*Smart system of renewable energy storage based on **IN**tegrated E**V**s and b**A**tteries to empower mobile, **D**istributed and centralised **E**nergy storage in the distribution grid*

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Executive summary

The main objective of the INVADE project is to study possibilities to increase RES penetration and integration in the power system by adding more storage, i.e., batteries. The analysis centres on the flexibility services that different types of storages can provide, namely: centralized, distributed and mobile (EVs). The focus of the work package 5 (WP5) is to assess flexibility and perform analysis in order to investigate the optimal deployment of flexibility sources. Solutions to reduce the challenges brought by variable RES and EV charging include both the added flexibility on the supply and load side. Combining the different characteristics of these resources is essential in assessing the value of distributed energy resources in the power system and in the energy market. The main objective of this WP is to study how to achieve optimal deployment of flexible energy storage in distribution systems. This would lead to an improved use of existing power system infrastructure and reduce issues caused by variable renewable energy sources in the physical electricity systems and at the electricity markets.

Deliverable D5.3 provides a simple model for flexibility operation and planning to serve distribution system operators (DSO), balance responsible parties (BRPs) and Prosumers. This is a simplified model that will be initially implemented in the INVADE Platform. This report contains *the first version of flexibility management allocation and operation algorithms*. The focus is to develop an optimisation method for the operation of stationary and EV batteries as energy storage assets in the distribution grid. The motivation is that storage applications could help to improve the flexibility of the demand side, which again enables a more efficient integration of supply from renewable energy sources. To cope with the intermittent output of RES production, the charging/discharging scheduling of battery storage systems will be carried out with respect to the load and supply variations. The reaction of batteries to net-load variation provides a fast response to imbalances in the system before other frequency control activation. This can effectively help the frequency quality of a RES dominated power system. Moreover, we include the optimal siting and sizing of batteries from the use case, application and grid operation point of view. This is important to ensure that the batteries can effectively contribute to the network management and mitigation of operating challenges.

Deliverable 5.3 is split in two main documents, i.e., 1) “Flexibility operation algorithms – phase 1” and 2) “Placement and Sizing of Batteries in Low and Medium Voltage Grids”. The first document details the modelling framework for the flexibility operation algorithm. It provides an outline of the background and the purpose of flexibility services to three entities (DSO, BRP and Prosumer) and describes the flexibility services associated with the different INVADE pilots. In the modelling chapter, the document describes the different flexibility services associated with the three entities in detail and describes the meaning of flexibility for generation units, storage units and loads. Then the scope of the INVADE flexibility services are linked to the operational models for generation, storage and flexible loads. Since the 5 pilots will demonstrate certain use case(s) of these flexibility services, their roles, resources, interrelations and constraints are presented. This is followed by a chapter that details the information and planning horizon structure of the flexibility resources and the methods for implementation. In the last chapter, the mathematical formulation to model the flexibilities of different units for a specific service are provided.

The second document deals with the optimal sizing and sitting of batteries in an electric network. A detailed discussion is presented about the impacts on battery size and the benefits for the user (i.e., sizing problem for DSO, BRP and prosumer). This is explained along with the complications associated with the siting problem. A bi-level optimization approach is proposed to address the sitting-sizing decisions. Moreover, the document discusses methods to analyse capacity and investment planning for batteries. Then, an illustrative chapter applies simple sizing methods to two prosumer pilot cases.

Deliverable 5.3 presents the necessary methods and models for the development of task T8.3: initial INVADE flexibility cloud platform to serve 5 pilots based on the framework described in D4.2. In the future, further work will be done to expand these models in the “Advanced Battery techno-economic model” task, developed in T6.3.

*Smart system of renewable energy storage based on **IN**tegrated E**V**s and b**A**tteries to empower mobile, **D**istributed and centralised **E**nergy storage in the distribution grid*

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Abbreviations and Acronyms

Acronym	Description
AHES	AMI Head End system
API	Application programming interface
BMS	Battery Management System
BRP	Balance Responsible Party
BS	Balance Scheduling
CEM	Customer energy management system
CPO	Charge point operator
DER	Distributed Energy Resources
DMS	Distribution management system
DSO	Distribution System Operator
EMG	Energy Management Gateway
EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
FEP	Front End Processor
FO	Flexibility Operator
IEC	International Electrotechnical Commission
IED	Intelligent Electronic Device
IIP	Integrated INVADE Platform
LV	Low Voltage
MDC	Meter Data Concentrator
MDM	Meter data management
MR	Meter Reader
MV	Medium Voltage
NA	Not Applicable
OCHP	Open Clearing House Protocol
OCPI	Open Charge Point Interface
OCPP	Open Charge Point Protocol
OM	Operation meter
OSCP	Open Smart Charging Protocol
PRIME	PoweRline Intelligent Metering Evolution
PV	Photovoltaic

Acronym	Description
RTU	Remote Terminal Unit
SCADA	Supervisory control and data acquisition
SDC	Smart device controller
SGAM	Smart Grid Architecture Model
SM	Smart Meter
TBD	To Be Determined
ToU	Time-of-Use
TSO	Transmission System Operator
USEF	Universal Smart Energy Framework
V2G	Vehicle to Grid
WP	Work Package

Executive summary

A central deliverable in the INVADE project is the Integrated INVADE platform, which will be developed in WP8. The platform will support many different functional areas, but the main development in the INVADE project is the cloud based flexibility management system, which will be used in the daily operations of the different flexibility services. A first, simplified version of this system will be delivered to the pilots in June 2018.

This document contains a description of the algorithms that will be used in the daily operations. First, the problem is described, and basic modelling concepts are proposed and discussed with regards to flexibility from stationary batteries, loads, EVs and generation. Then the pilots are described with the target to analyse of how their technical and commercial setup will influence the design of the flexibility algorithms. This is followed by a discussion of possible approaches for handling uncertainty, including the length of the planning horizon and how detailed the time resolution should be. Finally, the first version of the mathematical formulations is given.

A key finding in the document is that the way to model flexibility and how much value that can be extracted from the flexible sources, are tightly connected to the amount of information that is available. This challenge must be addressed in other WPs and tasks.

1 Introduction

According to the DoA the deliverable *D5.3 Simplified Battery operation and control algorithm* contains the first version of flexibility management allocation and operation algorithms worked out in two tasks: *T5.3 Energy storage units allocation/positioning and sizing algorithm* and *T5.4 Design and program the flexibility management operation algorithm*. The current document covers the part connected to T5.4, whereas *D5.3 Optimal Placement and Sizing of Batteries in Low Voltage Grids* covers the part connected to T5.3.

The work in this document is built upon the content in several other deliverables in different work packages: D4.1, D4.2, D5.1, D5.2 and D10.1.

The main purpose with this document is to define the flexibility algorithms that will be implemented in the Integrated INVADE platform through the task T8.3.

The different flexibility services and how they will be implemented in the different pilots are defined in D4.2 (downloaded 09/11/2017), see Table 1:

Table 1: Flexibility services to be used in each pilot (Y: yes; N: no).

Flexibility customer	Flexibility services INVADE	Norwegian pilot	Dutch pilots	Bulgarian pilot	German pilot	Spanish pilot
DSO	Congestion management	N	Y	N	Y	Y
	Voltage / Reactive power control	N	Y	N	Y	Y
	Controlled islanding	N	N	N	TBD	Y
BRP	Day–ahead portfolio optimization	N	Y	TBD	N	TBD
	Intraday portfolio optimization	N	Y	TBD	N	Y
	Self-balancing portfolio optimization	N	Y	TBD	TBD	Y
Prosumer	ToU optimization	Y	Y	Y	Y	TBD (phase 2)
	kWmax control	Y	Y	Y	Y	TBD (phase 2)
	Self-balancing	Y	Y	Y	Y	TBD (phase 2)
	Controlled islanding	TBD	N	TBD	Y	N

It is, however, not finally decided which services that will be in phase 1 and 2. A working assumption is that the prosumer services for ToU optimization, kWmax control and Self-balancing plus the DSO service Congestion management will be in phase 1. These are the only services that will be covered in this document.

The rest of this document is organized as follows: Chapter 2 contains the problem description and the basic modelling concepts. A description of the INVADE pilots are described in Chapter 3, with emphasis on flexibility algorithm specific issues. Chapter 4 outlines and discusses issues related to the information structure and the decision process. The mathematical model formulations are given in Chapter 5.

2 Problem description and modelling concepts

2.1 An illustrative example

This section contains a specific and simplified example aiming at giving the reader an overall idea about the problems that this document address.

Consider a household with the following resources:

- A PV panel
- A set of inflexible loads
- Two EV charging points
- A stationary battery
- A main meter that meters the net exchange with the grid, i.e. the purchase and the sales
- Separate meters for the PV panel, for each of the charging points and for the battery

Since the household both produces and consumes electricity, it is a prosumer.

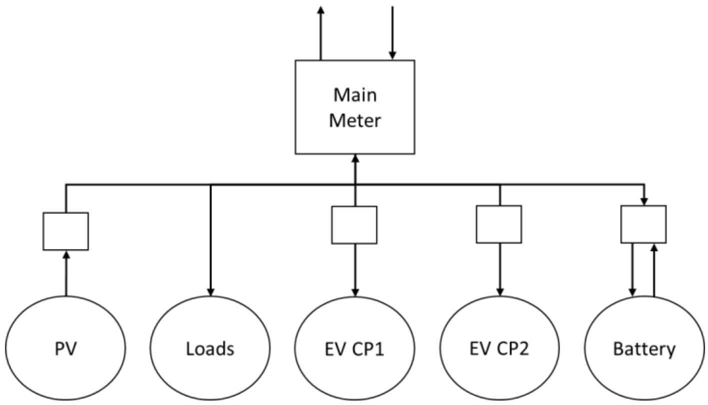

Figure 1. The prosumer with resources (circles) and meters (squares)

The prosumer has three flexible resources:

- The EV charging points, where the power levels can be controlled continuously between 0 and 4 kW
- The battery, which can be charged and discharged with power levels between 0 and 4 kW. The energy levels can be between 0 and 10 kWh

Further, assume that the prosumer has a contract with an electricity supplier, also denoted a retailer, with prices that vary hour by hour (ToU) according to prices at the Day-ahead market. We consider one given day, where the prices fluctuate according to Figure 2.

Figure 2. Example of ToU prices

In addition, the prosumer has a grid contract with the local DSO. This contract contains a price element for kWmax: For every kWh that is bought above 7 kWh/h, the prosumer must pay a price equal to twice the ToU price.

Finally, when the prosumer sells surplus electricity back to the grid, he/she is compensated to the price equal to half of the ToU price. Figure 3 shows the net exchange for a sample day in the case where no flexibility is used. The kWmax limit is also illustrated.

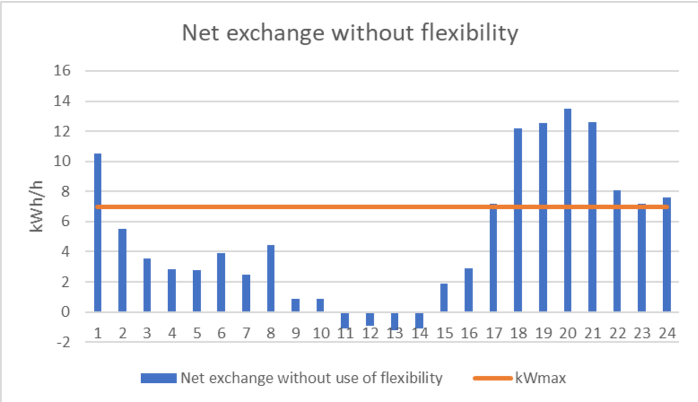

Figure 3. Net exchange for a day in the case where no flexibility is used

Observe that the prosumer will sell in the middle of the day, in the hours 11 to 14, and purchase for the rest of the day. The purchase varies considerably during the day, with a peak in hour 20, and with 7 hours where the purchase is above the kWmax limit. Finally, notice that the high purchase in the evening coincide with the high ToU prices.

The ToU contract with fluctuating prices, the kWmax which doubles the cost when the purchase is above 7 kW and the fact that selling back surplus electricity is compensated to low prices, are all incentives to utilize the available flexibility. The overall objective for the prosumer is to select a strategy with decisions to control the battery charging/discharging and the EV charging in such a way that the total costs are minimized. This task will be performed by the Flexibility Operator (FO).

The best thing to do is to:

- Shift as much purchase as possible from high price hours to low price hours, which means to shift from morning and evening to night and mid-day. This corresponds to the prosumer service ToU
- Reduce as much as possible the purchase above 7 kW. This corresponds to the prosumer service kWmax control
- Reduce as much as possible the surplus sales. This corresponds to the prosumer service Self-balancing

Notice that some of these objectives are contradictory. One example is hour number 1, where the net exchange is above 7 kW and hence the high kWmax price kicks in. This gives an incentive to reduce the purchase. At the same time, the ToU price is low, which gives an incentive to increase the purchase.

How much it is possible to reduce the costs is highly dependent on how much flexibility that is available. If we look only at using the stationary battery, we see that due to the limitations both in power level (max 4 kW) and in energy (max 10 kWh), it will only be able to **reduce** the purchase above 7 kW, not eliminate it.

A possible strategy for the battery is shown in Figure 4. By this strategy the kWmax is avoided in hour 1, all the sales is avoided and the high cost ToU purchase and kWmax is reduced in the hours 18 to 21. However, we do not know if this is the best possible strategy, i.e. the strategy that gives the minimum total cost.

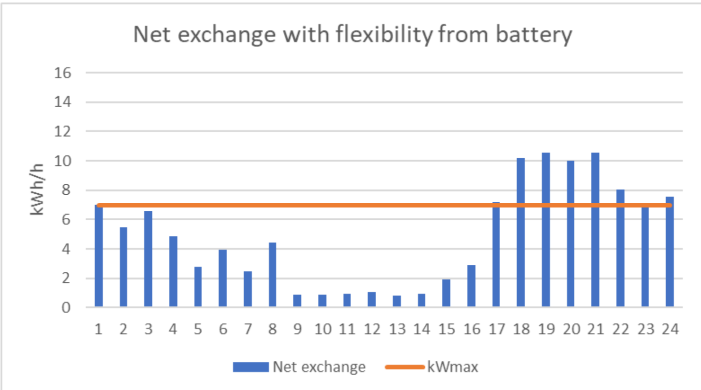

Figure 4. Net exchange with use of flexibility from the battery

If we also take the control of the EV charging into account, we may reduce the costs further, for instance by eliminating the kWmax purchase totally. However, this is again dependent on how much the EVs are charging and at what times.

The example above is a nice story that illustrates a subset of the problems that this document handles. However, the story has a major shortcoming: It does not reflect a real-life situation. The assumption that we know with certainty what is going to happen over the complete day does not hold in real life. For instance, we will not know what the PV production will be, nor the load profile. We will not know when the EVs will connect and disconnect or how much charging they need. Consequently, we do not know the net exchange. Then it is a fundamentally difficult task to make the right decisions. A risk is that we empty the battery for some hours, and later it turns out that the battery could have provided higher value if it was fully charged. So, the best strategy would have been to wait with the discharging.

One way of dealing with information we do not have, is to make predictions and to make decision based on these. For production and consumption, the nature of the predictions will be so that they may be quite good for the coming minutes or hours, but the further out into the future we get, the larger the prediction errors will be. This might be handled by repeatedly updating the predictions and rerunning the decision model. For instance, we could update the predictions each hour, we could make new decisions each hour, and each time we only implement the decisions for the nearest hour. However, when making the decisions, we look at the whole day, to reduce the risk of making "wrong" decisions.

To be able to do this, we need a suitable decision support model. In this document we use mathematical programming, also called optimization, which deals with problems where one seeks to maximize or minimize a real function by choosing the values of variables from an allowed set. In our small example, we seek to minimize the total cost. This is the objective, formulated in the objective function. An applicable model must also reflect all the technical constraints, for example the battery's limitation in maximum charging and discharging power of 4 kW, and the maximum capacity of 10 kWh.

In order to update predictions and correspondingly update the decisions, the optimization model will be integrated into the Integrated INVADE Platform. The process needed to run the optimization model is illustrated in Figure 5.

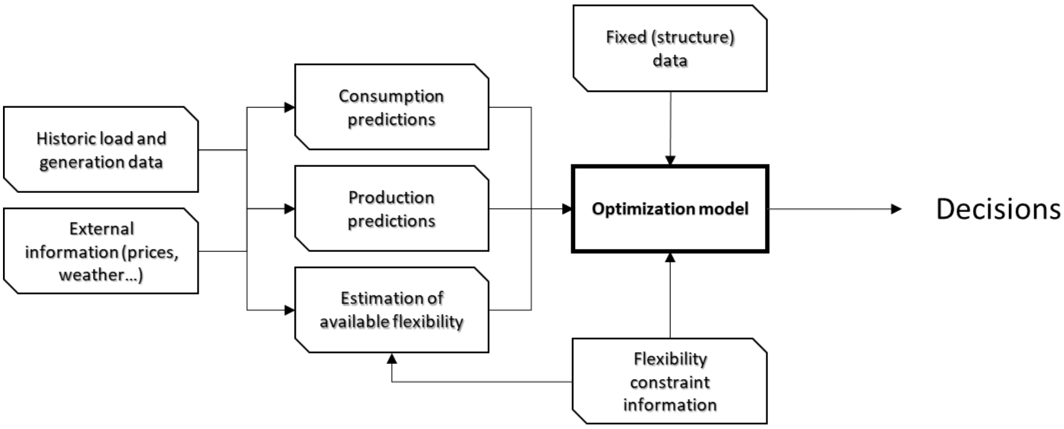

Figure 5. Illustration of the optimization model in an integrated environment

The output from the model, the decisions, is how to charge and discharge the battery and when and how much to charge the EVs. Examples are shown in Figure 6.

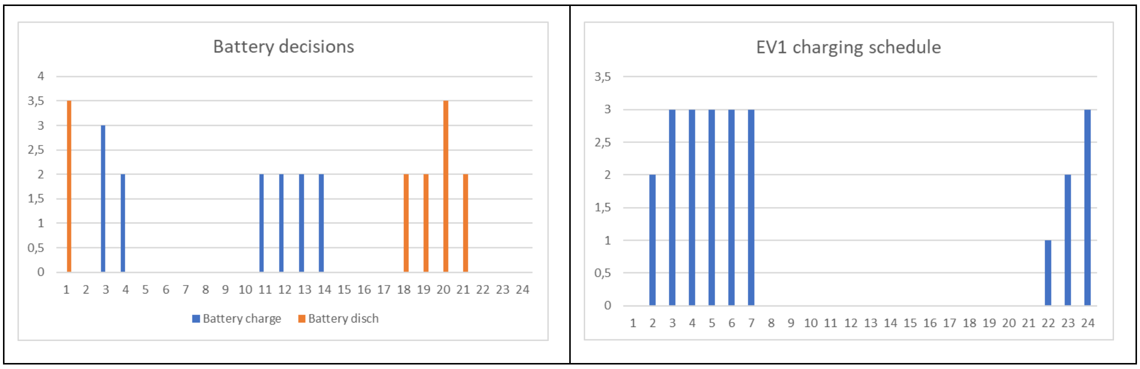

Figure 6. Examples of decisions for battery and EV1 for one day

As we saw in the example, one issue is how to detect the need for flexibility usage, since the net exchange is the basis for the decisions. Another issue is how to know how much flexibility that is available. For the battery it is quite easy, since we have full control of charging and probably have access to meter values for the energy level. For the EVs it is a bit more complicated. First of all, we most likely do not know in advance when they will connect and disconnect, or how much charging they need. However, apps might be used to increase the level of information. Perhaps other information channels can be used in addition to predictions. Anyway, it is clear that the more information we have available, the smarter decisions we can make.

2.2 Flexibility services for the DSO

In this document, the flexibility service *congestion management* is included as the only service for the DSO. According to *D4.1 Overall INVADE architecture*, congestion management is defined as follows:

Congestion management refers to avoiding the thermal overload of system components by reducing peak loads where failure due to overloading may occur. The conventional solution is grid reinforcement (e.g., cables, transformers). The alternative (load flexibility) may defer or even avoid the necessity of grid investments.

The congestion management service in the INVADE project is based on the EMPOWER-concept as described in [1]. The DSO requests activation of flexibility when needed, for instance in cases where a substation is overloaded. The Flexibility Operator (FO) delivers the requested flexibility provided by a portfolio of prosumers with flexible resources, see Figure 7.

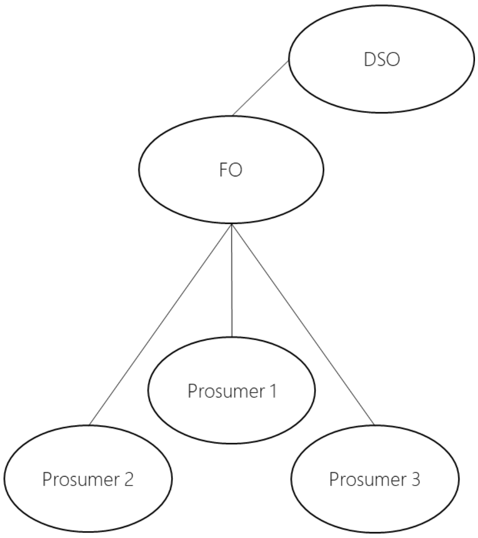

Figure 7. Congestion management services delivered to the DSO

The FO's problem is to generate a plan for when and how much to activate the different flexibility resources in such a way that:

- The request from the DSO is met
- No constraint is violated
- The activation is done to the minimum cost

2.3 Flexibility services for Prosumers

According to *D4.1 Overall INVADE architecture*, the prosumer services covered in this document are defined as:

***ToU optimization** is based on load shifting from high-price intervals to low-price intervals or even complete load shedding during periods with high prices. This optimization requires that tariff schedules are known in advance (e.g., day-ahead) and will lower the Prosumer's energy bill.*

***kWmax control** is based on reducing the maximum load (peak shaving) that the Prosumer consumes within a predefined duration (e.g., month, year), either through load shifting or shedding. Current tariff schemes, especially for C&I customers, often include a tariff component that is based on the Prosumer's maximum load (kWmax). By reducing this maximum load, the Prosumer can save on tariff costs. For the DSO, this kWmax component is a rudimentary form of demand-side management.*

***Self-balancing** is typical for Prosumers who also generate electricity (for example, through solar PV or CHP systems). Value is created through the difference in the prices of buying, generating, and selling electricity (including taxation if applicable). Note that solar PV self-balancing is not meaningful where national regulations allow for administrative balancing of net load and net generation*.

Which roles that are involved in the prosumer services, will vary from case to case. The incentives for ToU, kWmax and self-balancing can come from a combination of terms in the prosumer's contracts with the DSO and the retailer, in addition to physical conditions. The flexibility management is taken care of by the FO.

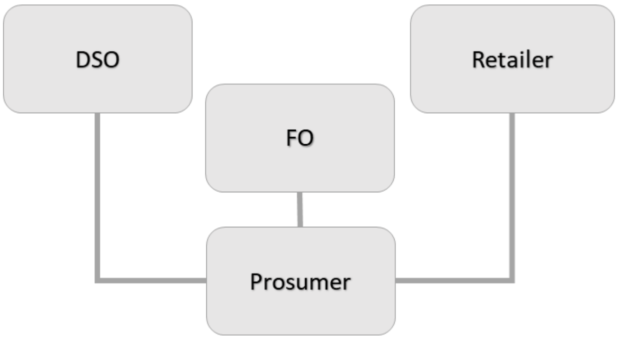

Figure 8. Possible role setup for prosumer services

In contrast to flexibility services for the DSO, that are initiated based on an occasional signal from the DSO in some given situations, the flexibility services for the prosumer must be planned continuously and without an external request. Furthermore, a combination of two or three of the prosumer flexibility services may exist simultaneously. Then, the model must take into account costs and constraints for all the involved services when making the decisions. A typical objective is to minimize the total costs.

Another complicating issue, compared to the DSO services where the requested amount is externally and clearly defined, is that the flexibility need is not unambiguously given in advance. For instance, an unexpected increase in consumption may require additional use of flexibility in order not to violate a kWmax constraint. In general, uncertainty related to production and consumption levels are more important for prosumer services. These issues are described in more detail in Chapter 4.

Notice that each of the services may have multiple interpretations:

- ToU optimization. The definition covers cases where prices vary over a given time period, for instance a day. However, in the Bulgarian pilot ToU optimization is used in a bit different context. Here, the prices are flat, but changing the load profile by shifting load from peak to off-peak periods gives Albena a stronger position to negotiate reduced future prices.
- kWmax control. This service can be linked to a tariff structure that implies a penalty for maximum purchase. Or it can be linked to a physical limitation, for instance at a main fuse.
- Self-balancing. The definition covers cases where the value of consuming self-generated electricity is higher than selling back. However, there might also be situations where selling back surplus generation is not allowed.

2.4 Prosumer and site

The starting point for the INVADE concept is the prosumer and site model as defined in the EMPOWER project. A site is a location with a main meter. A site can represent a dwelling, a house, a commercial building, an industrial facility, a charging station and probably other types. A prosumer (consumer that also produces electricity and/or that provides flexibility) is a legal entity (person or business), and a site must have one prosumer connected to it. Prosumers can move in and out from a site, but at a specific time only one prosumer can be active.

As stated above, each site will have a main meter, which is the basis for the grid contract with the DSO and the retail contract with the chosen retailer. In addition, a site can have one or several resources, where each resource is categorized in one and only one out of four types:

- Generator resources
- Load resources
- Electric vehicles (EVs)
- Storages

Each resource can be a single appliance or a virtual collection of several appliances or circuits. Furthermore, each resource can be metered or not and controllable or not. Meter values from the main meter (net energy in and out) and from the sub meters (at the resource level) will be collected in real time with fine time granulation (currently each 10 seconds in the EMPOWER project). Which control options that exist will depend both on the technical characteristics of each resource/control equipment and on the agreement with the prosumer. All registered resources will be linked to one and only one site, to which a main meter is connected. The model is illustrated in Figure 9.

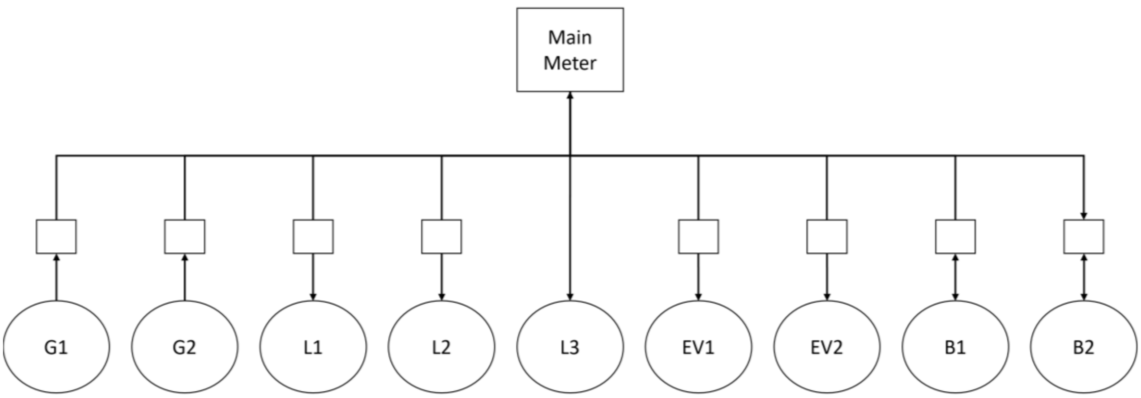

Figure 9. Prosumer model

The model is easily interpreted in cases where each controllable resource is one single device. However, in some cases one resource is a collection of devices. A typical example is when an EV resource consists of several charging points.

2.5 Flexibility

As described above, some of the resources may be controllable. Then, they can provide flexibility, defined as *the modification of generation injection and/or consumption patterns* *in reaction to an external price or activation signal in order to provide a service within the electrical system* [2].

Our objective is to utilize the flexibility to meet different objectives without violating constraints. Below, a description of possible flexibility characteristics is described for each resource type. Later, in Chapter 4.1, the different characteristics are formulated mathematically.

The starting point for the flexibility descriptions are from [3], which are further developed in the EMPOWER project [1]. However, it is expected that the descriptions will be refined and adapted through the work in INVADE.

Since flexibility is defined as “a modification”, it must be compared to some baseline, which for instance can be an original schedule or a prediction. The flexibility is then the difference between the baseline and the revised plan, see Figure 10.

Assume the blue bars represent a baseline consumption and that the orange line represents the revised plan. Then, we have flexibility provision in period 4 and 8, equal to 5 kW.

The provision of flexibility is called regulation, which can come in two directions: Up and down. Up-regulation means increased production or decreased consumption, while down-regulation means decreased production or increased consumption.

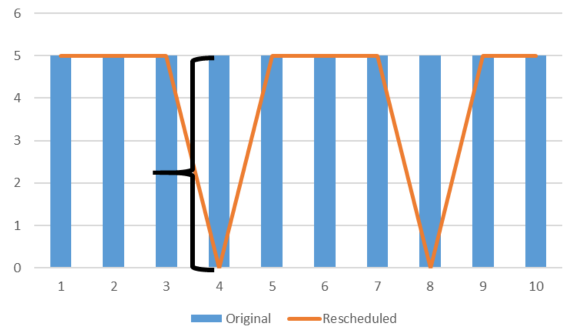

Figure 10. Original and revised schedule and the provision of flexibility

Focus on flexibility provision directly is important in cases where flexibility is sold and bought as a service, for instance to the DSO.

2.5.1 Flexibility from batteries

Batteries provide high flexibility as they are fully dedicated to this task. An example is shown in Figure 11, where a battery provides energy and stores energy in different time periods to offer some requested service by a prosumer or a FO. The battery has a certain energy capacity storage limit and a charge and discharge power limit.

