °C, with a result that the end-user noticed the change in the indoor temperature of their offices and reduced the temperature by -3 °C that led to lower energy reduction. For this reason, the aggregator did not deliver the agreed flexibility (i.e. delivered a total of 88 KWh instead of 100 KWh agreed), so some kind of penalty should be paid for the 12 KWh that were not delivered. This in turn means that the aggregator's revenues will be less than initially expected (i.e. during the market clearing process described above).

The third DR event that is presented in Figure 23, was again a "power save" DSO request for the UCY Microgrid of 300 kWh, 150 kWh the first hour and 150 kWh the second last hour (minimum). The DR event resulted to an energy reduction of 314 kWh (or an average energy reduction of 32.5%) and lasted for two hours. The buildings participated in this DR event were the Faculty of Economics & Business, Library and Administration buildings, and it was successful.

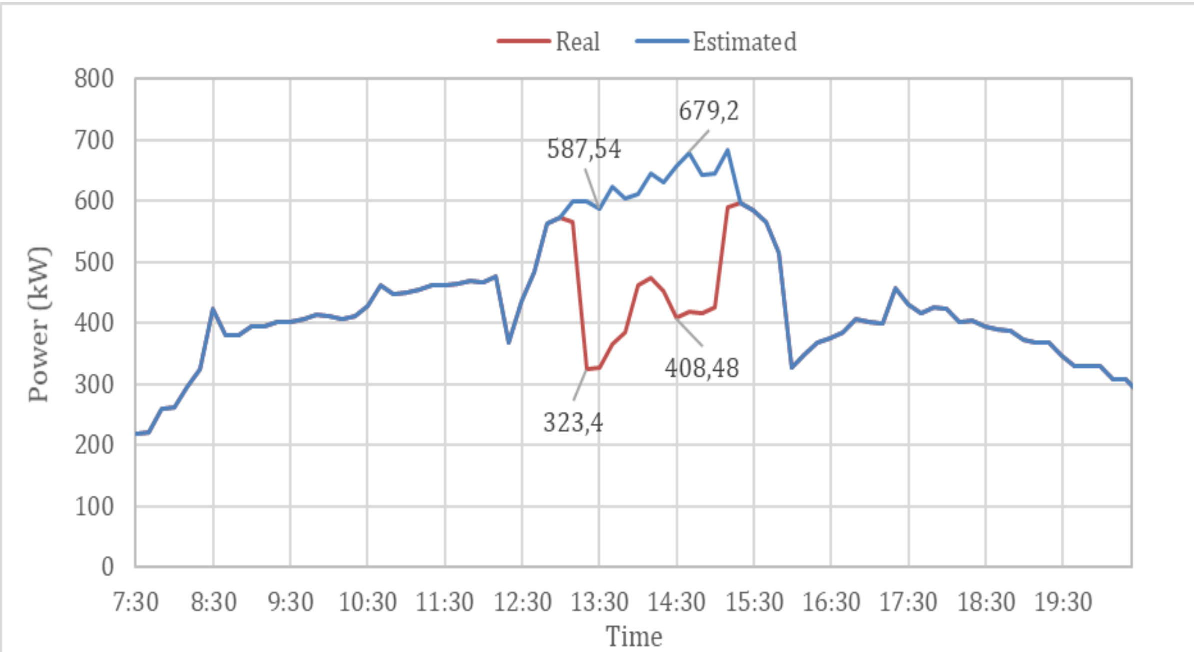

Figure 23: DR Event Results at UCY Microgrid for 300 kWh.

2.3 Nanogrid Demand Response Events – Reduce energy consumption

2.3.1 Experiment Description

The concept of dispatching the DR events signals is the same as with the Microgrid, as seen in Figure 24. The main difference between the two setups is the operation of the grid, which is explained in more detail in the following section.

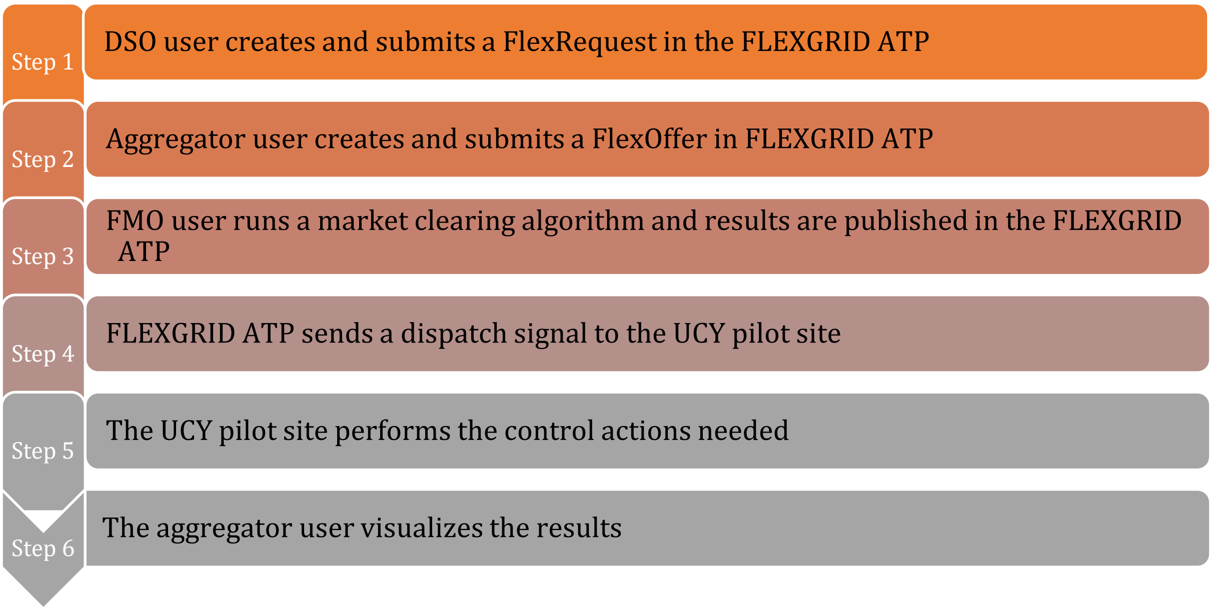

Figure 24: Flowchart for dispatching the DR events signals at UCY Nanogrid.

2.3.2 Experiment Setup

Although the concept of dispatching the DR event signals is the same as with the Microgrid, the experiment setup is quite different. UCY microgrid is controlled by the centralised BEMSs, where the control actions modify the energy consumption of the whole university, even if the signals are sent to specific chillers for specific buildings. This solution is suitable for large commercial buildings that have also a centralised architecture control system. On the other hand, PVTL consists of various components that each one of them communicates and can be controlled and monitored differently. Various communication protocols have been used like z-wave, intesis, MODBUS TCP, etc, in order to establish a communication with all assets and transform PVTL into a fully operational Nanogrid that can participate in Time-of-Use, generation curtailment and energy reduction demand response schemes. This solution can be applied in smart homes as well as in commercial buildings, because the IoT/OpenHAB solution is interoperable and functional for either small or big areas.

The communication between the smart PV inverter (see Figure 25) and any external device or controller is enabled using several communication protocols; non-serial communication protocols (e.g., Modbus TCP/IP, SunSpec Modbus or power line communication) and/or wireless communication protocols (e.g., ZigBee). Among those communication protocols, Modbus TCP/IP and SunSpec Modbus (a standardized Modbus protocol for solar PV applications), are among the solutions currently used for research applications and utility-scale PV plants. In the case of the Cyprus pilot site - Nanogrid, the smart PV inverters communicate with protocols ModBus TCP/IP and SunSpec Modbus. The communication protocol Modbus TCP/IP also permits the communication with external Application Programming Interfaces (API) such as programming in Python. That way, by using Python programming and provided that the characteristics of the Modbus TCP/IP system are known (i.e., IP address configured in the inverter, device ID, and register map), the PV inverter can be remotely monitored and controlled through a Python command prompt or Integrated Development Environment (IDE).

Figure 25: Two PV systems and their inverters. The SMA inverter (red) is connected with the 3kWp system and the Fronius Primo (grey) with the 2kWp system.

Apart from the PV inverters, offices/premises of the PVTL comprise of various Internet of things (IoT), see Figure 26 and Figure 27. These control 24 dimmable LED lights (using Fibaro switches) and 4 HVAC units (using intesis boxes), and monitor significant parameters such as temperature, humidity, luminance, power consumption (using multiple isensors and clump meters). The offices are separated into 6 zones, and each zone is independent with its own control and monitoring points.

Figure 26: IoT installed at the premises/offices of PVTL.

PV zone 012 – Includes 6 Dimmable LED lights, 1 multisensor, 1 intesis and 2 fibaro Switches

PV zone 014 – Includes 1 Dimmable LED light, 1 multisensor, 1 intesis and 1 fibaro Switch

Figure 27: Zones 012 and 014 of PVTL.

All IoT devices are integrated with an open source platform, the 'OpenHAB', which enables the remote control and monitoring of our loads (see Figure 28). The platform was used for enabling the execution of the control dispatching in order to achieve successful DR events. The platform is integrated with a developed software (python script) for automatic control, based on scheduled DR events, curtailments, load shedding, etc.

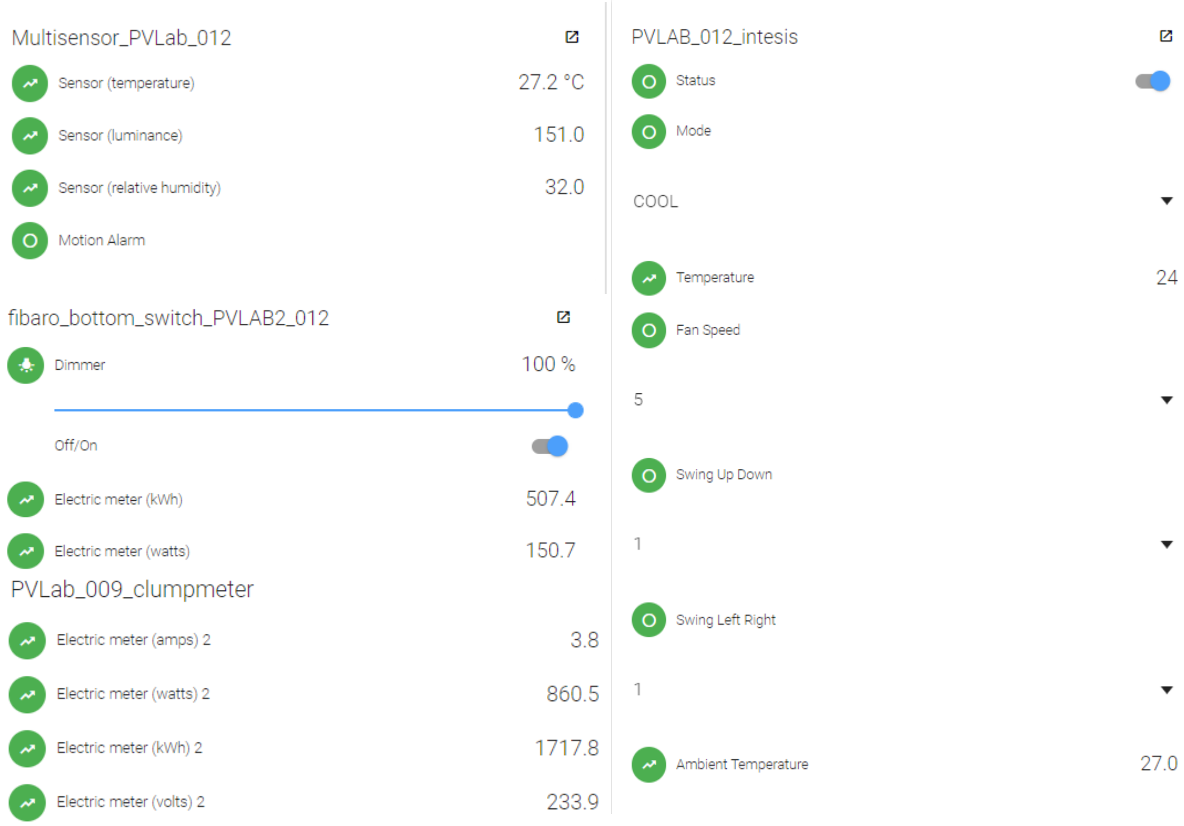

Figure 28: OpenHAB monitoring and control platform.

2.3.3 Performed Tests and Results

For the PV Technology Laboratory Nanogrid of the UCY pilot, most of the events were downward flexibility DR events, one upward and three generation curtailments for the PV system with the Fronius inverter. The total energy saving for the following four DR events was 4257.69 Wh, which corresponds to an average energy consumption reduction of 29.16%.

The first DR event that is presented in Figure 29, were two consecutive power save DSO requests for the PVTL Nanogrid with minimum 1500 Wh and 500 Wh decrease respectively, from the AC unit at zone 009 of PVTL common offices. The DR event, lasted for 30 minutes, and 2180.17 Wh were saved (average energy reduction > 75%).

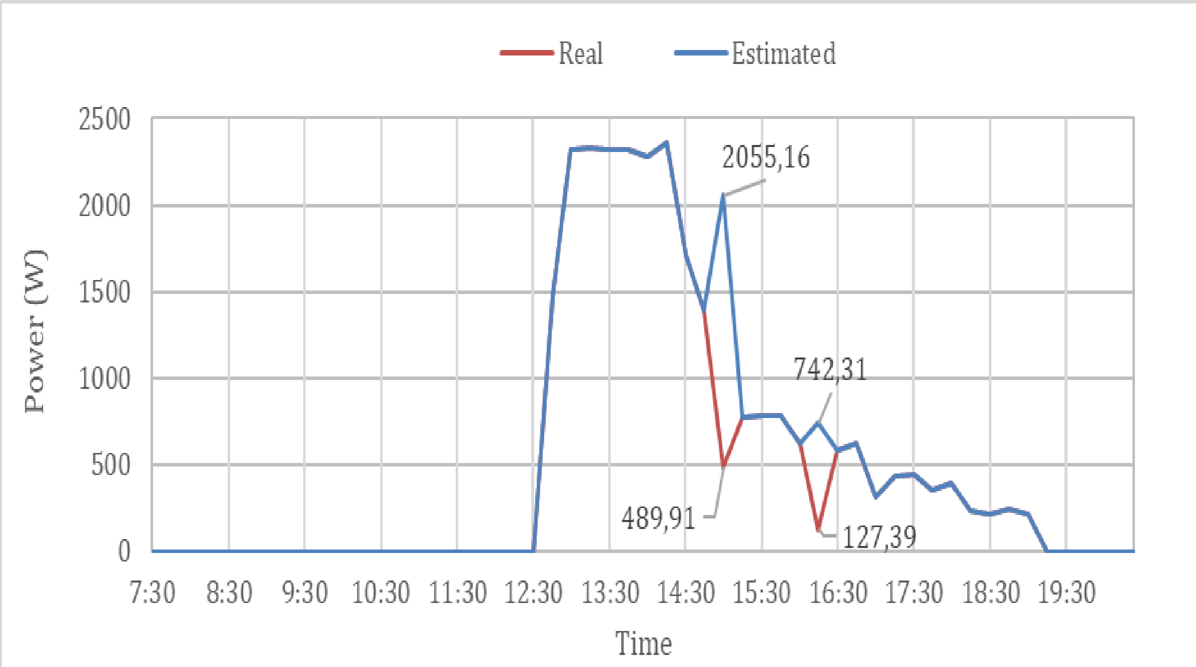

Figure 29: DR Event Results at UCY Nanogrid for 2 kWh power save electricity consumption with AC units.

The second DR event that is presented in Figure 30, represents one power increase consumption and three consecutive "power save" DSO requests for the PVTL Nanogrid; 1) minimum 1500 W increase, 2) 1000 W decrease, 3) 1000 W decrease and 4) 500 W decrease from the AC units at zone 009 and zone 012 of PVTL common offices. The one-hour DR event was successful with a total energy reduction of 891 Wh (first an increase of 1686.34 Wh followed by three reductions of totally 2577.35 Wh) - an average energy reduction/increase of more than 75%.

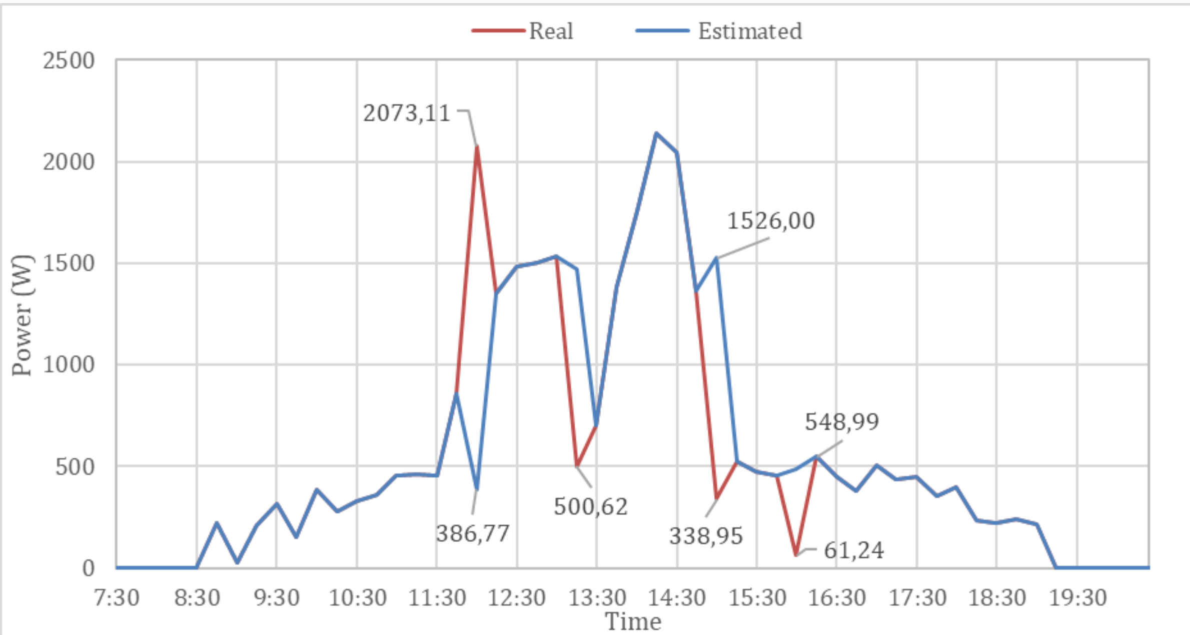

Figure 30: DR Event Results at UCY Nanogrid for 1.5 kW boost, and 2.5 kW power save electricity consumption with AC units.

The third DR event that is presented in Figure 31, were three consecutive “power save” DSO requests (0.35 kWh each) for PVTL Nanogrid, which results to 1 kWh decrease from all dimming lights at zones 009, 010, 011, 012, 013 and 014. The DR event was successful, resulting to an energy reduction of 1185.6 Wh (or an average energy reduction of 40%).

Figure 31, Figure 33, and Figure 35 show the Flexibility Requests, the Flexibility Offers and the Market Clearing respectively (Flexibility level: Medium and granularity: 60) with the corresponding prices for 10:00 timeslot, which relate to the UCY pilot, while Figure 32 and Figure 34 show the corresponding curves.

Figure 31: Indicative screenshot for creating a FlexRequest for UCY Nanogrid.

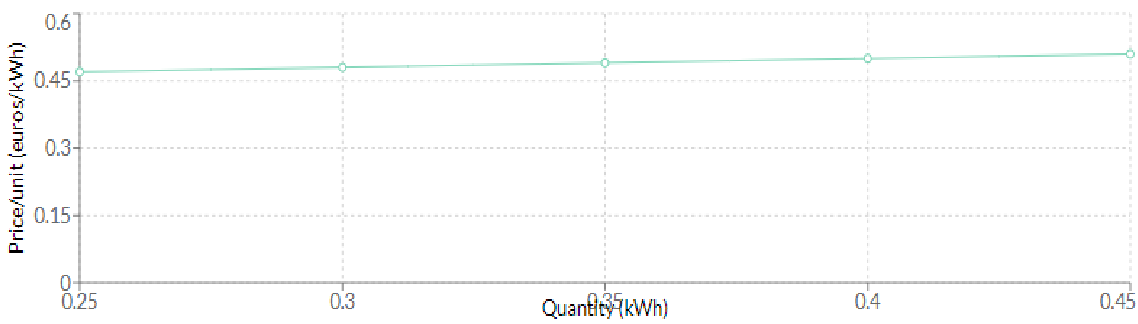

Figure 32: Resulting FlexRequest price curve (EUR/kWh).

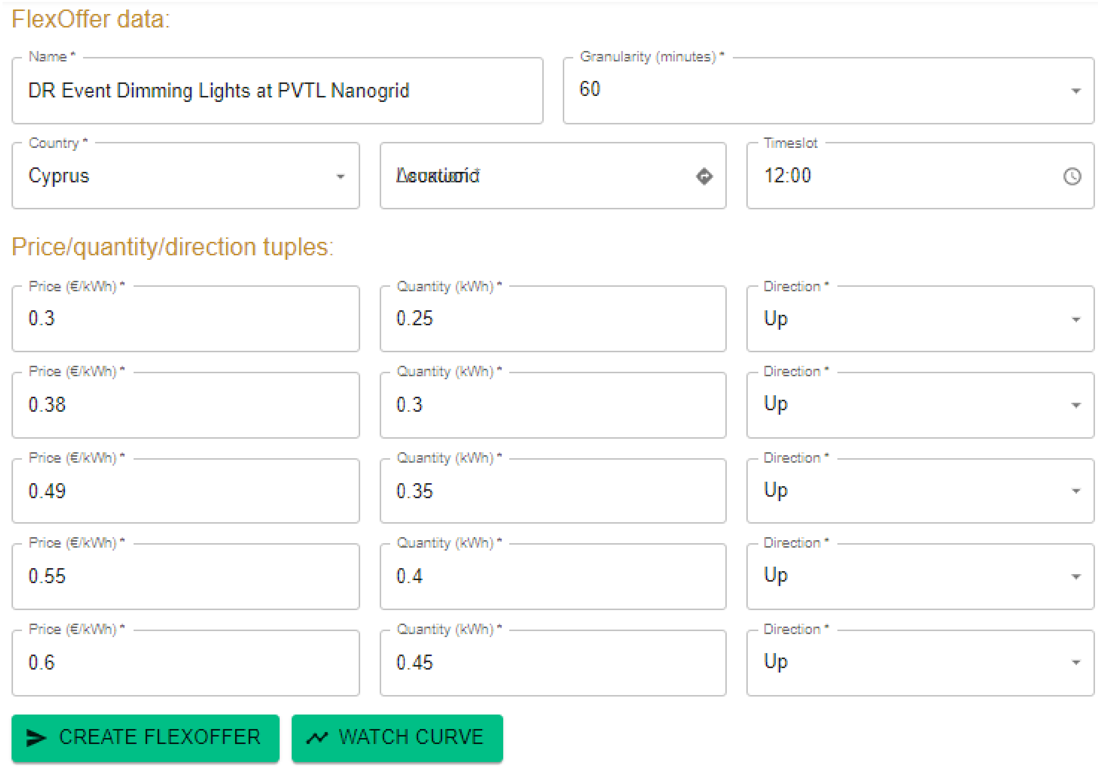

Figure 33: Indicative screenshot from ATP for creating a FlexOffer for UCY Nanogrid.

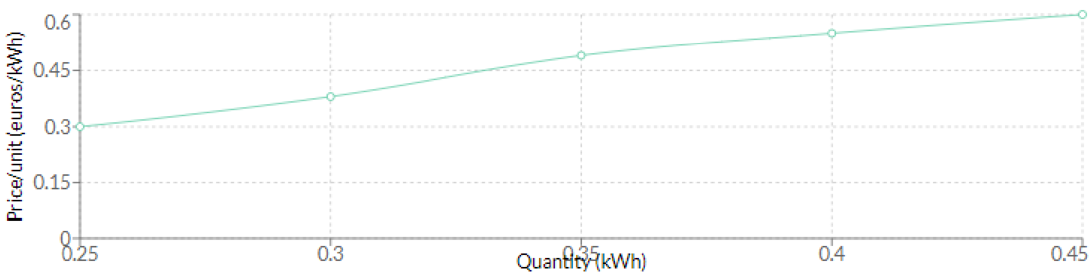

Figure 34: Resulting FlexOffer price curve (EUR/kWh).

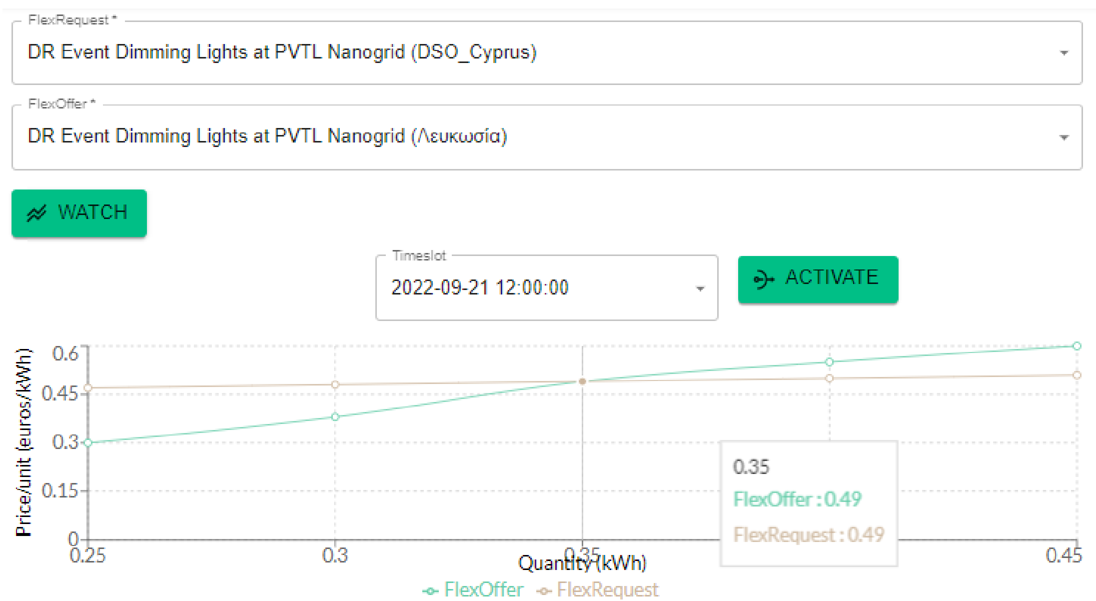

Figure 35: Market Clearing Results (matched at 0.49 €/kWh for 0.35 kWh for one hourly timeslot).

The results of the FlexRequest dispatch optimizations are shown in Figure 36, Figure 37, and Figure 38. More details about the UCS 4.1 ATP GUIs and their operation are described in D6.3 [FleD63]. It is interesting to note that energy reduction results shown in the ATP (cf. figure 37) and results shown in UCY's local control system are the same, demonstrating thus the successful integration with FLEXGRID S/W platform.

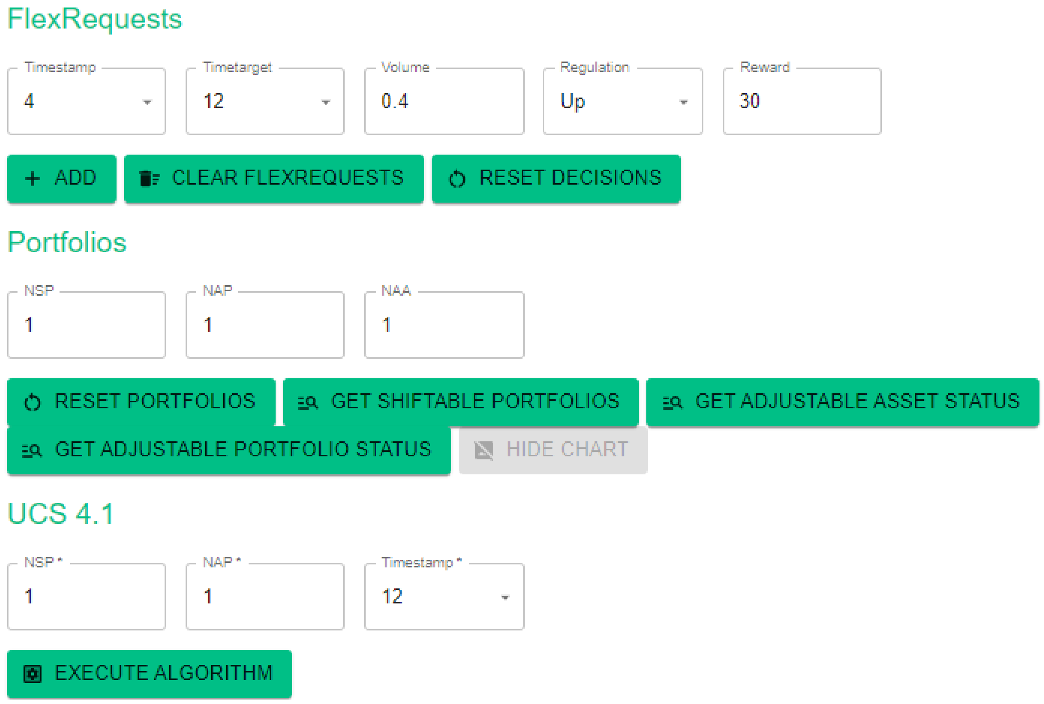

Figure 36: FlexRequest dispatch optimizations (via UCS 4.1 ATP GUI).

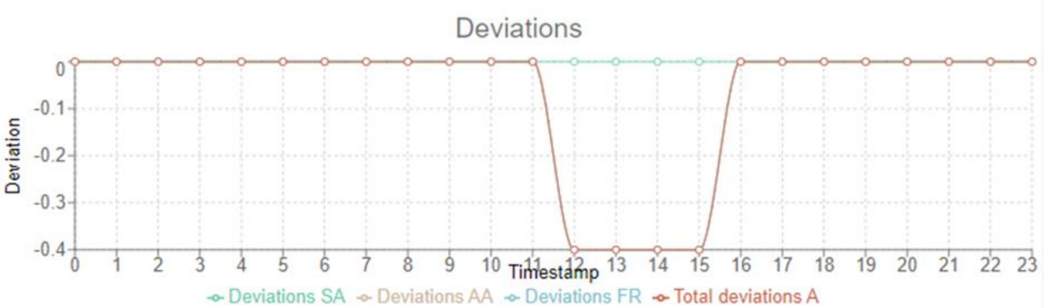

Figure 37: Results of the FlexRequest dispatch optimizations (via UCS 4.1 ATP GUI).

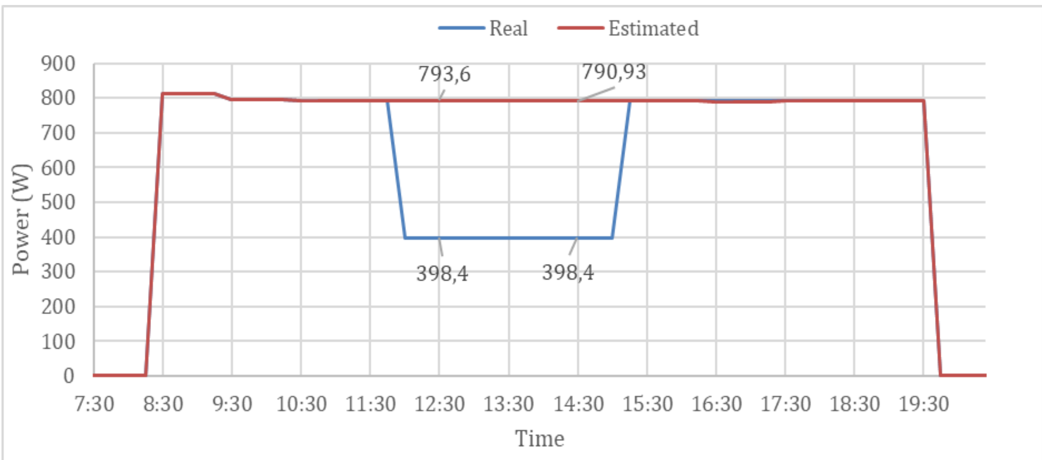

Figure 38: Results at UCY Nanogrid for 1 kWh power save electricity consumption with Dimming Lights.

The final DR event was actually curtailment signals at UCY's 'smart' PV inverter Fronius. As can be seen in Figure 39 below, we send 7 DR signals for curtailing the generation of the rated power 2 kWp, by changing the active/real power setpoint. The resulting curtailed PV generation can be seen in Figure 40.

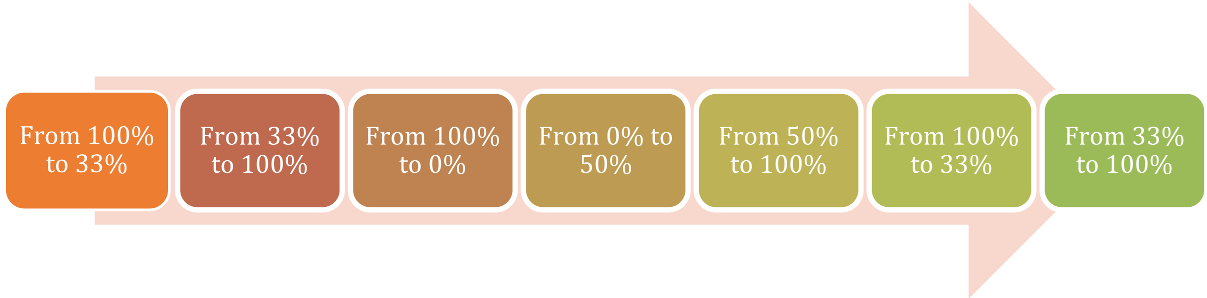

Figure 39: Curtailment signals sent to the PV inverter.

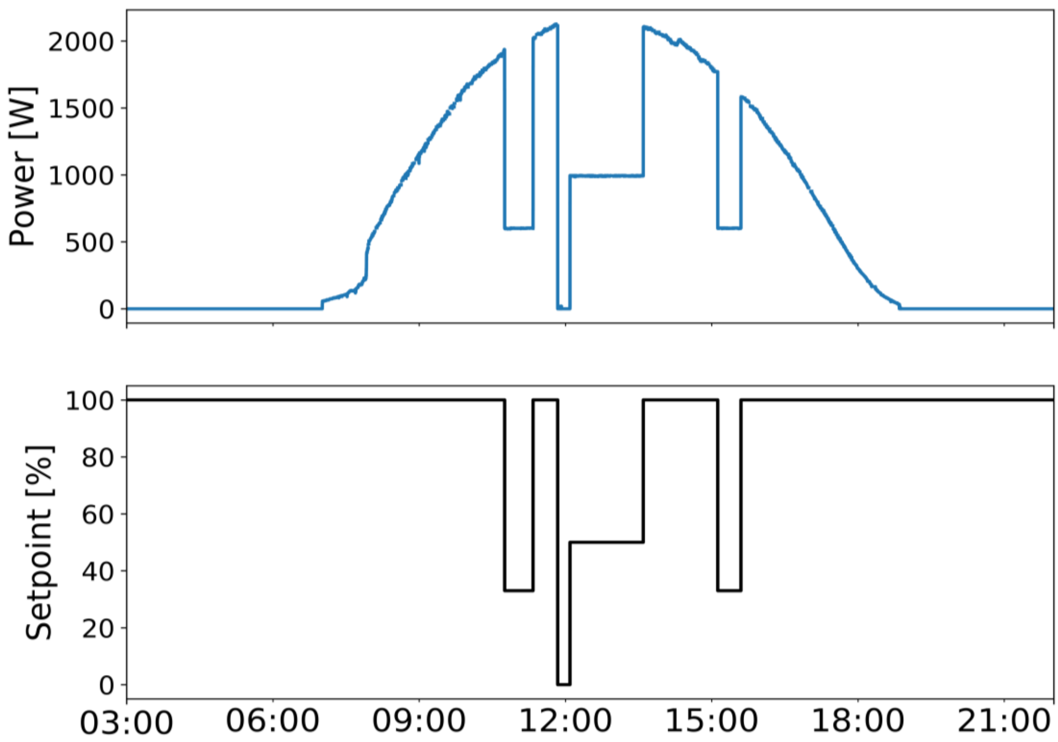

Figure 40: Generation Curtailment at UCY Nanogrid Fronius PV inverter.

Essentially, the meaning of this DR event is to show that with the controllability over the smart inverters, we are able to modify the generation of the PV systems, either to match the stand-alone consumption with the generation, either for curtailing the generation in order to protect the security and the stability of the power network, or for any other reason. This is also important in order to have additional "internal" flexibility in UCY pilot to deal with situations, in which a DR target cannot be met (cf. the second unsuccessful DR event of UCY Microgrid described above).

2.4 Evaluation of Results

As mentioned above, the UCY pilot was used for demonstrating two different solutions at the UCY tertiary buildings and the PVTL premises.

Regarding the UCY microgrid (that considers a centralized BEMS architecture), most of the DR event tests and results were successful. For the cases that the DR events were not successful, the proportion of the end-users' input could not be evaluated. Therefore, the failure of the DR event was attributed either only to the end-users' input or to a combination of other factors (such as open doors/windows in the areas, high occupancy in the tertiary buildings, slow response time of the BEMSs, etc.). By monitoring the end-users' inputs, more crucial information can be provided for the assessment and evaluation of the results. However, this solution could be used to other centralised systems and with scheduled DR events, the energy consumption and the CO_2 emissions could be reduced significantly.

Regarding the PVTL, the IoT/OpenHAB solution is suitable for all types of end-users, due to its interoperability. Moreover, with the usage of the open-source platform OpenHAB, all electrical loads are easily controlled and monitored. However, during the tests, we faced some power issues (e.g., unplugged devices), connectivity issues (i.e., lack of network connectivity) and faulty/damaged equipment, where maintenance was required.

An expert person is thus required to detect and fix those issues. The expert should be able to perform troubleshooting at the premises and re-establish the communication with the OpenHAB platform. Overall, the solution (combined with systematic monitoring of the equipment) is a useful tool that can be used by aggregators to monitor and control various electrical loads with high accuracy, offering flexibility for flexibility trading throughout the day.