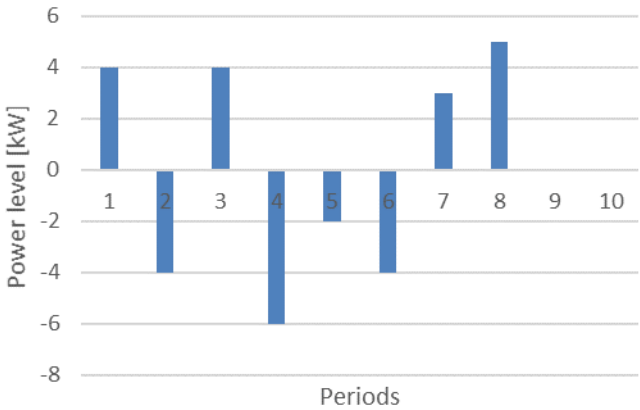

Figure 11. Battery flexibility example

Batteries are electrochemical energy storages with complex nonlinear characteristics and interdependencies. The most important characteristics are the capacity, open-circuit voltage (OCV), and internal impedance, which also dictate the energy capacity, efficiency and power capability. Moreover, batteries are very sensitive to temperature. Too low temperature results in poor performance and low efficiency, while too high temperature results in increased rate of degradation and even decomposition and safety risks. All these characteristics cause constraints and limitations for the usage in order to achieve safe operation and long lifetime. The battery characteristics are explained in more detail in *D6.1 Storage system dimensioning and design tool*.

Each battery chemistry has a unique OCV curve and a voltage window. The specified maximum and minimum voltages should not be exceeded in any case as it may cause increased rate of degradation and even cell decomposition and permanent damage. Therefore, high and low cutoff voltage are specified for each cell to ensure safe operation and long lifetime. The controller algorithm must be capable to prevent the voltage to reach these cutoff voltages during use. This can be implemented by setting limitations for the usable SOC (state-of-charge) window as well as discharge power when approaching fully discharged state and charge power when approaching fully charged state.

During loading, polarization losses occur when a load current passes through the electrodes. These polarization losses consist of ohmic polarization, activation polarization and concentration polarization. The presence of these losses can be seen as a difference between the OCV and the terminal voltage during loading. As the polarization effects increase with increasing current, the low cutoff voltage is reached earlier when discharging with higher rates. This is known as the rate effect. However, the capacity is not lost, but is usable once the voltage has recovered. Full relaxation takes hours to complete. Rate effect is illustrated in Figure 12 , which shows an A123 lithium-ion cell performance under different power extractions. The area below the curve is the total energy extracted, and it is smaller as the power extracted increases.

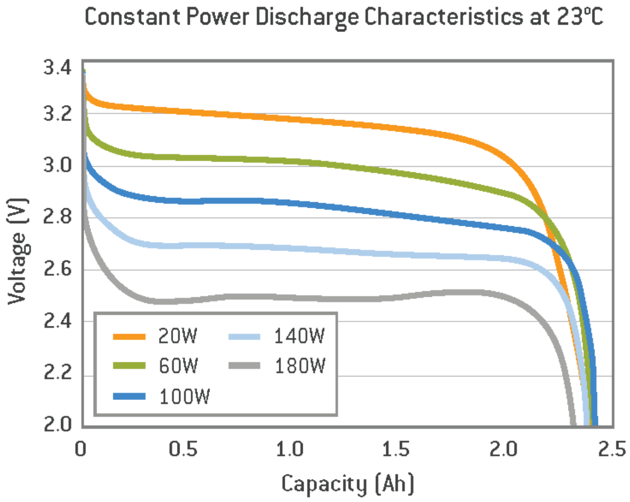

Figure 12. Power vs round-trip efficiency relation from A123 nanophosphate high power lithium ion cell data sheet

The battery model must reflect the technical characteristics of the combination of battery type and battery management system. We assume that we are able both to control whether the battery is going to be charged and discharged and the power levels. In addition, restrictions may be given by the owner/operator of the battery, for instance related to different times that the battery can be used, a limitation of the number of charging/recharging cycles (to prevent aging) and potentially also limited bandwidths, in cases where the battery is also used for other purposes.

The subsections below describe the main battery parameters to be used in the INVADE model.

2.5.1.1 Battery energy storage capacity

Battery energy storage capacity is the total energy capacity of a battery, which is specified in the data sheet of a battery. Capacity is normally modelled in kilowatt-hours (kWh), which is preferred over ampere-hours (Ah).

2.5.1.2 Maximum charge and discharge power

Maximum charge and discharge power are the maximum power that the battery can handle. These are limited by the inverter, the transformer and the cross section area of the charging wire. Whereas an EV can potentially deliver a power of more than a hundred kW, this would normally not be the case in a V2X situation due to thermal limitations on inverters and cables. Although lithium ion batteries can have a relatively high maximum charge and discharge power, the battery often has thermal constraints meaning that the maximum charging power can only be utilized for a certain amount of time. Therefore, batteries can be modelled with both a maximum and a continuous charge and discharge power, in order to avoid creating operation decisions that are not in line with real constraints.

2.5.1.3 Charge and discharge power resolution

Depending on the equipment specifications, the charge and discharge power has a limited resolution. Whereas a model can handle a linear high resolution charging power, the real charging device could have discrete steps, for example one step per ampere. Higher resolution could also potentially increase the calculation time of the optimization. It is in general assumed that continuous charging current and therefore power can be configured.

2.5.1.4 Charge and discharge efficiency

The instantaneous efficiency of a battery is dictated by the current, the internal resistance, and the OCV, as follows:

$$\eta = 1 - \frac{R}{U_{\mathrm{oc}}} I$$

where U_{oc} is the open-circuit voltage (OCV), R is the internal resistance, and I is the discharge current. However, because the OCV cannot be measured directly during loading, roundtrip energy efficiency is used in determining efficiency. The roundtrip energy efficiency is defined as the ratio of the discharged energy to the charged energy. Because of the complex and nonlinear impedance and OCV characteristics of Li-ion batteries, the actual energy efficiency depends on the rate and duration of the loading, the SOC, the temperature, and the ageing of the battery.

In general, the rate has a high impact on the efficiency. Typically, the roundtrip energy efficiency of a full discharge–charge cycle of a large Li-ion battery at room temperature is higher than or equal to 97% for low rates less than or equal to C/3. Here, C is the charge/discharge speed, i.e. C/3 means full charge or discharge in 3 hours.

Impedance curves are typically almost flat in the mid-SOC area from 20-80%. Therefore, in that area, the SOC affects the efficiency mostly via the OCV slope, which is dependent on the battery chemistry. As the OCV decreases with decreasing SOC, the efficiency decreases with decreasing SOC as well. Outside the mid-SOC range, especially below 20% SOC, the impedance characteristics rise significantly, which reduces the efficiency directly. Furthermore, efficiency decreases as the ageing increases. This is a consequence of the tendency of the impedance to increase due to ageing.

The internal impedance of a battery changes as a function of temperature. Nominal or rated values are typically given at room temperature. At colder temperatures, the impedance increases and the efficiency decreases, and at higher temperatures, the impedance decreases and the efficiency increases.

When determining the energy efficiency of a storage system, one must take into account also the losses that occur in the power electronic converters and grid interface. The efficiency of the power electronic converters depends on the operating point. In ref. Schimpe et al. [4] the efficiency of a grid-connected inverter including a grid connection was modelled and measured. The efficiency was low (<80%) at very low power (<5% rated power) and high (>95%) for the most of the operating range (>20% system power).

A constant storage system efficiency is used in the INVADE controller algorithm in the first phase. In [4] a storage system of 192 kWh with LFP batteries was modelled and simulated for several different use strategies and scenarios. The optimum roundtrip energy efficiency of 87% was obtained under constant cycling with partial load, while most of the scenarios resulted in 70–80% roundtrip efficiencies. In INVADE pilots, the base scenario is that a low rate is typically used, which results in high efficiency for the battery and the inverter. Based on these findings, 85% will be used as the starting point for the storage system roundtrip efficiency. This equals to the discharge and charge efficiency of 92%. However, the efficiency parameter can be adapted to each pilot. Low power operation (less than 10% of system power) should be avoided due to relatively low efficiency of the power electronics.

The pilot adaptations as well as more advanced methods to implement the efficiency characteristics will be investigated in WP6, and the results will be adapted to the controller algorithm in a later phase. One possibility is to set the efficiency parameters outside the optimization algorithm before executing the algorithm.

2.5.1.5 Cost of degradation

Battery performance degrades as a result of ageing. The performance degradation can be divided into capacity fading and power fading. Degradation happens to all batteries regardless of whether they are used or not. Cycle ageing happens during discharging and charging, while calendar ageing happens when the battery is not used. The rate of degradation depends on the use profile, storage SOC and ambient conditions.

The models presented in this deliverable have no degradation cost taken into account. However, this is implementable, and will be taken into account in a later phase. The degradation mechanisms are very complex and dependent on the use profile and ambient conditions. These stress factors and their modelling methods are studied in WP6, and the results will be included in the final controller algorithm.

2.5.1.6 Self-discharge coefficient

Self-discharge is not included in present models, but could easily be implemented. Self-discharge is basically a battery losing state of charge slowly when not being used, where all batteries have an own self-discharge coefficient depending on technology. Because most batteries in the pilots are intended for daily or at least weekly use, self-discharge is not the most important factor, but could in theory be included if considered to be relevant.

2.5.1.7 Capacity utilization factor

In power systems the control variable is typically power instead of current. At CV (constant voltage) regions close to the cutoff voltages, maximum available power values can be reduced to mimic CV operation.

During charging, the boundary between the normal operation and the voltage-limited operation depends on the rate, the internal impedance, and the OCV characteristics. Typical SOC values for the boundary at C/3, 1C, and 2C rates are 95%, 90%, 80%. However, these numbers vary and depend especially on the cell chemistry.

During discharging, the actual boundary between the constant-current or constant-power operation and the cutoff or CV operation is typically close to 0% SOC for discharging with rates of less than 3C. Nevertheless, the power limiting region should start at around 10% SOC to prevent abrupt ending of the discharge due to accidentally reaching the cutoff voltage. Also the efficiency starts to reduce significantly already before that, and the heat generation rate increases rapidly as the SOC approaches 0%.

For full utilization of the battery performance without voltage-based limitations, a SOC range that allows full-power operation can be defined. Moreover, this region can be further reduced in order to take into account other aspects such as increased rate of aging at high SOC and lower efficiency at low SOC.

2.5.2 Flexibility from loads

A load unit is an appliance or a virtual collection of appliances that consume electricity. We split load units into three main classes: Inflexible, curtailable and shiftable. Inflexible load units are devices that can not be controlled, for instance TVs or food cooking appliances.

Curtailable load units can be disconnectable if the only options are to be on or completely switched off. Or they can be reducible if the power levels can be controlled. Figure 13 shows a possible baseline consumption for load unit. If the load unit is inflexible, the schedule will be equal to the baseline.

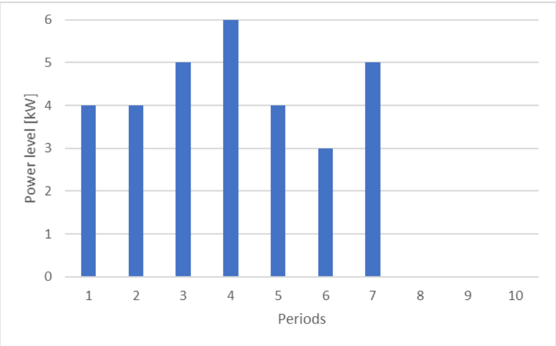

Figure 13. Baseline consumption for a load unit

If the load unit is disconnectable, a possible schedule is illustrated in Figure 14, where the unit is disconnected in periods 4 and 5.

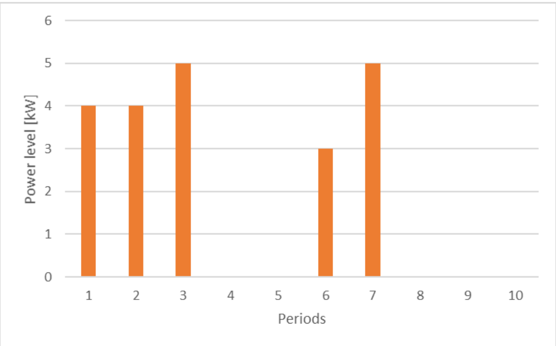

Figure 14. Up-regulation provided from consumption disconnection

A corresponding example for reducible load unit is illustrated in Figure 15, where the consumption level is reduced down to 2 kW in periods 4 and 5.

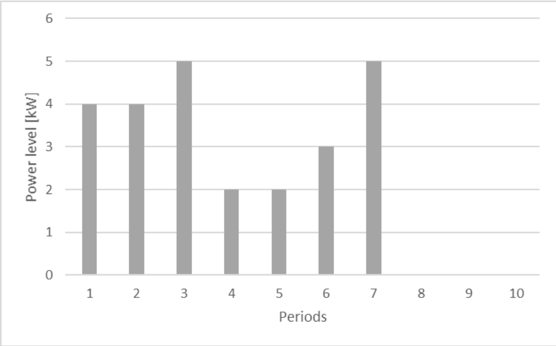

Figure 15. Consumption reduction in hours 4 and 5

While for curtailable load units, the consumption that is reduced will not be delivered later, shiftable load units have the flexibility to deliver the consumption at other times. Some shiftable load units fall into the category of shiftable profile, where the complete profile is delayed (or forwarded) without changing the power levels. A typical example is a washing process.

Figure 16 shows an example of an original consumption profile (still Figure 13) is delayed three periods.

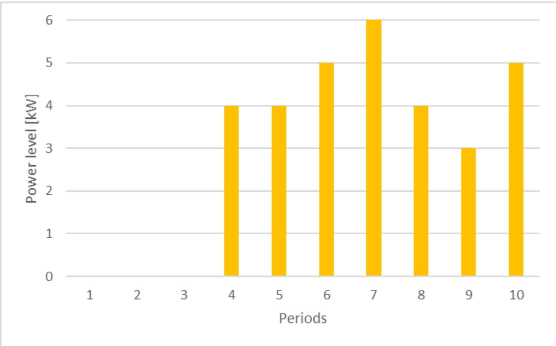

Figure 16. Consumption in case with shifting three periods

For some load units there exists a possibility to control the power levels, which means that the consumption can be shifted in time, but in addition, the profile can be changed. We denote this type shiftable volume, since the volume must be met. Some also call this type for storable loads. Freezing rooms are examples of consumption that can be shiftable volume, if there is a possibility to control the power levels directly or indirectly through changing the temperature setpoints.

Figure 17 shows an example where the baseline consumption is shifted one period and also reshaped totally.

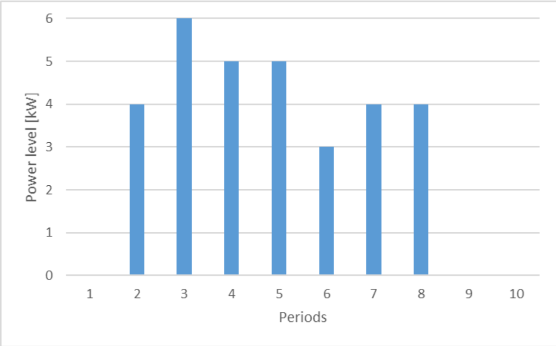

Figure 17. Consumption in case with shifting and shaping

In order not to induce to large disadvantages for the prosumers and to keep inside physical limits, it must be possible to limit the controllability of the different load units. These constraints will be different between the different categories of flexibility:

Curtailable disconnectable: Curtailment is allowed only for certain periods. A curtailment can have a maximum duration before it must be reconnected. After a reconnection, the load unit must have a minimum rest time before the next disconnection.

Curtailable reducible: The limitations will be the same as for curtailable disconnectable. In addition, the reduction must be within specified limits.

Shiftable profile: There must be limitations related to how much a consumption can be shifted forward or backward, or in other words: earliest start and latest finish period.

Shiftable volume: Same limitations as shiftable profile. In addition, minimum and maximum power levels must be defined.

Utilizing flexibility from load resources may induce added costs or discomfort for the prosumers.

For curtailable load units, we have the foundational issue that we can not meter how much we have curtailed. One approach is to estimate the volume curtailed and then compensate according to prices per curtailed kWh. Another, more straightforward approach, is to compensate based on the number of periods curtailed. In the EMPOWER project the latter is chosen.

For shiftable load units, a natural approach is to compensate according to the length of the delay, or in general: how long the consumption is moved away from the baseline. For shiftable profile load units this is a straightforward strategy: You just count the number of periods the start or the end is shifted and multiply with a price per period. For shiftable volume load units, it is a bit more complicated. In the example in Figure 17 both the start and the end is delayed with one period, so the delay is easy to handle here. However, we also see that some of the consumption is shifted to earlier periods, so on average, the volume is not delayed with one whole period. Other examples could be even more complicated, see Figure 18 that illustrates two possible new profiles where both the start and end periods are the same (and hence, no delay), but where most of the consumption is met earlier and later, respectively.

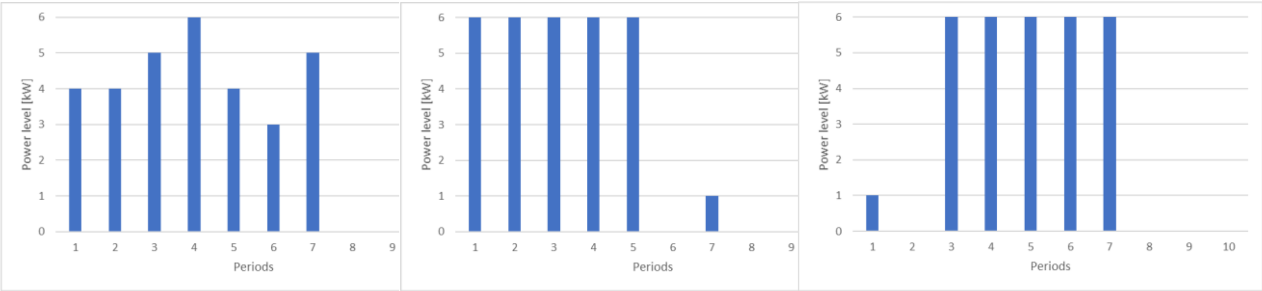

Figure 18. Original consumption profile (left) and two possible reshaped profiles (middle and right)

To handle all these situations in a uniform way, we introduce the term weighted average delay (wad), which indicates how much later or earlier the energy volume is delivered on average. Since the wad also is an expression in number of periods, the strategy to compensate based on number of periods shifted, can be used also for this category of load units.

The load units described above are modelled based on time constraints. For some load types, defining these constraints properly may require some preprocessing. For thermal loads, a different approach is to model the temperature behaviour directly instead of the time constraints.

The detailed modelling of thermal loads requires more measurements and physical parameters specific to every particular thermal load. For example, the detailed modelling of electric water heater (EWH), requires measurement of water inflow, outflow, hot water temperature and ambient temperature. The parameters specific to the water heaters are hot water tank capacity, thermal insulation properties of the tank, power rating of the heating element. For smart grid energy applications, simple data models based on historic measurement are sufficient. The temperature and power consumption profile of EWH is shown in Figure 19. The EWH generally has one or two duty cycle in 1 hour during normal operation.

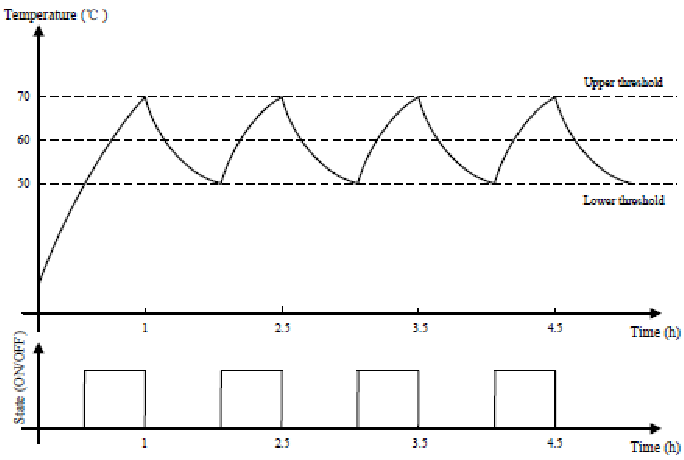

Figure 19. Temperature and power consumption of EWH [5]

Lu et al [6], present a simple state queue model (SQ model) of thermal loads, which considers the temperature profiles of the thermal loads are linear between the upper (T+) and lower (T-) threshold points at which the thermostat changes its switching state from

ON to OFF or vice versa due to the hysteresis of the thermostat. Figure 20 shows the temperature profile of a EWH and the SQ model representation.

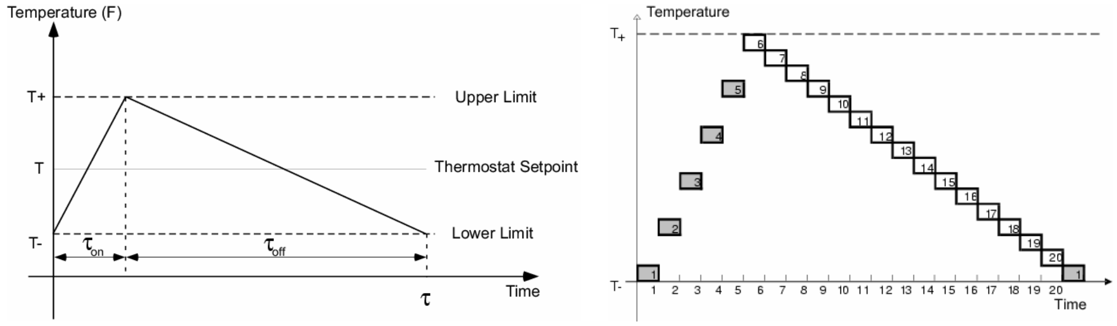

Figure 20. SQ model representation of EWH temperature [6]

The two temperature profiles between the upper and lower temperature threshold limits are divided in to may states. When the EWH is switched OFF, its temperature state is moved from one temperature profile to the state in the other temperature profile corresponding to the same temperatures. Thus the flexibility duration can be predicted from the number of states in the temperature profiles.

The SQ model considers the temperature profiles as a linear one. In real life they are not linear. Venkat et al [7] developed a black box model for another thermal load refrigerator, which considers the temperature profile as a piecewise linear. The slopes of the temperature profiles are derived from the previous temperature cycles. When the thermal load's state is changed, the model calculates the duration for which the thermal load can be switched ON or OFF by reconstructing the temperature profile from the slopes of temperature profile in the previous temperature cycle. Figure 21 shows the temperature and OFF time prediction for a refrigerator using the black box model technique.

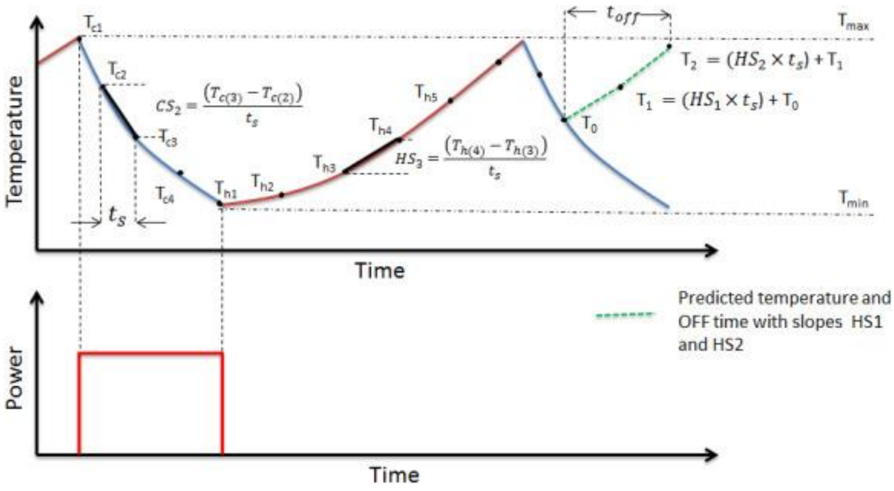

Figure 21 Temperature and OFF time prediction method in black box model for refrigerators [7]

Both the SQ model and black box model do not consider the physical properties like thermal insulation, thermal mass, ambient temperature and mass flowrate etc. Both the models use only two measurements namely the temperature and the power consumption of the thermal loads.

By considering the measurement constraints in the pilot tests, the thermal loads, for example EWH can be modelled with linear temperature profile between T- and T+ as shown in the Figure 20 with two different temperature slopes for heating and cooling segments. With the assumption of no external disturbances like change in ambient temperature and change in mass flowrate of thermal mass (in this case inflow and outflow of water), the objective function for prosumer cost minimization is

$$\min \sum_{t}^{N} \left(E_{(t)} * Cel_{(t)}\right)$$

where

$Cel_{(t)}$ is cost of electricity at time period (t)

$E_{(t)}$ is energy consumption by the EWH at time period (t) which is defined as

$E_{(t)} = (\Delta\tau_{ON\ (t)} * \tau_{ON}) * P_{(EWT)}$

where

$P_{(EWT)}$ is power rating of the EWH

τ_{ON} the duration for which the EWH stays ON during normal operation

$\Delta\tau_{ON\ (t)}$ is the fraction of ON time calculated for the period (t) such that $0 < \Delta\tau_{ON(t)} < 1$

The temperature constraints are defined as follows

$T_{(t)} = T_{(t-1)} + (TSL_{ON} * \Delta\tau_{ON\ (t)}) - (TSL_{OFF} * (1-\Delta\tau_{ON\ (t)}))$

where

$T_{(t)}$ is the temperature of water in EWH at time (t)

$T_{(t-1)}$ is the temperature of water in EWH at time (t-1)

$TSL_{ON} = \Delta T / \tau_{ON}$

$TSL_{OFF} = \Delta T / \tau_{OFF}$

ΔT is the difference between upper (T+) and lower (T-) threshold temperature of EWT as shown in the Figure 20.

This model is very similar to battery model where T- and T+ replaces the SOC_{min} and SOC_{max} respectively, and the changing energy of the battery is replaced by the heating energy. Unlike the battery, the EWH do not deliver energy back to the network. It can be considered as self-discharge of a battery.

Real-time implementation issues:

At (T+) the thermostat disconnects the EWT from the mains power. This disconnection remains until the temperature reaches (T-) due to the hysteresis of the thermostat. Therefore, any external control will not be possible at and above (T+). This constraint restricts preheating above (T+). By considering a new upper threshold temperature a few degrees lower than the actual upper threshold temperature (T+) during control, full control can be provided over all time. As for as the user is concerned, the temperature has to be within the set temperature band.

Another issue related to real-time implementation is delivering the calculated energy in the sub periods of the duration (t). If the ($\Delta\tau_{ON\ (t)}$ * τ_{ON}) calculated as the result of optimization, is above 50% of τ_{ON} and the $T_{(t-1)}$ is also above 50% of the temperature band, then the total energy for the time period (t) cannot be delivered at once continuously. The reason is that the temperature $T_{(t)}$ will reach the upper threshold (T+) sooner than ($\Delta\tau_{ON(t)}$ * τ_{ON}), the ON time calculated, consequently the internal thermostat of the EWH will disconnect the heater from the mains power. One of the simple ways to avoid such situations, is by delivering the energy in 2 or 4 parts within the sub periods of the duration (t). For example, if the length of the period (t) is 60 minutes, the EWH can be activated for half of ($\Delta\tau_{ON(t)}$ * τ_{ON}) duration in every 30 minutes.

2.5.3 Flexibility from EVs

The EV model must reflect technical characteristics of the charging point in combination with the car. First, we must distinguish between the ones that support V2X, (Vehicle to Grid, Vehicle to Home, Vehicle to Building), i.e. where electricity can be retrieved from the EV battery, and the ones that purely can be charged. The latter category is partly similar to a load. Furthermore, we must distinguish between the control options that may exist at the charging point. Some cannot be controlled at all, and are hence inflexible. As an illustrative example, assume that an EV has a charging profile according to Figure 22. Here, the x-axis shows the general term period, which may be an hour, 15 minutes or some other time span. A non-controllable EV will contribute with this load.

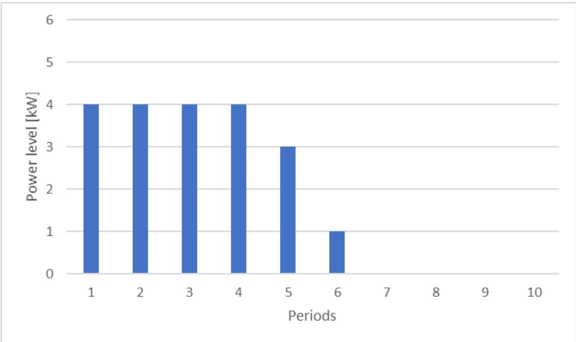

Figure 22. Baseline charging schedule

Some charging points provide possibility to delay the charging, similar to introducing a timer. Then the whole charging profile is shifted a number of periods. This is illustrated in Figure 23, where the profile from Figure 22 is shifted 4 periods.

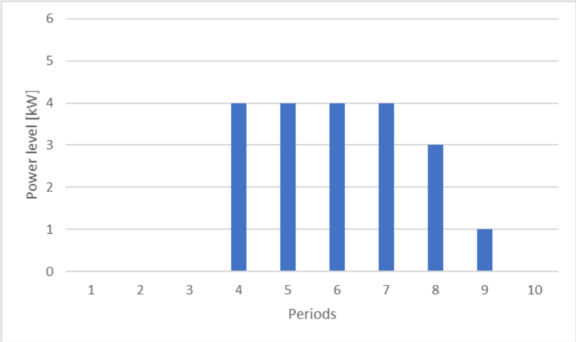

Figure 23. Shiftable charging

Since flexibility is defined as the difference between the baseline and the new schedule, this shifting means up-regulation for some periods and down-regulation for others, see Figure 24. Hence, time shifting can be done both in cases where up-regulation is needed and in cases where down-regulation is needed. However, it is important to realize that a shifting will represent both, so decisions must be taken with care.

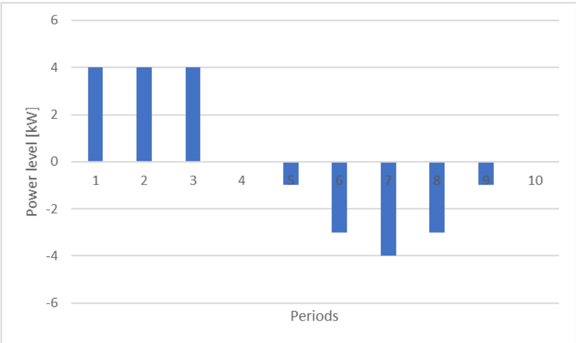

Figure 24. Flexibility provision from shifting charging

Other charging points have the possibility to shift and to interrupt. Then the charging profile will be kept, but each original will be shifted different number of periods, as shown in Figure 25.