3 Evaluating Forecasting Methods for DSO Services – bnNETZE Pilot Evaluation

3.1 Pilot Overview

As already described in D7.1 [FleD71], pilot site operation was intended to be divided into three periods:

1. The first period focused on simulations and theoretical analyses. Control of real devices was not intended. The goal was to set the stage for any forward-looking flexibility management in relation to reliable grid operation, as well as creation of additional value by marketing flexibilities. The focus laid on the implementation and improvement of several forecast algorithms in collaboration with FLEXGRID research partners AIT und UCY (M19-M26).
2. Partly in parallel, the second period focused on preparing the real pilot site consisting of one large energy storage and ten private energy prosumers that provide bnNETZE control access to their facilities. The central motivation was to get all devices as well as communication links operational to be tested later together with the FLEXGRID ATP in the third period as a whole system (M25-M30).
3. The third period was dedicated to real operation of the test site controlled by FLEXGRID ATP and its algorithms. The goal was to show that the system works reliably and contributes to the selected business case. This should confirm the precision of the FLEXGRID forecasts. For this purpose, real measurement values from our grid control system and comparative forecasted values were to be taken into account. Subsequently, the business case of peak shaving for the entire bnNETZE grid was followed and evaluated (M27-M36).

Forecasting is an important skill for both existing and new future energy markets. The objective within FLEXGRID was to focus on enhancing three streams of Artificial Neural Networks (ANN) forecasting models. Models for PV Generation, Load and Electricity Price forecasting were developed and in an iterative process enhanced by researching and evaluating the most significant influence factors. For all classes of forecasts mentioned above, the relevant data sets were provided by bnNETZE. Once the associated partners had trained their algorithms, bnNETZE analyzed the resulting values and compared them to real measurements. The aim was to find the most relevant drivers for significant deviations. Each algorithm was adapted individually depending on what kind of forecasting approach had been chosen in detail.

3.2 Pilot Environment

In the following, the setup of the pilot site is described. A hybrid approach was performed consisting of one large, centralized energy storage combined with ten (10) decentralized systems of prosumers.

3.2.1 Centralized Energy Storage

In D7.1 [FleD71], it was described to use an existing grid-friendly operating Centralized Energy Storage (CES) connected at an end-feeder in the suburb “Freiburg-Opfingen”, which is a community remote from the main city of Freiburg and located at the outer rim of the distribution network. This region is predestined for PV-systems, because it’s settled with many farmhouses with barns and extended roofs. This area is perfectly suitable for the configuration of PV-modules. In the selected case, a farmer’s house is located at the end of a feeder. The property is equipped with four PV plants with a total installed power of 30.5 kWp. All four PV plants are connected via one single grid connection point to the public low voltage grid. In fact, voltage limits at its grid connection point are violated by the local generation of electricity several times over the year. A further extension of the existing PV systems is not possible, even if there is more than enough free space left on the barn’s roof. By using a battery storage system, the PV plant can fully feed-in into the local distribution grid even during peak production periods. Generation peaks of the PV plants are temporarily stored in the battery. For special purposes of the DSO a time restricted override over the local energy management routine is possible.

So, the focus in battery operation lays on offering local services to the grid and to the general needs of the DSO or a flexibility operator. The storage is used in multi-purpose ways:

1. Congestion management and voltage control to avoid grid expansion (local)
2. Peak-shaving for the entire grid (general)

This battery is based on the innovative and environmentally friendly “Redox-Flow” principle. Figure 41 shows the device.

Figure 41: Originally foreseen redox-flow CES.

Unfortunately, this battery was no longer available for the FLEXGRID project as the owner of the land terminated the lease. A prolongation was not possible. Therefore, the battery had to be removed. As there was now enough operating experience with the "Redox-Flow" principle, bnNETZE decided to realize a new lithium-iron-phosphate battery storage instead at a different location and with different tasks. The battery was realized at the premises of the grid control center. A PV system already exists there. In addition, charging points for electric vehicles will be installed soon. The battery will primarily perform two tasks there: On the one hand, it will increase the self-consumption rate of produced PV electricity on the premises. Excess PV energy will be temporarily stored and retrieved from the battery storage during the night. Due to the 24/7 operation of the grid control center, consumption is also comparatively high at this time. On the other hand, the battery performs peak shaving for the site and regulates the electrical power at the grid connection point to a maximum permissible value.

The dimensions of the battery are typical for medium sized commercial customers. Its technical parameters are as follows:

- 80 kWh nominal capacity, 64 kWh useable capacity
- 24 kVA nominal electrical power

This battery provides some unique selling points:

- No danger caused by fire or explosion due to the use of iron-phosphate-cells. They are inflammable. This is relevant as the grid control center is a site of special importance for the public supply. Any danger by fire must be avoided.
- The cells are not able to leak or to outgas. This is relevant under environmental aspects.
- The battery provides a very innovative battery management system, which is capable to handle mixes of battery cells. So, cells from different manufacturers, with different technical parameters and in different stages of aging can be combined. This is a very special feature. It opens the possibility to use second life battery cells e.g., from old electric vehicles and extend their lifetime. This improves their eco balance significantly! This control approach is patented under the brand “pacadu”. The battery management system is realized on a SIEMENS Sinamics control platform.
- The battery was manufactured in Freiburg by a Small & Medium Enterprise called ASD. So, the local welfare could be increased, too.

Figure 42 and Figure 43 show the new battery.

Figure 42: New CES (outside and inside)

Figure 43: New CES (control device)

3.2.2 Distributed Energy Storages

The connection of prosumers, equipped with PV-systems, Distributed Energy Storages (DES), home management systems and partly EV charging facilities is the second part of the hybrid pilot implementation of bnNETZE.

Nowadays, the costs for self-produced energy from a home solar system is about 15 ct/kWh, which is—especially with the current European energy crisis—much lower than the energy bought from an energy supplier. This is one reason why the number of yearly new installed PV systems is high in Germany. Because of the significant lower price, there is a strong incentive to use as much as possible of the self-produced energy. As a result, the market for private PV storages developed rapidly over the last few years. Today, more or less, all new PV systems are sold together with a PV storage as well as a home management system to maximize self-sufficiency and to minimize expensive energy supply from an energy supplier.

As described in D7.1 [FleD71], the pilot test site focuses on testing the additional flexibility potential of households already optimizing their self-sufficiency with a home management system, evaluating the business idea in means of supporting a reliable grid operation and financial market potential as well as testing the technical feasibility of the setup. The home management system takes the role of a local energy management authority at the unit level. This is an important advantage as FLEXGRID does not have to deal with a variety of proprietary communication standards of devices on the lower house level. Instead, FLEXGRID can focus solely on connecting to the Sunny Home Manager as the lower energy management authority and this device deals with the control of all local home devices.

Normally, the main target of the system is to maximize self-sufficiency of the customer and at the same way to minimize the energy consumption from the grid. With the current high energy prices in Europe, the tariffs for residential customers are at least two times as high as the production costs from the own PV-system. However, the optimization algorithm in the Sunny Home Manager focuses only on the local building. A connection to a superior optimization level is not realized right now. This was the special challenge during test site preparation to realize a special channel for handling external control commands. This was realized by a special communication gateway in addition to the standard configuration. As described in D7.1 [FleD71], ten “Energy Pioneers” were contracted, and their systems were successfully made externally controllable by the FLEXGRID ATP (Figure 44).

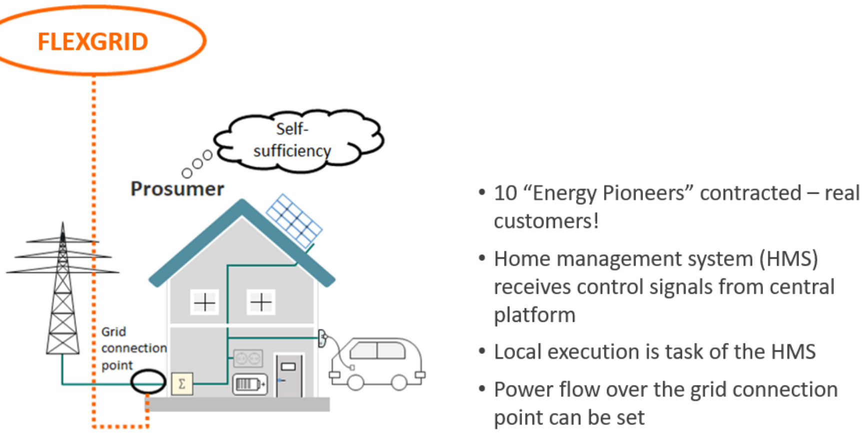

Figure 44: External control of an “Energy Pioneer”

Furthermore, a remote monitoring of all energy pioneers was established. Via a platform, all devices as well as the residual load on the grid coupling point can be plotted and exported. So, it became possible to check, if the energy pioneers reacted exactly the way that the FLEXGRID ATP (via the market clearing results and respective dispatch commands) intended. Figure 45 shows the example of the visualization of one “Energy Pioneer”.

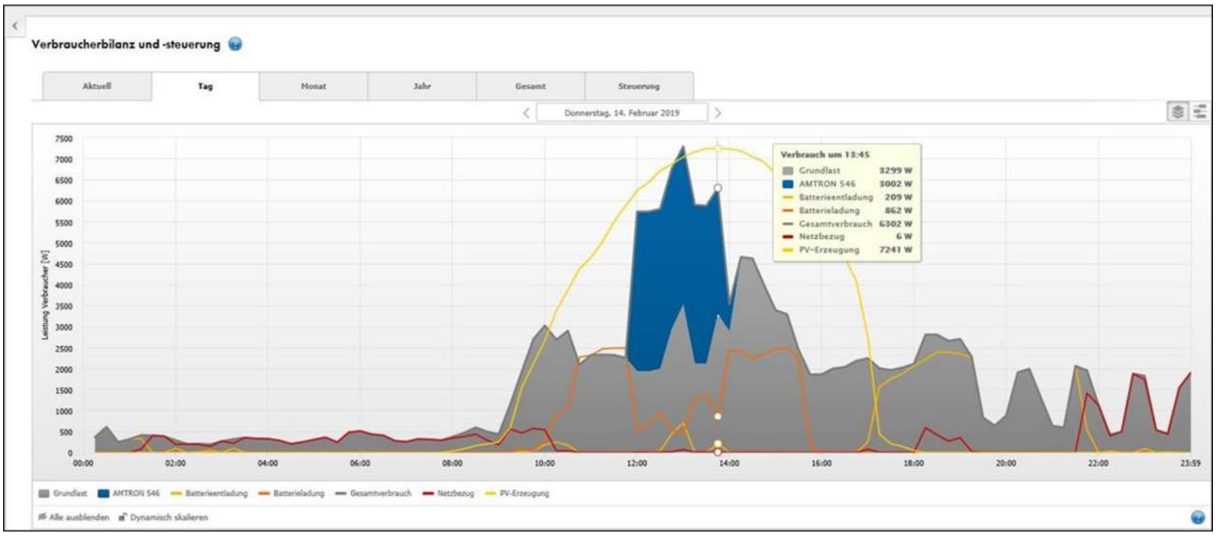

Figure 45: Visualization of an “Energy Pioneer”

The communication plan could be realized as described in D7.1 [FleD71] with only minor changes. The intended automatic protocol conversion from the SMA platform to the FLEXGRID ATP and back was replaced by a manual conversion done by the operator. For the pilot site operation this did not have any influence. The scientific results remained the same.

Figure 46 illustrates the setup and communication for the participating customers with DES. The detailed plan for the data flow is as follows: The DSO sends FlexRequests to the FLEXGRID ATP, if flexibility is required. They will always be limited to a certain time frame and sent some time in advance. Then the FLEXGRID platform matches the requests with FlexOffers provided by ESPs/aggregators. If the price curves match, a deal is settled and an activation command is produced. This message is sent to the contracted ESP and from there, it is forwarded via the communication gateways of the DES. In all participating customer households, these gateways were installed to make them capable in handling external control commands. The gateway stands as a communication interface between the FLEXGRID platform and the Sunny Home Manager finally executing these commands.

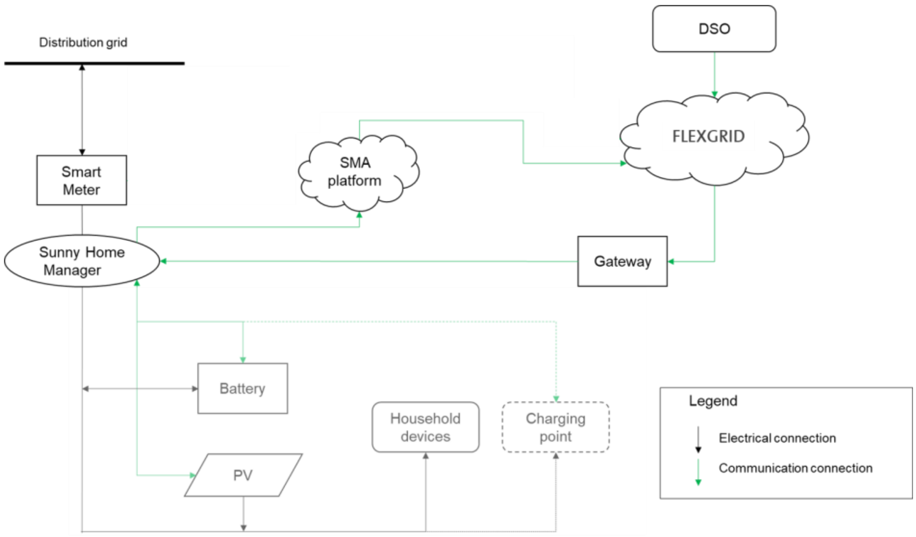

Figure 46: Communication plan setup

3.3 PV forecast

The forecast algorithm for PV was developed by UCY under support by bnNETZE. The work was part of WP4. The approach and the results are already described in D4.3 [FleD43]. So, this deliverable focuses only on the main results of the iterative improvement of the algorithm.

As stated earlier, the UCY team and bnNETZE used a normalized Root Mean Square Error (nRMSE) to evaluate the performance of the PV Forecasting algorithm. After the first attempt, which included the aggregated PV data & weather variables such as Forecasted Global Horizontal Irradiance, Forecasted Ambient Temperature, Elevation Angle of the Sun, Azimuth Angle of the Sun, and Energy (Output), the nRMSE percentage was at 11.3%. However, on particular days with very high irradiance, the nRMSE was at a percentage of over 20.

For the second attempt, the weather input variables stayed the same. However, instead of using the aggregated PV data in total, the data from the six significant individual PV systems were incorporated to see if this affected the accuracy of the forecasting. The nRMSC value stayed about the same of 11.28%. Therefore, it was decided to move forward with using just the aggregated PV data. The more significant improvements in forecasting were due to including the factor for snow coverage and cloud coverage. The snow days factor improved the nRMSE by a full 1% to 10.3%. The cloud coverage variable further improved the nRMSe value to 9.79%. With this improved data, the lowest forecasting error occurred in the summer time, when there were consistent sunny days occurring. The largest error occurred in the fall, when there is a largest weather variability occurring. The suggestions by bnNETZE led to an improvement of 1.5% from the first to second attempt.

In the third attempt, the NWP data sets partly acquired from "Deutscher Wetterdienst" (DWD) and fully constructed utilizing the QGIS4WRF plug-in -for the QGIS software were employed. It can be observed that the overall error of the forecasting methodology was reduced by approximately 1%. The recorded nRMSE for this attempt was 8.69%, indicating the significance of the weather data quality for strong forecasting accuracy of PV production. In tandem, the Cloud Coverage variable was improved to categorize the type of day. The days were specified as "Clear Sky", "Moderate", and "Overcast". The best performance was recorded for the Clear Sky days, with a nRMSE of 6.41%. Clear Sky days only accounted for 40 days of 365, while the majority of the days (200) were characterized as "Moderate" with a nRMSE of roughly 8.7%. Figure 47 shows the performance of each type of day and the percentage of each type of day.

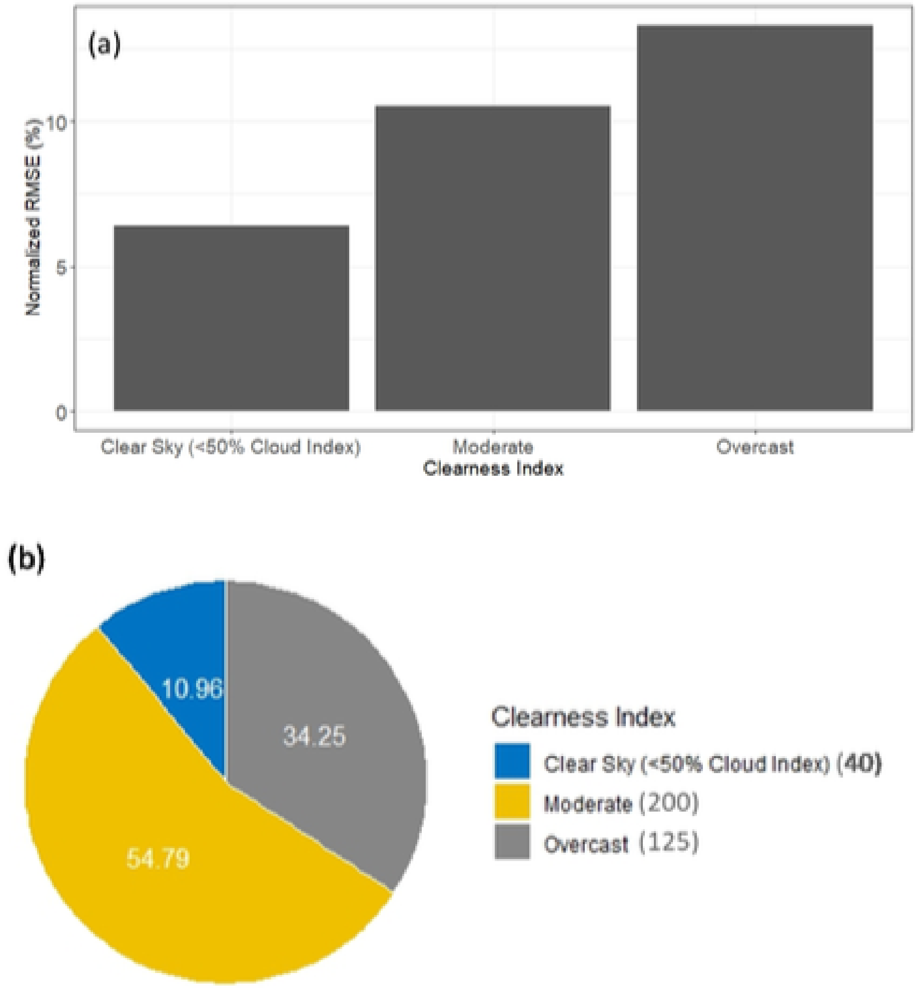

Figure 47: Results from the PV forecast: (a) nRMSE of the Different Categories under the Clearness Index; (b) Percentage of Times the Categorized Clearness Index Days Occurred

The final forecasting attempt included the addition of two more weather variables that had potential to improve the algorithm. When the forecasting was performed with the addition of Wind Speed and Relative Humidity data, the improvement was slight, only resulting in an improvement of 0.20%. The updated nRMSE for this forecasting attempt was 8.46%. Due to the insignificance of the improvement, the p-value test was employed to reject the null hypothesis. The null hypothesis was set to a value of 0.05. To reject the null hypothesis, the p-value must be less than 0.05. The p-value demonstrated a value of 0.041. Therefore, the p-value can be characterized as marginally significant, indicating that the Wind Speeds variable's improvement on the methodology might also include some random effects.

The results for PV forecasting had a significant improvement from the first attempt to the fourth attempt. The suggestions provided by bnNETZE consistently improved the forecasting algorithm. Overall, the model's accuracy was improved by an impressive 2.6%. Utilizing a combined WRF and PV Power Day-Ahead forecasting model along with the initial weather variables that were included provided a strong initial foundation for the accuracy of the model. These input variables all have a strong correlation on the output of PV forecasting. In order to mathematically improve the accuracy of the model, adding weather parameters that are significant to the Freiburg region had the strongest impact on the RMSE. The most relevant drivers for the improvement of this model were related to cloud coverage/sky clearness index.

3.4 Price forecast

The price forecast algorithm was developed by UCY too, again under the consulting support by bnNETZE. The approach and the results are already described in D4.3 [FleD43]. So, this deliverable focuses only on the results of the iterative improvement of the algorithm. The resulting RMSE is shown in Figure 48.

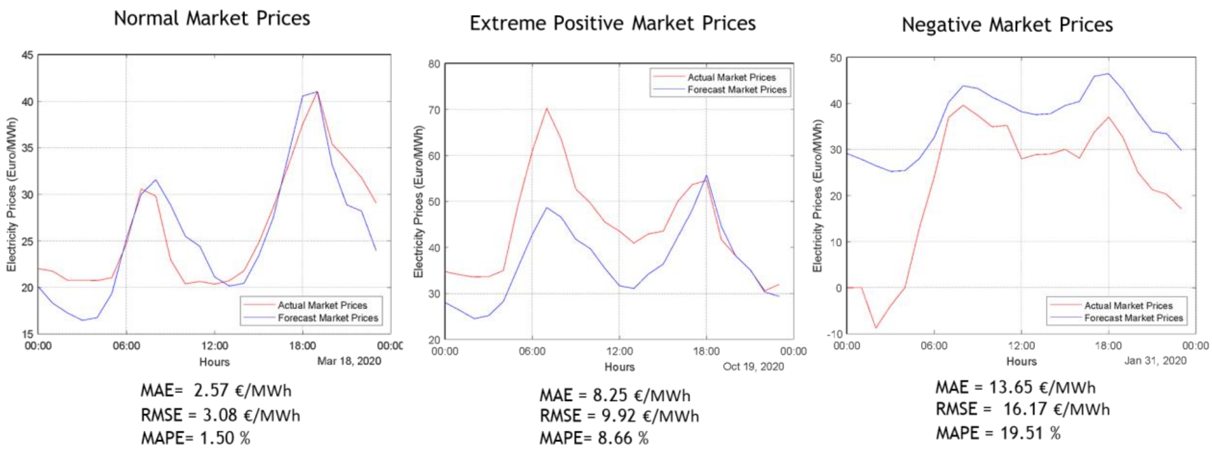

Figure 48: Accuracy of price forecast

The proposed methodology for Market Price forecasting aims to facilitate the optimal FlexOffer process for effective ESP/Aggregator involvement in all types of flexibility markets at the distribution level and wholesale/balancing markets (i.e., transmission system level). The availability of forecasts can enable risk assessments that in turn could provide insights to ESPs/Aggregators planning and management of their flexibility assets.

In a nutshell, it can be stated that:

- For normal market prices, the obtained results demonstrated the effectiveness of the proposed method for market price forecasting,

- For Negative or Extreme positive market prices, the algorithm needs further optimization, and
- Negative or Extreme positive market prices affect the forecasting accuracy of normal prices.

3.5 Load forecast

3.5.1 Experiment Description

One business case, which was selected to be analyzed in detail within FLEXGRID, was preventing peak loads in the entire electrical grid from the perspective of a DSO. Figure 49 illustrates the peak shaving approach on the example of bnNETZE's main electrical grid. It is common in Germany that a DSO must pay a grid usage fee for the highest physical peak load in its grid over a one-year period. The highest quarter hour value is relevant for settlement and clearing. The measured power values over all coupling points are aggregated to evaluate the total peak. Typically, load peaks in the grid occur in the morning, around noon or in the evening. There is a strong dependency on daytime, day type, seasons, temperature, solar radiation and even wind speeds.

If it is possible to forecast the expected peak time precisely, it is possible to activate flexibility in the grid accordingly, and to reduce this expected peak load. DERs could offer their flexibility potential directly or via an aggregator to the DSO. This would result in substantial cost savings over a one-year period. However, all peaks occuring later must be kept under this new limit too. Hence, one single attempt will not be sufficient to ensure the cost savings until the end of the year.

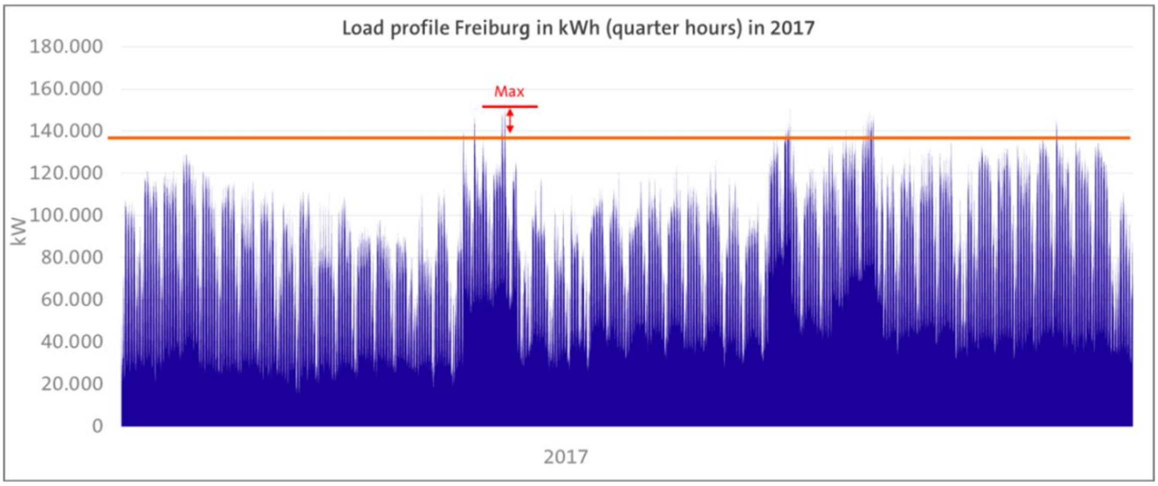

Figure 49: Peak shaving example for the main electrical grid of bnNETZE

Electrical grids are always technically designed to cover the highest expectable peak loads. If it is possible to reduce the peak load certainly, weaker grid structures can be built (or else grid reinforcements can be postponed). This implies additional significant cost savings during the planning and construction phase. The other positive effect is the direct cost savings of the DSO as the grid usage fees to be paid to the upstream grid operator are reduced. The counterfactual scenario considered for this business case is a DSO operating a local distribution grid without trying to reduce peak load. In this case, DSO is only in the role of an observer. What is needed from the grid is physically served by the upstream grid and paid at the end of year in the settlement and clearing process.

An essential prerequisite for efficient peak shaving is the most precise possible prediction of the so-called "residual load". This is the actual physical energy flow over all interconnection points from the upstream network. The residual load is therefore a mix of the actual consumption of all load types in the grid minus the feed-in, e.g. from PV systems, wind power or combined heat and power plants.

Within the framework of FLEXGRID, a forecasting algorithm was selected together with the project partner AIT in Vienna, trained with historical data and tested and optimized in an ongoing real operation environment.

During the training period, bnNETZE evaluated the forecasted values with the real measurements. The forecast accuracy was improved in an iterative process by analyzing the relevant drivers for significant deviations. In several iterations the overall accuracy was improved step by step. It is important to point out, that the goal for load forecasting in the context of the DSO’s business case “Peak Shaving” is not necessarily being able to predict the residual load precisely for each quarter hour interval or the very exact magnitude of the load peaks, rather to be able to accurately predict the correct quarter hour interval that the peak will occur. If flexibility assets in the grid are activated too early or too late, then the peak will be missed and, in the settlement and clearing process, the full peak will be charged.

3.5.2 Experiment Setup

Aim of the experiment setup was to develop a data driven algorithm for residual aggregated day ahead load forecasting with the focus on load peaks (point in time and magnitude) which can be used for a live demonstration. This approach was done in three steps: Providing historical data, choosing an algorithm, training the model as well as proofing the concept in a live operation environment. Figure 50 shows the process on a high level whereas Figure 51 illustrates it in detail. The whole process for the finally used trained algorithm involves several iterations and offline test phases with different sets of data, varying features and changed model structures. The finally applied model was trained offline.

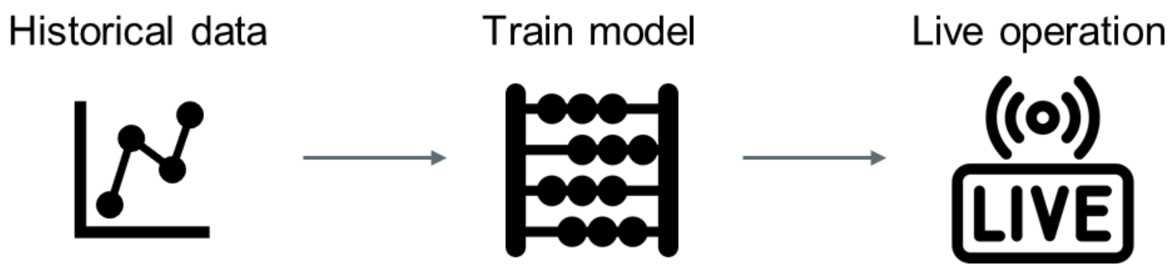

Figure 50: Development of a forecast algorithm (high level)

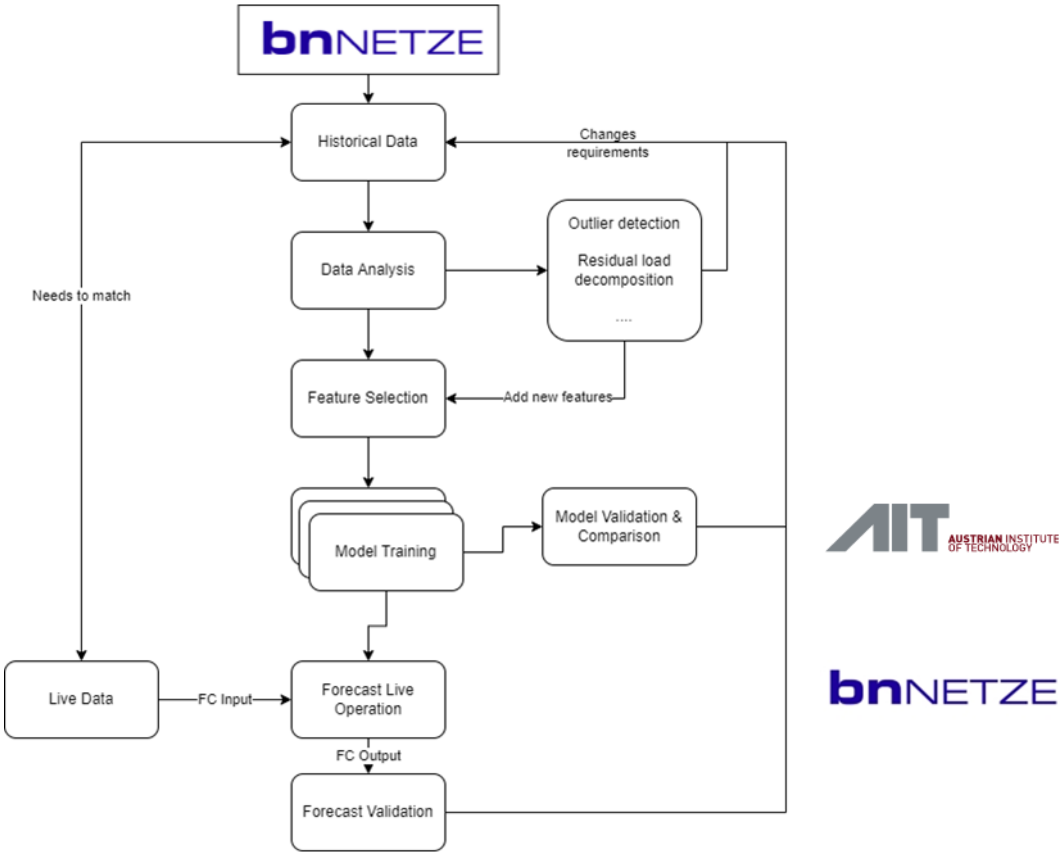

Figure 51: Development of a forecast algorithm (detailed description)

3.5.2.1 Algorithm

Forecasting techniques have been employed by stakeholders in the energy sector for many years. On the simplest level of categorization, forecasting techniques can be classified as either quantitative or qualitative. A quantitative forecasting approach can be used when the following two primary conditions are met:

1. historical data is available and
2. One can deduce that the patterns of the past would repeat in the future to some extent.

Since the goal of this pilot is to predict future values using historical data as one of the input parameters, the chosen forecasting methods is based on time-series data. In time-series forecasting, it is common that seasonal or cyclical patterns occur in the time series data. For energy-related forecasting, often a seasonal, weekly or daytime pattern is likely to occur. When choosing a forecasting method, it is important to identify which kind of patterns or trends are occurring in the data and choose an algorithm that is the best suited to deal with the patterns.

Another simple way to categorize forecasting methods is by defining them as statistical, computational or mathematical programming approaches. These can further be broken down if they are an integration or "hybrid" of multiple statistical approaches or computational methods. Regarding the forecasting timeframe, statistical methods are best suited for shorter periods (i.e., day-ahead), whereas computational methods are suitable for all durations of time. Figure 52 below shows an overview of how often statistical and computational methods have been chosen for different energy forecasting modeling objectives. Some of the most popular methods of forecasting are Artificial Neural Networks (ANN), Autoregressive Integrated Moving Average (ARIMA), Linear Regression, and Autoregressive Moving Average (ARMA). Autoregressive modelling essentially takes previous data into account to predict future values.

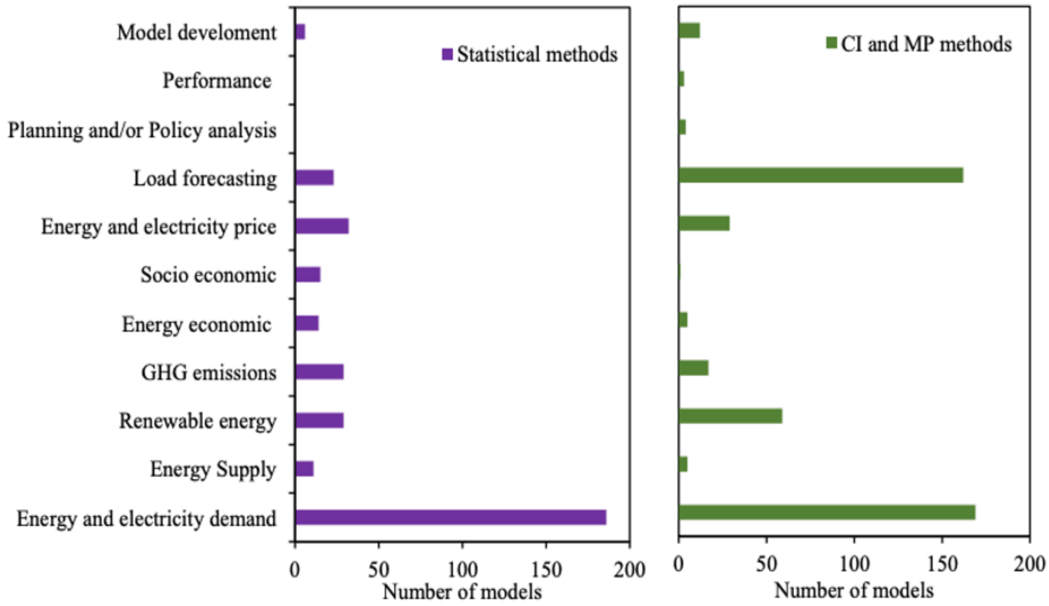

Figure 52: Energy forecasting modelling broken down by chosen approach [Deb18]

Forecasting time-horizons for load can be categorized as short-, medium-, or long-term. Short-term can be quantified as day-ahead forecasting, medium-term can capture weeks and up to a year, and long-term can cover any time frame exceeding one year. AIT proposed to use a 'Recurrent Neural Network' (RNN) method for load forecasting as it has shown the most promising results in previous forecasting projects they have conducted. A RNN is a type of 'Artificial Neural Networks' (ANN) that has a dynamic training process. This means every trained sample in the past has impact on the next following sample (sequence). RNN makes use of the past data in an efficient manner and is slightly more complex than ANN. Like an ANN, a RNN consists of multiple inputs and contains a hidden layer of neurons that assign a weight to each of the input neurons before providing an output or predictive value. Additionally, RNNs take the patterns of the inputs into account as well as patterns they learn as the algorithm is being trained. A quantitative forecasting approach can be used when the following two primary conditions are met: *1)* historical data is available *2)* One can deduce that the patterns of the past would repeat in the future to some extent. Since the goal of this pilot is to predict future values using historical data as one of the input parameters, using RNN as the forecasting method is an appropriate approach for this time-series model.

Exactly a "RNN LSTM" model was chosen realized in Python via the package keras. Figure 53 shows the chosen layer structure of the RNN. Compared to a simple feed-forward neural network, a RNN works on the principle of saving the output of a particular layer and feeding this back to the input to predict the output of the layer. The LSTM (Long Short-Term Memory) structure in general allows to consider the patterns of changes in time series data. This means, a predicted time stamp is dependent on the times before, resulting in a dynamic behaviour.

This goes along with higher efforts in the trading process, since the RNN is trained with vectors. The closer a time stamp is to a predicted value, the more important it is and vice versa.

Several RNNs with similar structure have been trained. They differ in the input and output layer. The hidden layers stay the same. The input layer represents the selected features and the time period considered for training. The output layer represents the residual load and the time period to be forecasted in the feature.

```
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Dropout

regressor = Sequential()
regressor.add(LSTM(units=20, return_sequences=True, input_shape=(X_train.shape[1:])))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units=20, return_sequences=True))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units=20, return_sequences=True))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units=20))
regressor.add(Dropout(0.2))
regressor.add(Dense(units=y_train.shape[1]))
regressor.compile(optimizer='adam', loss='mean_squared_error')
```

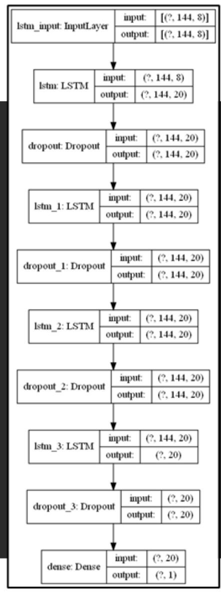

Figure 53: RNN LSTM model realized in Python keras

3.5.2.2 Assessing Forecasting Quality

There are several types of metrics that can be used to assess the accuracy of forecasting. Accuracy metrics can be categorized into three widely used categories: scaled, scale dependent and percentage errors. The most common indicators for each category are:

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- Mean Absolute Percentage Error (MAPE)
- Mean Absolute Squared Error (MASE)

MAE determines the average degree of error in the forecasted outputs and does not consider whether the deviation is negative or positive. It is one of the most widely used accuracy indicators for forecasting because it is easy to interpret and compute. MAE can be mathematically expressed as:

$$MAE = \frac{1}{n}\sum |e_t|$$

Similarly, RMSE also determines the average degree of error in the predicted values and is indifferent to the direction of the error. However, unlike MAE that assigns an identical weight to all errors, RMSE assigns a more significant weight to larger errors. This is because the errors in RMSE are squared before the average of the errors is taken. RMSE can be mathematically expressed as:

$$RMSE = \sqrt{\frac{1}{n}\sum |e_t^2|}$$

RMSE was decided by the project partners to assess accuracy of the forecast attempts.