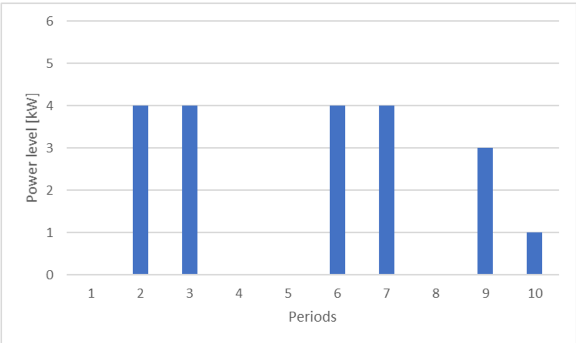

Figure 25. Shiftable and interruptible charging

A more advanced option is when also the power level can be controlled, probably between a minimum and a maximum power level. An example is shown in Figure 26, where the total charged energy volume is the same as in Figure 22.

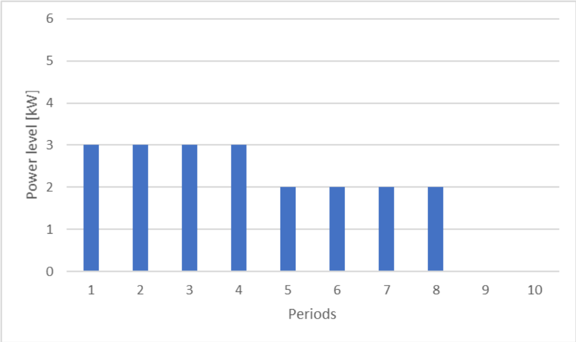

Figure 26. Controllable power level charging

It should be mentioned that if the IEC 61851-1 standard is followed, every EV can be controlled. However, not every charge point supports control commands from a platform nor does every charging point have the ability to locally manage the load of the EV. If we include the possibility to discharge the battery (V2X), we can control both the charging and the discharging power levels. An example is given in Figure 27, where a discharging is performed in periods 3 and 4, while charging is done in all the others. In the end, the total net energy charged to the battery is equal to the case in Figure 22.

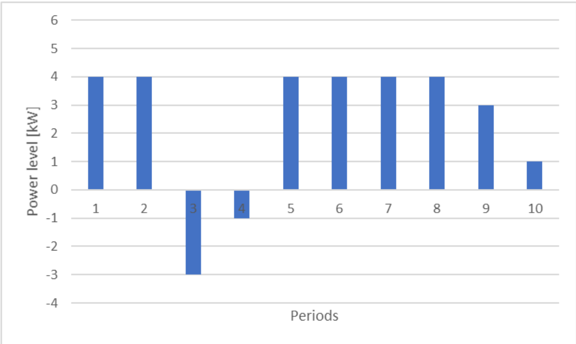

Figure 27. Charging with V2X capabilities

Notice that in the V2X case, the amount of flexibility provided can be high, see Figure 28, which shows the flexibility provided when baseline is according to Figure 22 and schedule is as presented in Figure 27.

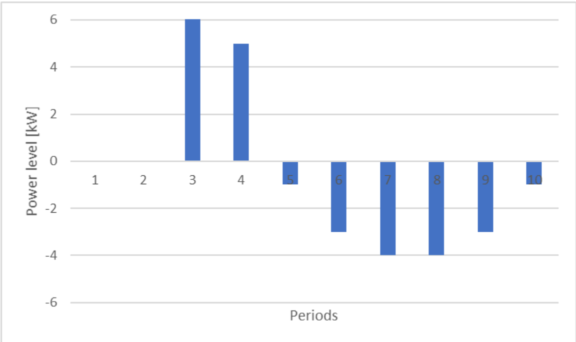

Figure 28. Flexibility provision with V2X capabilities

All the cases illustrated above have the same sum net charging energy. In an operational setting, the possibility to obtain this is dependent on what information that is available. Key parameters are:

- The connection and disconnection periods
- The battery state of charge when connecting, or eventually the charging demand/preferences

Section 2.6 discusses about EV modelling options depending on available data.

2.5.4 Flexibility from generation units

A generation unit is a technology that produces electricity. In this document, we focus on local, renewable generation units like wind turbines and solar panels. Which flexibility options that exist will be dependent on the technology at hand, but basically we divide into **inflexible** and **curtailable** generation units. The latter is again divided into two groups: **disconnectable**, i.e. that either must be on or completely off, and **reducible**, where the power level can be controlled.

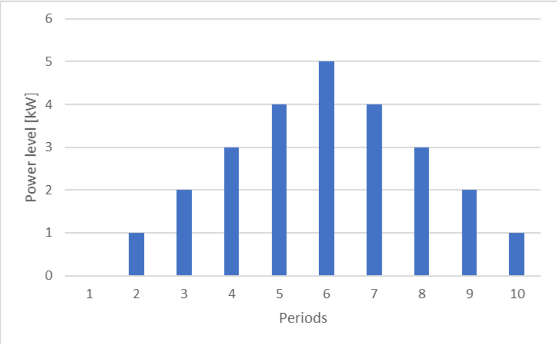

Figure 29. Baseline production for a solar panel

For illustration, assume that a solar panel has a baseline production profile according to Figure 29. If it is of type curtailable disconnectable, a possible revised profile is shown in Figure 30, where it is disconnected in period 6 and 7. Hence, the production is 0 in these periods.

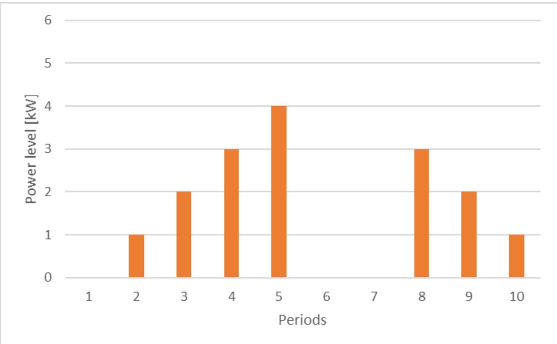

Figure 30. Schedule for disconnectable generation unit

If the solar panel is in the category of curtailable reducible a possible revised profile is shown in Figure 31, where production is reduced to 2 in the periods 6, 7 and 8.

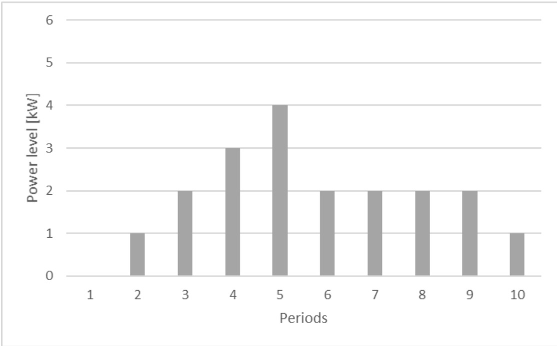

Figure 31. Schedule for reduceble generation unit

In this document we assume that there are no timing constraints related to when regulations can be performed, meaning that curtailment can be done at any time and with any duration. However, constraints can be introduced according to the ones described under curtailable load units.

Also recall that we only treat wind mills and solar panels in this document. Other generation technologies like hydro power plants and thermal units, will have different properties and constraints.

2.5.5 Flexibility from aggregated resources

The cases described in the previous section regarding batteries, EVs, loads and generation units are explained in case of having information of each single device. For instance one load appliance or one charging point. In some cases, this might not be the situation. A typical example is when there are several charging points below one charging site, and our model is not able to control each of them. Another example is if a household is modelled as one single resource without having detailed information about the internal appliances.

In cases where the expected output is an aggregated flexibility curve, some considerations are necessary.

First of all, in case of having all possible information from flexible assets, the problem should be handled as previously. Therefore, the aggregated curve from the Integrated INVADE platform optimization algorithm is composed by all flexible devices and the local platform can change that scheduling if needed.

2.5.5.1 Flexibility from aggregated resources with partial information at device level

If the information available is just an aggregated curve with different flexibility sources, it makes flexibility decision problems very complicated as there are no constraints limiting the feasible flexibility. Therefore, even if the final individual schedule plan is taken by a local controller or central system, aggregated decision should be taking all devices into account.

One possibility is that the optimization algorithm suggests a feasible schedule plan at device level minimizing the cost. Then, the result of this scheduling problem is sent to the local controller who takes the final decision based on their priorities.

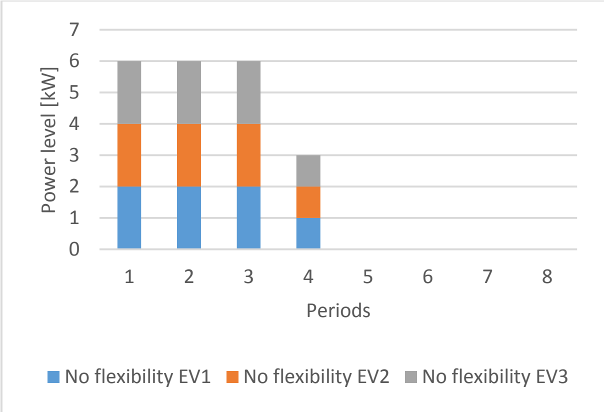

Figure 32. Baseline charging schedule

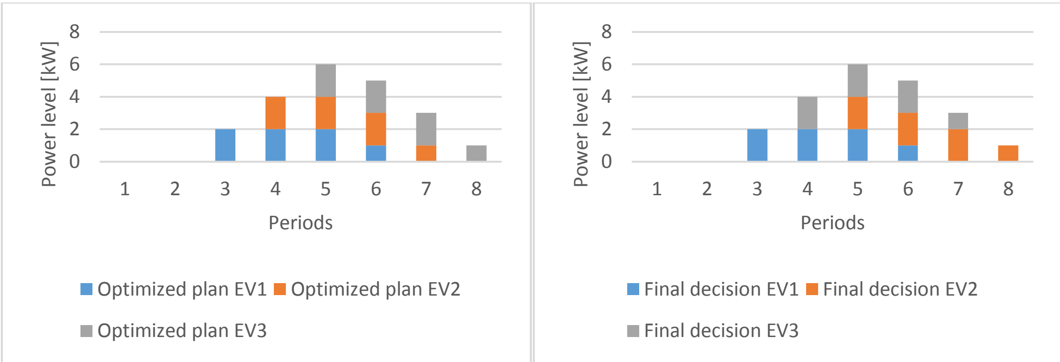

Figure 33. Optimized and final decision schedules

Notice that both solutions consumes the same energy aggregated but the EV 2 starts charging at the 5th period instead of 4th period.

2.5.5.2 Flexibility from aggregated resources without information at the device level

In case of not knowing which resources that form the flexibility portfolio, a more generic, high level model must be defined. One possible approach is to introduce a new resource type which represents a virtual, flexibility resource.

Assume we have a site (a building or a charging site) with an expected load profile. The site also has a virtual flexibility resource, see illustration in Figure 34.

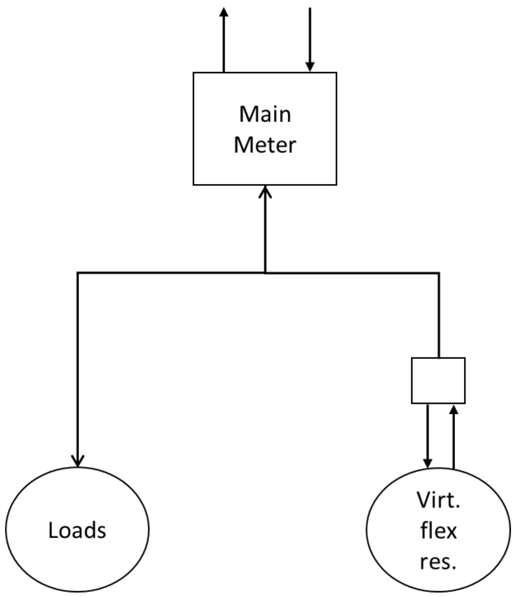

Figure 34. Site with virtual flexibility resource

The virtual flexibility resource is characterized with the following properties: For each period of the day it has a given amount of available flexibility for load reduction (i.e. flexibility up) and down (i.e. load increase). Furthermore, the flexibility comes to a cost that also can vary over the day. The figure below illustrates a load and the capabilities for up and down regulation.

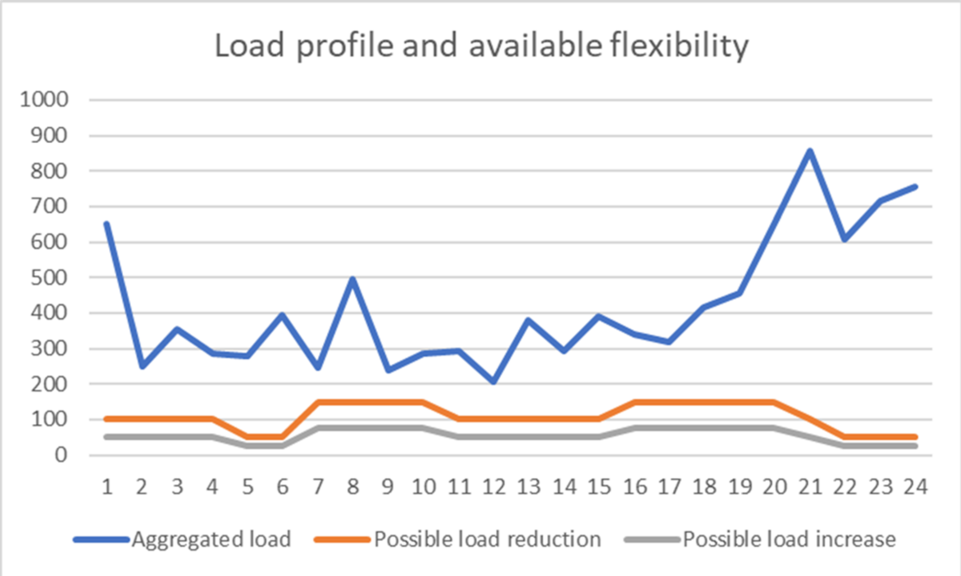

Figure 35. Predicted aggregated load curve and available aggregated flexibility

By adding the possible load reduction and increase to the load profile, we get a band width which defines the possibility space for the resulting net load profile. This is illustrated in Figure 36.

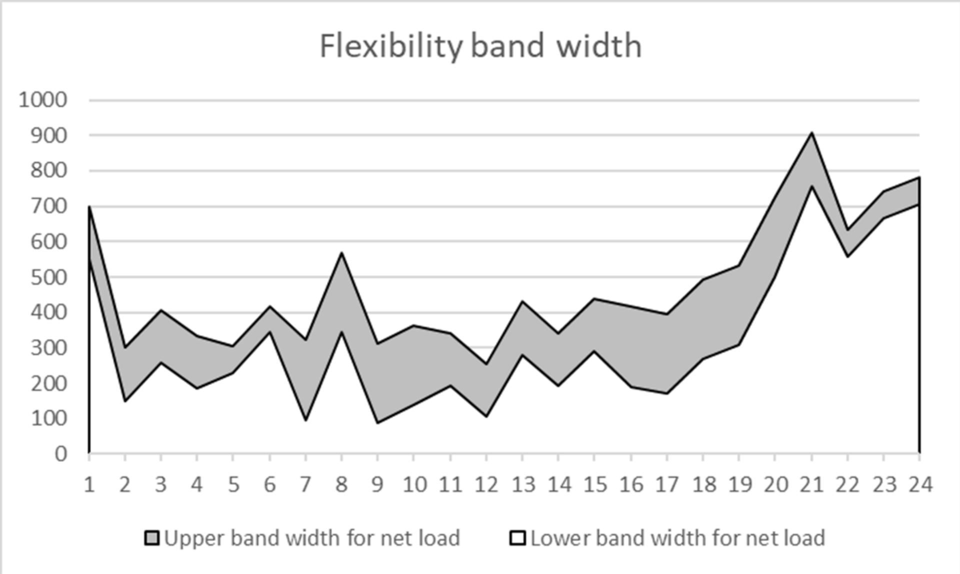

Figure 36. Aggregated flexibility band width

Notice that this approach probably will require that the flexibility availability must be calculated outside the Integrated INVADE Platform. Moreover, compared to representation at lower level, with this model we lose the connection to the physical limitations and the interdependencies between the periods (timing constraints, energy levels and so forth), and hence, smaller amounts of flexibility are expected to be harvested compared to a detailed model.

2.6 EV flexibility models

There are two approaches to model EV flexibility: to model an EV as a load or as a battery. Each approach can be more suitable depending on the available EV data. Additionally, load- or battery-based approaches can have different control capabilities. This section is focused on exposing pros and cons of each approach.

The first approach is using the flexible load models for EVs (see section 2.5.2). This is a suitable approach in case of very low available information. For example, in case of not knowing the EV model or its departure time, it could be a way to model EV flexibility. However, this approach relies on EV energy demand forecasting and this approach could be not useful in cases with high consumption volatility.

Additionally, the load approach has the following limitations:

1) Load-based models do not include minimum SOC before departure requirements. It may cause suboptimal solutions.

2) Power reductions at high SOC levels could be not considered and the model could consider the battery fully charged when it is not.

3) Including discharging energy capability from V2G stations could be complicated.

In contrast to the load-based approach, a battery-based EV flexibility model (see section 2.5.1) offers additional advantages. However, the battery-based model requires to know the EV SOC. This information can come from the vehicle directly, through the EV driver app, or be estimated using forecasting algorithms.

The following list exposes the input parameters necessary to implement a battery-based EV flexibility model and Figure 37 shows their relation:

1) EV field data:
    a. EVSE control: fullflex, on-off, inflex
    b. EV user ID
    c. Battery state of charge[1].
    d. Arrival and departure time
    e. Expected battery SOC
2) EV data hub:
    a. EV battery capacity and control capabilities
    b. Flexibility fee
    c. Flexibility periods

However, depending on pilot specifications, information some of these could not be collected.

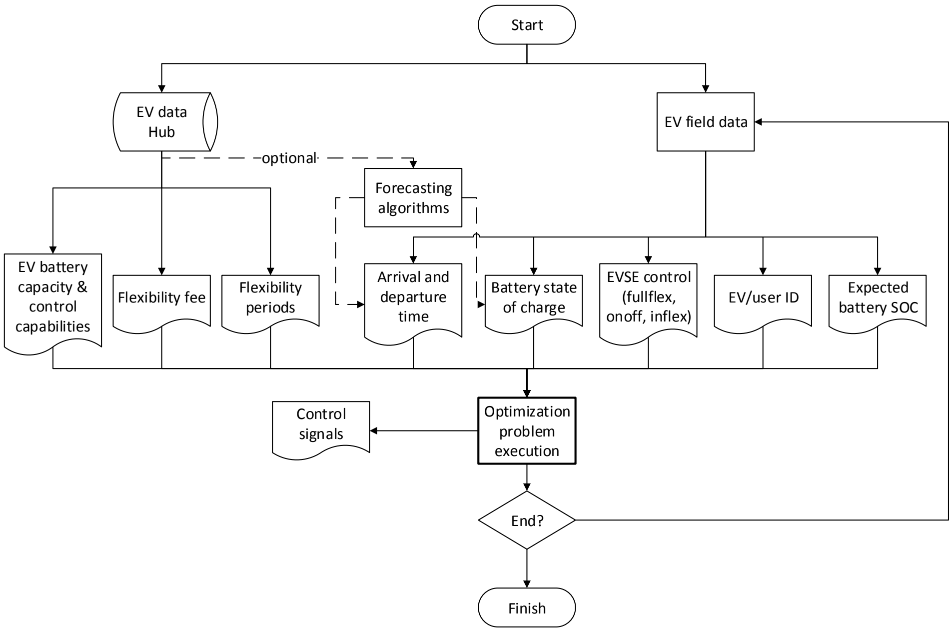

Figure 37. EV data flow diagram

In order to provide some recommendations about EV flexibility modelling for implementation project stages, the following list exposes three main cases and their

[1] It can come from forecasting tools or from the EVSE directly.

modelling options. Depending on available data and the flexibility service, the EV flexibility modelling can follow one of the following options:

1. In case of having full information, including SOC, and connection/disconnection times[2], the battery-based model is recommended. In this case, the FO can send control signals to each EV individually or an aggregated value for all charging points. The second option requires having local intelligence in the charging station to distribute flexibility between EVs.
2. In contrast, if some information is not known, it is necessary to forecast this data to estimate the EV flexibility. In this case, EV flexibility can be modelled as a battery or as a load, depending on the available information.
3. Finally, if the FO does not know which EV is connected to each charging point, the forecast reliability is much lower than in the second modelling option. If the energy needs and departure times are quite uncertain, flexibility decisions should be more conservative. Therefore, the flexibility obtained from an EV could be very limited. This case can only use load-based models.

Subsections below expose EV flexibility model characteristics in each case. EV model mathematical formulation is included in section 5.2.3. Sections 5.2.3.5 and 5.2.3.4 describe the battery-based models and their mathematical formulation. The first model includes V2X capabilities and the second model is a simplified battery model adapted to EVs.

2.6.1 EV flexibility in households

In case of EV in households, each EV charger will be usually linked to a single EV with its characteristics and its owner. Households with 2 electric vehicles will most probably have their corresponding charging points.

The most probable situation in this case is having partial information (the second modelling option described above), knowing the EV characteristics but without knowing its SOC or departure time. Therefore, EV flexibility can be modelled as a load or as a battery, depending on available information.

In case of EV owners highly engaged and willing to share their SOC and departure times, the EV can be modelled as a battery following the modelling option 1.

2.6.2 EV flexibility in multiple charging points

In cases of multiple charging points within the same installation like office buildings, shopping centres or similar, the information available can be different and the EV flexibility model must include their specificities.

[2] It includes expected arrival and departure times, in case of EV drivers booking charging stations, and real arrival and departure times coming from the charging station once the driver arrives or leaves.

In this situation, very limited information may be available. In offices with EV charging stations for dedicated workers, EV characteristics can be known if the building manager collects information. Additionally, it could be necessary to include priorities between EVs. For example, office visitors could be charged first in case of coming from far away and leaving early when their meeting ends. Therefore, the second modelling option can be applied offering better flexibility decisions.

In contrast, if there is no information available, the third option should be applied.

2.6.3 EV flexibility in public charging sites

Public charging sites for any EV driver can be difficult to manage due to the lack of available information. However, in some cities or towns, drivers use mobile apps for paying parking fees. Drivers have to define their departure times in an app. This would be a very relevant information for the algorithm in case of accessing to the corresponding database. This has to be explored in each pilot.

Additionally, their energy needs could be complex to forecast because any car type at any moment with any energy need can be plugged. Nevertheless, the aggregated forecasting errors in large charging stations could be lower than in households due to the large number of connections and EVs. For that reason, the second and the third modelling options could be applied depending on each case.

2.6.4 EV flexibility in V2X charging stations

Finally, all information possible including SOC is desired for managing EVs connected to a V2X charging station. In such case, the EV can be modelled as a battery following the modelling option 1. Therefore, very simple rules can be applied like discharging EV batteries between 100% and 85% of their capacity.

In addition, it is necessary to mention the need of analysing the pros and cons of allowing or not the EV charge by default. For example, it could be an authorization command under request at the EV connection instant. In contrast, the EV could be disconnected after some minutes charging the EV once the Charge Service Operator[3] takes decision. However, this issue is out of the scope of this report and this is an input for other project tasks.

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[3] Charge Service Operator, defined by the OCSP protocol v1.0, is the party that operates a network of charge points and has contracts with CSPs to allow their customers to use the charging facilities. The CSP is the Charge Service Provider who pays the electricity with which the EV is charged

3 Pilot sites

This chapter describes each of the pilot sites from the perspective of the optimization model. The description is included here to ensure that the optimization models takes into account every possible case at the pilot sites. On the other side, this is also about making the pilots conscious about what they need to discuss and clarify. Since the pilot sites for the time being are not clearly and in detail defined for all pilots, this chapter will be updated along with the pilot developments.

3.1 Norway

3.1.1 Introduction

According to D4.2 the focus with the Norwegian pilots will be the Prosumer and the following flexibility services:

- ToU optimization
- kWmax control
- Self-balancing

There will be three types of Prosumers in the Norwegian pilot:

- A number of private households
- A number of housing cooperatives
- Charging site connected to an office building

3.1.2 Roles and their interrelations

In the Norwegian electricity market, each consumer and prosumer must have two different contracts: one with the DSO that they are physically connected to and one with a free of choice retailer. In our context the FO will perform the control actions.

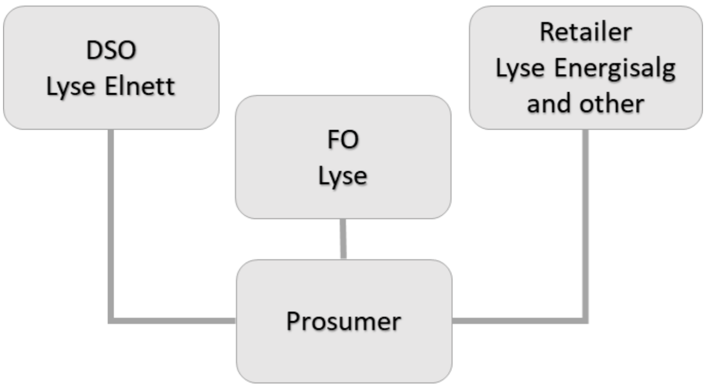

Figure 38. Relations between prosumer, flexibility operator, DSO and Retailer

Notice that the different pilot customers (prosumers) can have different retailers with different contracts and prices.

3.1.3 Resources and their interrelations and constraints

3.1.3.1 Private households

The private households are divided into the following types/profiles:

- Profile A: PV panels and control of water heater + space heating to improve utilization of local generation. 10 customers
- Profile B: Control of EV charging in low-price periods. 5 private customers
- Profile C: Battery management for peak shaving. 10 private customers
- Profile D: PV plus battery management to improve utilization of local generation. 5 customers
- Profile E: PV plus battery and EV charging management for peak shaving. 6 private customers
- Profile G: PV plus management of EV charging and water heater to improve utilization of local generation

A generalized setup is illustrated in the figure below, but must be specified for each single household:

Norway, Lyse Households

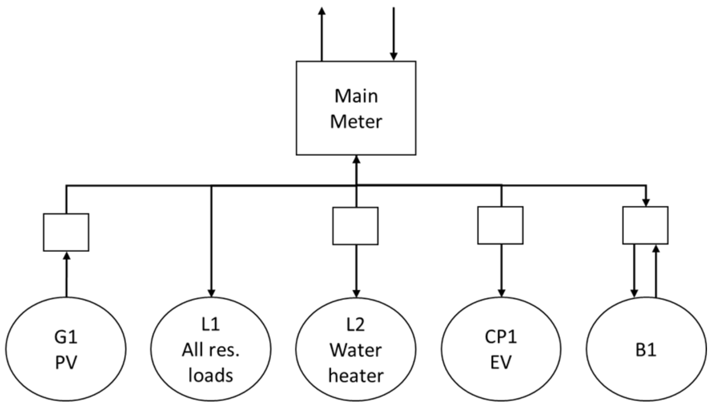

Figure 39. Principle illustration of a household in the Norwegian pilot

3.1.3.2 Housing cooperatives

According to Lyse's setup this covers Profile F: EV charging management for peak shaving. This section is still to be worked with, since the cooperatives have not been selected yet. Loads, generation and batteries may be included at a later stage.

The setup with only charging points is illustrated in the figure below, but must be specified for each single cooperative:

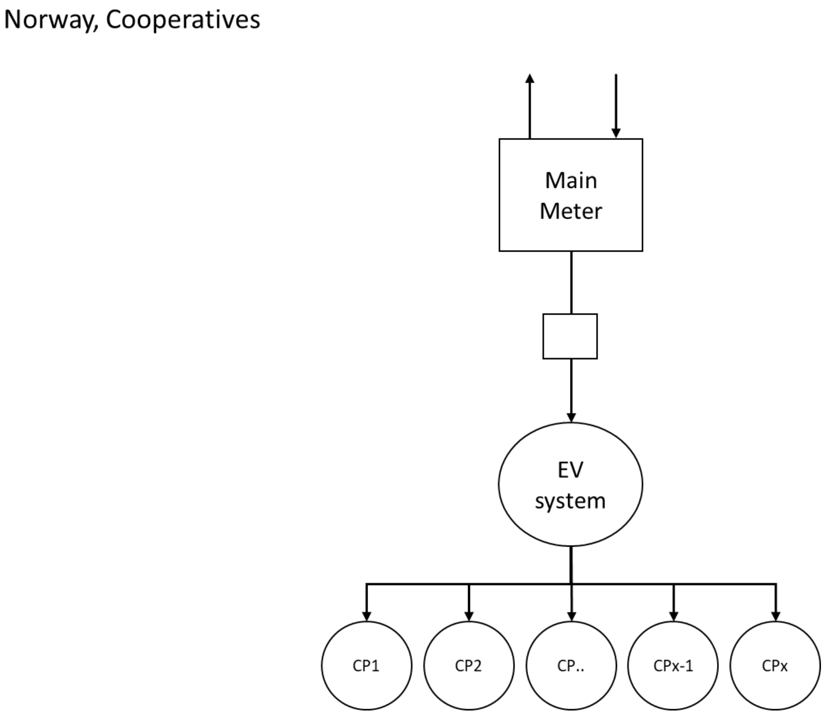

Figure 40. Principle illustration of a cooperative in the Norwegian pilot

3.1.3.3 Charging site connected to an office building

The office building in the Lyse pilot is the head quarter of the Lyse company. This is according to Profile H: PV, battery and EV charging. Notice that the load in the building itself is not part of the pilot, only the charging site, including a PV panel and a battery. From the flexibility algorithm point of view, it consists of the following resources:

- A PV panel with installed capacity 7 kWp
- An EV system with chargers and control system delivered by Zaptec, with 11 charging points
- A battery with capacity 10 kWh

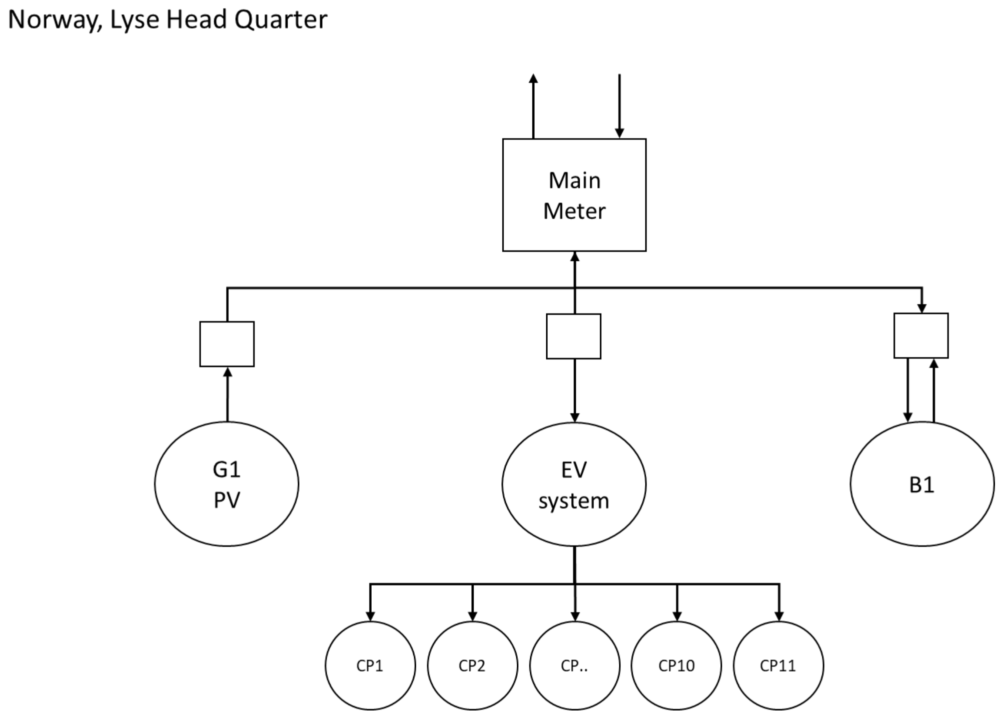

Figure 41. Illustration of the office building in the Norwegian pilot

3.1.4 Contracts and prices

Each prosumer will have two contracts: A grid contract and a retail contract. Lyse Elnett will be the grid company (DSO) and Lyse Energisalg or other companies will be the retailer.

The grid contract will consist of the following elements, prices given for 2017[4]:

[4] https://www.lysenett.no/getfile.php/reslysenettno/Bilder%20nye%20lysenett.no/nyhetsbilder/Prishefte%20nettleie%20jan2017%20%2802%29.pdf

Table 2. Grid contract parameters

Type of fee	Price
Fixed fee (not relevant for the optimization problem)	For private customers: 2.100 NOK/year For commercial customers: 3.100 NOK/year
Energy fee purchase	For private customers: 42,4 øre/kWh incl. VAT and taxes. For commercial customers: 51,0 øre/kWh incl. taxes
Energy fee sell	-4 øre/kWh
Demand charge winter*	For private customers: 0 For commercial customers: 75,00 NOK/kW/month
Demand charge summer	0
Energy taxes	17,32 øre/kWh (Consumption tax and energy fund tax). NB! These are included in the energy fee

* Winter defined as the months November, December, January, February, March (to be confirmed by Lyse).

In addition, 25 % VAT will be added to all elements for purchase. This is only valid for households.

AMI, advanced metering infrastructure including smart meters, are currently being deployed for all Norwegian consumers and prosumers. A result is that hourly values then will be available for all consumers (outtake) and prosumer (outtake and feed in). The Norwegian regulator currently evaluates new grid tariff structures, where one target is to avoid costly grid reinforcements by introducing tariffs that gives incentives to flatten the profile. One option is to introduce demand charge for all consumers and prosumers. Norgesnett, a Norwegian DSO, has introduced a slightly different version of the tariff described above. Here, the demand charge is based on the average of the three highest monthly values, where the three values must be at different days.

Another option, that seems more likely for the time being, is a model based on the principle called “subscribed power”. Here, the consumer/prosumer is placed into a power level, let us say 4 kW. Then, a fixed monthly fee must be paid, based on the power level (higher cost the higher level). Next, an energy fee must be paid, with one (low) price for all consumption lower than the subscribed level, and another (much higher) price must be paid for consumption above the subscribed level. The regulator indicates that the high price may be in the magnitude of 10 times the low price.

The retail contract with Lyse Energisalg will consist of the following elements:

Table 3. Retail contract parameters

Type of fee	Price
Fixed fee (not relevant for the optimization problem)	47 NOK/month
Price for buying	For private customers: Elspot price from Nord Pool Spot for the area NO2/Bergen[5] + a mark-up 3,9 øre/kWh For commercial customers: Elspot price from Nord Pool Spot for the area NO2/Bergen + a mark-up 4,6 øre/kWh
Price for selling	2*Elspot price from Nord Pool Spot, see price for buying[6]

For other retailers, the contracts will be different. The model must cover different types, for instance fixed prices for longer time intervals and other types where the price varies according to Elspot price, but with other mark-ups.

For prosumers, the sales of surplus electricity is regulated through the retail contract. Also here, different models exist. The most usual model currently, is that the surplus electricity is compensated with the same price as the deficit. In other words, the buying and selling price are the same. However, it must be commented that although the retail prices are equal, the cost of one kWh used is much higher than the revenue from one kWh sold. The reason for this is the grid tariff and the taxes.

In order to make it easier for consumers to turn into prosumers, the Norwegian regulator has introduced what they call the “plus-customer arrangement”. Traditionally, a consumer must enter an agreement with the DSO for outtake, while a producer must enter an agreement for feed in. Through the plus-customer arrangement the prosumer can only have one agreement. However, a prerequisite for participating in this arrangement is that the net feed in never is more than 100 kWh/h. For small prosumers, this is not a problem, but for larger buildings and industries it might be a challenge. Flexibility, for instance represented by batteries, may then be used to avoid breaking this constraint.

[5] http://nordpoolspot.com/historical-market-data/

[6] https://sol.lyse.no/stromavtale/

3.2 The Netherlands

3.2.1 Introduction

According to D4.2 the focus with the pilots in the Netherlands will cover the following flexibility services:

- DSO
    - Congestion management
    - Voltage/Reactive power control
- Prosumer
    - ToU optimization
    - kWmax control
    - Self-balancing

In addition, the BRP services are listed as TBD, but will not be covered in this document.

BRP services can be based on balancing needs considering the current (im)balance positions and commercial changes on short term energy markets of BRPs. BRPs can develop services based on:

- Position and possibilities on day-ahead market (short-term wholesale market)
- Position and possibilities on intra-day market (short-term wholesale market)
- Possibilities on ancillary markets (FCR, aFRR, mFRR is not considered suitable for EVs). FCR is now (as means of pilots open for other parties than BRPs. There are plans to experiment with aFRR as well)
- Possibilities and changes regarding own imbalance position (towards TSO or ISO). This is called passive imbalance management and is the difference between the nomination and current position. This is internal within the BRP and focus is to limit imbalance fines to gain commercial value on (one of the above) markets. This position is also nit public.

Furthermore, the pilots will be in 4 different pilot cases (email from Lennart Verheijen 27/11/2017):

- **Pilot 1. Private charging case 1.** Private charging at home
- **Pilot 2a. Semi-public charging case 1.** Semi-public charging at a parking lot with roof-mounted solar panels
- **Pilot 2b. Semi-public charging case 2.** Semi public/private charging at parking lot of a company building.
- **Pilot 3. Elaad office**. Charging at Elaad premises, incl. storage
- **Pilot 4. Public charging.** Charging at public places where each charger has its own connection to the grid.

For pilot 1 and 2 GreenFlux is responsible, for pilot 3 and 4 Elaad is responsible

3.2.2 Roles and their interrelations

3.2.2.1 Pilot 1

This pilot is a private home situation with one charge point directly connected to the main meter in the home. The home owner has a contract with the DSO (this cannot be chosen) and with a retailer/energy supplier. There can be small variations where the owner has 2 charging points, but both for own private usage. A PV system can be connected to the home, when placed on the roof of the home. GreenFlux is the FO.

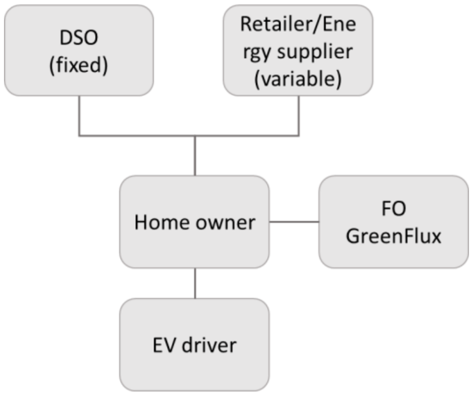

Figure 42. Illustration of the roles in the Dutch pilot 1

3.2.2.2 Pilot 2a

This pilot is a parking lot with a charging site connected to a commercial building. The building owner/renter has a contract with the local DSO and a retailer. In addition, the building owner sells charging services to EVs for visitors. GreenFlux is the FO.

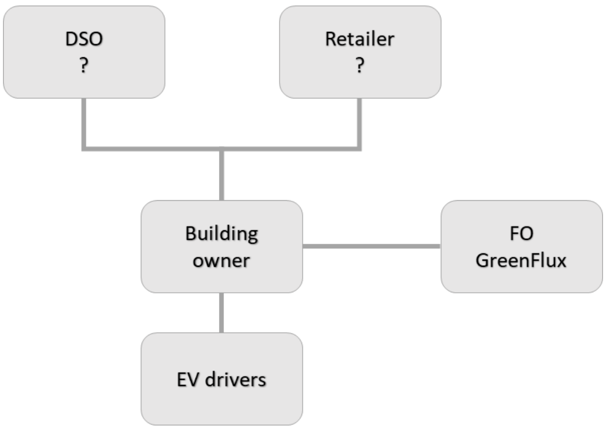

Figure 43. Illustration of the roles in the Dutch pilot 2

3.2.2.3 Pilot 2b

In this pilot GreenFlux will be the FO that controls the charging below specified limits. No other roles are involved.

3.2.2.4 Pilot 3: Small scale office

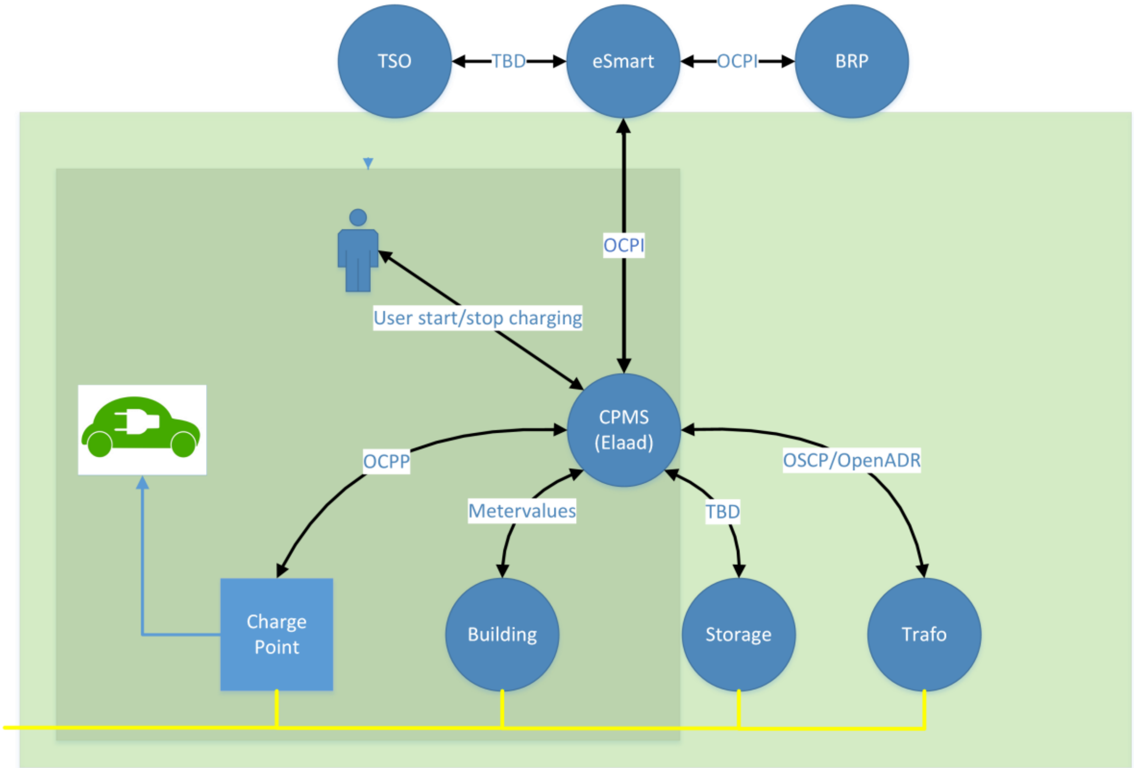

Figure 44. Pilot 3

At this pilot site we consider 3 optimization levels:

- Locally behind the connection point (done by CPMS Elaad). We will construct the system / architecture that we can work here with different (optimization) algorithms.
- Locally in agreement with the local DSO. DSO contracts flexibility for local congestion challenges (done by us and the resp. DSO first based on meter values in later stage based on de facto standard OSCP)
- National level; flexibility is provided to BRP (portfolio-optimization) and TSO (frequency mgt , ancillary markets) and higher level (MV) DSO grids (congestion); (this we can provide to eSmart / Invade platform)

We can offer from the large scale office site an aggregated profile of tomorrows load with bandwidths, an aggregated forecast which is already locally optimised. The bandwith consists of the (expected) flexibilities of the ev-drivers+the storage unit+building. Local optimisation first, then local congestion mgt to local DSO. Then the flex which is left is sent to the aggregated platform.

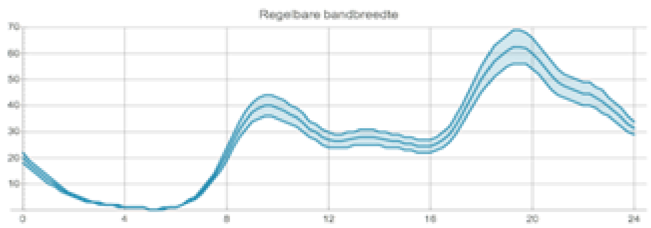

Figure 45. Bandwith

The invade platform can send us and aggregated flexibility request (see yellow), but the Aggregated system has to respect the bandwith. It cannot claim more flex than locally offered.

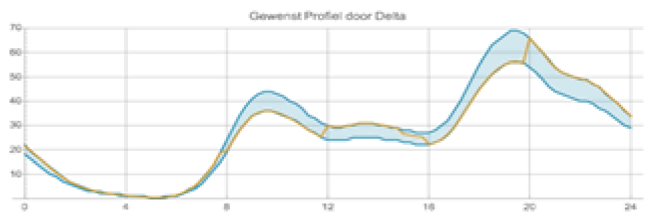

Figure 46. Flexibility request and bandwidth

3.2.2.5 Pilot 4: Large scale public

At the public charge stations of ElaadNL we want to test/demonstrate the combination of short term congestion management through the use of ‘variable capacity (contracts)’ and the combination of smart charging from the perspective of BRP.

Partly real-life with the BRP connected to our stations and partly through simulation.

This BRP wants to combine ‘self-balancing portfolio optimization’ and use the opportunities on the Dutch imbalance market, the automated Frequency Restoration Reserve (aFRR). Behind the ‘self-balancing’ of the BRP’s portfolio lies the positions and the existing commodity prices on the intraday and day-ahead market (and the LT-market). Which considerations (algorithm) the BRP has to decide to ask for smart charging (to the aggregator and the aggregator to ElaadNL; see graph below) is out of scope. As given before the BRP sents request to the back-office managing the different charge stations, but needs to combine this with ‘congestion mgt-requests from the DSO.

In most parts of the country there is no congestion situation yet. So we decided to generate a simple variable capacity profile resembling the opposite of the general electricity profile for households in the Netherlands. This more or less standardised profile is provided to the aggregator which has to combine this profile with the BRPs needs/wishes.

This leads to the following profile. Which can be applied only for customers (customer-centric approach) which are contracted to be part of this pilot.

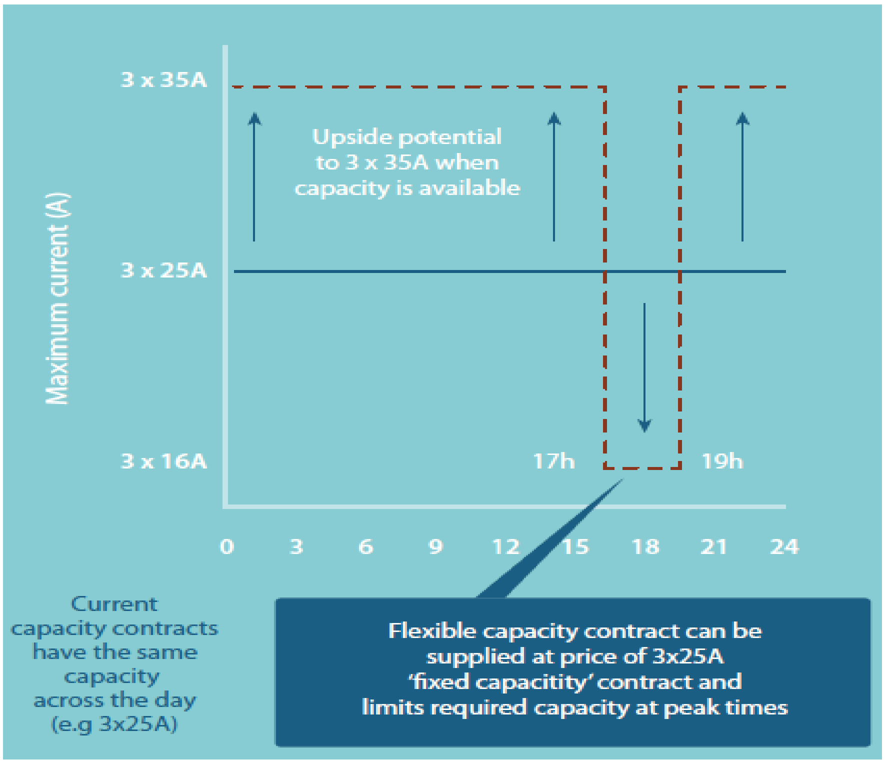

Figure 47. Capacity profile

In the large scale public pilots we, as said want to combine this with BRP services. We want to consider the variable capacity profile as the boundaries for BRP services / smart charging, leading to the following:

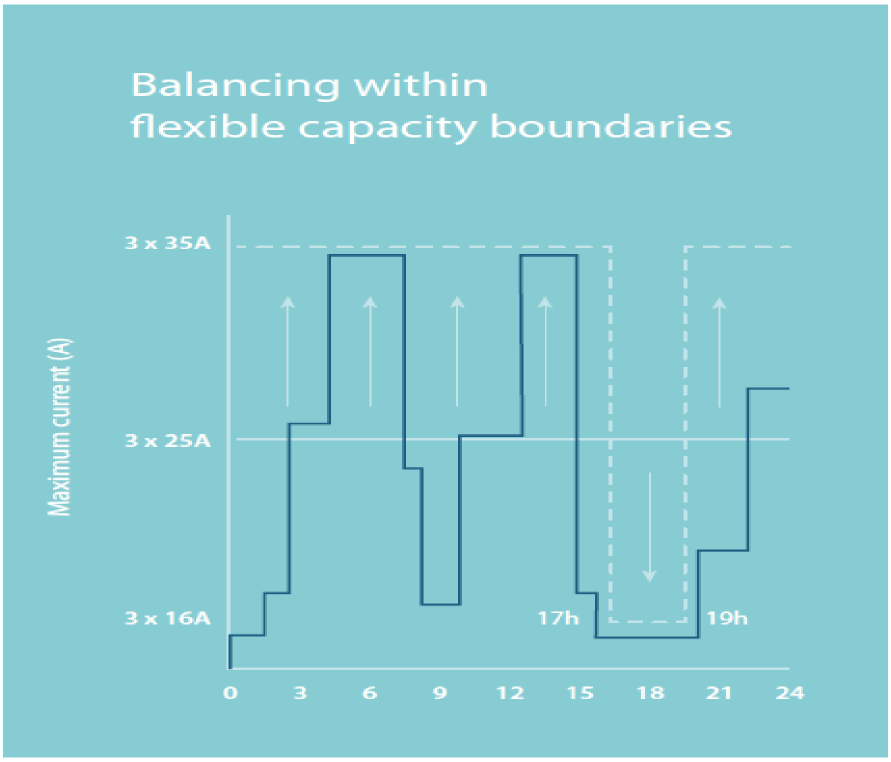

Figure 48. Flexible capacity profile

Stations in the field are single or duo-socket stations all managed by ElaadNL. Grid connection is 3x25A or 3x35A. the ElaadNL system will receive input from BRP and effectuates the charging profile within the given DSO limits.

3.2.3 Resources and their interrelations and constraints

3.2.3.1 Pilot 1

In this case a home has 1 private charge point. The charge point is connected to the main meter in the home, however for monitoring and control issues, each station has its own meter as well and is connected to a charge point management system. The home is using an average consumption of 4000 kW per year. The charge point can deliver max 11kW. In the situations where PV is available on the roof of the homes, it delivers on2000kW per year on average.

The purpose of smart charging is to optimize the business case for the combination of the PV-system and the EV charger. The secondary goal is to charge the EV as fast as possible. This means that:

- The EV will increase its charge rate if the real time solar production increases
- The EV will decrease its charge if:
  - The real time solar production decreases
  - The other consumption in the household significantly increases. The total grid connection of the household is 3x25A, this should never be overloaded[7].

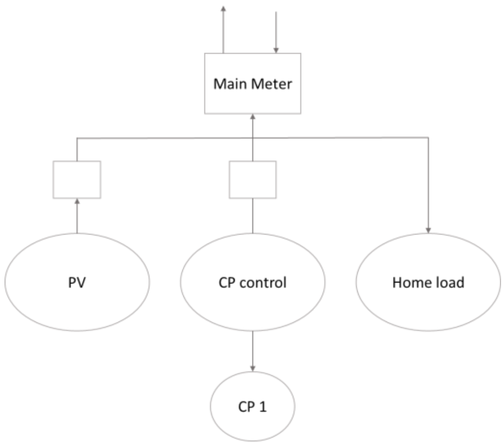

Figure 49. Illustration of pilot 1 in the Dutch pilot

[7] Theoretically it is possible to charge at higher rates than 3x25A with the EV. E.g. if the household consumes nothing and the solar panels produce 3x10A, then the EV *could* charge at 3x35A. This is however not allowed by the Dutch grid operator. Maximum charging speed of the EV may never be higher than the grid connection: 3x25A.

3.2.3.2 Pilot 2a

This case is a parking lot that consists of 20 charge stations, each with 2 charge points, meaning that up to 40 EVs can be connected simultaneously. Each charge point can deliver up to 22 kW. In the coming years, this pilot will be expanded to 150 charge points. EV drivers might get the possibility to select priority charging. Finally, the parking lot has a PV panel with capacity 450 kWp.

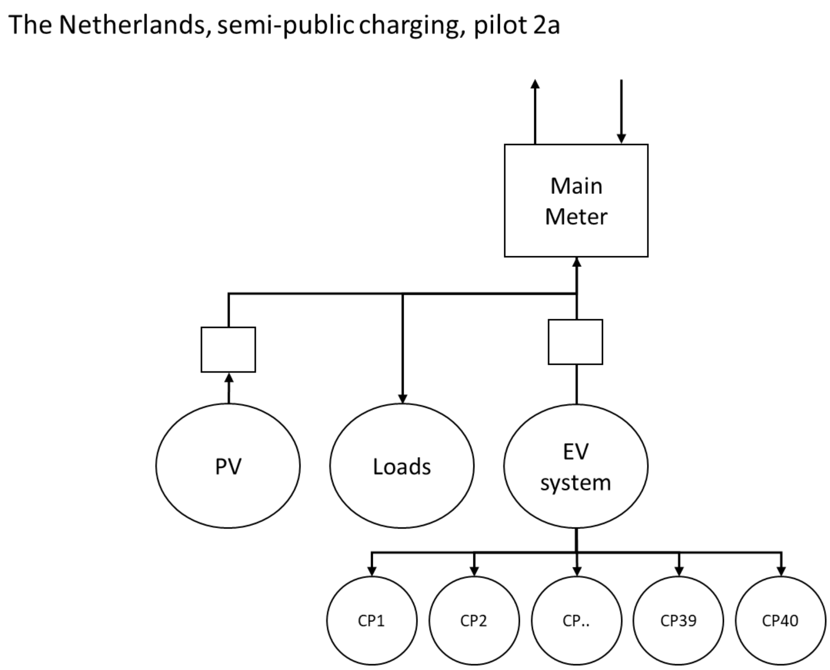

Figure 50. Illustration of pilot 2a in the Dutch pilot

There is a capacity limitation for the charging, which cannot be larger than 346 kW.

3.2.3.3 Pilot 2b

This is a charging site in a parking lot in the basement of an office building. The rest of the building load is not flexible. The charging points can deliver up to 22 kW.

The Netherlands, semi-public charging, pilot 2b

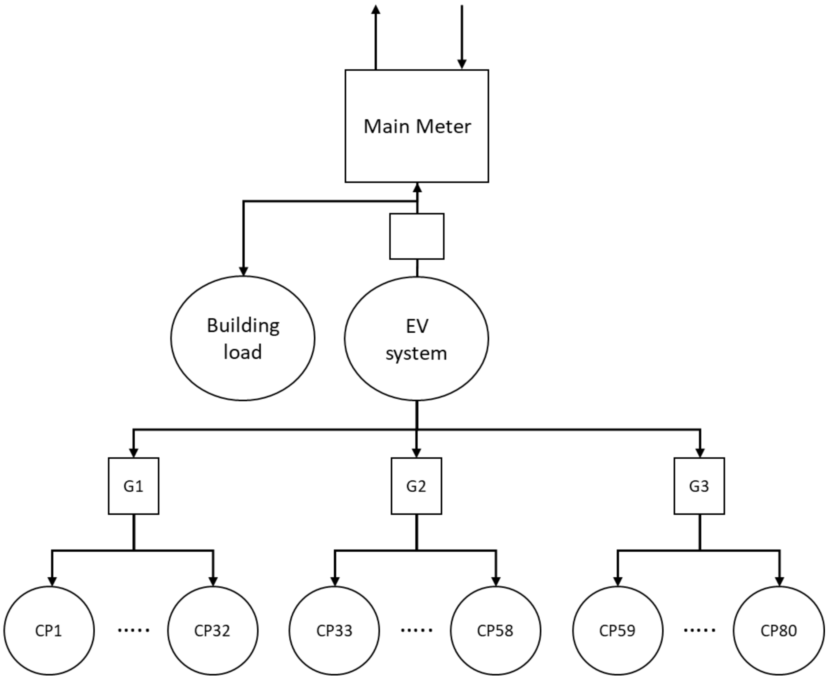

Figure 51. Illustration of pilot 2b in the Dutch pilot

There are two levels of capacity limitation:

- Each of the three charging point groups must be below 173 kW
- The total consumption (building load + EV) must be below 436 kW

3.2.3.4 Small scale office

This site was recently extracted. The following situation exists.