3.5.2.3 Algorithm Training Attempt 1

For the training phase bnNETZE provided real measured historical data from 2016-2018. Configuration and training of the load forecast algorithm was executed by AIT. bnNETZE provided load data from 2016, 2017 in quarter hour granularity to AIT to train the forecasting algorithm for the year 2018. The forecasted values for 2018 could then be compared to the real measured value for the same year.

As already stated, above AIT employed a RNN in Python for their forecasting endeavor. It was imperative that before feeding the algorithm a data analysis was conducted to ensure that there were no missing values or unusual gaps. After assessing the raw data and confirming that there were no discrepancies in the data sets, AIT started with the training. Training of the algorithm was conducted in two attempts.

In the first attempt, the initial input variables included in this model were only residual load time series with associated date/time stamps for each quarter hour value. The feature enrichment broke down the initial data/time information into more specific categories to identify ‘day of the year’, ‘day of the week’, ‘hour of day’, and ‘weekday vs weekend’. It was important that the algorithm accounted for this determinization as electrical consumption depends strongly on these categories. In order to conduct day-ahead forecasting, AIT used previous 96 timestamps (four 15-minute intervals per hour x 24 hours) to predict the future 96 intervals.

This forecasting attempt was evaluated with several forecast performance indication methods, but to keep the assessment process consistent between all forecasting algorithms, RMSE was the chosen accuracy indicator. The results from the first attempt were already strong despite being a fairly simple model. With only two input variables- load data provided in kilowatt (kW) and the associated quarter hour time stamp- the RMSE was already 8.1% (Table 2). But, to capture the exact quarter hour interval of when peaks in load may occur, the algorithm needed to be further developed.

Table 2: Load forecasting results from attempt 1

Accuracy Indicator	Value
MSE	0.0065
RMSE	0.081
MAE	0.059
Pearson Correlation	0.897

3.5.2.4 Algorithm Training Attempt 2

It was decided to disintegrate the residual load profile further into its main constituent parts: consumption and generation from different sources. This to further improve forecast accuracy especially regarding the exact quarter hour interval when a peak in the physical energy flows occurs. The generation part within the residual load-flow profile consists of several different subcomponents such as:

- PV generation (thousands of systems from 3 kW up to 2,5 MW)
- Six wind turbines located on two areas (“Rosskopf” and “Holzschlaegermatte”)
- Four major CHP plants up to several MW referred to by their location in Freiburg, (“Haslach”, “Weingarten”, “Vauban”, and “Stadttheater”)
- The “Waermeverbundkraftwerk” (WVK) which is an industrial CHP plant with 40 MW nominal power in total.

The data was also enriched with time related features as: hour of day, day of year, day of week, week, month, quarter, year. The features are derived from the time stamps.
It was also possible to get some free weather data for the location of Freiburg from Solcast, including following features: Air temperature, cloud opacity, global, diffuse and direct irradiation, precipitable water, relative humidity, snow depth, surface pressure, wind direction and wind speed.

A correlation analysis has been done among the features. Figure 54 shows the resulting correlation values, where “y” is the residual load. A correlation of 1 represents a high direct proportional correlated value, whereas -1 a high indirect proportional correlated value. Values close to 0 represent feature without any relevant correlation. High absolute values are desired features. Figure 55 for example shows a high correlation between the consumption sub-component and the residual load. Figure 56 shows an example of low absolute correlation between the air temperature and the residual load. The finally trained RNN will consider the high correlated features with higher weights compared to low correlated features. Figure 57 shows another important feature – the hour of day. The daily pattern is crucial in forecasting the daytime peaks of the residual load.

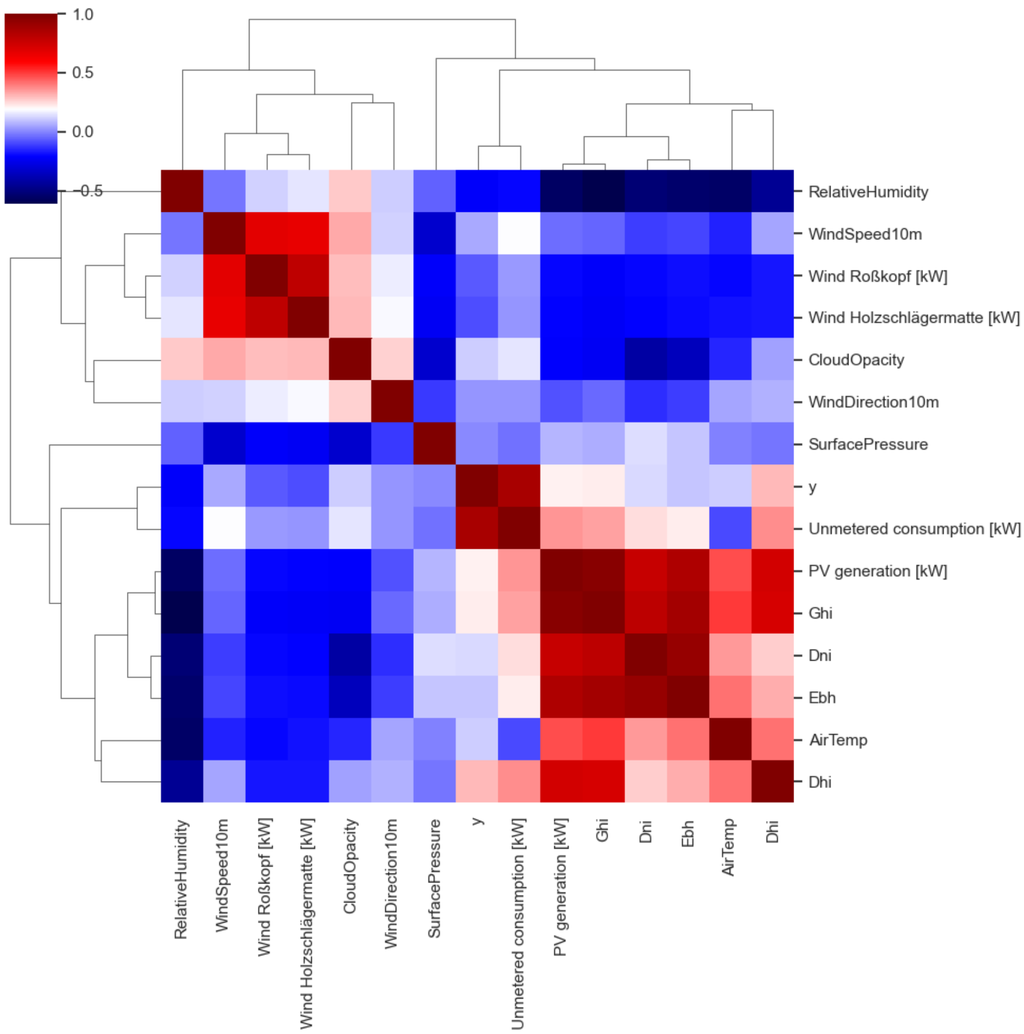

Figure 54: Correlation cluster map of features

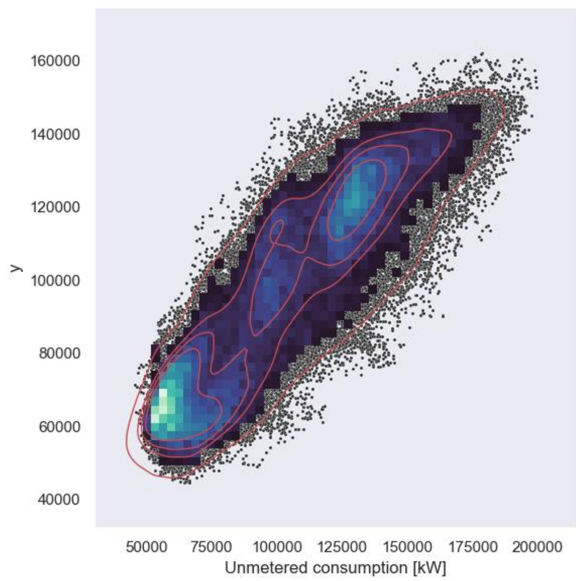

Figure 55: Example of a high correlated feature

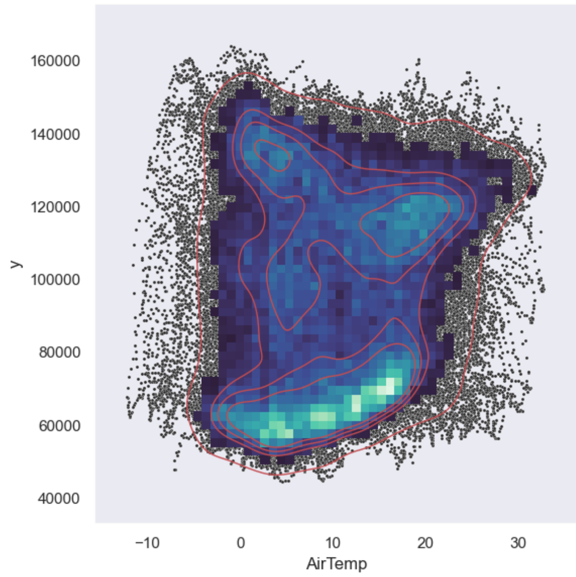

Figure 56: Example of a low correlated feature

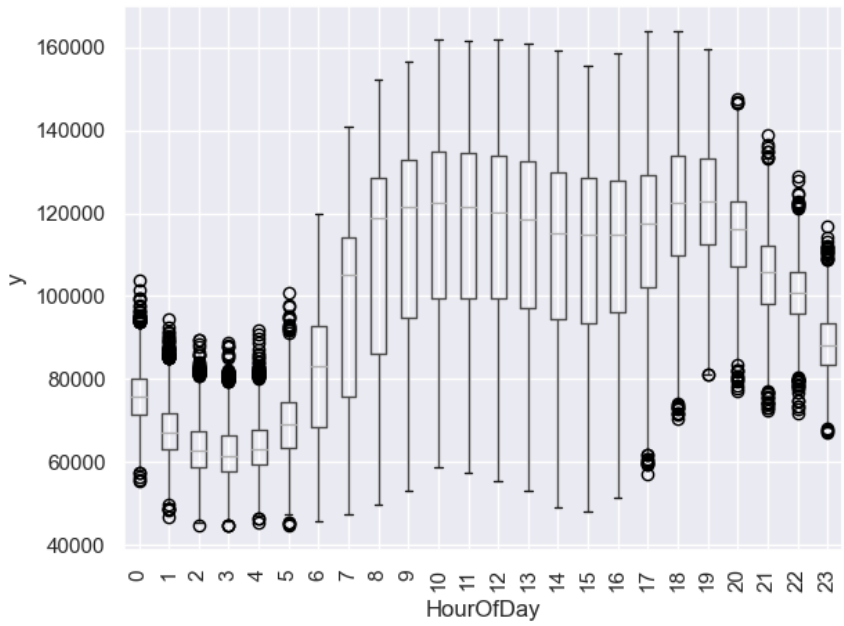

Figure 57: Residual load dependent on the hour of day

So, what is relevant for the DSO's peak shaving business case is not only the pure electrical consumption in the grid, but also the local generation, which in total lead to the residual load flow measured on the coupling points. This mix is relevant for settlement and clearing process and therefore for the financial outcome in the end.

The physical load flow over the coupling transformers itself is composed of twelve separated time series given by the twelve coupling transformers to the upstream electrical grid. Figure 58 illustrates the disaggregation of the residual load profile in its components.

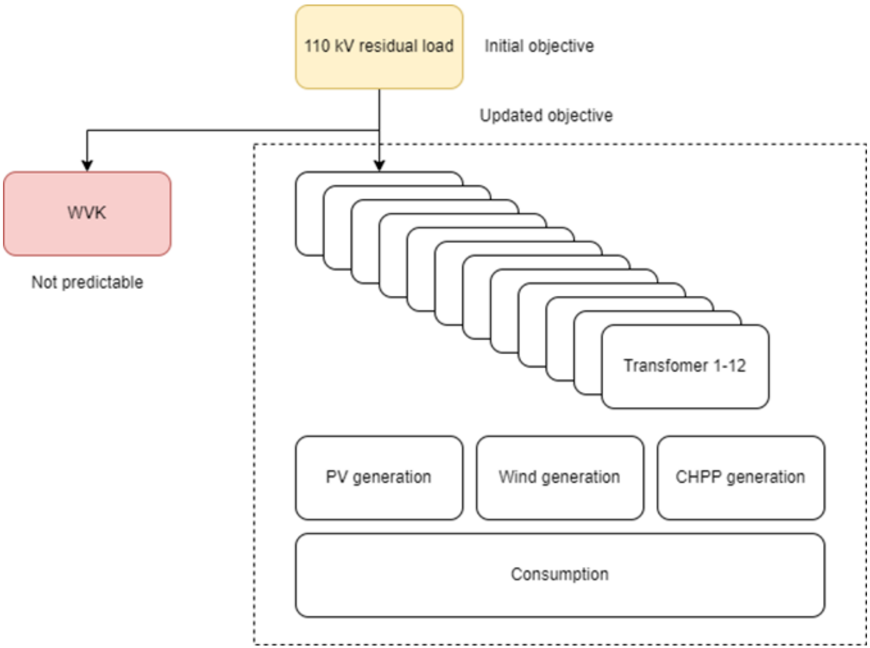

Figure 58: Disaggregation of the residual load profile into its main constituent parts

It turned out, that one of the most important influencing factors within the main grid is this industrial Combined Heat and Power (CHP) plant (shown as WVK in Figure 58) operated by the private company CERDIA with two gas turbines with 20MW each. Sometimes planned and unplanned outages occur here, which have a direct impact on the physical load flow over the grid coupling points. This industrial plant accounts for a significant portion of Freiburg's load profile and outages here have a substantial impact on the load.

Figure 59 explains the strong effect of WVK on the residual load profile. The orange plot shows the output from WVK. The negative values represent the net generation from the DSO's perspective. During the outage occurrences, the WVK output reaches to zero, representing no operation from WVK plant. The blue plot in the upper graph is the resulting residual load over the coupling transformers. It can be seen, that always during outages of the WVK peaks occur. The blue curve in the lower figure shows the residual load cleaned from this effect.

Due to not being able to acquire congruent data sets for all the subcomponents for the given time period 2016-2018, past regression was conducted on the PV generation, wind generation and the four CHP plant time series in order to have timely consistent data. The data was extended by using simple multiple linear regression models. Figure 60 shows all the different data sets used for optimizing the forecast algorithm after the post regression modelling process.

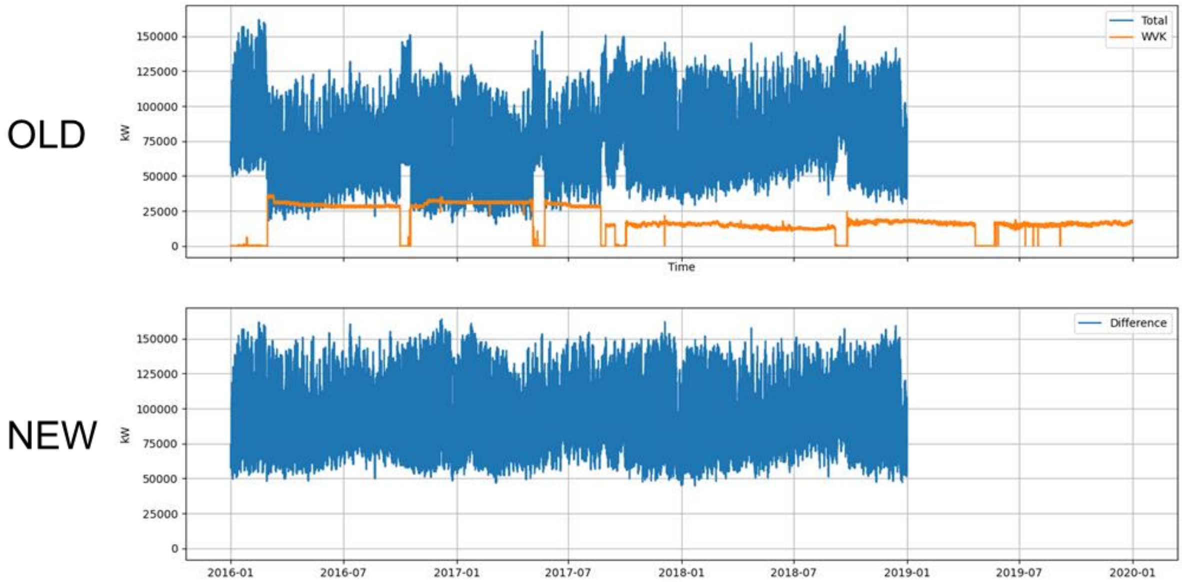

Figure 59: Influence of the WVK on the residual load profile of Freiburg

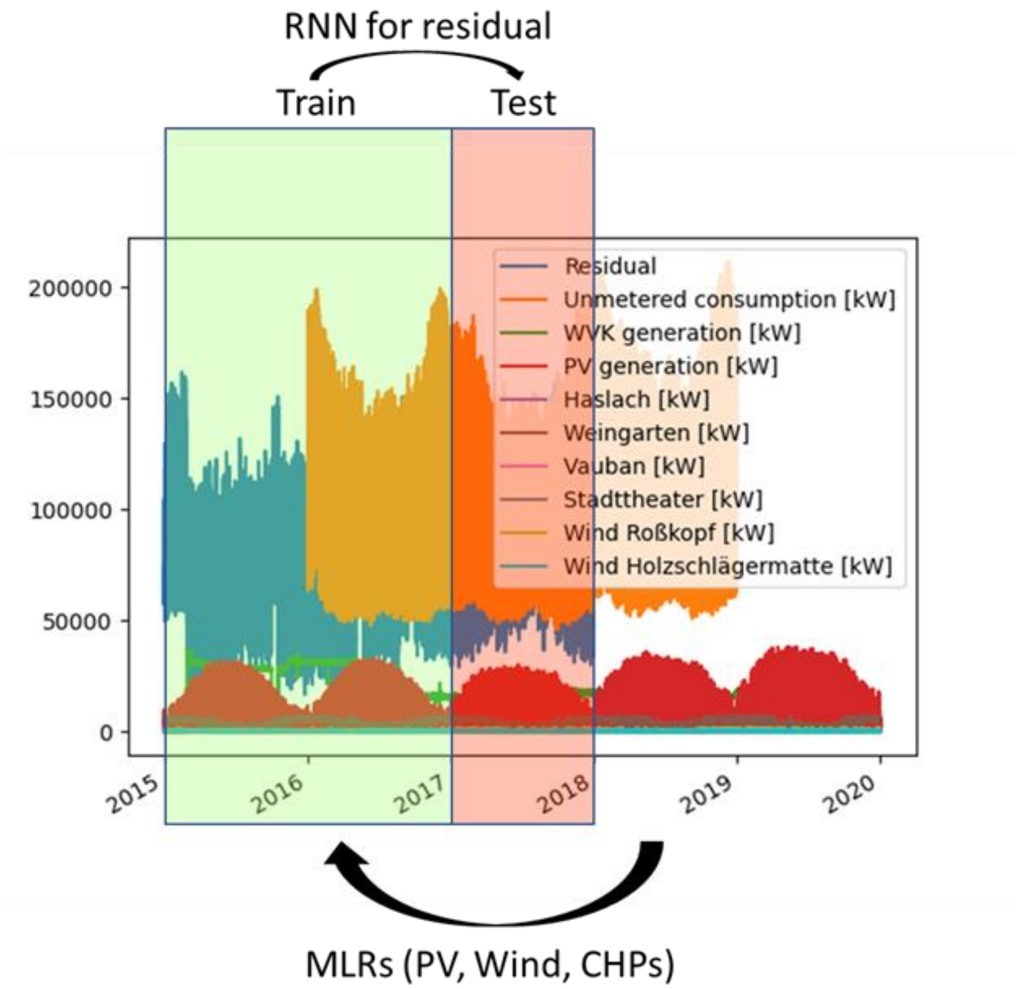

Figure 60: Data profiles of all subcomponents after post regression modelling

The following Figure 61 shows the impact of the different subcomponents on the behavior of the total residual load.