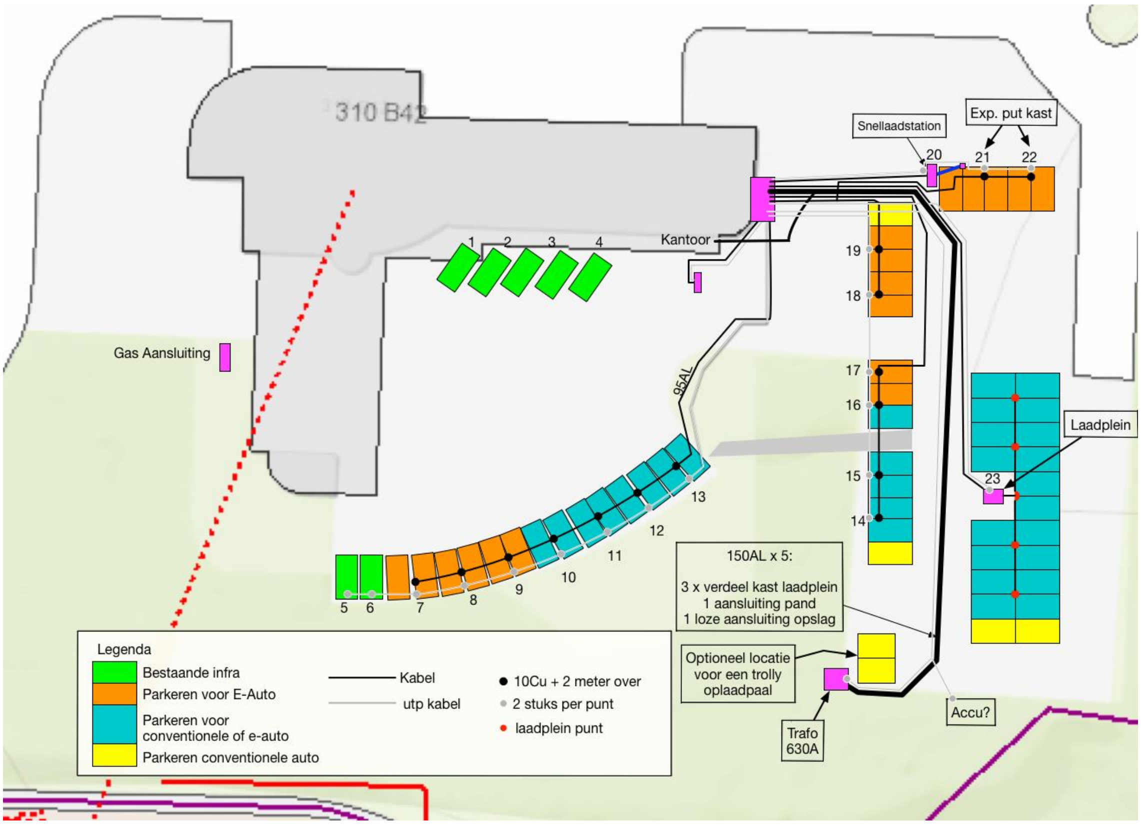

Figure 52. Small scale office

- Numbers 1 - 19: charging stations (single or dual socket)
- Number 20: dc charging station
- Numbers 21 - 22: locations for experimental charging stations
- Number 23: charging site

At the site there is installed

- 4 kWp solar system
- Local server and network (that communicate with cloud services and can perform smart charging based on different optimization algorithms)

The ‘technical situation’ is:

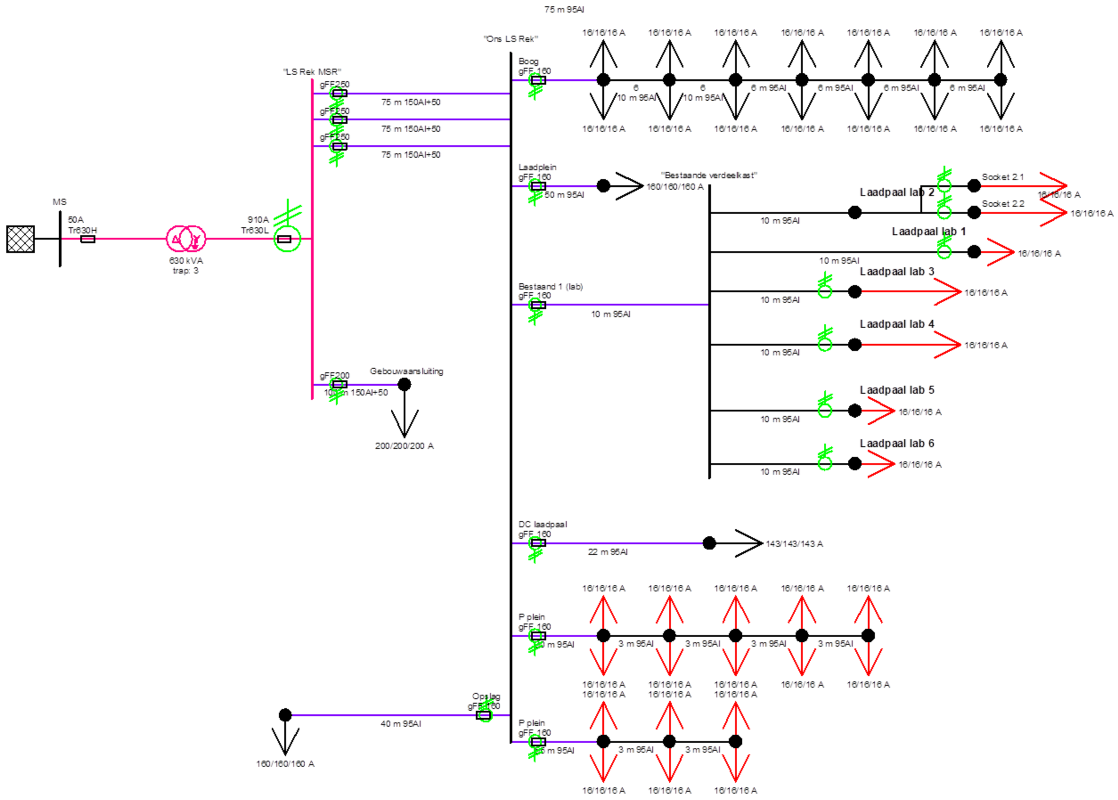

Figure 53. Technical solution

- Main cables have power quality meters
- Numbers 1 - 6 have power quality meters
- Numbers 7 - 19 have normal meters

3.2.3.5 Large scale public

The basic charging network of ElaadNL / EVnetNL is given below:

Figure 54. Charging network of ElaadNL/EVnetNL

The installed base consisted of approximately 1750 station throughout the Netherlands offering a total of 3000 sockets, all 11 kW (3x16A) per socket. Since the transfer of charging stations to local communities the installed base will contain 820 stations:

Figure 55. Installed base

The average daily usage of the installed base:

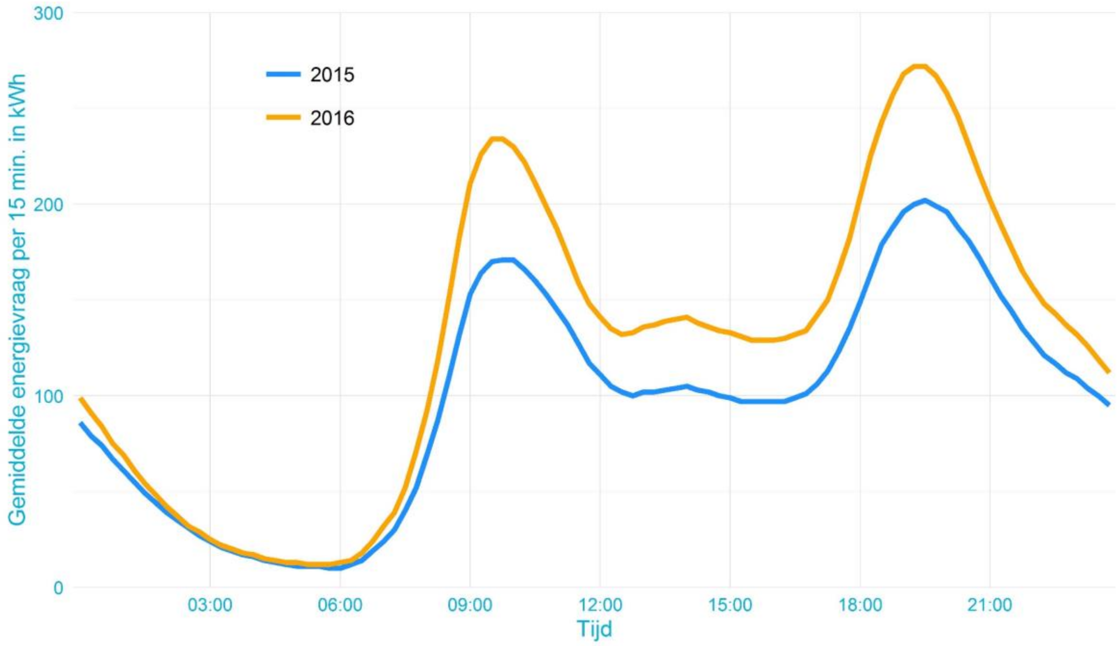

Figure 56. Daily average use of the installed base

The percentage of charging sessions is given below. The graph shows the hour within the charging session is started. This graph (although consisting of averages) shows the fact that EV charging is increasing the already existing peak demand at peak times.

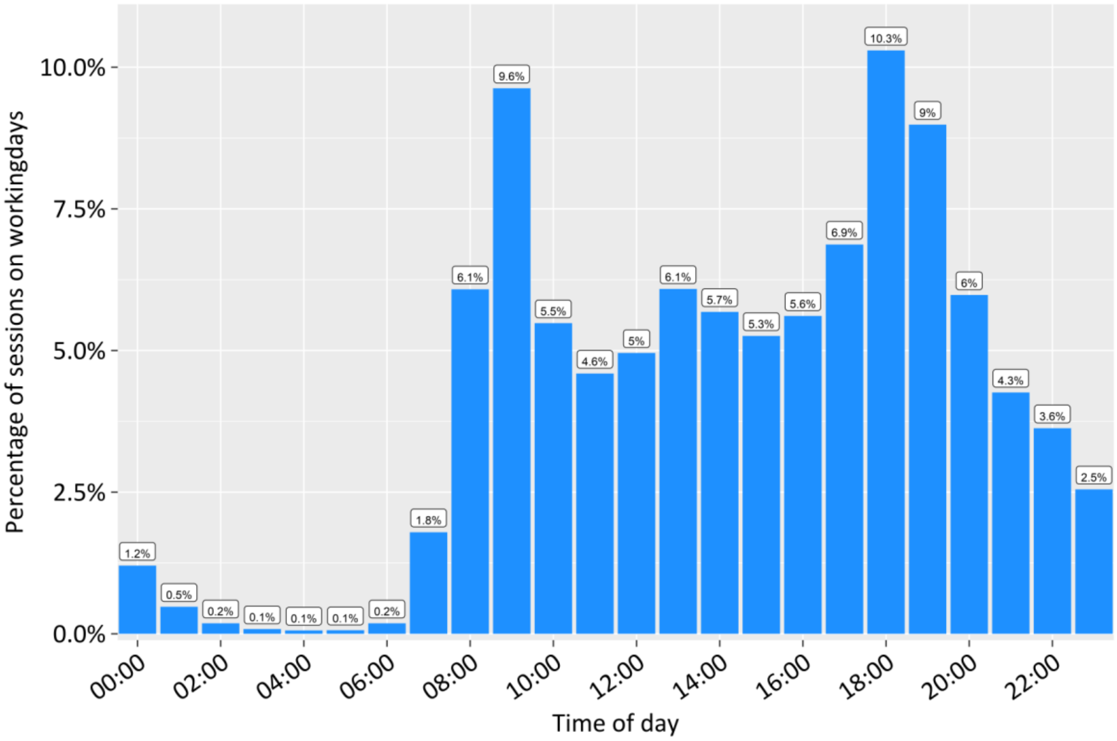

Figure 57. Percentage of charging sessions starting up

At the same time, we see that there is quite a lot of flexibility present during the charge sessions. When we compare the ‘connection time’ with the ‘charging time’ we get the following result;

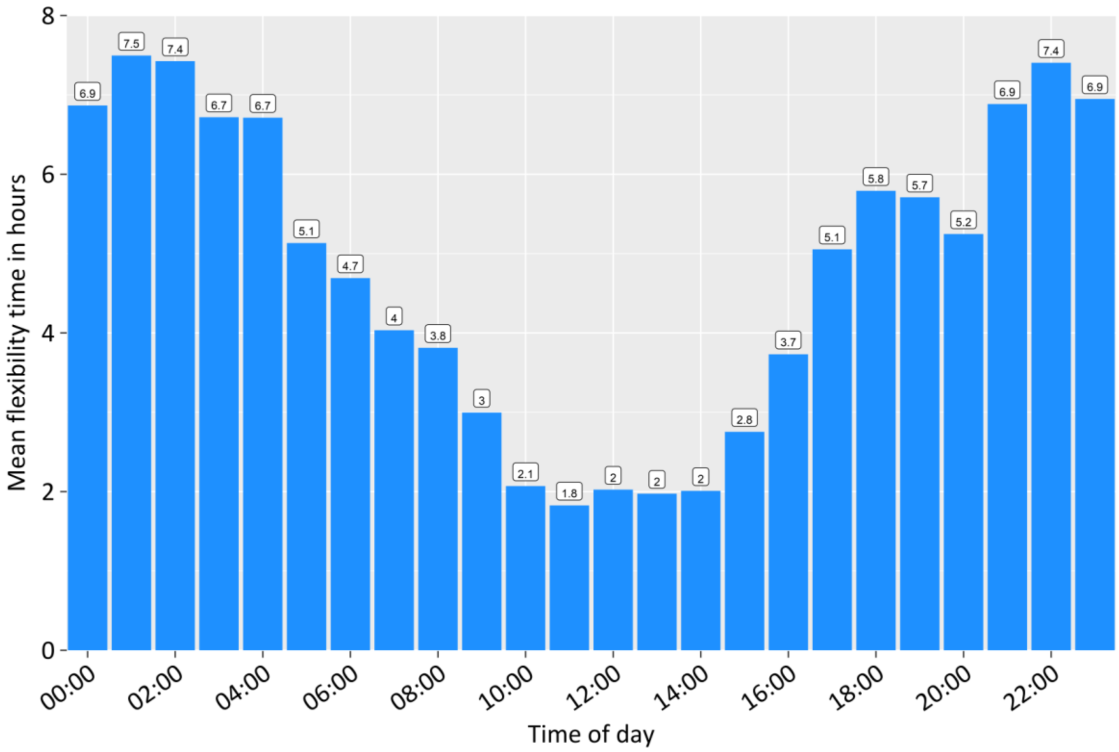

Figure 58. Flexibility from charge sessions

We see a lot of flexibility potential at the evening and night.

3.2.4 Contracts and prices

3.2.4.1 Pilot 1

There are two contracts that are involved in this pilot: The grid contract and the supply/retail contract.

The grid contract is based on a peak demand charge for the year. This means that it is an incentive to reduce this peak (hourly value) as much as possible.

The supply contract for buying electricity is normally an average fixed price for a full period (1 or 2 years). This pilot is using contract where energy retail prices are based on hourly prices at EPEX Spot[8] without any mark-up or other fees that are relevant for the flexibility algorithm. This contract also regulates the price for sales of surplus electricity sales. This price is 0,18 €/kWh on average. The price change per hour. The home owner pays the average price and get a refund or surplus at the end of a period depending on the real prices and usage.

[8] https://www.apxgroup.com/market-results/apx-power-nl/dashboard/

3.2.4.2 Pilot 2

There are three contracts that are involved in this pilot: The grid contract, the supply/retail contract and the “contract” with the EV to deliver charging energy.

The grid contract is based on a peak demand charge for the year. This means that it is an incentive to reduce this peak (hourly value) as much as possible.

The supply contract for buying electricity is based on hourly prices at EPEX Spot[9] without any mark-up or other fees that are relevant for the flexibility algorithm. This contract also regulates the price for sales of surplus electricity sales. This price is 0,05 €/kWh on average, but it is not known whether this is fixed or varying over the day.

Finally, there is an income from selling charging energy to the EVs. This is a fixed price of 0,29 €/kWh and goes is paid by the EV-driver, via its service provider and charge point operator, to the owner of the charging station.

3.2.4.3 Pilot 3 Small scale office

As given before at this pilot site we consider 3 optimization levels:

- Locally behind the connection point
- Locally congestion mgt in agreement with the local DSO.
- National level; flexibility is provided to BRP and TSO

Control on the first level will be done based on self-balancing needs. Since this is a single site where ElaadNL performs this local load mgt within the site there are no external parties involved at this level. the technical capacity is 630 KVA, contracted capacity is…..X

On the second level there is no price / product / tariff in place at the DSOs (yet). This is part of the R&D work within the DSO’s

At the third level flexibility can be priced as the combination of the prices on the potential markets given before ((short term) wholesale; day-ahead and intra-day (like EPEX) and ancillary markets FCR and aFRR) and the own current (im)balance position of the BRP.

3.2.4.4 Pilot 4 Large scale public

Connections are 3x25A or 3x35A, yearly connection prices are: 225 incl VAT and 816 incl VAT. There are no volumetric price drivers. Nor is there (yet) a contracted capacity component in place.

[9] https://www.apxgroup.com/market-results/apx-power-nl/dashboard/

3.2.5 Objectives

3.2.5.1 Pilot 1

The objective is to minimize the total costs for the home owner by controlling the EV charging. These costs include:

- Grid contract based on maximum outtake (kWh/h) over the year
- Retail contract with revenues for sales of surplus electricity
    - The more locally produced 'own' energy is used, the lower the amount that needs to be paid to the retailer.

3.2.5.2 Pilot 2

The objective is to minimize the total costs for the building owner/renter (prosumers?) by controlling EV charging. These costs include:

- Grid contract based on maximum outtake (kW) over the year
- Retail contract with costs for purchase based on hourly EPEX Spot price
- Retail contract with revenues for sales of surplus electricity
    - The more locally produced 'own' energy is used, the lower the amount that needs to be paid to the retailer.
- Revenues for selling charging services to the EVs

The objective is to maximize the total delivered charging by controlling and balancing charging in such a way that none of the capacity limitations are violated. This way cost of energy consumption can be reduced and extension of the grid connection can be prevented.

3.2.5.3 Pilot 3

The objective of the Small scale Office pilot is local capacity management on EVSE while gathering real-time information on the energy use of both the other EVSEs and other loads on the local site. Controlling a single site is in many ways a faster way to achieve the monitoring and control possibilities that are not yet available on the public infrastructure at large.

3.2.5.4 Pilot 4

This pilot focusses on the function of controlling EVSEs and their energy supply to EVs, connected to a management system of the CPO. We experiment with large scale public charging in the Netherlands, using grid congestion management and BRP services (possibly containing frequency containment reserve support). More specifically, this pilot will follow the steps researching the extent to which charging stations are capable of providing BRP support using by central control.

Current pricing regime is based on flat, fixed prices dependent on fuse size (grid contract?). However, new tariff regimes will be tested in the project.

A new grid tariff type is the "Dynamic capacity" which works like this:

- The customer has a given main fuse size, e.g. 3X35 A. Normal tariff rate is a fixed fee, e.g. 800 €/year
- If the customer can guarantee that he/she will not surge above 3X25 A in certain peak hours, he/she will pay a reduced rate, e.g. 200 €/year. Which hour that are included in the definition of peak hours are dynamic, but will be known in advance

Figure 59 illustrates the principle. Here, up to 24 kW can be bought in the non-peak hours defined by the hours 8 – 10 and 17 – 21. For the peak hours 8 – 10 and 17 – 21, the capacity is reduced to 17 kW.

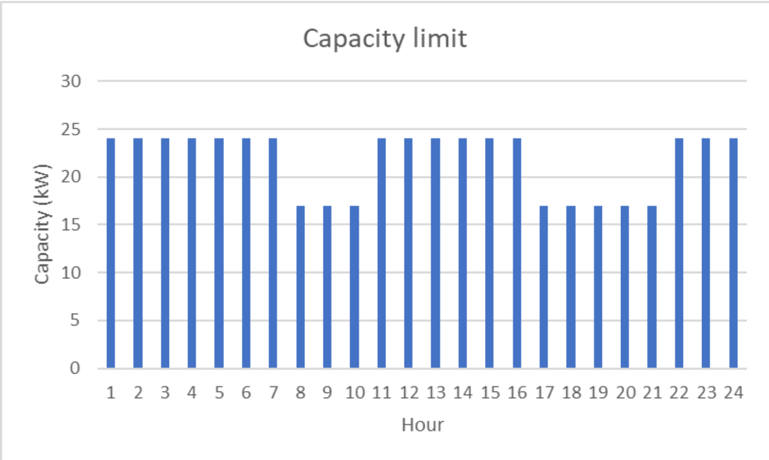

Figure 59. Illustration of the tariff type "Dynamic capacity"

A central question to clarify is what happens if the customer goes above the capacity limit for the peak hours:

- Black-out?
- It is allowed, but then the higher fee must be paid?
- It is allowed, but only a limited number of times each month/week

Another question is whether the limit is instant (kW) or per hour (kWh/h)?

3.3 Spain

3.3.1 Introduction

According to D4.2, the focus in the Spanish pilot will be the following flexibility services to the DSO and BRP:

- DSO:

  - Congestion management
  - Voltage / Reactive power control
  - Controlled islanding
- BRP:
  - Intraday portfolio optimization
  - Self-balancing portfolio optimization

Services to the BRP will be developed in the second implementation phase of the project, so they are not covered in this document and will be described in D5.4. In addition, services for prosumers will not be tested in this pilot.

There will be one pilot site, consisting of one secondary substation and its area of influence, which includes the EPESA headquarter.

3.3.2 Roles and their interrelations

The FO role is played in this pilot by the retailer company Mercator, which is also owned by EPESA. Flexibility is obtained from the centralized battery owned by Mercator and it is used to offer services to the DSO (EPESA) and the BRP/retailer (Mercator). As it can be seen in Figure 60, some of the different roles will be played by the same actor. In addition, EPESA is one among the prosumers inside the area of influence of the affected secondary substation, so it will be also benefited by the controlled islanding service.

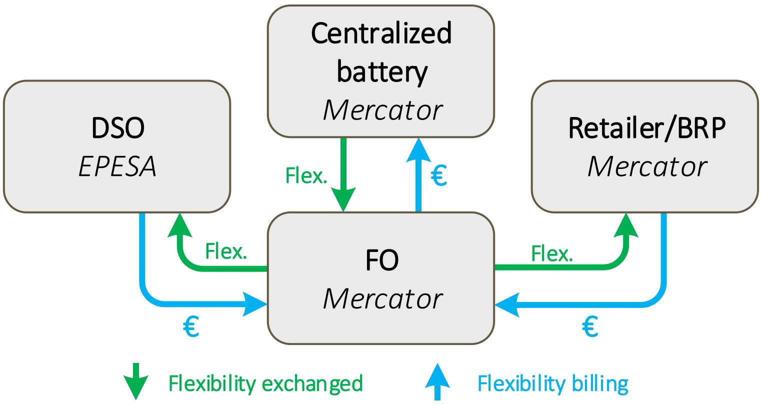

Figure 60. Relations between prosumer, flexibility operator, DSO and Retailer/BRP

3.3.3 Resources and their interrelations and constraints

According to the pilot proposal, the pilot consists on a unique centralized battery with a capacity of 200 kWh and a limited charge and discharge power of 100 kVA. It can be connected in one of the following parts of the low voltage grid: at the low voltage bus between the transformer and the low voltage cabinet, at the low voltage cabinet on the consumption side, or in an intermediate point of the low voltage grid. The final decision will depend on the preference of the electrical department inside the DSO.

Part of the battery capacity has to be reserved to provide supply to the controlled islanding. The rest of the capacity can then be used to provide other services to the DSO and BRP indistinctly.

The battery will have a smart meter to monitor and invoice its energy exchanges with the grid. The control capabilities will be fully integrated into the SCADA and the distribution management system.

3.3.4 Contracts and prices

According to the current regulation applied in Spain, the battery cannot be considered as a generator, so its discharges cannot be reimbursed and only its charges will be invoiced.

Regarding the invoice of energy, the electric tariff present in the Spanish pilot includes two main components, a per kW charge (contracted power) and a per kWh charge (energy consumption). It has the following general structure:

$$Electric\ Bill = [(\chi_{y,t,s}^{grid-import} \times P_{y,t,s}^{grid-import} + CP \times PT \times Time) \times ToE + REM \times Time] \times VAT$$

where:

- Energy term ($P_{y,t,s}^{grid-import}$): it multiplies the energy consumption ($\chi_{y,t,s}^{grid-import}$) recorded between the dates of the reading for the price of kWh.
- Power term (PT): it multiplies the contracted power (CP) by actual days of billing and the unit price for kW. The contracted power is a fixed value and can be only changed once a year. In households, if this power is exceed, the smart meter cuts the supply and it needs to be rearmed manually.
- Tax on electricity (ToE): it is a tax regulated by the National Tax Agency. It is calculated by multiplying the sum of the terms of power and energy by a fixed amount of 1.0511269.
- Rental of equipment of measure (REM): price that the DSO charges if the client does not own the meter (which is usually the most common case).
- VAT quota: application of the percentage of current VAT (21%).

In addition, tariffs can have several periods with different energy prices. In bigger consumers (>15 kW), there is a penalization if the monthly maximum power exceeds 105% of the CP, and a discount of 15% is applied if the monthly maximum power is below 85% of the CP. In addition, customers pay a significant penalty each month if their PF is below 0.95. Available tariffs for CP>15kW are:

- 3.0 A with 3 energy time periods and 3 power time periods. This tariff has three periods. These periods are peak (P1), shoulder (P2) and off-peak (P3), in which shoulder rates usually apply in between peak and off-peak periods.

Table 4 shows the schedule of the time periods for the 3.0 A tariff, and Table 5 gives an example of yearly-fixed rates for the tariff 3.0A with more than 15 kW contracted power offered by Mercator.

Table 4. Schedule of the time periods of 3.0 A tariff.

Tariff name	Periods	Winter	Summer
3.0A (CP>15 kW)	P1 (Peak)	12h to 15h	19h to 22h
	P2 (shoulder)	9h to 18h and 23h to 24h	9h to 11h and 16h to 24h
	P3 (Off-peak)	0h to 8h	0h to 8h

Table 5. Example of yearly-fixed rates for 3.0 A tariffs[10].

Tariff name	Periods	Power term (PT)	Energy term ($P_{y,t,s}^{grid-import}$)
3.0A (CP>15 kW)	P1 (Peak)	0,113818 €/kW/day	0,115625 €/kWh
	P2 (shoulder)	0,068291 €/kW/day	0,099795 €/kWh
	P3 (Off-peak)	0,045527 €/kW/day	0,071165 €/kWh

3.3.5 Objective

The flexibility for the DSO in the Spanish pilot will be used for multiple purposes: island creation and to reduce the medium voltage grid congestions. A combination of the following actions will be utilized to obtain these objectives:

- To charge or discharge the battery during congestion hours according to DSO requests.
- To ensure that enough capacity is available in the battery to provide these services to the DSO, prioritizing the charge of the battery during off-peak hours and the discharge the battery during peak periods.

3.4 Germany

Since the German pilot is not completely defined yet, it is left out in this document.

[10] Tariffs given for 2017. www.estabanell.cat/serveis/tarifes

4 Uncertainty, information structure and the planning process

4.1 Problem description

Optimized operational scheduling of different types loads (shiftable, controllable and curtailable) and battery charging / discharging with the maximum utilization of RES generation is the key for providing flexibility services. The optimization process uses the models of the generation, storage and load units and the other input parameters to produce the best possible operation schedules of the units for future periods. At the time of scheduling of the operation, many of the input parameters are not known certainly. The accuracy of these input parameters decide the quality of the flexibility services. The optimization process can show significant sensitivity to the uncertainties in the input parameters, and produces suboptimal solution or even end up in infeasible solution. Thus, the process of optimization becomes potentially worthless [1].

The dependency of the input parameter and the impact due to their uncertainty varies for different services defined in the INVADE as per D4.2.

Some of the examples of uncertain input parameters are listed below

1. Total solar energy production from PV units and their power generation at every instant or in a time period.
2. Energy consumption of different load units, their load profile and time of operation.
3. EV charging consumption, their availability for charging, arrival and departure time.
4. Energy prices at different hours of the day.
5. The time of service request from the DSO to provide flexibility service, start time of service delivery and duration of service.

The different optimization methods handle these uncertainties with different approaches. They have their own advantages and disadvantages in terms of computational time, degree of closeness to the global optimal values and the level of complexity to implement as an automatic software service.

Further sections in this chapter will detail the uncertainties associated with different input parameters, the different methods followed to produce optimum operational scheduling under such circumstances, information structure for handing input parameters to produce scheduling decisions, the planning time horizon for their effective utilization and the time resolution of the control actions. Finally, an overview of the operational scheduling optimization process is presented.

4.2 Uncertainty and information revelation

4.2.1 Solar PV production

PV production reflects how much power is injected into the system as a result of solar irradiation on the PV panels. Though weather forecasting can predict PV production in near future, the exact production is not known before real time. In general, the certainty of predictions decrease as the forecast is further away from the time of forecast.

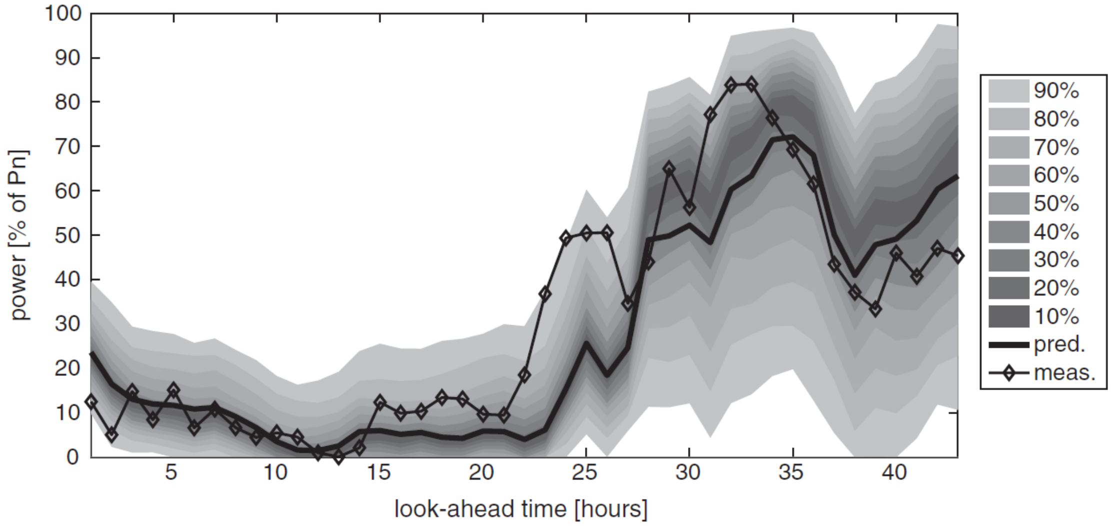

Figure 61. Forecasting of wind power production

Figure 61 shows how forecasting is done for wind power production [8]. As forecasting horizon increases, the uncertainty increases. The grey shades indicates the probability of future power production within the described limits.

For PV production, forecasting is different compared to wind production. For example, as one can with certainty know that there will be no PV production during night. Sunrise and sunset time varies from day to day and are known for all days of the year. The exact sun path is also known for every day of the year, which means that also maximum production is also known for all days. Ramakrishna et al [9] shows how uncertainty changes depending on type of weather. When clouds are not expected, the production follows a very clear pattern which can be predicted with high certainty as seen in Figure 64. With cloudy weather as shown in Figure 62, the certainty is reduced. For mixed weather shown in Figure 63, uncertainty varies. In other words, the earlier statement that certainty increases the closer we are to real-time, is only partially true. The PV production forecast for a cloudy tomorrow is more uncertain than the forecast for the day after which is a clear and sunny day.