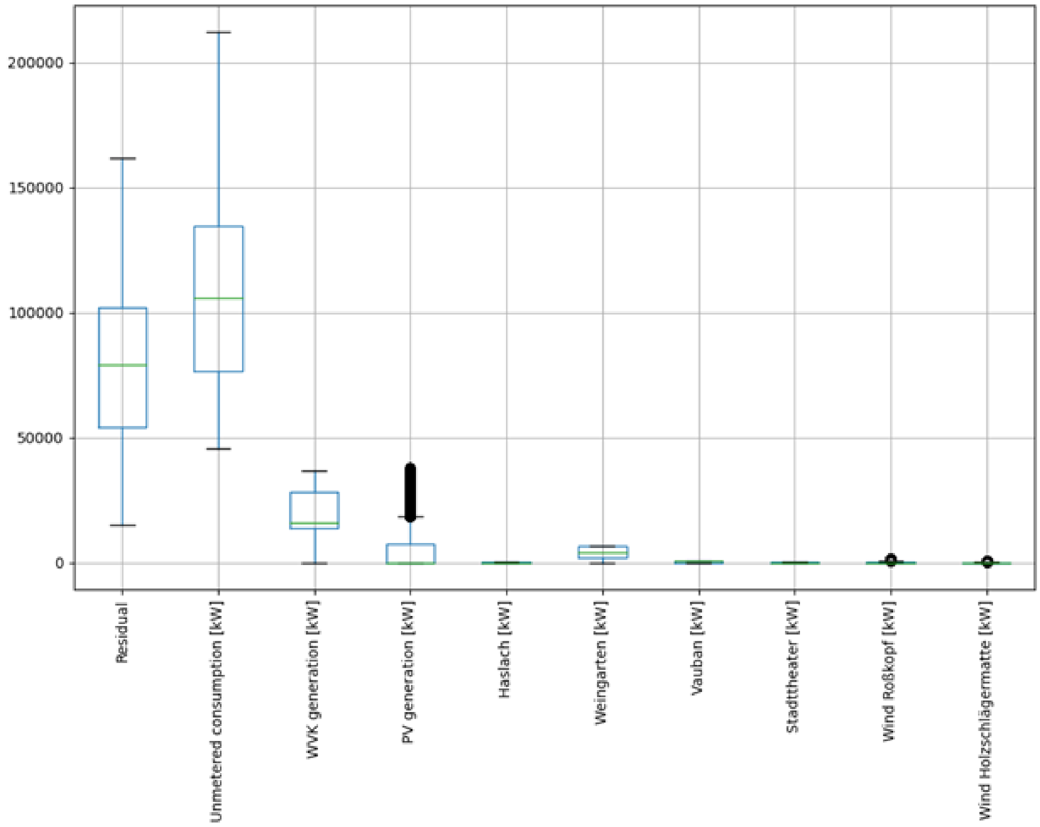

Figure 61: Impact of the different subcomponents on the behavior of the total residual load

Once the past regression was performed and congruent data sets were created, seven different forecasting scenarios were run using the original RNN model structure with the additional variables of all of the subcomponents and the WVK data. The forecasting scenarios considered:

- Varying Time Horizons
  This evaluates considering different time intervals to include in the model. 96-time stamps for one day models. 144 timestamps for a day and a half model. The different time-horizons were evaluated to see if the model outputs a stronger accuracy depending on the how many timestamps are provided as an input.
- Included/Excluded WVK
  This evaluated if including or excluding the load profile from the WVK increases the accuracy of the predictive model. The WVK has many unplanned outages, which can be nearly impossible to forecast. It was important to forecast scenarios including/excluding it to evaluate if the RNN adjust with the shift in load.
- Included/Excluded forecasted subcomponents
  This evaluated if the modelled subcomponents should be considered in the model to improve its forecasting accuracy or if they should be left out due to not being significant contributors to the load profile.
- Varying Loss Functions
  This evaluated different loss functions such as MSE and MAE. The seven forecasting

scenarios compared the different inputs and the model with the best accuracy was used to move forward with the project.

The scenario that performed the best came with an RMSE of 0.051, which is an improvement from the previous RMSE of 0.081. Not only is the overall RMSE better but including the subcomponents models increases the estimation of the magnitude of the peaks. Additionally, excluding the WVK from the model, the accuracy of the model increased . It was simply unrealistic to try to forecast the unplanned outages of the WVK.

To conclude, the modelling of sub-components supports quality of residual load forecasting. It is important to do the classical time series analysis/decomposition for each subcomponent in advance or during the modelling of the forecast. This should be done mainly to know statistics about the four main decomposed components of a time series (trend, cyclical, seasonal, irregular/noise).

The overall improvement of the load forecasting model from the first attempt to the second was an impressive 3%.

3.5.2.5 Transition in real operation

The next major challenge was to transfer the forecast algorithm, which had been trained so far only with historical data, to daily operation and to feed it with operating data that was as up-to-date as possible. Meter data was unsuitable for this application, as it is not available until the following day. Thus, the algorithm would have had to perform a forecast day+1 with data day-1. The accuracy to be achieved with this was found to be insufficient. Therefore, another way had to be found to provide the algorithm with the most current data possible for the calculations. This data is available only in the grid control center of bnNETZE. For security reasons, however, this is separated from the rest of the bnNETZE IT system by an additional firewall. This is to make hacker attacks from the outside as impossible as possible. Even bnNETZE employees cannot access this data without special authorization. So, the challenge was to open a data channel and find at least one way to transfer the current operating data beyond firewall 1 into the normal company IT network of bnNETZE. An automatic routine was programmed for this purpose. The data is automatically stored on a transfer drive of bnNETZE. From there, they are transferred manually over the second firewall to an FTP server of AIT in Vienna. From there, the AIT forecast algorithm retrieves the data. The forecast result is also stored there and can be used by bnNETZE. Figure 62 illustrates the data transfer.

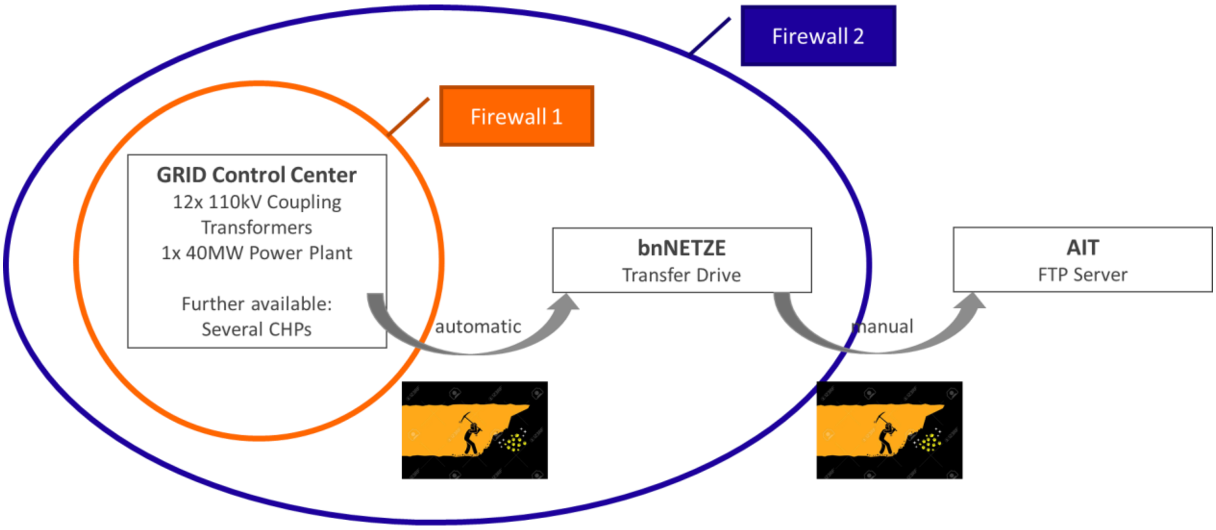

Figure 62: Data transfer in real operation for residual load forecast

The system was successfully installed and tested. After this, two versions of the algorithm were tested under real operation conditions during the period 1st of January 2022 to 31st of May 2022. The two versions only use the 12 transformer measurement data and the aggregated summed up measurement data. The discussed subcomponents like PV installations, wind power plants and CHPs were not used because the data could not be accessed in the needed live demo operation time. This circumstance turned out to be an important learning for further short-term prediction use cases. It is important to check beforehand, which data can be acquired during the live operation. The same feature needs to be available as historical data for a couple of years for the training process.

3.5.3 Performed Tests and Results

The difference between the two versions of the algorithm tested under real operation conditions laid in the used input data:

1. Residual load in total + time feature data as input
2. Individual time series of the 12 coupling transformers + time feature data as input

The load forecasts were conducted 24 hours ahead based on the last 24 hours available at the moment of calculation. The time interval was 15 minutes.

The analysis of the load flow over several years showed, that only days with a peak load higher than 140 MW are relevant for the settlement and clearing process. During the analyzed time interval, exactly 10 days could be identified. These can be supposed to be the relevant days for the whole year as the highest peak loads always occur always in the beginning of the year.

Table 3 shows the characteristics of the several days. It shows the exact date, and if a change between day type happened. Every time a change between working day and weekend or between weekend and working day happens, these days are to be considered as especially challenging because consumption patterns change significantly. Further changes in weather are of special importance. So, in Table 3 changing of weather conditions are noted also. Over all six different types of variations occurred. They are marked with different colors.

Table 3: Categories of peak load days > 140 MW

1	**11.01.2022**	Monday --> Tuesday	2x cloudy
2	**12.01.2022**	Tuesday --> Wedndesday	Cloudy --> Sunny
3	**20.01.2022**	Wednesday --> Thursday	Sunny --> cloudy
4	**26.01.2022**	Tuesday --> Wedndesday	Sunny --> cloudy
5	**27.01.2022**	Tuesday --> Wedndesday	Sunny --> cloudy
6	**31.01.2022**	Sunday --> Monday	2x cloudy
7	**02.02.2022**	Thursday --> Friday	2x cloudy
8	**15.03.2022**	Tuesday --> Wedndesday	Sunny --> cloudy
9	**25.04.2022**	Sunday --> Monday	cloudy --> cloudy
10	**16.05.2022**	Sunday --> Monday	sunny --> cloudy
	day change	**yes**	**no**
	no change		
	sun -> cloud		
	cloud -> sun		

Table 4 shows the accuracy indicators for all analyzed peak load days with more than 140 MW for both versions of the forecast algorithm. The same is shown inFigure 63 in another way. It can be clearly stated that version 1 (i.e. indicated as "OLD") delivers the best results.

Table 4: Accuracy indicators of peak load days > 140 MW

		OLD			NEW		
No.	Day	MAE	MAPE	RMSE	MAE	MAPE	RMSE
1	11.01.2022	5.38	5.56	6.46	11.96	14.71	14.61
2	12.01.2022	6.44	6.42	7.41	10.50	11.37	11.79
3	20.01.2022	5.93	5.96	6.91	11.88	14.65	14.71
4	26.01.2022	9.22	7.91	10.76	13.42	13.72	15.31
5	27.01.2022	6.36	5.80	7.67	14.07	14.54	15.45
6	31.01.2022	7.08	7.77	8.85	15.90	19.71	18.16
7	02.02.2022	5.85	6.03	7.48	12.31	15.58	14.94
8	15.03.2022	7.44	6.77	10.56	11.14	14.05	13.77
9	25.04.2022	13.30	13.80	16.49	21.90	25.15	26.01
10	16.05.2022	7.61	7.25	9.59	18.28	19.19	20.73
	Mean:	7.46	7.33	9.22	14.14	16.27	16.55

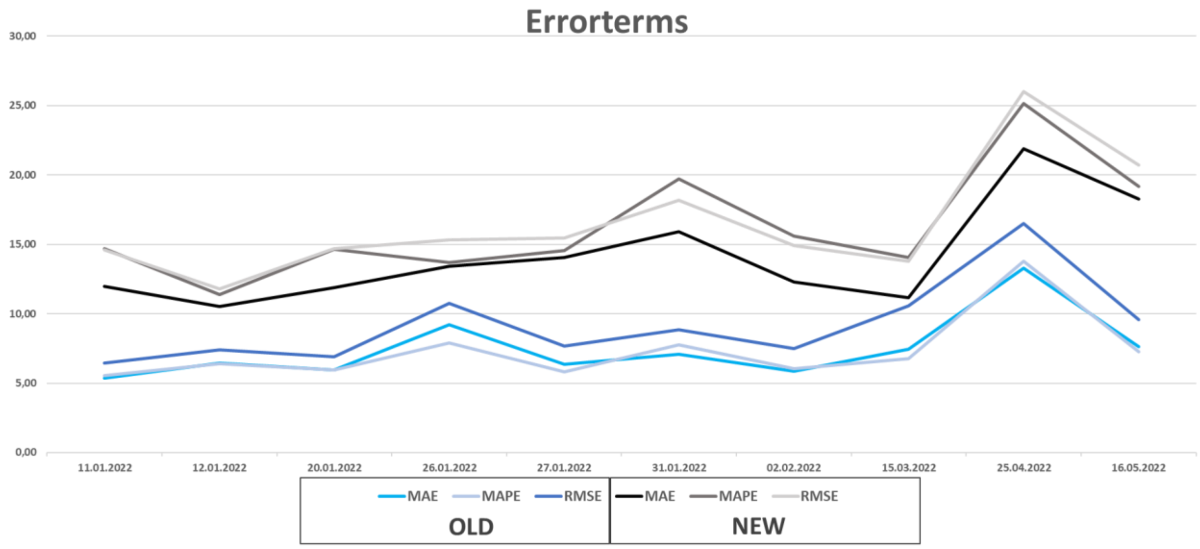

Figure 63: Accuracy indicators of peak load days > 140 MW

In the following the results for the two versions of the forecast algorithm are plotted for each single day. Figure 64 shows the results for the days without change in weather. Figure 65 shows the results for the relevant days with a change in weather from sunny to cloudy. Finally, Figure 66 shows the result for the day with a change in weather from cloudy to sunny.

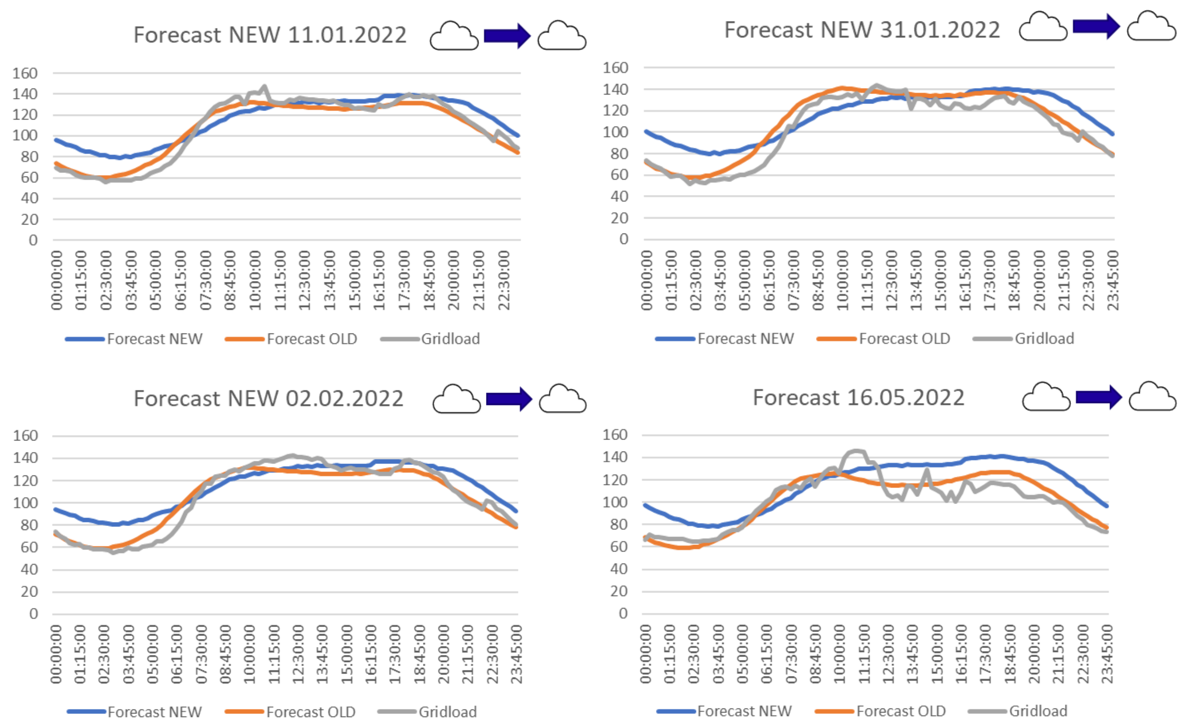

Figure 64: Forecast results for the days without change in weather

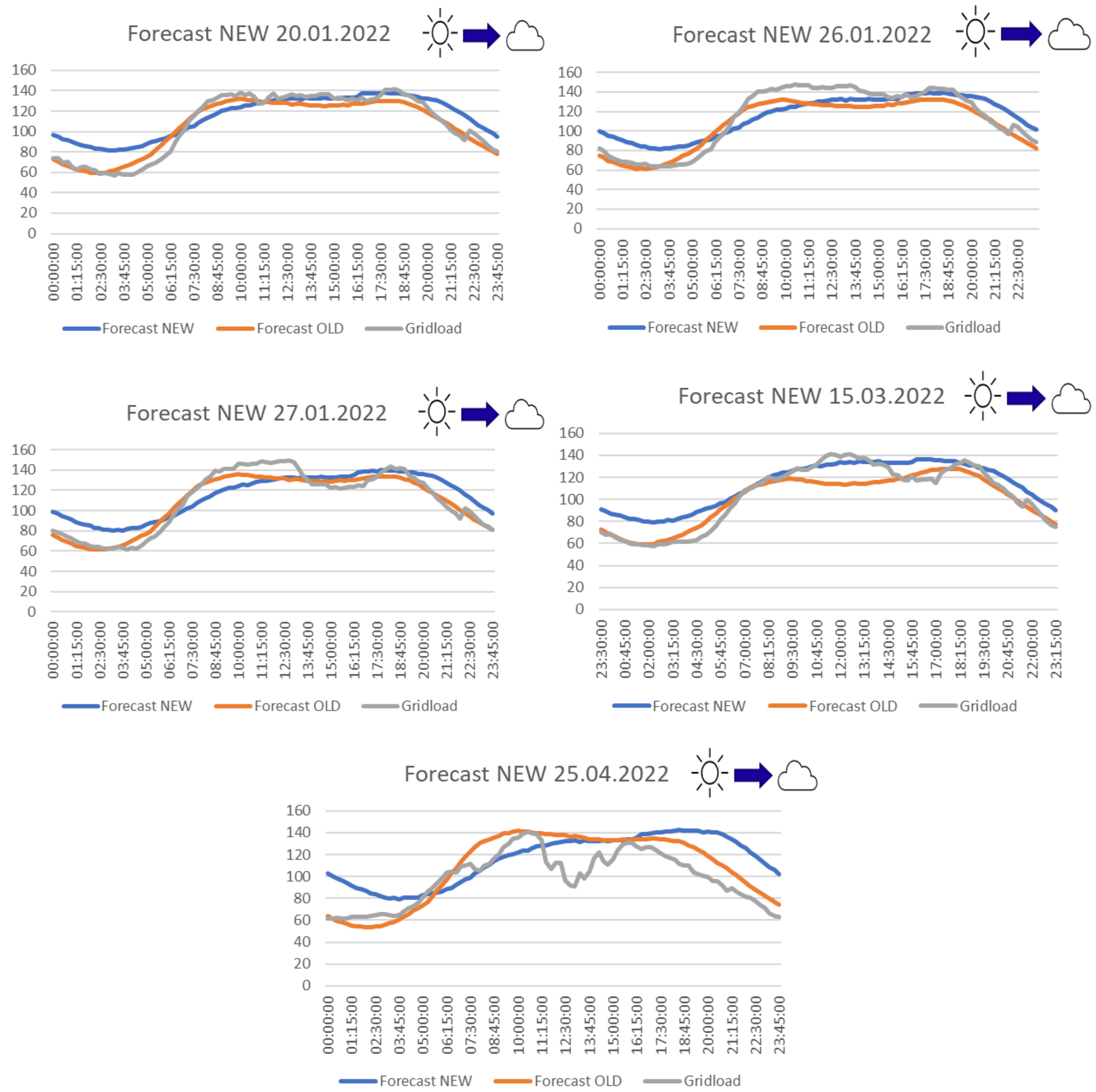

Figure 65: Forecast results for days with a change in weather from sunny to cloudy

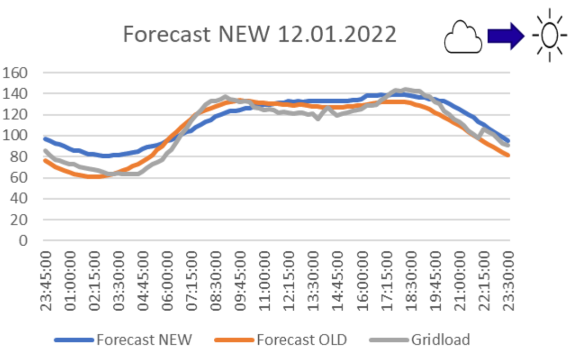

Figure 66: Forecast results for days with a change in weather from cloudy to sunny

3.6 Full Pilot Site Operation

3.6.1 Experiment Description

After the first version of the FLEXGRID ATP was available the full test operation of the pilot site could be started. First, some minor bugs in handling the GUI and creating the control commands by FLEXGRID ATP had to be fixed. Later on, the full pilot site operation could be started. Figure 67 shows the interaction of the individual players within the badenova Group with the FLEXGRID ATP as well as the devices used. bnNETZE was assigned the role on the flex demand side as part of the business case “peak shaving”. Accordingly, FlexRequests were created via the FLEXGRID ATP based on the daily load forecast. On the other side, the energy trading of badenova had taken over the FlexSupply role. For the contracted prosumers and the central battery storage, FlexOffers were created via the FLEXRID ATP based on individually created price/quantity curves that represent BADENOVA’s willingness to provide specific amounts of flexibility units at a specific price per unit. If matches occurred, the components were controlled accordingly and their reaction to the control commands was monitored.

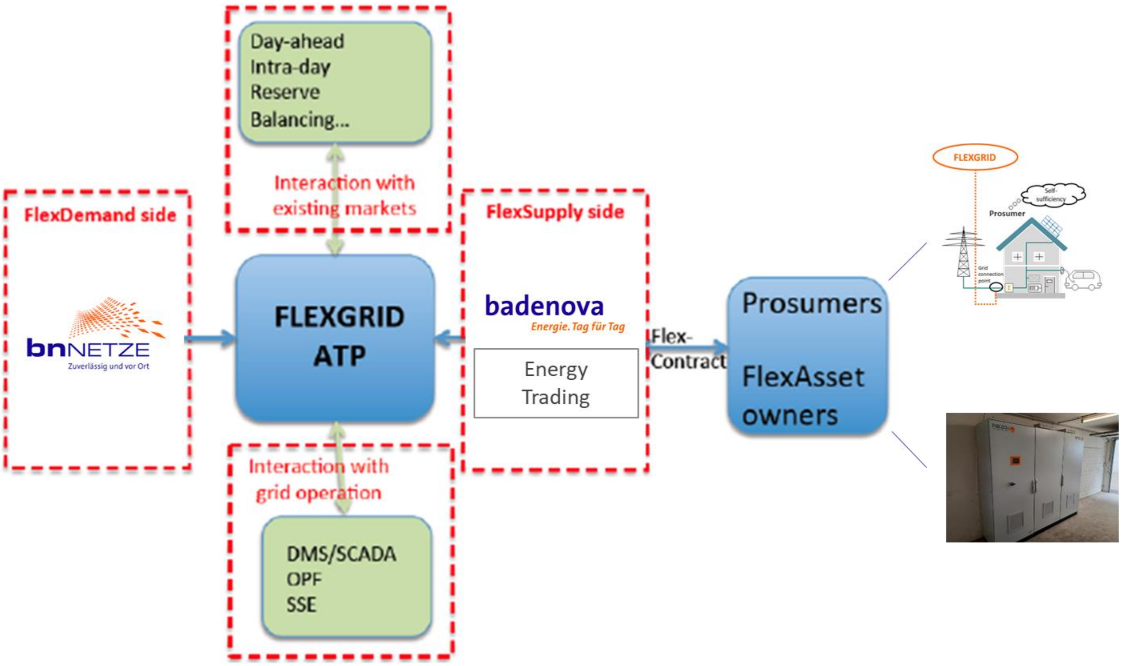

Figure 67: Full pilot site operation

The most important results of the full pilot site test operation are explained in the sections below.

3.6.2 Experiment Setup

3.6.2.1 Scenario development

Potential states on the test site were considered and grouped into scenarios. This served to maintain an overview of the large number of tests and to determine the focus on a controlled result field. This consideration resulted in the four scenarios, seen in Table 5.

Table 5: Scenarios considered for the full pilot site operation.

Scenario	Price Settings (p)	Description
A	$p_{prosumer\ n} < p_{max\ DSO}$ $p_{Battery} > p_{max\ DSO}$	This scenario describes the situation in which only prosumer households contribute to counteracting a peak in the electricity grid.
B	$p_{Battery} < p_{max\ DSO}$ $p_{prosumer\ n} > p_{max\ DSO}$	In scenario B, the FlexRequest of the DSO is only served by the large-scale battery.
C	$p_{Battery} < p_{max\ DSO}$ $p_{prosumer\ n} < p_{max\ DSO}$	In this scenario, the FlexRequest is served both by prosumers and the large scale battery.
D	$p_{Battery} > p_{max\ DSO}$ $p_{prosumer\ n} > p_{max\ DSO}$	In this scenario, none of the FlexOffers are below the threshold price of the DSO and thus no flexibility provider is contracted.

3.6.2.2 Test Site Setup

In the following, a description of the actual test site is given. For one part, the set-up of the bnNETZE test site for the real live tests consisted (in the end) of 8 prosumer households in the area of the main electricity grid of Freiburg. One of the before 10 prosumers suffered from a severe damage in the energy storage system that was not repairable on such a short notice. An additional prosumer dropped out due to construction works at their home and a resulting instable internet connection, which is prerequisite for a reliable participation in the test. The systems of the remaining prosumers were able to provide a power of 3.0 kW without and up to 6 kW with additional PV generation to the grid. The controllability was achieved via an installed gateway that could overwrite settings by the local energy home management system by commands provided via a FTP server.

The second element of the test site consisted of the iron phosphate large scale battery (described in section 3.2.1 above) located at the grid control centre of bnNETZE in the city of Freiburg. The unit is embedded in the high security IT-network of the facility and was controlled by the respective grid operator.

3.6.2.3 Operation of the test site

In order to verify the working principle of the FLEXGRID approach and to allow the ATP in a later step to back up the results, the steps as shown in Figure 68 were executed.

Figure 68: Test site operation scheme.

In the first step the grid data of the main bnNETZE Freiburg grid was downloaded from the respective servers (see Figure 62). This data contained the actual load in the grid in the year 2022 right to the point in time when it was downloaded. The set of files consisted of 12 CSV sheets - one for each coupling transformers of the bnNETZE grid to the next higher level in the grid hierarchy. These files were pushed on a FTP server hosted by AIT. From there, the forecast algorithm withdrew the data and calculated the forecast for the residual load in the grid for the next 24 hours. The result from the forecast was saved in a separate file on the FTP server. Based on the forecast, the absolute value for peak load as well as the estimated hour were selected as the basis for the placement of a FlexRequest by the DSO. For the same time interval, the prosumers and the large-scale battery created FlexOffers.

The maximum price a DSO would pay to mitigate a peak was calculated to 6.14€/kW/request, with an estimated activation rate of 40 times per year. This takes into consideration that the forecast is not 100% correct and no profits are kept by the DSO. This price served as the upper limit for offers made by the aggregators to be accepted. Prices for power possibly useable by the aggregators were available for the full day and investigated for the time of the potential peak.

The prices of the DSO for the FlexRequest and the aggregator prices were compared and matched. The resulting market clearing showed which participant would be accepted to contribute to the FlexRequest. The duration of the energy provision was always set to be one hour with the peak being in the middle. For example: To counteract a potential peak at 10:00 AM a FlexRequest from 09:30 AM to 10:30 AM was placed and respective offers were considered. The exact amount of the FlexRequest was not specified and assumed that the DSO was willing to accept as much power as aggregators could provide under the given price maximum. This was done to obtain the highest possible amount of power provided by aggregators. The amount of power an aggregator was able to provide was individual and depended to a large extent on their system. Prosumer households could not provide as much energy as the large-scale battery. Furthermore, real life conditions had a large impact on the power providing capabilities of the systems.

The results from the market clearing were passed on to the respective units via control commands. The control channel towards the prosumer households used an FTP server that communicated with a gateway connected to the home energy management system of the household. On the FTP server, the control commands for the prosumers were placed as a profile, specifying the output power for each hour, e.g., feed in 3 kW from 09:30 AM to 10:30 AM at the given date. This information was translated by the installed gateway and executed through the local home management system. The control pathways towards the large-scale battery at the bnNETZE grid control centre was realised through manual controls set by the grid operator in charge. Due to high security restrictions in the IT-environment of the grid control centre, a direct operation via external control commands was not possible.

The evaluation was a crucial step in the operation of the test site. Via different online visualisation tools, it was possible to monitor the behaviour of components of the test site individually. For the prosumer households, the software Chronograph was used. On the web GUI, several physical parameters of linked energy systems can be displayed. Relevant for the evaluation were the state of charge of the energy storage system given in percent of maximum charge and the value of the grid connection point of the household to the surrounding grid given in kW.

3.6.3 Performed Tests and Results

During test site operation, the scenarios presented in Table 5 tested in numerous attempts. Table 6 gives a summary of selected tests.

Table 6: Summary of executed tests.

Test No.	Date	Peak Time	Scenario	Magnitude Peak	Quantity Dispatched
13	15.08.2022	18:45	A	118 MW	24 kW
19	16.08.2022	19:30	A	111 MW	12 kW
45	23.08.2022	19:15	A	110 MW	3 kW
50	24.08.2022	19:15	A	109 MW	12 kW
55	25.08.2022	19:00	A	111 MW	12 kW
60	26.08.2022	18:45	A	108 MW	6 kW
77	02.09.2022	19:15	A	106 MW	6 kW
65	30.08.2022	20:30	B	108 MW	6 kW
7	11.08.2022	19:15	B	111 MW	6 kW
27	18.08.2022	10:00	C	120 MW	9 kW
32	19.08.2022	10:00	C	113 MW	9 kW
37	22.08.2022	10:30	C	120 MW	12 kW
61	29.08.2022	10:00	C	124 MW	12 kW
69	31.08.2022	18:30	C	111 MW	16 kW
70	01.09.2022	10:00	C	116 MW	15 kW
25	17.08.2022	19:15	D	114 MW	0 kW

3.6.3.1 Scenario A

Seven tests for Scenario A were executed. Table 7 shows the tests for Scenario A. Test 13 from 15.08.2022 is considered here in more detail as an example.

Table 7: Tests for Scenario A.

Test No.	Date	Time Peak	Magnitude Peak	Dispatched Prosumers	Quantity Dispatched
13	15.08.2022	18:45	118 MW	4	24 kW
19	16.08.2022	19:30	111 MW	2	12 kW
45	23.08.2022	19:15	110 MW	1	3 kW
50	24.08.2022	19:15	109 MW	2	12 kW
55	25.08.2022	19:00	111 MW	3	12 kW
60	26.08.2022	18:45	108 MW	2	6 kW
77	02.09.2022	19:15	106 MW	2	6 kW

For Test 13, the forecast for the power grid on 15.08.2022 can be seen in Figure 69. It shows the load in MW over the course of 24 hours. The forecast resulted in a forecast peak at 18:45 at a level of 118 MW. On this basis, a FlexRequest was created by the DSO to obtain flexibility in the period from 18:30 to 19:30. How this Request is created in the Flexgrid ATP is shown in Figure 70.

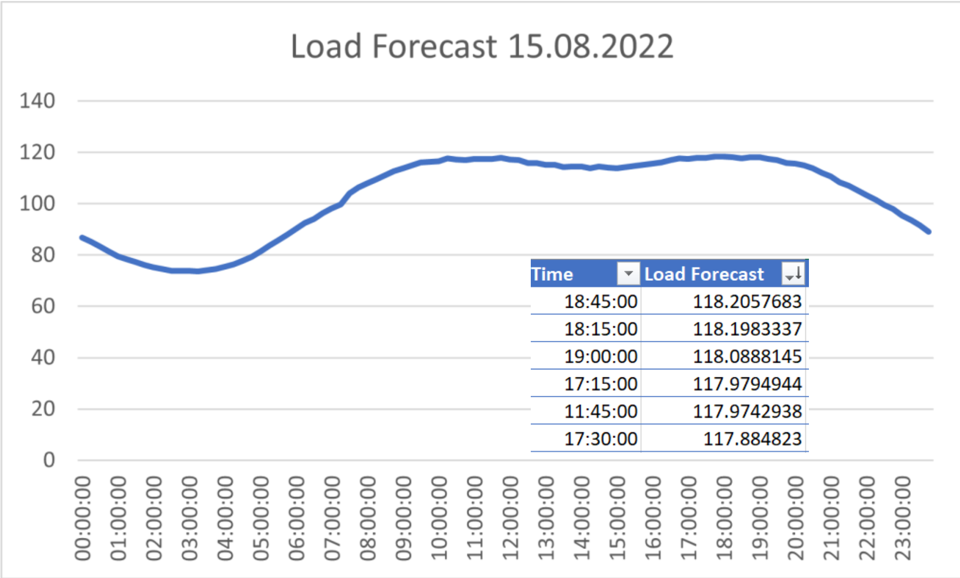

Figure 69: Load forecast

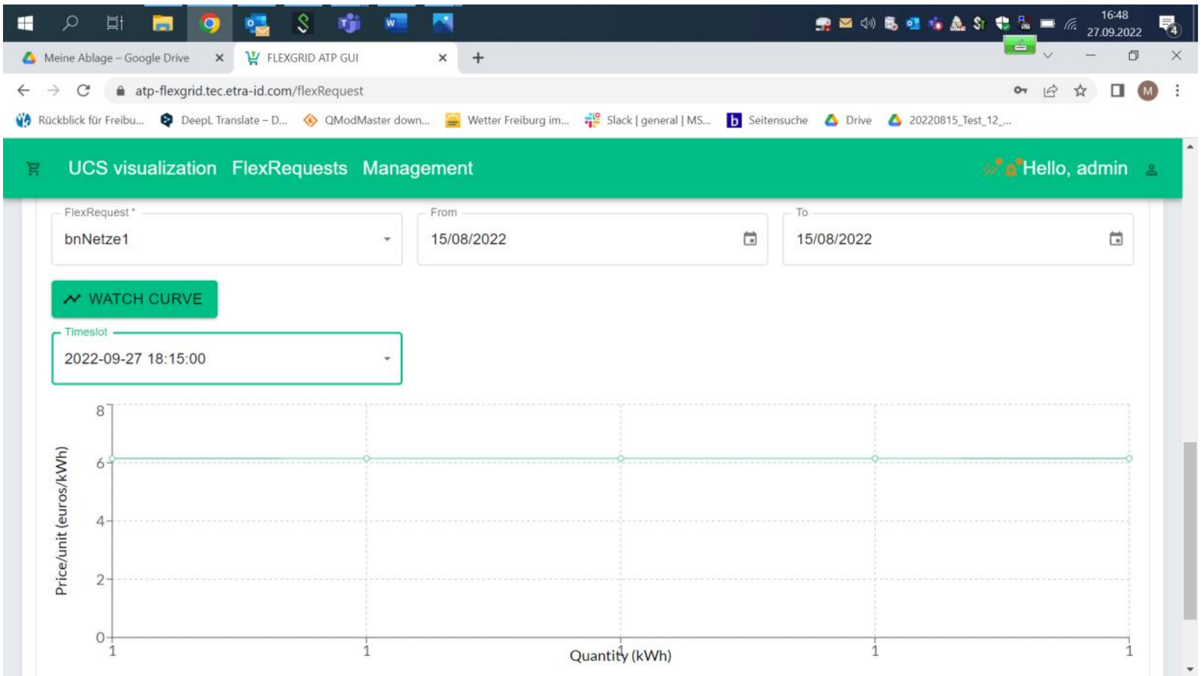

Figure 70: FlexRequest on Flexgrid ATP (DSO GUI)

The maximum price that would be paid per kW in the corresponding time interval by the DSO was 6.15€ /kW. Figure 71 shows the price curves for the participants in the market in Euros for the time interval of the forecast peak. It can be seen that the prices of prosumers 1, 3, 10 and 13 are below the marginal price of the DSO. The prices of the other prosumers and the large-scale battery are above the maximum price of the DSO for the provision of flexibility in this period.

Figure 71: Market clearing and price curves for scenario A

A representation of how this is realized in the Flexgrid ATP is exemplary shown for Prosumers 1 and 8 in Figure 73 and Figure 74 respectively.