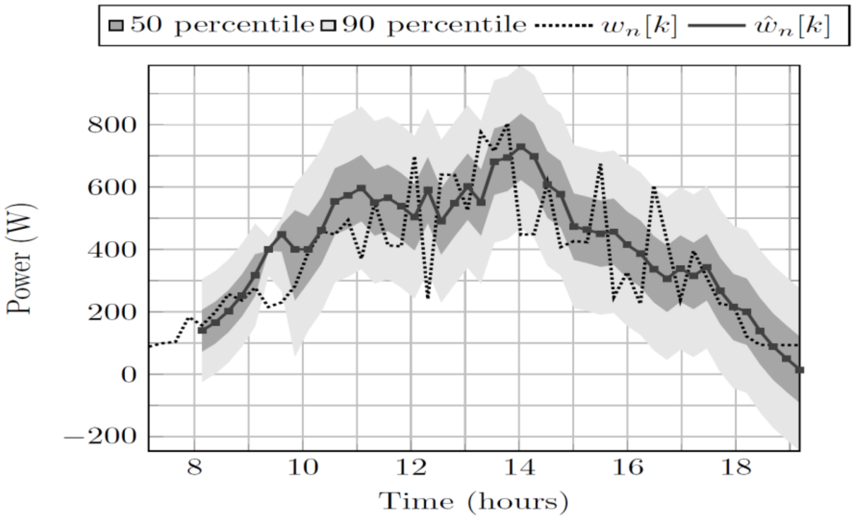

Figure 62. PV forecasting on a cloudy day

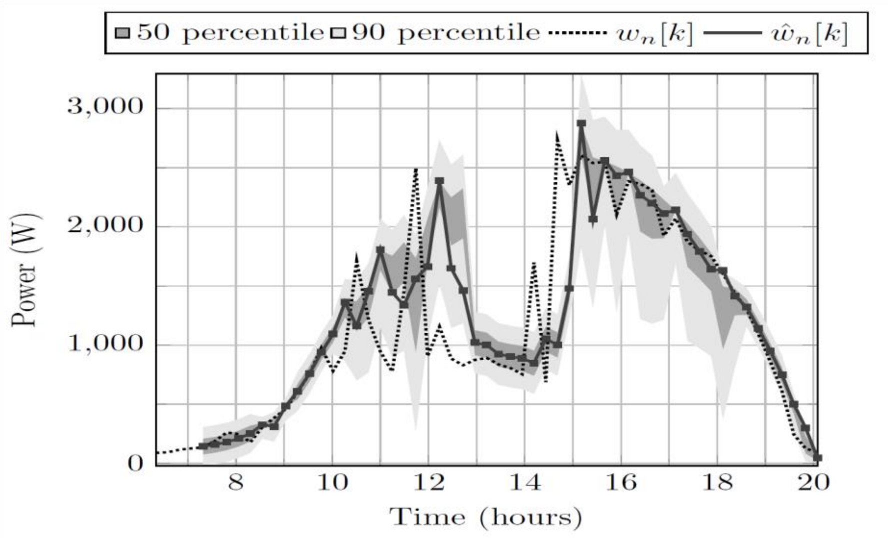

Figure 63. PV forecasting on a day with mixed weather

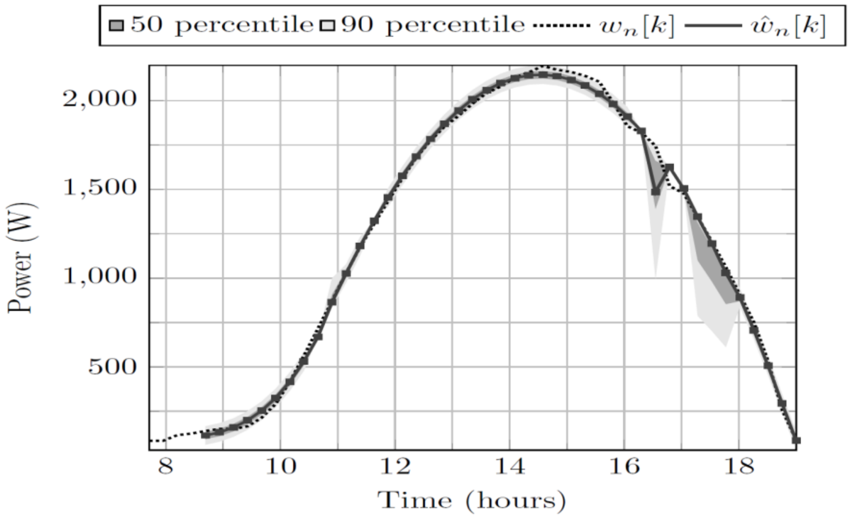

Figure 64. PV forecasting on a sunny day.

4.2.2 Consumption at load limits

Load unit consumption uncertainty differs greatly from device to device. Some load units like freezers have a fairly predictable load consumption as they are rarely opened, are well isolated and are in a constant ambient temperature location. Other load units are less predictable and can only be predicted with very high uncertainty such as water boilers or TVs.

Load predictions can be made for the future, but certainty does not necessarily increase greatly the closer to the presence the forecast time horizon is. Some things are known:

- The load will be between 0 and the installed capacity of the electrical device
- Devices have different characteristics
  - Some devices are either on or off
    - Water heaters, water boilers, lights (mostly), TVs
  - Some devices can be configured to different power levels
    - Heat pumps, stoves

Depending on type of load, it is possible to make some predictions. The possible time of operation of those loads that are used when people are home are forecasted to get activate at hours when the resident is at home. If we assume a normal working schedule, appliances such as stoves, TVs, lights and speakers can be assumed to mainly be used from 4 pm until midnight and from 6 am to 9 am in the morning. In other words, there is high certainty in the load forecast from midnight to 6 am and from 9 am to 4 pm compared to the other hours of a day. The certainty of these loads prediction is close to 100% at 4 am every day of the year, but can only be predicted with lower certainty at 8 pm. In other words, uncertainty does not necessarily increase the close to real-time we get for these loads. However, the historical data can reveal consumer behaviour patterns which can be used to make decent predictions.

Space heating loads normally correlate well with ambient temperature, and can therefore be forecasted fairly well. However, uncertainty varies depending on what kind of heating device it is. Some heating devices switch ON and OFF and are automatically regulated by a control device which has a temperature sensor. This means that by knowing ambient temperature, consumption over a longer time period (e.g. 24 hours) can be predicted with low uncertainty, compared to the prediction of their real-time duty cycle. Other space heating devices are not automatically regulated, but are controlled by end users manually.

4.2.3 Aggregated consumption of load units

Though it is difficult to predict the individual, real time consumption of thermostatically controlled devices like floor heaters and electric water heaters, their aggregated consumption can be predicted with more certainty. In the case of an FO controlling hundreds or thousands of floor heaters or water tank heaters, forecasting with high certainty is realizable, as heating demand is easier to predict over a longer time, both for space heating and hot water demand.

4.2.4 Consumption at a site

Let us assume a site (a building, a residence) with a certain amount of load units, uncertainty in demand prediction decreases as the number of devices increases. In other words, it is easier to predict the aggregated load profile of several loads than the exact load profile of individual loads. It is known for a site, the load will be between 0 and the rated power of the main fuse or any other given power limitation. Figure 65 shows the average consumption (kWh/h) of a large Norwegian residence divided by hour of the day and weekday. Although the figure indicates that load on average increases from 14-15 to 15-16, this does not necessarily depend on the activities of the residents. For an arbitrary residence, the probabilities of load change (from hour 15 to hour 16) could be the following:

- 85 %: residents arrive, load increases with 1-2 kWh/h
- 10 %: later arrival, load stays the same but increases in a few hours

- 5 %: travelling, load remains at background[11] load level

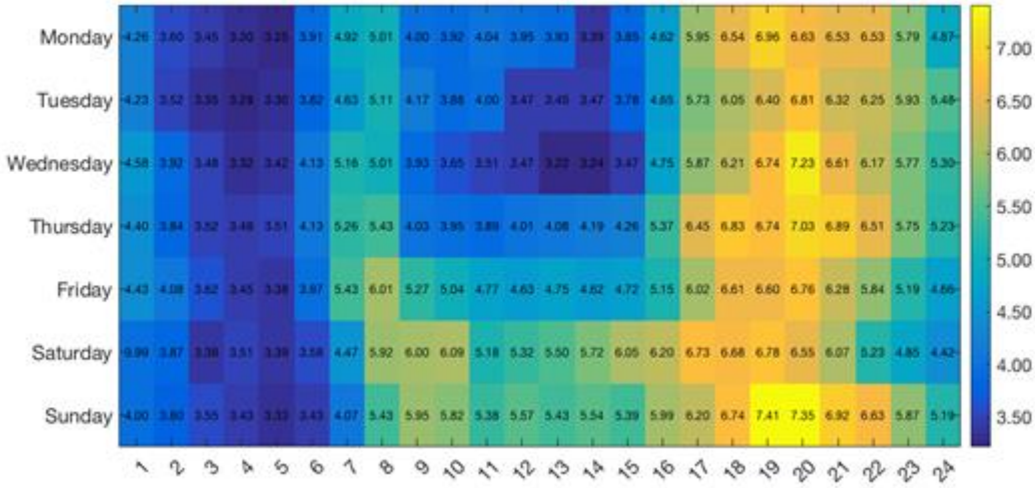

Figure 65. Load heatmap of a residence.

Such predictions can be made more precise by machine learning. Still, there will always be some uncertainty. If the forecasting tool makes a decision based on the most likely outcome, optimal results can be achieved when the decision matches real life events. However, the consequences of unlikely outcome are unknown. If the appearance of unlikely outcome is high, a weighted decision could be more optimal. A simple approach is to assume the expected load, where the probability of the different scenarios is multiplied with their resulting load change.

4.2.5 Consumption at a charging point

The charging point power consumption depends on many factors. The actual consumption is not known with certainty until real time. The certainty of the consumption at the charging point may increases with level of details known about the EVs, charging point technical specification etc. This subsection discusses the associated information which decides the certainty of the charging point consumption.

The charging point consumption has to be between zero and the maximum installed capacity of the charging station. However, how much power is withdrawn between these two limits are dependent on the following:

1. Number of cars connected

[11] Background load in this case is the load when nobody is home. This load represents the load consumption of space heating, water heating, refrigerators etc.

2. Charging power of each cars

In addition, the certainty of demand at the charging point depends on the following details:

1) The EVs availability at the charging point (arrival time and duration for charging)
2) The SOC of the EVs at the time of arrival (in % or kWh or can it be derived for the EV model information)
3) The amount of energy required for charging
4) Type of the EV connected (normally have a given capacity span [12] and charging power limitation)

In general, the more information known, the higher the certainty will be. Depending on type of charging point, the above list could change.

For an individual charging point at a domestic household, the historical load data may reveal some of the information listed above. Apart from the information available at the individual charging points, more information can be collected in addition to improve the demand prediction certainty at the charging point through alternative methods. For example, the EV drivers can be asked to provide some of the information through a Smart phone application interface.

For the charging station at neighbourhood level, it is more difficult to have an overview of the type of EVs connected. Also, if only the aggregated load profile of multiple charge points is available for a neighbourhood level, the individual EVs charging characteristics cannot be derived from that.

For the charging stations at office buildings, the case is similar to neighbourhood charging stations. Detailed information about cars is less likely to be known, but number of charging points dampens uncertainty. For both work place and neighbourhood charging stations, charging patterns should be easy to predict by machine learning.

Apart from the direct information, the indirect information like weather and drive patterns will improve the certainty of the EV availability, SOC and charging energy demand prediction. For example, cold or rainy weather will increase the probability EV usage compared to the warm dry days. Similarly, the EV usage on weekdays and in weekends have distinct patterns.

[12] Nissan Leaf currently has 24 or 30 kWh, Tesla Model S has 60 to 100 kWh etc.

For a public charging station, it is unlikely to have very specific information about each EVs that connects (unless this is standardized). Again, the uncertainty on the aggregated demand for charging decreases with the increased number of charging points inside a given charging site. It is also likely that there is a correlation between charging and traffic around the charging station, meaning that traffic forecasts could be utilized to predict charging.

4.2.6 Prices

The electricity price will often be the most deciding decision factor to avail the flexibility from the demand side and is therefore very important to know. The electricity price has more than one component which influences the energy price. Some of the components of the price changes more frequently and some changes lese frequently.

Grid tariffs:

Grid tariffs prices are fixed price the consumer pays as connecting charge to the grid for their load capacity The grid tariff does not change every day or in hourly basis. Therefore, the change in grid tariff affects the investment planning rather than the day today operational optimization and planning.

Taxes:

Similar to the taxation on electricity usage changes very less frequently and therefore affects the investment planning rather than the day today operational optimization and planning

Spot price:

The electricity market spot price is the most uncertain type of price. Day-ahead prices are normally published at noon, and contain hourly prices for the next day. This means that if the optimization algorithm is run at 11.59 am, spot prices are only known for the next 12 hours. However, if run 1 minute later at noon, day-ahead prices are published and available for the entire next day, i.e 36 hours ahead. Small prosumer batteries can normally do a full charging cycle in approximately 4 hours. In other words, decisions are mostly decided by the price development in the next 4 hours of operation. Thus, the worst case scenario where spot price is only known for the next 12 hours should not be a problem. If it for some reason is required to know spot prices for more than the 12-36 hours that are available, some kind of spot price forecasting is required.

Figure 66. shows how the knowledge of future spot prices is depending on which hour of the day we are in. The top example shows the scenario where we are running the optimization at noon, just after day-ahead prices are released. The bottom example

shows the case where we run the optimization just before prices are released, and prices are only known for the next 12 hours. In other words, the “deterministic horizon” is dependent on which hour we are in.

Figure 66. Spot price availability in intraday

4.2.7 Flexibility request from a DSO

The uncertainty regarding the flexibility request from a DSO is depending on the communication structure between the DSO and FO. What kind of time resolution is being used, and long before activation must the request be submitted? The longer ahead the request is being made, the higher the certainty for the given request period we have. If flexibility requests work like the balancing energy markets, a request would have to be handed in approximately 30-45 minutes before activation. Still, there is some uncertainty connected to the next time period, unless the DSO has made it clear that a certain amount of flexibility will be needed for a given time period. In other words, the uncertainty varies depending on how the contract between the FO and the DSO is shaped, and what time resolutions are being used.

4.3 Possible planning approaches

The uncertainties associated with the input parameters are unavoidable. The result of optimization is highly depend on the values of input parameters. A small error in the value of one of the input parameters can make the optimum solution infeasible and computationally intractable [10]. Different optimization approaches treat this uncertainty in a different manner [11]. In the following text gives a brief idea about three different optimization approaches.

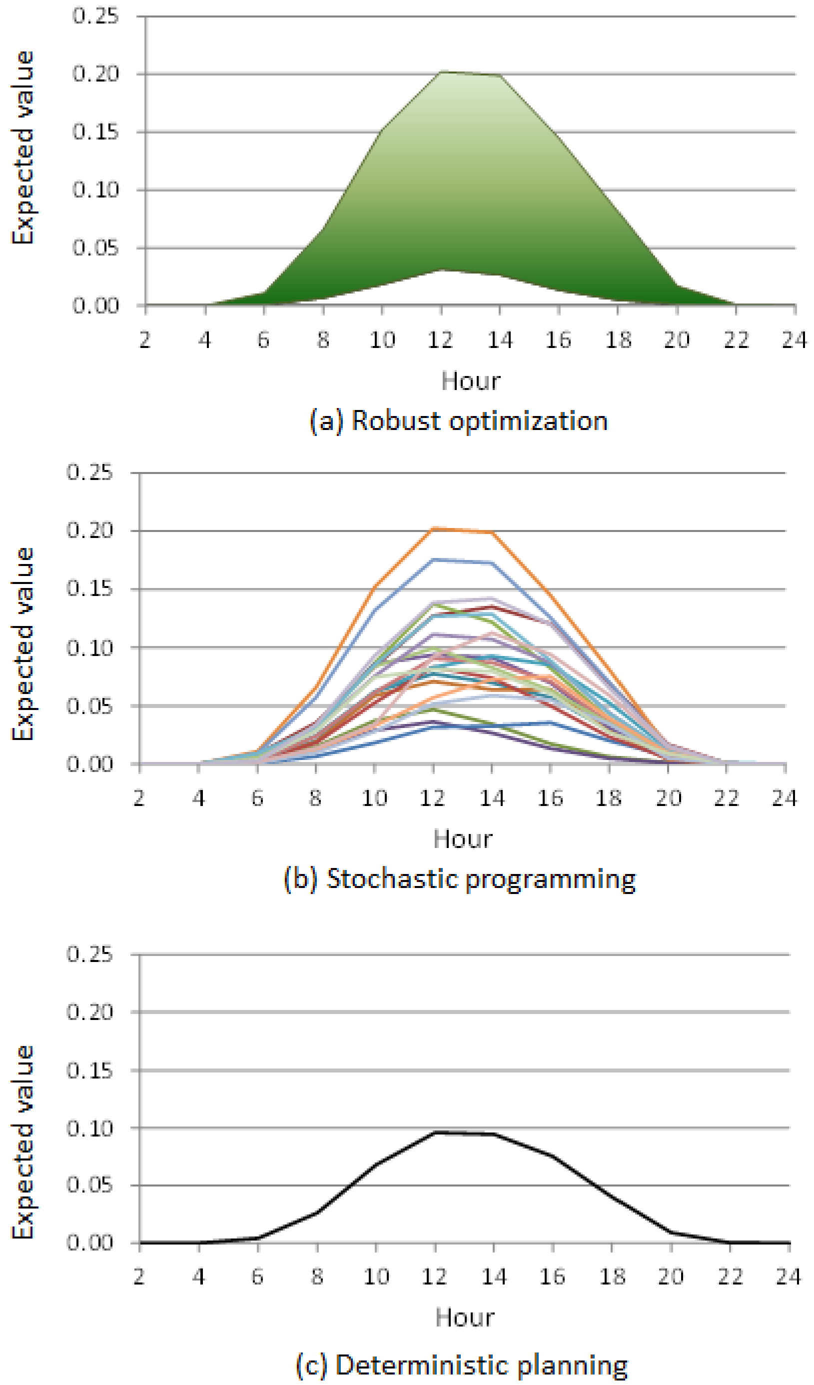

Figure 67. Representation of expected value the three different optimization approaches.

4.3.1 Robust optimization technique

Robust Optimization (RO) technique assumes a model for the uncertainties in the input parameter which is deterministic and set based [11]. RO method optimizes the objective over these set of robustly feasible solutions. By making a set of feasible solution, the RO method can make the problem computationally tractable [10]. The set of robustly feasible solutions guarantee to remain feasible for all uncertainty in the input parameters within the set.

Thus, an optimal solution is available for all permissible values of input parameters within the set. The solution obtained by RO method is not absolute optimal solution (global optimum) for the given objective function [11]. This is the price paid for the robustness of the solution for all possible inputs values. For example, the expected values of RO for a PV plant to of certain installed capacity for the next 24 hours will be similar to Figure 67 (a). RO is best suited for the problems in which uncertainty matters, computational time is valuable, estimation of probability distribution is difficult, and the decision should not be risky.

4.3.2 Stochastic programming

In stochastic optimization, the assumption is that the uncertainties in the input parameters have a probabilistic distribution. Within the probability distribution of the uncertain input parameters, the objective function produces a collection of random variables. The optimization process selects the best in these results, which satisfies the objective function's criterion. The stochastic optimization method tries to immunize the solution in some probabilistic sense to this stochastic uncertainty. However, the stochastic optimization always makes it feasible to achieve the solution, but the solution obtained is only expected to be optimal for the given scenario. For example, the expected values of stochastic programming for a PV plant of certain installed capacity for the next 24 hours will be similar to Figure 67 (b). The different expected value curves represents different scenarios. The solution approach is based on the scenarios that are complex to generate. This makes the stochastic optimization method to formulate the optimization problem as a huge one with substantial data requirements [10].

4.3.3 Rolling horizon deterministic planning

The stochastic optimization assumes that there is random noise in the input parameters and/or the choice is random to select the search direction when the algorithm starts to iterate towards the solution (Monte Carlo) [11]. In contradictory, the deterministic method assumes that a perfect information is available about the input parameters [11]. For example, the expected values of deterministic programming for a PV plant to of certain installed capacity for the next 24 hours will be similar to Figure 67 (c). With the available information on the future values of the input parameters, the optimization process can schedule the flexible and inflexible units (generation, load and storage) to certain time horizon called planning horizon with multiple periods as shown in the Figure 68 (a).

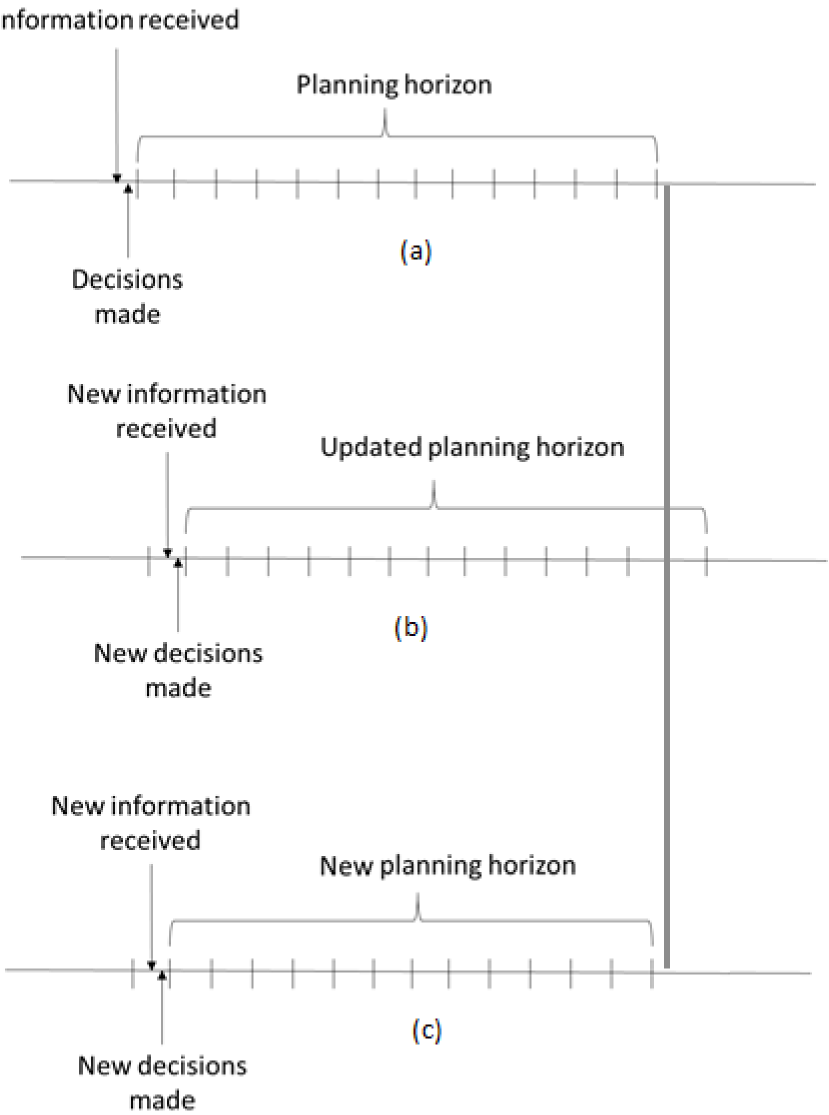

Figure 68. Deterministic programming with rolling and receding methods.

The assumption is that the input parameters are more certain in these periods. Based on the optimization decision, the control actions take place only for the immediate next period or few nearest periods depends. In model predictive control (MPC) approaches, it is always customary to make control decision for one time step and wait for the system response to decide further control decisions (next time steps) [12], [13]. During the present control execution period, the new update on some of the input parameters will be available with more certainty than the previously available values. The new optimization process will include the latest update on the input parameters and makes a new schedule. During this optimization process, the length of time horizon may be extended based on the available input data as shown in Figure 68 (b). This method of extending the planning horizon on the new optimization process is called rolling horizon method. If the new information for the input parameters does not provide update for the time periods beyond present on the planning horizon, the optimization process will maintain the same horizon with shorter length as shown in the Figure 68 (c). This method is called receding horizon method.

4.3.4 Rule-based method

The above three methods optimize the operation schedule of different units (load, generation and storage) based on the available information about the input parameters for the future periods. They have different methods to handle the uncertainty associated with forecasted or predicted input parameters. Rule-based method does not consider the future periods. The decisions are made for present period only with the input parameter values for the present period, which are certain. Therefore, it is easy to implement. The rules-based method selects the most flexible resource first from the available list of resources to fulfil the flexibility service. If the first resource is not available or the flexibility offered by that resource is not sufficiently large to fulfil the service request, the flexibility from the second resource is activated to fulfil the residue and this selection process continues until the flexibility service request is fulfilled. The rule-based method repeats the whole process from the beginning for the second period based on the available resources at that point of time.

4.4 The information structure

In real-time, the operational scheduling has to include the updated values available for the input parameters in the optimization process. The method to include every newly available values for the input parameters and to produce new set of optimized decision variables is called information structure. The long optimization horizon will be divided into equal multiple short periods. The length of one period is constrained by many parameters which is discussed in detail later in this chapter in section 4.6. The optimization process is executed with the latest input parameter values and the decisions are made for the whole planning horizon to produce operational plan to get the best possible value for the flexibility. In some cases, the flexibility can have better value in the later periods than availing it in the nearer periods or vice versa. Although the scheduling is done for the whole horizon, the actual decision implementation is done only for the first period as shown in the Figure 69 (a).

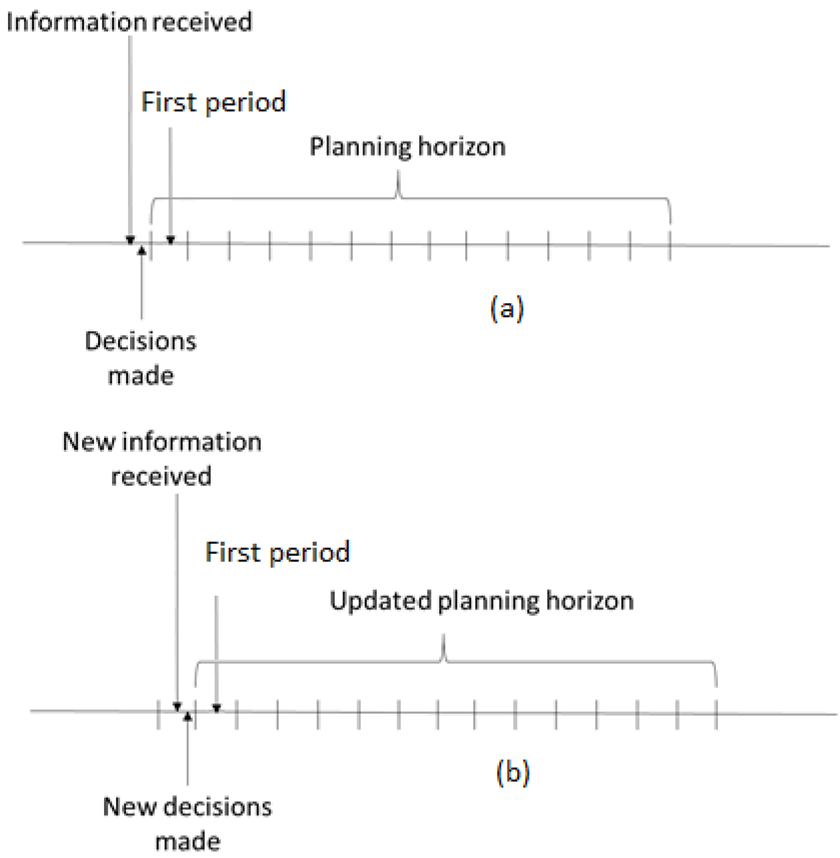

Figure 69. Operational information structure and first period decision implementation

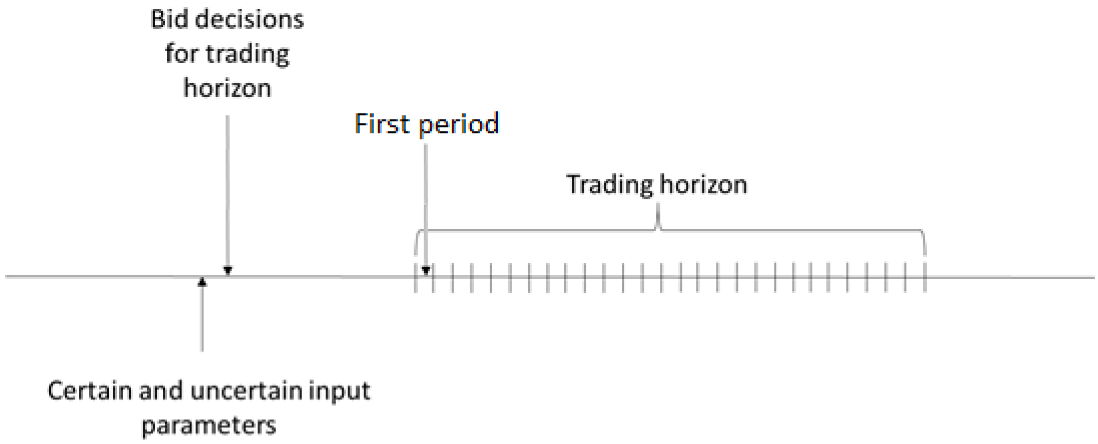

Figure 70. Operational information structure and first period decision implementation for day ahead market.

It should be noted that the actual time of the first period is application dependent. For example, if the flexibility is traded in the day ahead market, in reality, the actual first period appears in the next day as shown in the Figure 70. The optimization process is iterated whenever there is an update about the input parameter value and the new schedule is produced and the process continues with first period decision implementation structure as shown in the Figure 69 (b).

4.5 Length of the planning horizon

The optimization process is executed after every time a new information received and the decisions are made for a number of periods in the planning horizon as shown in the Figure 71. Many parameters have their influence on the length of planning horizon. It depends on application, information availability and validity, error tolerance level of the system, computation complexity of the optimization problem and length of the sub periods within the planning horizon. Table 6 illustrates various applications with different planning horizons and forecast methodologies.

Table 6. Example of existing approaches with different planning horizons and use cases

Problem setting and use	Proposed planning horizon methodology	Features • Planning horizon (PL) • Resolution (R) • Flexibility service (FS) • Case/customer (user)	Forecasting tools
Congestion and voltage management with battery storage [14]	Battery used to mitigate the voltage problem associated congestion management due to high share of solar PV. Distributed-receding horizon optimization method for battery operation is proposed for congestion management and adaptive receding horizon optimization method for battery operation is proposed for voltage management.	**PL:** 24 hours **R:** 15 minutes **FS:** Voltage control and congestion management **User:** DSO	Solar and demand forecast are generated from the historical data incorporating random, normally distributed fluctuations.
Micro grid energy management with storage [15]	A rolling horizon based energy management for a micro grid with multiple RES (wind and solar) and battery storage is proposed. The overall strategy is to prepare the control schedule for 15min intervals based on 48 hours prediction. Then, move to the next interval.	**PL:** 48 hours **R:** 15 minutes **FS:** Self-balancing **User:** Large prosumer	Load forecast is neural network based. Solar and wind production is forecasted phenomenological models with weather forecast using Global Forecast System.
Frequency regulation with storage [12]	Stochastic Model Predictive Control (MPC) for frequency regulation with battery storage is proposed and compared with the deterministic MPC.	**PL:** 720 hours **R:** 1 hour **FS:** Frequency regulation **User:** TSO	The forecast of demand, energy price and frequency regulation signal are done with Ledoit-Wolf covariance estimation method. (The forecast is for only 1 hour)
Grid-connected Micro grid energy management [14]	A mixed integer linear program optimization method for energy management in a grid connected micro grid with RES (solar and wind) and battery storage is proposed. The battery extreme uses are penalized to avoid such usages.	**PL:** 96 hours **R:** Variable 30 minutes – 12 hours **FS:** KW max and self-balancing **User:** Large prosumer	The RES production forecast depends on the weather forecast data from external agencies. A variable time step ranging from 30 minutes in nearer and 12 hours near horizon is adapted to reduce the computational load.
Energy storage sizing [16]	A two-stage MPC optimization considering the sizing scenario at primary level and operational scenario at the secondary level is presented.	**PL:** 24 hours **R:** 10 minutes **FS:** Self balancing **User:** Large prosumer	The wind forecast is from the historic data added with wind forecast error as a random variable with a Gaussian probability distribution.
RES coupled to storages with probabilistic forecasts [17]	The battery operation is optimized for the maximum utilization of RES with 2 level control. The offline scheduling is done with optimization and the online hourly control is done with MPC	**PL:** 48 hours **R:** 1 hour **FS:** self balancing **User:** Large prosumer	Data driven regression model of order 3 is used to forecast demand and RES generations.