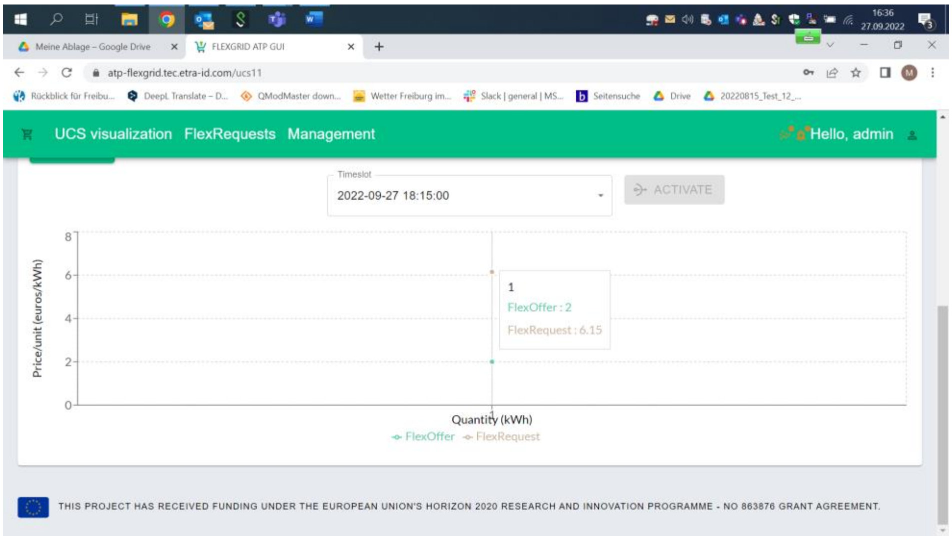

Figure 72: Market Clearing for Prosumer 1 (Flexgrid ATP GUI)

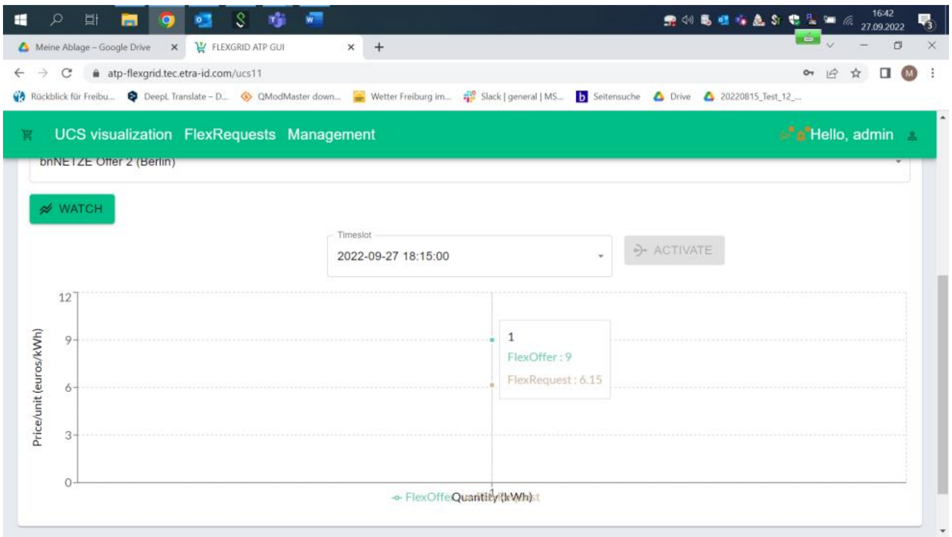

Figure 73: Market Clearing for Prosumer 8 (Flexgrid ATP GUI)

The result of the market clearing was transmitted to the corresponding gateways by means of the communication channel for the prosumers and executed by the local power systems. In Figure 74 below, the visualization tool for prosumer 1 can be seen. It shows that the control command of Prosumer 1 was implemented. In the upper part of the graph, the SoC of the installed energy storage system is shown, firstly as an actual value in percentage, and additionally over time in percentage. The lower graph represents the power applied at the household's grid connection point within the last 24 hours. This graph shows that in the period from 6:30 pm to 7:30 pm, a power of 6 kW was delivered to the surrounding grid.

Figure 74: Evaluation of Prosumer 1.

The systems of prosumers 1, 3, 10, and 13 each delivered 6 kW and thus a total of 24 kW was fed to the grid and thus contributed to the satisfaction of the FlexRequest. The large-scale battery installed at the grid control centre, which was priced above the DSO price limit, did not supply any energy and the same was valid for the residual prosumers.

3.6.3.2 Scenario B

Two tests were executed for Scenario B, as seen in Table 6. In the following, the test case for 30.08.2022 is described in more detail as an example of this. The forecasted peak in the Freiburg electricity grid for 30.08.2022 was 108 MW and was expected to occur at 20:30. The market for flexibility for the surrounding period was as shown in Figure 75.

Figure 75: Market clearing and price curves for scenario B

It can be seen that only the price of the large-scale battery falls below the marginal price of the DSO and thus only the energy provided by the battery can be used to mitigate the peak during this period. Consequently, the amount of energy provided for the FlexRequest on 30.08.2022 at 20:30 is 6 kW. The fact that this energy was actually provided by the battery for the grid can be seen in the course of the active power of the battery on 30.08.2022 in Figure 76.

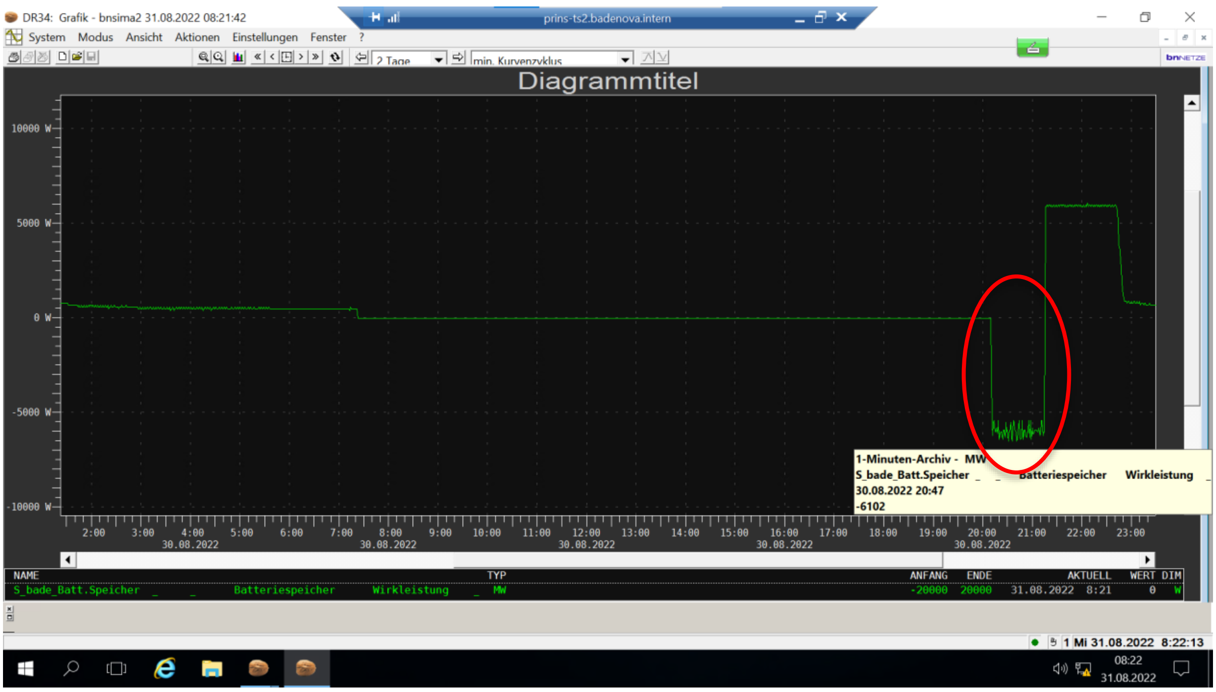

Figure 76: Evaluation of the large-scale battery.

3.6.3.3 *Scenario C*

For Scenario C, seven tests were executed, where both prosumer households and the large-scale battery contributed to the satisfaction of a FlexRequest. As an example, Test 70 for the day of 01.09.2022 is described in the following. The peak for this day was forecasted to occur at 10:00 AM and was expected to be 116 MW. The maximum price that the DSO was willing to pay in this time interval was 6.15€ / kW. Together with the FlexOffers, this resulted in the market situation shown in Figure 77.

Figure 77: Market clearing and price curve for scenario C

From the graph, it is clear that the prices of prosumers 3, 4, and 10 and the large-scale battery were below the DSO marginal price. On this basis, the FlexOffers of the aforementioned flexibility suppliers were accepted. Together, an energy of 15 kW was delivered over the period from 09:30 to 10:30.

3.6.3.4 Scenario D

One test was executed for Scenario D. The forecast peak for 17.08.2022 was calculated to 114.3 MW and was scheduled for the one-hour time interval around 19:15. The maximum price of the DSO to buy flexibility was again 6.15€/ kW. None of the prosumers or large battery unit were below this price. As a result, no flexibility was provided by the prosumers as well as the large-scale battery to satisfy the DSO’s FlexRequest. The market situation is shown in Figure 78.

Figure 78: Market clearing and price curves for Scenario D

A representation of case D as displayed in the Flexgrid ATP is shown in Figure 79. In this scenario, none of the FlexOffers fell under the maximum DSO price.

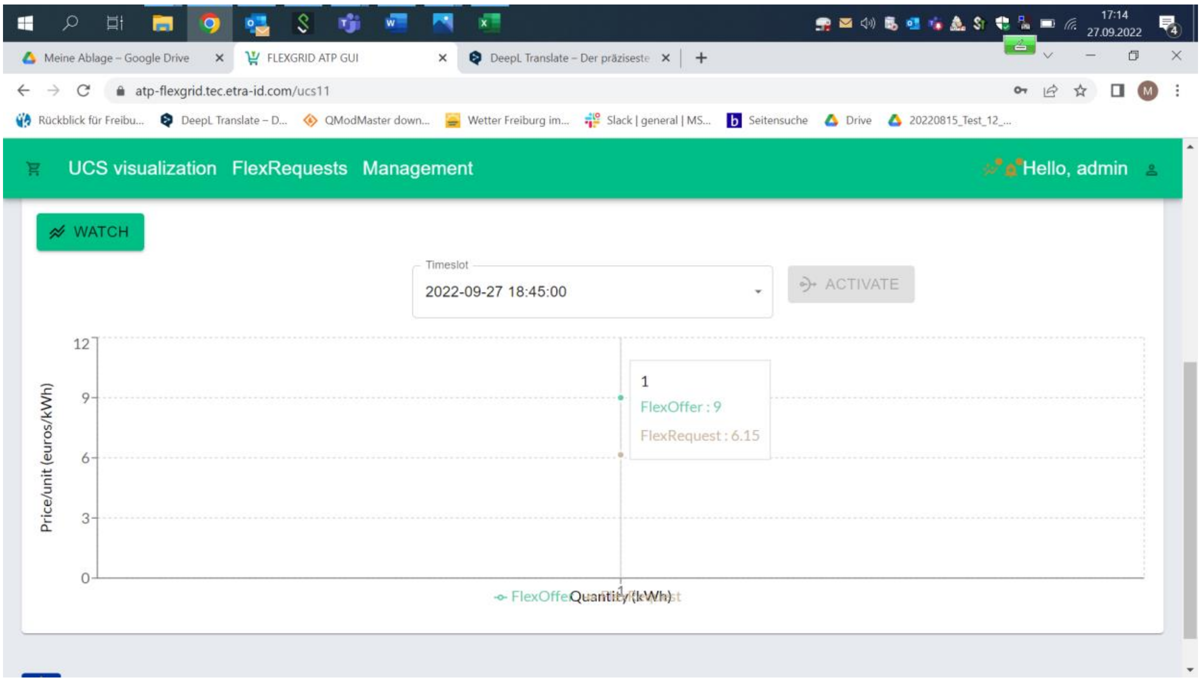

Figure 79: Market Clearing Flexgrid ATP Prosumer 5 (ATP GUI)

3.7 Evaluation of Results

Relevant peaks in the electricity grid occur predominantly in the cold winter months in Germany. During winter, consumption especially for heating is high and generation, for example by photovoltaics, is low. This results in high load peaks in the grid. Reducing these peaks through targeted measures is in the great interest of grid operators. For bnNETZE, relevant peaks in the sense of the peak shaving use case are peaks with a capacity of at least 140 MW. The test period fell on the warm period in late August. It is characterised by a low electricity load volume. Peaks that occurred during the test period were all below 140 MW. The highest forecast peak was 124 MW on 29.08.2022. Based on this fact, it was only for the test purpose that the DSO sets a FlexRequest at the times of the predicted peaks. It should also be added to this test purpose that the DSO did not make a FlexRequest in a fixed amount but was prepared to accept all FlexOffers, which were below a marginal price. The marginal price, in turn, was the price that should not be exceeded by offers from aggregators, even during relevant peaks.

A test period in summer in Germany is associated with a high sunshine duration. The average sunshine hours during the test period were 8.6 hours per day. Since both the prosumer battery storage and the large-scale battery are charged via PV systems, it became apparent that the storage was mostly full, and the systems fed fully into the grid. As a result, it was sometimes physically impossible to limit the systems to a certain value for the purpose of test operation. Furthermore, due to the unavailability of some of the prosumers (e.g., vacation), not all systems were always available. Nevertheless, it was still possible to execute tests in order to map and document all relevant scenarios in very good quality.

To further strengthen the validity of the results, it would now make sense to repeat the tests at other times of the year. A test period in December and January would make the most sense, since most of the relevant peaks in the grid occur at this time. It should be noted that the conditions for the installed energy systems are also fundamentally different. The yield from PV will be much lower than in this test period due to reduced solar radiation, and it is likely that energy storage systems could be less full or empty as a result.

In spite of problems to operate the test site such as connectivity problems to prosumers and the system limitations due to the summer season, it should be stated that the test operation in the end fulfilled all the initial expectations. First, it was possible to realize an actual test period over more than three weeks with real prosumers and a large-scale battery – both controllable by bnNETZE and monitored on different platforms. Furthermore, all relevant scenarios could be found in the results of the tests and give a proof to the working principle of the approach regarding the DSO's business case of peak shaving (see more details about this business case in D8.3 [FleD83]).

4 Conclusions and Recommendations for the Future

In this deliverable, the implementation and the results from tests done in the two pilot validation strands: (i) Automated Energy Flexibility Aggregation and (ii) Evaluating Forecasting Methods for DSO Services. The first validation strand focuses on validating aggregator services and were carried out as pilot tests at UCY's campus grid. This strand studies how the FLEXGRID methods can be used for optimal aggregation of flexibility for different use cases. The second validation strand focuses on FLEXGRID's services directed towards DSOs and how these can be optimally provided by ESPs. This strand was also carried out as a pilot using bnNETZE's test system in and around the city of Freiburg, Germany. Here, the goal was to study how the advanced forecasting methods and the collaboration possibilities between the DSO and ESPs developed in FLEXGRID can be used by the DSO for "peak-shaving" business case. This section contains some lessons learned from the two real-life pilot sites.

For the first validation strand, the next step is to upgrade and improve the infrastructure so as to have a fully automated Smart Campus at UCY. Based on the performed tests and the results assessment of the DR events (that have been successfully deployed at both UCY Microgrid and Nanogrid), we are now able to improve the integrated solutions with some adjustments. Currently, we are evaluating the performance of the DR events based on the chiller's consumption of the whole Campus. By installing extra smart energy meters at each building, that will capture some extra data, this will enable further analysis of the DR events per building level, and the aggregator will have independent prosumers and consumers inside the UCY campus. Furthermore, we will solve the current issue when some buildings are participating in a DR event, but, at the same time some other buildings consumed more energy, the overall energy centre results (chillers consumption) couldn't capture the flexibility that was saved.

For the PV Technology Laboratory, a detailed baseline profile (that will include apart from the energy consumption, the luminance, indoor and outdoor temperature, humidity etc.,) will be used to analyse the behaviour of the end users throughout the year and we will be able to forecast their behaviour/actions over the installed controllable loads.

Both UCY's Nanogrid and Microgrid could participate in future electricity/flexibility markets as an aggregator with multiple end users (both prosumers and consumers), and trade significant amounts of energy without altering and putting at risk their security, the stability and energy efficiency levels. To conclude, both UCY's Microgird and Nanogrid are expanding their infrastructure with cutting-edge technologies that will be integrated with the existing and future algorithms/solutions, which is going to fulfil all the DSO requests in the future electricity/flexibility markets.

For the second validation strand, the following conclusions were made. Real life testing is always linked to unpredictable difficulties that can never be excluded. Nevertheless, it is important to run these tests to get results that go beyond theoretical considerations. The prosumer group was bigger than needed to cover potential outages. Still, this number was maybe not high enough to provide a constant number of prosumers of 10. To further decrease the number of interruptions in the connection, a more intensive communication with the involved participants could help. However, a strong contact line with numerous prosumers is hard to realize and still not a guarantee.

In terms of scalability, the extent to which the bnNETZE's test site would have to be enlarged in order to see actual effects on the network was not possible for the FLEXGRID project but does not stand in the way of a generally possible scalability of the approach. For a first approach, a test site with a maximum of ten prosumers was used. Each of these prosumers could provide a maximum of 3.0 kW. So, in an ideal scenario where all prosumers contribute equally to FlexRequests, the total yield would be 30 kW. This is considerably low taking into account a peak of greater than 140 MW in the Freiburg grid. If the number of participants were scaled up to around 500, the peak could be lowered by 1% , which would save the DSO costs of 159 460 € under optimal conditions. Taking into account the more than 10,000 single family houses in the city area of Freiburg it can be stated that at least the gross number of potential prosumers is given to achieve an upscaling in a serious power range.

5 References

[Bla16] M. Blank, S. Lehnhoff, K. Heussen, D. E. M. Bondy, C. Moyo, and T. Strasser, “Towards a foundation for holistic power system validation and testing,” in 2016 IEEE 21st International Conference on Emerging Technologies and Factory Automation (ETFA), Sept 2016, pp. 1–4.

[Deb18] Debnath, Kumar Biswajit, and Monjur Mourshed. “Forecasting methods in energy planning models”. Renewable and Sustainable Energy Reviews, Pergamon, http://www.sciencedirect.com/science/article/abs/pii/S1364032118300200, 15 March 2018

[ERI21] ERIGrid, “ERIGrid – H2020 Research Infrastructure Project”, Mar. 2021, https://erigrid.eu/

[Eur22] European Environment Agency, “Greenhouse gas emission intensity of electricity generation in Europe”. Available online: https://www.eea.europa.eu/ims/greenhouse-gas-emission-intensity-of-1. Published 2022. Accessed September 19, 2022.

[FleD43] FLEXGRID D4.3, “Final version of advanced ESP and RESP BMs”, Available online: https://flexgrid-project.eu/assets/deliverables/FLEXGRID_D4.3_30112021.pdf

[FleD63] FLEXGRID D6.3, “Data Model of FLEXGRID architecture”, Available online: https://flexgrid-project.eu/deliverables.html

[FleD71] FLEXGRID D7.3, "Pilot demonstration setup plan, experimentation plan and validation methodology", Available Online: https://flexgrid-project.eu/assets/deliverables/FLEXGRID_D7.1_final_24032021.pdf

[FleD72] FLEXGRID D7.2, “Report on validation activities of FLEXGRID system and individual research tools”, Available online: https://flexgrid-project.eu/deliverables.html

[FleD83] FLEXGRID D8.3, “Final version of business modeling, dissemination and exploitation of results”, Available online: https://flexgrid-project.eu/deliverables.html