The planning horizon should be long enough to avoid suboptimal decisions. For example, If a curtailable load is allowed to be disconnected only once in a day or if the shiftable load is constrained to operate at least once in a day, then the planning horizon should cover at least all hours of a day. Similarly, if an EV is connected to the charging point between 1600 pm of a day and 0700 am of the day after, all periods till 0700 am of the day after should be included.

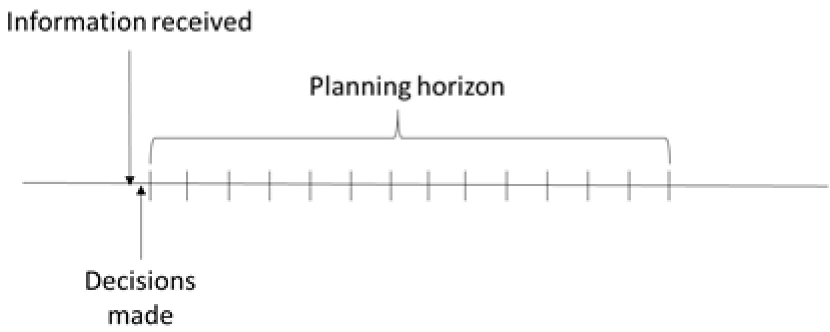

Figure 71. Planning horizon for optimal operation.

As the length of the planning horizon increases, the optimization process takes longer time to compute due to more number of periods and more scenarios under consideration. If the optimization results are not available before the time of their actual implementation, they are useless. Therefore, the planning horizon should be short enough to avoid such scenarios. The number of periods within the planning horizon may vary, every time the when the system executes the optimization process to make new decisions. This depends on the available information, their time resolution and system sensitivity.

4.6 Time resolution

The time resolution of the optimization will be different from case to case, depending on what kind of objective function we are looking at. In general, higher resolution increases the precision of the optimization and allows for a greater optimum. The longer the duration, the less of physics can be taken into account, as fluctuations in real life surroundings could potentially violate constraints on a short time basis, which are not violated when resolution is lower. This also means that the longer the duration is, the more decisions and responsibilities have to be handled by the local system. On the contrary, the higher the time resolution, the more data must be handled. This kind of data can be new and different forecasts/predictions like a weather update, the connection of new EVs, local decisions made due to fluctuations or unforeseen events etc.

Market rules play a role because they decide important factors such as spot price. For a prosumer case, resolution can not be lower than the time resolution of the prize; 1 hour.

One could also change the time resolution depending on where in the time horizon it is. For example, a 15 minute time resolution could be used for the next 6 hours, whereas 1 hour is used from 6 to 48 hours ahead as fine tuning is less relevant in the future where uncertainty is greater. Such an approach would ensure optimal decisions in close time horizon while still giving an indication of operation in a longer time perspective without increasing the computational time too much.

4.6.1 Prosumer

In general, the time resolution should be equal to the factor that requires the highest resolution. However, this is not always realizable. For example, an objective function maximizing the profit (savings) of a prosumer, will need to take load, PV production and price into account when deciding how to operate a battery, EV battery or other flexibility services. Although the price is updated on an hourly basis, the PV and load can change in a matter of seconds. What happens if an EV connects just after a new periods has started? With a high time resolution, the EV can be integrated into the decisions quickly, whereas a low time resolution the EV will not be taken into account before a new time period starts. For some cases (e.g. home charging), this might not be a problem because the car might be connected for a long time, whereas public charging stations would have to provide some power to the EV right away. Still, it is not possible to make a new optimization every minute. In other words, time resolution should be chosen to be a reasonable value after analysing the benefits and drawbacks of different resolutions, and if a time resolution is chosen which can't handle specific real life events, some rule based or simplified solution has to be made until a new period starts.

4.6.2 DSO

Congestion management services can only be provided within the same time resolution of the model, meaning that if a 15 minute resolution is used, a request to provide flexibility at 15:55 is not possible. For the DSO case, a time resolution of 15 minutes was used in EMPOWER.

Congestion management and voltage control are problems mainly based on one factor: consumer demand. In other words, the time resolution should be as high as the demand changes, which due to the continuity of real life demand is impossible. The platform needs to have a reasonable time resolution which can handle most of the problems connected to congestion management and voltage fluctuations while still having a longer time resolution than the computational time of the optimization.

4.6.3 BRP

For a BRP case, resolution would have to be minimum the resolution of the market. In Norway, this is 1 hour, whereas it is 15 minutes in Germany. Minimum time resolution would have to be changed accordingly.

4.7 Overall operational scheduling optimization process

Figure 72 shows the overview of the operational scheduling optimization process. The optimization model receives input parameter values for consumption, generation and available flexibility. These values are dynamic, depend of external factors and have uncertainties associated with them. These values are derived from their historical data and external information like electricity prices, weather forecast and booking information of EV charge posts etc. The other fixed data structure, for example the installed capacities of PV generation and battery storage, maximum charge/discharge powers and network physical constraints are also fed to the optimization model. The result of optimization is control decisions for the planning horizon. The results formatted to meet the local generation, load and battery units' communication protocol requirements and communicated in a way to activate only the first period decisions. If the optimization model complaints that the problem is infeasible, default control decisions will be followed.

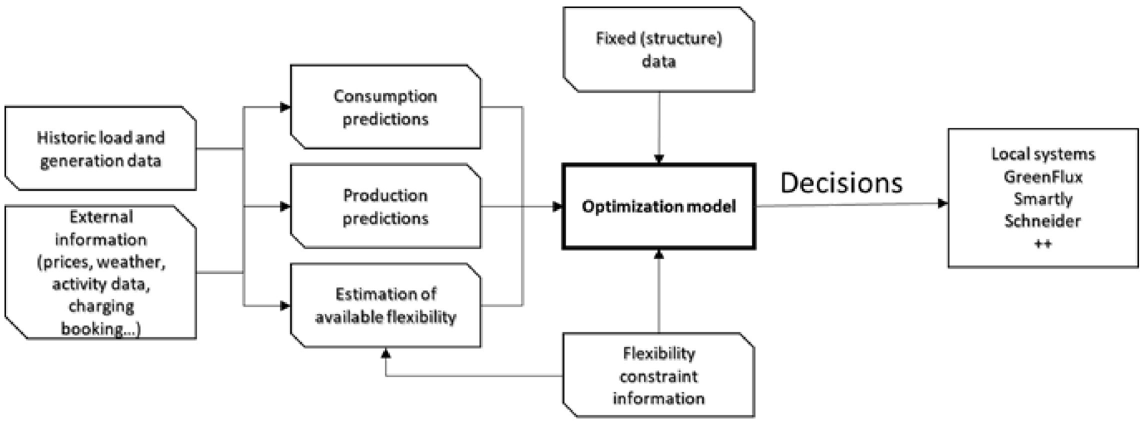

Figure 72. Overview of the operational scheduling optimization process

5 Mathematical formulations

5.1 Overview of sets, parameters and variables

5.1.1 Sets

T	Set of periods/time slots in the planning horizon
T^c	Subset of periods where curtailment is allowed
B	Set of battery units
V	Set of electric vehicles
V^i	Subset of electric vehicles that are inflexible
V^s	Subset of electric vehicles that are shiftable
V^d	Subset of electric vehicles that are disconnectable (shiftable interruptible)
V^c	Subset of electric vehicles that are reducible (fully controllable)
V^2	Subset of electric vehicles that can be discharged (V2X)
I	Set of load shift intervals
L	Set of load units
L^i	Subset of load units that are inflexible
L^r	Subset of load units that are curtailable reducible
L^d	Subset of load units that are curtailable disconnectable
L^p	Subset of load units that are shiftable profile
L^v	Subset of load units that are shiftable volume
G	Set of generation units
G^i	Subset of generation units that are inflexible
G^r	Subset of generation units that are curtailable reducible
G^d	Subset of generation units that are curtailable disconnectable

5.1.2 Parameters

$P_t^{retail-buy}$	Price at energy part of retail contract for buying electricity in period *t* [€/kWh]
$P_t^{grid-buy}$	Price at energy part of grid contract for buying electricity in period *t* [€/kWh]
$P_t^{grid-buy-low}$	Price at energy part of grid contract for buying electricity in cases with subscribed power in period in period *t* if bought electricity is below subscribed level [€/kWh]
$P_t^{grid-buy-high}$	Price at energy part of grid contract for buying electricity in cases with subscribed power in period in period *t* if bought electricity is above subscribed level [€/kWh]
P^{tax}	Sum price for all taxes that are related to buying electricity in period t [€/kWh]
P^{VAT}	Parameter that adds VAT to the amount bought [fraction]
$P_t^{retail-sell}$	Price at energy part of retail contract for selling electricity in period *t* [€/kWh]
$P_t^{grid-sell}$	Price at energy part of grid contract for selling electricity in period *t* [€/kWh]
P^{peak}	Price at grid contract for peak fee [€/kW/month]
$X^{imp-cap}$	Maximum import capacity [average kW]
$X^{exp-cap}$	Maximum export capacity [average kW]
M	Limitation of basis for peak fee [kW]
O_b^{min}	Minimum state of charge allowed for battery b [kWh]
O_b^{max}	Maximum state of charge allowed for battery b [kWh]
$O_v^{EV,min}$	Minimum state of charge allowed for EV unit v [kWh]
$O_v^{EV,max}$	Maximum state of charge allowed for EV unit v [kWh]
$O_{v,t}^{EV,min,t}$	Minimum state of charge allowed for EV unit v at period t [kWh]
O_v^{CD}	Total charging demand for EV unit v [kWh]

$O_v^{CD,min}$	Minimum charging demand supplied during the charging process of EV unit v [kWh]
Q_b^{ch}	Maximum charging power allowed for battery b [kW]
Q_b^{dis}	Maximum discharging power allowed for battery b [kW]
$Q_v^{EV,ch}$	Maximum charging power allowed for EV unit b [kW]
$Q_v^{EV,dis}$	Maximum discharging power allowed for EV unit b [kW]
A_b^{ch}	Efficiency parameter for charging storage unit *b* [#]
A_b^{dis}	Efficiency parameter for discharging storage unit *b* [#]
$A_v^{EV,ch}$	Efficiency parameter for charging EV unit *v* [p.u.]
$A_v^{EV,dis}$	Efficiency parameter for discharging EV unit *v* [p.u.]
S_b^{ch}	Threshold in battery unit b charging process [p.u.]
S_b^{dis}	Threshold in battery unit b discharging process [p.u.]
S_b^{end}	Threshold in battery unit b of stored energy at the end of the planning horizon [p.u.]
$P_{b,t}^{B,ch}$	Price for charging battery unit *b* at period *t* [€/kWh]
$P_{b,t}^{B,disc}$	Price for discharging battery unit *b* at period *t* [€/kWh]
$S_v^{EV,ch}$	Threshold in EV unit v charging process [p.u.]
$S_v^{EV,dis}$	Threshold in EV unit v discharging process [p.u.]
$W_{v,t}^{EV}$	Baseline charging schedule for EV v in period t [kWh]
E_v^{min}	Minimum charging power allowed for vehicle v [kWh]
E_v^{max}	Maximum charging power allowed for vehicle v [kWh]
E_v^{start}	Remaining battery energy of EV unit *v* at the arrival period [kWh]
$P_{v,t}^{EV}$	Price for shifting charging for EV unit v with 1 kWh [€/kWh]
$P_{v,t}^{EV,V2G}$	Price for discharging 1 kWh from EV unit v [€/kWh]

$P_v^{EV,NS}$	Price for non-supplying 1 kWh of the expected charging demand of EV unit *v* [€/kWh]
T_i^{start}	First period in load shift interval *i* [#]
T_i^{end}	Last period in load shift interval *i* [#]
$T_v^{EV,start}$	First period for EV control of unit *v* [#]
$T_v^{EV,end}$	Last period for EV control of unit *v* [#]
V_i^{start}	First period in load shift interval *i* where the load unit has a baseline consumption [#]
V_i^{end}	Last period in load shift interval *i* where the load unit has a baseline consumption [#]
$W_{l,t}^{load}$	Baseline consumption at load unit *l* in period *t* [#]
$P_{l,t}^{c}$	Price for reducing consumption for curtailable load unit *l* in period *t* [€]
$P_{l,t}^{s}$	Price for shifting consumption for shiftable load unit *l* with 1 period in period *t* [€/period]
D_l^{max}	Maximum duration of a regulation for load unit *l* [#]
D_l^{min}	Minimum rest time between two regulations for load unit *l* [#]
N_l^{max}	Maximum number of regulations for load unit *l* in planning horizon [#]
$W_{g,t}^{prod}$	Baseline production from generation unit *g* in period *t* [kWh]
$P_{g,t}^{G}$	Price for reducing production for generator unit *g* in period *t* [€]
N^{hour}	Periods per hour [#]

5.1.3 Variables

χ_t^{buy}	Amount of electricity bought in period t [kWh]
χ_t^{sell}	Amount of electricity sold in period t [kWh]
χ^{peak}	Basis for calculation of peak fee in cases where this is a part of the grid contract [kW]
$\psi_{g,t}$	Amount of electricity produced from generating unit g in period t [kWh]
ζ^{gen}	Total cost for utilizing generation flexibility [€]
$\omega_{l,t}$	Amount of electricity consumed from load unit l in period t [kWh]
$\varphi_{v,t}^{ch}$	Amount of electricity charged to EV unit v in period t [kWh]
$\varphi_{v,t}^{dis}$	Amount of electricity discharged from EV unit v in period t [kWh]
$\sigma_{b,t}^{ch}$	Amount of electricity charged to battery unit b in period t [kWh]
$\sigma_{b,t}^{dis}$	Amount of electricity discharged from battery unit b in period t [kWh]
$\sigma_{v,t}^{EV,ch}$	Amount of electricity charged to EV unit v in period t [kWh]
$\sigma_{v,t}^{EV,dis}$	Amount of electricity discharged from EV unit v in period t [kWh]
$\sigma_{v,t}^{CD,ch}$	Amount of electricity charged to EV unit v in period t [kWh]
$\zeta^{flexibility}$	Total cost for utilizing internal flexibility [€]
δ_t^{buy}	Binary variable = 1 if site is importing/buying electricity in period *t,* else 0
δ_t^{sell}	Binary variable = 1 if site is exporting/selling electricity in period *t,* else 0
$\sigma_{b,t}^{soc}$	Amount of electricity stored in battery unit b in period t [kWh]
$\sigma_{v,t}^{EV,soc}$	Amount of electricity stored in EV unit v in period t [kWh]
$\sigma_{v,t}^{CD}$	Amount of electricity stored to EV unit V in period t [kWh]
$\gamma_{v,i,c}^{EV}$	Binary variable equal to 1 if consumption for EV unit *v* is shifted *c* periods for load shift interval *i*, else 0
$\tau_{v,i}^{EV}$	Weighted average delay for controllable EV unit *v* in interval *i*

$\rho_{v,i}^{EV}$	Help variable to handle positive and negative values of $\tau_{v,i}^{EV}$
$\zeta^{EV,shift}$	Cost for shifting EV charging [€]
$\zeta^{EV,control}$	Cost for controlling EV charging [€]
$\zeta^{EV,V2X}$	Cost for controlling EV charging and discharging [€]
$\delta_{l,t}^{start}$	Binary variable equal to 1 if regulation of load unit *l* starts in the beginning of period *t*, else 0
$\delta_{l,t}^{run}$	Binary variable equal to 1 if regulation of load unit *l* is running in period *t*, else 0
$\delta_{l,t}^{end}$	Binary variable equal to 1 if regulation of load unit *l* ends in the beginning of period *t*, else 0
$\gamma_{l,i,c}^{load}$	Binary variable equal to 1 if consumption for load unit *l* is shifted *c* periods for load shift interval *i*, else 0
$\tau_{l,i}^{load}$	Weighted average delay for shiftable load unit *l* in interval *i*
$\rho_{l,i}^{load}$	Help variable to handle positive and negative values of $\tau_{l,i}^{load}$
$\zeta^{loadcurtail}$	Cost for curtailing load [€]
$\zeta^{loadshift}$	Cost for shifting load [€]
$\delta_{g,t}^{gen}$	Binary variable equal to 0 if generating unit *g* is disconnected in period *t*, else 1

5.2 Common/general constraints

5.2.1 Battery models

Each battery unit *b* has efficiency factors for charging A_b^{ch} and discharging A_b^{dis}, respectively. The battery state of charge, i.e. the storage content, $\sigma_{b,t}^{soc}$ for battery unit *b* in period *t* depends on the state of charge in the previous period, and charging $\sigma_{b,t}^{ch}$ or discharging $\sigma_{b,t}^{dis}$ in current period.

$$\sigma_{b,t}^{soc} = \sigma_{b,t-1}^{soc} + \sigma_{b,t}^{ch} * A_b^{ch} - \frac{\sigma_{b,t}^{dis}}{A_b^{dis}}, \qquad \forall\, b \in B, t \in T \tag{Eq. 1}$$

The state of charge must be within minimum and maximum limits:

$$O_b^{min} \leq \sigma_{b,t}^{soc} \leq O_b^{max}, \qquad \forall\, b \in B, t \in T \tag{Eq. 2}$$

Charging and discharging must be below maximum charging levels:

$$\sigma_{b,t}^{ch} \leq \frac{Q_b^{ch}}{N^{hour}}, \qquad \forall\, b \in B, t \in T \tag{Eq. 3}$$

$$\sigma_{b,t}^{dis} \leq \frac{Q_b^{dis}}{N^{hour}}, \qquad \forall\, b \in B, t \in T \tag{Eq. 4}$$

Previous constraints assume that the batteries are completely adjustable in terms of power input and output up to the maximum power specified Q_b^{ch} and Q_b^{dis}.

However, the following constraint ensures that the energy charged $\sigma_{b,t}^{ch}$ to the battery *b* is linearly decreased from S_b^{ch} state-of-charge, typically 0.8 (80%), until zero at 100% SOC.

$$\sigma_{b,t}^{ch} \leq \frac{-Q_b^{ch} / N^{hour}}{1 - S_b^{ch}} \left(\frac{\sigma_{b,t}^{soc}}{O_b^{max}} - 1 \right) \tag{Eq. 5}$$

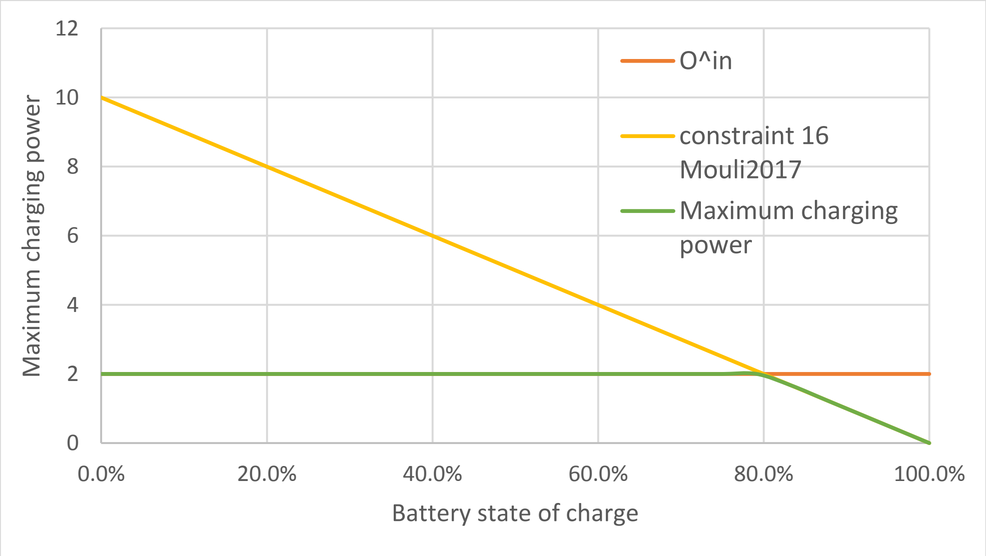

Figure 73. Battery state of charge as a function of maximum charging power

The same for discharging power $\sigma_{b,t,s}^{out}$ of battery unit *b* during period *t.* The lower threshold to limit the energy output is S_b^{dis}, typically 0.1 (10% SOC), until zero power output at 0% SOC.

$$\sigma_{b,t}^{out} \leq \frac{Q_b^{dis} / N^{hour}}{S_b^{dis}} \left(\frac{\sigma_{b,t}^{soc}}{O_b^{max}} \right) \quad \text{(Eq. 6)}$$

Finally, the battery SOC at the end of the planning horizon must be a certain level. Parameter S_b^{end} can be tuned depending on the planning horizon, storage services and case details.

$$\sigma_{b,t}^{soc} = S_b^{end} \cdot O_b^{max}, \qquad \forall\, b \in B, t = T \quad \text{(Eq. 7)}$$

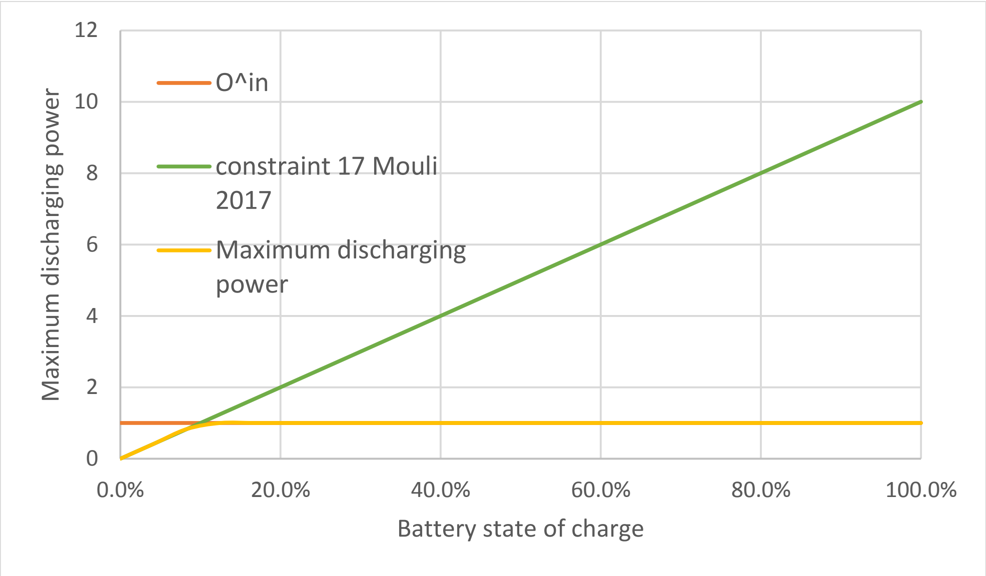

Figure 74. Battery state of charge as a function of maximum discharging power

5.2.2 Load models

As described in Section 2.5.2 the load unit models can be split into the following classes:

- Inflexible load units
- Curtailable disconnectable load units
- Curtailable reducible load units
- Shiftable volume (storable) load units
- Shiftable profile load units

5.2.2.1 Inflexible

For inflexible load units the scheduled load $\omega_{l,t}$ must be equal to the baseline (predicted) load $W_{l,t}^{load}$.

$$\omega_{l,t} = W_{l,t}^{load}, \qquad \forall\, l \in L^i, t \in T \quad \text{(Eq. 8)}$$

5.2.2.2 Curtailable

We introduce binary variables $\delta_{l,t}^{start}$equal to 1 if load unit *l* starts regulation in the beginning of period *t*, $\delta_{l,t}^{run}$ equal to 1 in periods where regulation runs after the starting period and finally, $\delta_{l,t}^{end}$ equal to 1 in the first period after a regulation is stopped.

A curtailment can start or run only in permitted periods:

$$\delta_{l,t}^{start} + \delta_{l,t}^{run} = 0 \quad \forall\, l \in L^c, t \notin T^c \tag{Eq. 9}$$

A curtailment can not start, run and end in the same period:

$$\delta_{l,t}^{start} + \delta_{l,t}^{run} + \delta_{l,t}^{end} \leq 1 \quad \forall\, l \in L^c, t \in T \tag{Eq. 10}$$

A curtailment that starts or runs in one period, must either continue to run or end in the consecutive period:

$$\delta_{l,t-1}^{start} + \delta_{l,t-1}^{run} = \delta_{l,t}^{run} + \delta_{l,t}^{end} \quad \forall\, l \in L^c, t \in T \tag{Eq. 11}$$

A load unit can not be curtailed any longer than D_l^{max}periods:

$$\sum_{i=t}^{t+D_l^{max}} \delta_{l,i}^{end} \geq \delta_{l,i}^{start} \quad \forall\, l \in L^c, t \in T \tag{Eq. 12}$$

A minimum duration D_l^{min} must exist between two load curtailments:

$$\delta_{l,t}^{end} + \sum_{i=t}^{t+D_l^{min}-1} \delta_{l,i}^{start} \leq 1 \quad \forall\, l \in L^c, t \in T \tag{Eq. 13}$$

The maximum number of curtailments in the planning horizon must not be greater than $N_{l,i}^{max}$:

$$\sum_{t \in T} \delta_{l,t}^{start} \leq N_l^{max} \quad \forall\, l \in L^c, t \in T \tag{Eq. 14}$$

We illustrate the constraints with a small example. A load unit is curtailed in periods 1 to 4 and 7 to 8. The values of the binary variables are then as shown in the table below.

Table 7. Example of binary variables for curtailable load units

	1	2	3	4	5	6	7	8	9
$\delta_{l,t}^{start}$	1	0	0	0	0	0	1	0	0
$\delta_{l,t}^{run}$	0	1	1	1	0	0	0	1	0
$\delta_{l,t}^{end}$	0	0	0	0	1	0	0	0	1

The first curtailment starts in period 1, hence $\delta_{l,1}^{start}$ is set to 1. The curtailment continues in periods 2, 3 and 4, and the $\delta_{l,t}^{run}$ are set to 1. The curtailment stops in the beginning of period 5 (or actually, in the end of period 4) so $\delta_{l,5}^{end} = 1$.

For reducible load units, the load schedule $\chi_{l,t}$ must be smaller than the consumption forecast $W_{l,t}^{load}$:

$$\chi_{l,t} \leq \left(\delta_{l,t}^{start} + \delta_{l,t}^{run}\right) * W_{l,t}^{load}, \ \forall\, l \in L^c, t \in T \qquad \text{(Eq. 15)}$$

For disconnectable load units, the load schedule must either be 0 or equal to the consumption forecast:

$$\chi_{l,t} = \left(\delta_{l,t}^{start} + \delta_{l,t}^{run}\right) * W_{l,t}^{load}, \ \forall\, l \in L^c, t \in T \qquad \text{(Eq. 16)}$$

Curtailable load units will have a cost equal to the curtailment price multiplied with the number of periods curtailed:

$$\zeta^{loadcurtail} = \sum_{t \in T} \sum_{l \in l^c} P_{l,t}^{load} \left(\delta_{l,t}^{start} + \delta_{l,t}^{run}\right) \qquad \text{(Eq. 17)}$$

5.2.2.3 Shiftable

For shiftable load units we introduce load shift intervals *I* similar to the charging sessions for the EVs.

For shiftable profile load units we introduce the variable $\gamma_{l,i,n}$ which is set to 1 if consumption for load unit *l* is shifted *n* periods for load shift interval *i*. Exactly one load shifting option must selected for each shiftable profile load unit in each load shift interval:

$$\sum_{n=T_i^{start}-V_i^{start}}^{T_i^{end}-V_i^{end}} \gamma_{l,i,n} = 1 \;\; \forall\, l \in L^p, i \in I(l) \qquad \text{(Eq. 18)}$$

The consumption forecasts must be allocated to the correct periods according to the decided load shifting option:

$$\omega_{l,t=} \sum_{n=0}^{T_i^{end}-T_i^{start}} \gamma_{l,i,(t-T_{l,i}^{start}-n)} W_{l,(T_{l,i}^{start}+n)} \;\; \forall\, t \in \{T_i^{start}, T_i^{end}\}, i \in I(l) \qquad \text{(Eq. 19)}$$

For shiftable profile load units, the cost for regulation is the product of the delay cost and the number of periods delayed. We calculate this cost according to the equation below:

$$\zeta^{loadprofile} = \sum_{l \in L^p} \sum_{i \in I} P_d^s \sum_{n=0}^{T_i^{end}-V_i^{end}} \gamma_{l,i,n}^{load}\, n \qquad \text{(Eq. 20)}$$

Contrary to shiftable profile load units, for shiftable volume load units we can control the power levels between a minimum E_l^{min} and a maximum E_l^{max} value.

$$E_l^{min} \le \omega_{l,t} \le E_l^{max}, \;\; \forall\, l \in L^v, t \in T(i) \qquad \text{(Eq. 21)}$$

In some cases, similar to charging of EVs, $\omega_{l,t}$ may be semi-continuous, which means that it must be according to Eq. 36 or 0.

For each load shift interval *i* the sum energy volume delivered to the load unit must equal the sum baseline forecast.

$$\sum_{t=T_i^{start}}^{T_i^{end}} \omega_{l,t} = \sum_{t=T_i^{start}}^{T_i^{end}} W_{l,t}^{load} \;\; \forall\, l \in L^v, t \in T(i), i \in I(l) \qquad \text{(Eq. 22)}$$

For shiftable volume load units, we introduce the concept of weighted average delay, which has number of periods as unit. This also takes into account not only when you meet the finale volume, but also how you do it (penalizes more if large volumes are shifted to the end). The weighted average delay for shiftable load unit *l* and load shift interval *i* is defined like as:

$$\tau_{l,i}^{load} = \frac{\sum_{t=T_{l,i}^{start}}^{T_{l,i}^{end}}((\omega_{l,t} - W_{l,t}^{load})t)}{\sum_{t=T_{l,i}^{start}}^{T_{l,i}^{end}} W_{l,t}^{load}}, \quad \forall \ l \in L^v, i \in I(l) \qquad \text{(Eq. 23)}$$

Since this weighted average delay also may be negative (by shifting volume backwards), we introduce a new variable $\rho_{l,i}^{load}$ defined as:

$$\rho_{l,i}^{load} \geq \tau_{l,i}^{load}, \quad \forall \ l \in L^v, t \in \left\{T_i^{start}..T_i^{end}\right\}, \ i \in I(l) \qquad \text{(Eq. 24)}$$

$$\rho_{l,i}^{load} \geq -\tau_{l,i}^{load}, \quad \forall \ l \in L^v, t \in \left\{T_i^{start}..T_i^{end}\right\}, \ i \in I(l) \qquad \text{(Eq. 25)}$$

The total costs for shifting volume load is then:

$$\zeta^{l,v} = \sum_{l \in L^v} \sum_{i \in I} P_l^s \psi_{l,i} \qquad \text{(Eq. 26)}$$

5.2.3 EV models

The present EV model has been developed with the purpose of finding the optimal dispatch for charging the EV in a private charging station to provide flexibility services to prosumer, DOS or BRP.

the constraints given both by the EV owner or external agents like DSO or BRP at private stations, typically at home. Public installations could require a different approach.

Similar to generation units and load units the EV charging process may also have different degrees and types of flexibility:

- Inflexible EVs
- Shiftable
- Controllable
- Controllable and interruptible
- V2X

5.2.3.1 <u>Inflexible EVs</u>

For inflexible EVs ($v \in V^i$), i.e. EVs where the charging process cannot be controlled, the charging $\varphi_{v,t}^{ch}$ scheduled to be delivered to EV *v* in period *t* is equal to the predicted charging demand $W_{v,t}^{EV}$.

$$\varphi_{v,t}^{ch} = W_{v,t}^{EV}, \qquad \forall \ v \in V^i, t \in T \qquad \text{(Eq. 27)}$$

5.2.3.2 <u>Shiftable</u>

For shiftable EV units $v \in V^s$ we introduce the term charging session $i \in I(v)$, defined by connection T_i^{start} and disconnection T_i^{end} periods, respectively. Furthermore, we define the first V_i^{start} and last V_i^{end} period where the EV has a charging demand, given that it is not shifted. We introduce the variable $\gamma_{v,i,n}$ which is a binary variable set to 1 if consumption for EV unit *v* is shifted *n* periods for charging session *i.* Exactly one shifting option must selected for each shiftable EV unit in each charging session:

$$\sum_{n=T_i^{start}-V_i^{start}}^{T_i^{end}-V_i^{end}} \gamma_{v,i,n} = 1 \;\; \forall\, v \in V^s, i \in I(v) \qquad \text{(Eq. 28)}$$

The predicted charging demand must be allocated to the correct periods according to the decided shifting option:

$$\varphi_{v,t}^{ch} = \sum_{n=0}^{T_i^{end}-T_i^{start}} \gamma_{v,i,(t-T_{v,i}^{start}-n)} W_{l,(T_{v,i}^{start}+n)} \;\; \forall\, t \in \{T_i^{start}, T_i^{end}\}, i \in I(v), v \in V^s \qquad \text{(Eq. 29)}$$

The model is illustrated in Table 8.

Table 8. Illustrative example shiftable EV charging

	1	2	3	4	5	6	7	8
$W_{v,t}^{EV}$	3	3	2					
$\varphi_{v,t}^{ch}$			3	3	2			

The EV at hand connects in period 1 and disconnects in period 7, so we have: $T_i^{start} = 1, T_i^{end} = 7$. If no shifting of the charging is performed, it will start in period 1 and end in period 3: $V_i^{start} = 1$. $V_i^{end} = 3$. There are 5 shifting options: To shift 0, 1, 2, 3, or 4 periods. It is not possible to shift more than 4 periods and still meet the charging demand. In the example, the optimization algorithm has decided to shift the charging 2 periods, so $\gamma_{v,i,1} = 0, \gamma_{v,i,2} = 0, \gamma_{v,i,2} = 1, \gamma_{v,i,3} = 0, \gamma_{v,i,4} = 0$

For shiftable EV units, the cost for regulation is the product of the delay cost and the number of periods delayed. We calculate this cost according to the equation below:

$$\zeta^{EVshift} = \sum_{v \in V^S} \sum_{i \in I} P_v^S \sum_{n=0}^{T_i^{end}-V_i^{end}} \gamma_{v,i,n}\, n \qquad \text{(Eq. 30)}$$

<u>Model limitations:</u>

- The EV charging cannot be interrupted
- The predicted EV consumption profile must be completed.

5.2.3.3 Controllable

With controllable EVs ($v \in V^c$) we both can delay the charging process, but also control the power levels. In other word we can shape the charging profile. An example is given in Table 9.

Table 9. Illustrative example controllable EV charging

	1	2	3	4	5	6	7	8
$W_{v,t}^{EV}$	3	3	2					
$\varphi_{v,t}^{ch}$		2	1	3	2			

The starting point is the same as the illustration for shiftable EV charging (Table 8). The optimization model now decides to start the charging in period 2 with a reduced level and end in period 5. Notice that the profile/shape is different, although the total energy delivered is the same.

For controllable EVs we can control the power levels so they must be between a minimum E_v^{min} and a maximum E_v^{max} value or 0. This can be formulated as:

$$E_v^{min} \leq \varphi_{v,t}^{ch} \leq E_v^{max} \; or \; \varphi_{v,t}^{ch} = 0, \;\; \forall \, v \in V^c, t \in T(i) \qquad \text{(Eq. 31)}$$

For each charging session interval *i* the sum energy volume delivered to the EV must equal the sum baseline forecast.

$$\sum_{t=T_i^{start}}^{T_i^{end}} \varphi_{v,t}^{ch} = \sum_{t=T_i^{start}}^{T_i^{end}} W_{v,t}^{EV} \;\; \forall \, v \in V^c, i \in I(l) \qquad \text{(Eq. 32)}$$

For controllable EV units, we introduce the concept of weighted average delay, which has number of periods as unit. This also takes into account not only when you meet the finale volume, but also how you do it (penalizes more if large volumes are shifted to the end). The weighted average delay for controllable EV unit *v* and load shift interval *i* is defined like as:

$$\tau_{v,i}^{EV} = \frac{\sum_{t=T_{v,i}^{start}}^{T_{v,i}^{end}} ((\varphi_{v,t}^{ch} - W_{v,t}^{EV})t)}{\sum_{t=T_{v,i}^{start}}^{T_{v,i}^{end}} W_{v,t}^{EV}}, \;\; \forall \;\; v \in V^c, i \in I(v) \qquad \text{(Eq. 33)}$$

Since this weighted average delay also may be negative (by shifting volume backwards), we introduce a new variable $\rho_{v,i}^{EV}$ defined as:

$$\rho_{v,i}^{EV} \geq \tau_{v,i}, \quad \forall \ v \in V^c, t \in \left\{T_i^{start}..T_i^{end}\right\}, \ i \in I(v) \qquad \text{(Eq. 34)}$$

$$\rho_{v,i}^{EV} \geq -\tau_{v,i}, \quad \forall \ v \in V^c, t \in \left\{T_i^{start}..T_i^{end}\right\}, \ i \in I(v) \qquad \text{(Eq. 35)}$$

The total costs for shifting charging is then:

$$\zeta^{EVcontrol} = \sum_{v \in V^c} \sum_{i \in I} P_v^s \rho_{v,i}^{EV} \qquad \text{(Eq. 36)}$$

Model limitations:

- The EV charging cannot be interrupted
- The predicted EV consumption profile must be completed.

5.2.3.4 Controllable and interruptible

For controllable and interruptible EV units $(v \in V^d)$ we can delay, interrupt and reschedule the EV charging process. An example is given in Table 9.

Table 10. Illustrative example controllable EV charging

	1	2	3	4	5	6	7	8
$W_{v,t}^{EV}$	3	3	2					
$\varphi_{v,t}^{ch}$		2	1	0	2	2	1	

An alternative approach for the previously explained controllable EV model $(v \in V^c)$ is presented in this section and it uses some battery model equations previously presented. This is a charging demand model which manages the needed energy by an EV between its arrival $(T_v^{EV,start})$ and departure $(T_v^{EV,end})$ times.

The energy forecasted $W_{v,t}^{EV}$ is used for creating the following charging demand parameters:

$$\sum_t W_{v,t}^{EV} = O_v^{CD}, \qquad \forall v \in V^c, t \in [T_v^{EV,start}, T_v^{EV,end}] \qquad \text{(Eq. 37)}$$

$$\sigma_{v,t}^{CD} = 0, \qquad \forall v \in V^c, t = T_v^{EV,start} - 1 \qquad \text{(Eq. 38)}$$

The state-of-charge equations are:

$$\sigma_{v,t}^{CD} = \sigma_{v,t-1}^{CD} + \sigma_{v,t}^{CD,ch}, \qquad \forall v \in V^c, t \in [T_v^{EV,start}, T_v^{EV,end}] \tag{Eq. 39}$$

$$\sigma_{v,t}^{CD} = O_v^{CD,min}, \qquad \forall v \in V^c, t = T_v^{EV,end} \tag{Eq. 40}$$

Notice in (Eq. 39) there is no charging efficiency parameter included because it is not necessary to be considered. Additionally, (Eq. 40) ensures that a minimum energy level ($O_v^{CD,min}$) is supplied to the EV unit *v* at the end of the charging process (*t*=*T*). It can be exactly the charging demand

The maximum charging demand per period is semi-positive and it is the EV charging station power limit:

$$\sigma_{v,t}^{EV,ch} \leq \frac{Q_v^{EV,ch}}{N^{hour}}, \qquad \forall v \in V^c, t \in T \tag{Eq. 41}$$

The following cost function compensates for the difference between the expected EV charging demand estimated by the FO ($W_{v,t}^{EV}$) and the result of applying the set-points ($\sigma_{v,t}^{CD}$). Additionally, this difference is relative to the total charging demand expected (O_v^{CD}). Notice that an EV could be rewarded even in cases that the EV is not fully charged when it leaves. This is included in the compensation fee ($P_v^{EV,NS}$) for every kWh not supplied

$$\zeta^{EV,control} = \sum_{v \in V^c} \sum_{t \in T} P_{v,t}^{EV} \frac{W_{v,t}^{EV} - \sigma_{v,t}^{CD}}{O_v^{CD}} + P_v^{EV,NS} (O_v^{CD} - \sigma_{v,T_v^{EV,end}}^{CD}) \tag{Eq. 42}$$

Model assumptions and limitations:

1) Charging power: The power input from the EV charger is assumed to be independent of the state of charge. This assumption holds true for chargers with a small power-rate which typical in residential installations. As this model is meant for mainstream and cheap charging technologies, the charger is assumed to have a small to medium power available. Typically, 3.3 kW and up to 11 kW.
2) Flexibility contracts: The information from flexibility contracts for EV and loads are the same. Therefore, the EV owner declares the periods when the EV can be shifted forward.
3) Information from EV users: This model assumes to not have information from EV SOC or departure time.

Input data:

This model relies on the forecasting tools capable to create the input data requested to execute the EV flexibility model for scheduling purposes.

1) $W_{v,t}^{EV}$: The expected EV energy consumption without external signals of each EV *v* at time period *t* [kWh].

Model limitations:

- It requires an accurate forecasting system for knowing the EV energy consumption and departure times in case of not having this information.

5.2.3.5 V2X

The state-of-charge equations are:

$$\sigma_{v,t}^{EV,SOC} = \sigma_{v,t-1}^{EV,SOC} + \sigma_{v,t}^{EV,ch} \cdot A_v^{EV,ch} - \frac{\sigma_{v,t}^{EV,dis}}{A_v^{EV,dis}}, \quad \forall v \in V^2, t \in [T_v^{EV,start}, T_v^{EV,end}] \qquad \text{(Eq. 43)}$$

Constraint (Eq. 44) ensures a certain EV SOC ($\sigma_{v,t}^{EV,SOC}$) at a particular instant (T^*) if it is required.

$$\sigma_{v,t}^{EV,SOC} = O_{v,t}^{EV,min,t}, \qquad \forall v \in V^2, t = T_v^{EV,start} \qquad \text{(Eq. 44)}$$

The following constraint ensures that the battery is not discharged below the state-of-charge level when the EV arrived to the charging station:

$$E_v^{start} = \sigma_{v,t}^{EV,SOC}, \qquad \forall v \in V^2, t = T_v^{start} \qquad \text{(Eq. 45)}$$

$$\sigma_{v,t}^{EV,SOC} \geq E_v^{start}, \qquad \forall v \in V^2, t = [T_v^{EV,start}, T_v^{EV,end}] \qquad \text{(Eq. 46)}$$

The maximum energy charged and discharged to batteries per period is semi-positive and follows:

$$\sigma_{v,t}^{EV,ch} \leq \frac{Q_v^{EV,ch}}{N^{hour}}, \qquad \forall v \in V^2, t \in T \qquad \text{(Eq. 47)}$$

$$\sigma_{v,t}^{EV,ch} \leq \frac{-Q_v^{EV,ch} / N^{hour}}{1 - S_v^{EV,ch}} \left(\frac{\sigma_{v,t}^{EV,SOC}}{O_v^{EV,max}} - 1 \right), \quad \forall v \in V^2, t \in T \qquad \text{(Eq. 48)}$$

$$\sigma_{v,t}^{EV,dis} \leq Q_v^{EV,dis}, \qquad \forall\, v \in V^2, t \in T \qquad \text{(Eq. 49)}$$

$$\sigma_{v,t}^{EV,dis} \leq \frac{Q_v^{EV,out} / N^{hour}}{S_v^{EV,dis}} \left(\frac{\sigma_{v,t}^{EV,soc}}{O_v^{EVmax}} \right), \qquad \forall\, v \in V^2, t \in T \qquad \text{(Eq. 50)}$$

The total cost for managing V2X charging stations is composed by two terms: discharging cost ($P_{v,t}^{EV,V2X}$) and the non-supplied energy cost ($P_v^{EV,NS}$). Discharging cost is proportional to the energy discharging from the EV battery each period ($\sigma_{v,t}^{EV,dis}$). Charging penalty fee is proportional to the non-supplied energy to the EV ($O_v^{CD} - \sigma_{v,T}^{CD}$).

$$\zeta^{EV,V2X} = \sum_{v \in V^2} \sum_{t \in T} \left(P_{v,t}^{EV,V2X} \sigma_{v,t}^{EV,dis} + P_v^{EV,NS} \left(O_v^{CD} - \sigma_{v,T}^{CD} \right) \right) \quad \text{(Eq. 51)}$$

5.2.4 Generator models

As described in Section 2.5.4 the generation unit models can be split into the following classes:

- Inflexible generation units
- Curtailable disconnectable generation units
- Curtailable reducible generation units

5.2.4.1 Inflexible

For inflexible generation units the scheduled production $\psi_{g,t}$ must be equal to the baseline (predicted) production $W_{g,t}^{prod}$.

$$\psi_{g,t} = W_{g,t}^{prod}, \qquad \forall\, g \in G^i, t \in T \quad \text{(Eq. 52)}$$

5.2.4.2 Curtailable

For curtailable reducible generation units, scheduled production must be between 0 and predicted production.

$$0 \le \psi_{g,t} \le W_{g,t}^{prod}, \qquad \forall\, g \in G^r, t \in T \quad \text{(Eq. 53)}$$

For disconnectable generation units, scheduled production must be either 0 or equal to predicted production.

$$\psi_{g,t} = \delta_{g,t} W_{g,t}^{prod}, \qquad \forall\, g \in G^d, t \in T \quad \text{(Eq. 54)}$$

The total costs for reducing generation volume is then:

$$\zeta^{gen} = \sum_{g \in G^d} \sum_{t \in T} P_{g,t}^{G} \left(W_{g,t}^{prod} - \psi_{g,t} \right), \qquad \forall\, g \in G^d, t \in T \quad \text{(Eq. 55)}$$

5.2.5 Aggregated flexibility models

Models at aggregated levels will be formulated at a later stage.

5.3 Specific models for DSO services

This section exposes the mathematical formulation of the DSO service. This service will be tested in the Spanish pilot. Following the description included in the Section 2.2, the following equations represent the system formed by the DSO, requesting flexibility, the FO, aggregating flexible assets and flexible assets, capable to supply flexibility.

5.3.1 Objective function

The following objective function is the total cost for the FO for activating flexibility to meet the DSO request.

$$\min z = \sum_{t\in T}\left(\sum_{g\in G} P_{g,t}^{G}\left(W_{g,t}^{prod} - \psi_{g,t}\right) + \sum_{b\in B} P_{b,t}^{B,ch}\sigma_{b,t}^{ch} + P_{b,t}^{B,disc}\,\sigma_{b,t}^{dis} + \sum_{l\in l^{c}} P_{l,t}^{load}\left(\delta_{l,t}^{start} + \delta_{l,t}^{run}\right)\right) + \sum_{l\in L^{v}}\sum_{i\in I} P_{l}^{s}\psi_{l,i} + \sum_{v\in V^{c}}\left(\sum_{t\in T}\left(P_{v,t}^{EV}\frac{W_{v,t}^{EV} - \sigma_{v,t}^{CD}}{O_{v}^{CD}}\right) + P_{v}^{EV,NS}\left(O_{v}^{CD} - \sigma_{v,T_{v}^{EV,end}}^{CD}\right)\right) \quad \text{(Eq. 56)}$$

This function reflects the reimbursed cost to flexible asset owners.

5.3.2 DSO services specific constraints

The total flexibility given by the portfolio is equal to the summation of all the individual flexibilities. Positive flexibility means upward regulation. This would be:

$$Flex_{t} = \sum_{b\in B}\left(\sigma_{b,t}^{dis} - \sigma_{b,t}^{ch}\right) + \sum_{g\in G}\left(\psi_{g,t} - W_{g,t}^{prod}\right) + \sum_{l\in L^{d}} W_{l,t}^{load}\left(\delta_{l,t}^{start} + \delta_{l,t}^{run}\right) + \sum_{L^{p}}\left(W_{l,t}^{load} - \omega_{l,t}\right) + \sum_{L^{v}}\left(W_{l,t}^{load} - \omega_{l,t}\right) + \sum_{v\in V^{s}}\left(W_{v,t}^{EV} - \varphi_{v,t}^{ch}\right) + \sum_{v\in V^{c}}\left(W_{v,t}^{EV} - \sigma_{v,t}^{CD}\right) \quad \text{(Eq. 57)}$$

the DSO can define for each hour a minimum and a maximum threshold for the flexible profile. The maximum and minimum level allows the DSO, in case of needed, to avoid a rebound effect after meeting DSO requests. This effect is shown in Figure 75.

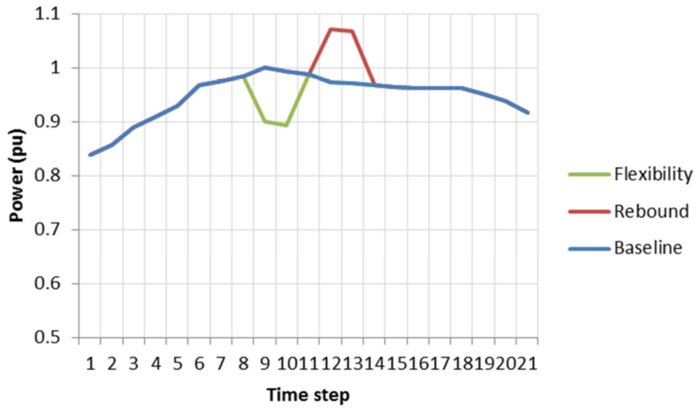

Figure 75. Example of flexibility activation and the rebound effect

This DSO will calculate this request based on the analysis of the network and the detection of congestion problems. The following equation shows how the constraints are set by the DSO.

$$D_t^{DSO,min} \leq Flex_t \leq D_t^{DSO,max} \qquad \text{(Eq. 58)}$$

Note that in this framework, the DSO does not necessarily require a maximum and minimum regulation simultaneously. An additional advantage of this approach is that in cases in which neither an up or down regulation is required the DSO can anyway give a limit to the flexibility demand [18].

The following figure shows one example case with double side request and the corresponding flexibility activated.

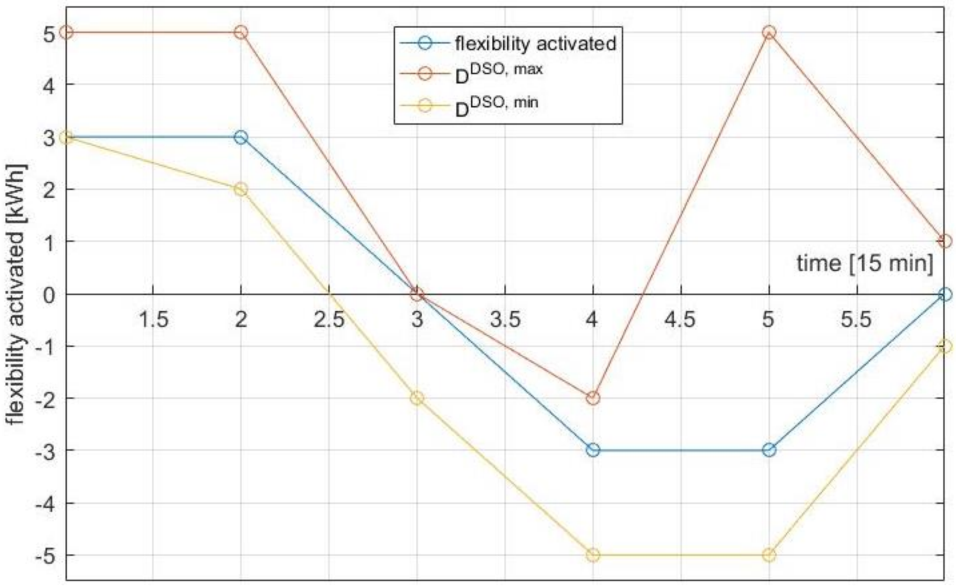

Figure 76. DSO max and min request and activated flexibility [18]

5.4 Specific models for Prosumer services

5.4.1 Objective function(s) and pilot specific constraints for prosumer services

5.4.1.1 Norwegian pilot

According to the description of the Norwegian tariff structure in Section 3.1.4, the prosumer objective function is as follows.

The objective is to minimize the total expected costs, consisting of costs for the electricity retail contract (energy related fee), electricity taxes, grid contract (energy and peak demand charge), and minus revenues from selling surplus electricity back to the grid. Finally, the costs for activating flexibility are included. The objective function is formulated in Equation (59):

$$\begin{aligned} \min z = \sum_{t\in T} \big[\big(P_t^{retail-buy} + P_t^{grid-buy} + P_t^{tax} \big)\chi_t^{buy} P^{VAT} \\ - \big(P_t^{retail-sell} + P_t^{grid-sell}\big)\chi_t^{sell}\big] + P^{peak}\chi^{peak}P^{VAT} \\ + \zeta^{flexibility} \end{aligned} \qquad \text{(Eq. 59)}$$

Here, $t \in T$ include all periods (time slots) within the planning horizon. The first parenthesis includes the costs related directly to the amount bought χ_t^{buy}, i.e. imported to the site in period *t*. This decision variable is multiplied with the prices for the energy part of the retail contract, the grid contract and the taxes, respectively. Recall that the grid contract might have different prices for different energy levels. In such cases, the price will be a function of the energy level, $P_t^{grid-buy}(\chi_t^{buy})$. The taxes consist of the following elements:

- Electricity tax, also named consumption tax. For 2017, the price is 0.1632 NOK/kWh[13]
- Energy fund tax, also named Enova-tax. For 2017, the price is 0.01 NOK/kWh

In addition, value added tax, VAT, must be included. This is a tax that is treated differently from the other taxes, since it comes on top of the other costs, including the peak fee. Currently the VAT is 25%, so we will have $P^{VAT} = 1.25$.

The second parenthesis covers the revenues from selling surplus electricity.

The third term covers the peak cost at the grid contract, which will be 0 in cases without a peak fee. An issue here is that the planning horizon probably will be a few hours or a day or two, while the peak fee is based on a month. More on this issue in the next section.

[13] https://www.energinorge.no/fagomrader/skatt-og-okonomi/nyheter-gammelt/2016/konsesjonskraftpris-og-skatte--og-avgiftssatser-2017/

The last part of the objective function is the cost for utilizing the flexibility from the internal resources. This cost may cover a wide variety of costs that must be further discussed, but some examples are:

- Loss of comfort from shifting or curtailing loads
- Disutility from delaying EV charging or even from not meeting the charging demand
- Battery aging

The contribution to $\zeta^{flexibility}$ has been described under each section for the different resource types.

5.4.1.2 Dutch pilot

The objective functions for the different Dutch pilot sites will be formulated at a later stage, after further discussions with Elaad and GreenFlux.

5.4.1.3 Bulgarian pilot

According to the pilot specification in section **Error! Reference source not found.**, the ain objective is to shift as much as possible of the load from the peak-load hours to the off-peak load hors. This can be formulated as:

$$min\, z_{Bulg1} = \sum_{t=9}^{20} \chi_t^{buy} \quad \text{(Eq. 60)}$$

An alternative formulation is to maximize the up-regulation in the peak load hours:

$$max\, z_{Bulg2} = \sum_{t=9}^{20} \left(\sum_{b \in B} \sigma_{b,t}^{B,out} - \sum_{b \in B} \sigma_{b,t}^{B,in} + \sum_{l \in L} \left(W_{l,t} - \omega_{l,t} \right) \right) \quad \text{(Eq. 61)}$$

Notice that this formulation only covers batteries and flexible loads. Also notice that it presupposes that the battery has no baseline schedule. If other resource types, like EV charging points are added, or batteries have a baseline schedule, the formulation must be changed.

5.4.1.4 Spanish pilot

Not applicable in phase 1.

5.4.2 Prosumer services specific constraints

5.4.2.1 Electricity balances behind the meter

The internal energy balance behind the meter allows of distinguishing the different value of energy self-generated, stored, imported or exported. To ease the explanation of the model, Figure 77 illustrates some key relations between the different types of resources and some decision variables.

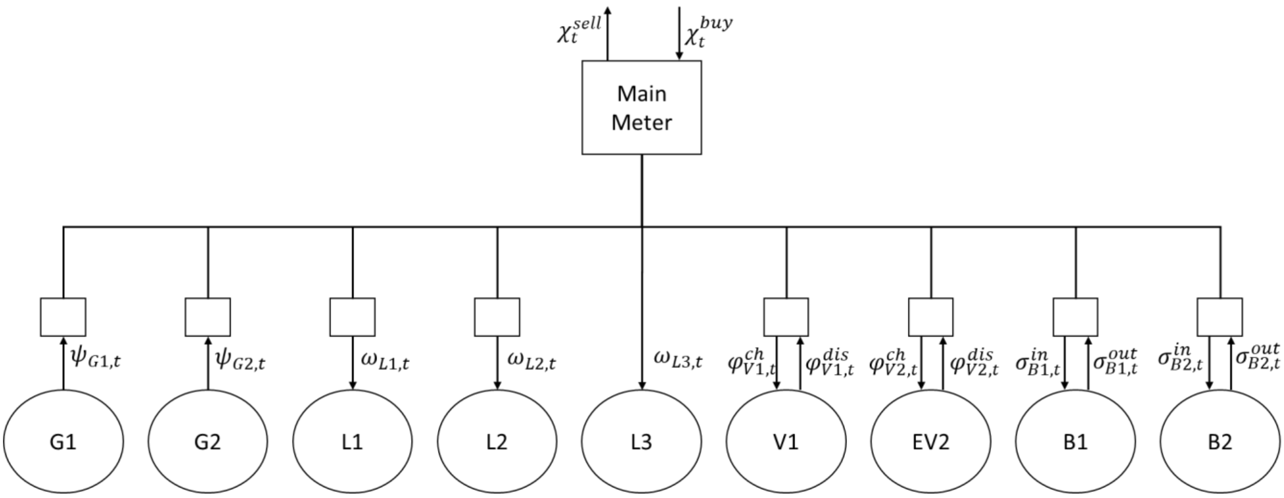

Figure 77. Illustration of model with some central decision variables.

The total import from or export to the grid must balance production from generation units, consumption in load units, charging and discharging of EVs and charging and discharging of batteries for each period:

$$\sum_{g\in G}\psi_{g,t}+\sum_{v\in V}\varphi_{v,t}^{dis}+\sum_{b\in B}\sigma_{b,t}^{dis}+\chi_t^{buy} = \chi_t^{sell}+\sum_{l\in L}\omega_{l,t}+\sum_{v\in V}\varphi_{v,t}^{ch}+\sum_{b\in B}\sigma_{b,t}^{ch}, \forall\, t\in T \qquad \text{(Eq. 62)}$$

We introduce binary variables $\delta_t^{buy}, \delta_t^{sell}$ which are 1 of the site is buying (importing) or selling (exporting), respectively, else 0. The site can not buy and sell in the same period:

$$\delta_t^{buy}+\delta_t^{sell}\le 1, \qquad \forall\, t\in T \qquad \text{(Eq. 63)}$$

Electricity bought or sold must be below capacity limits:

$$\chi_t^{buy}\le \delta_t^{buy}X^{imp-cap}, \qquad \forall\, t\in T \qquad \text{(Eq. 64)}$$

$$\chi_t^{sell}\le \delta_t^{sell}X^{exp-cap}, \qquad \forall\, t\in T \qquad \text{(Eq. 65)}$$

Notice that in cases with a kWmax value that is physical, $X^{imp-cap}$ must be set to this value. In some cases this value might be dynamic (?). Then we need to introduce a time index.

Also notice that in some cases $X^{exp-cap}$ will be a physical limit, while in others it might be a commercial or regulatory limit. The last is the case with the plus-customer arrangement in Norway. Then we will have $X^{exp-cap} = 100$ kW. In Bulgaria, where there is no arrangement for selling electricity back to the grid, we will have $X^{exp-cap} = 0$ kW.

In cases with subscribed power, the cost of the energy part of the grid fee $P_t^{grid-buy}$ will be dependent on the consumption level χ_t^{buy}. Assume that there will be two prices, $P_t^{grid-buy-low}$ and $P_t^{grid-buy-high}$, where the low price is valid for periods where the bought volume is below a threshold value. This can be formulated:

$$P_t^{grid-buy} = P_t^{grid-buy-low}, if\ \chi_t^{buy} \leq X^{subscribed} \quad \text{(Eq. 66)}$$

$$P_t^{grid-buy} = P_t^{grid-buy-high}, if\ \chi_t^{buy} > X^{subscribed} \quad \text{(Eq. 67)}$$

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INVADE

*Smart system of renewable energy storage based on **IN**tegrated E**V**s and b**A**tteries to empower mobile, **D**istributed and centralised **E**nergy storage in the distribution grid*

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Table of contents

Abbreviations and Acronyms

Acronym	Description
AC	Alternating Current
BD	Benders Decomposition
BRP	Balancing Responsible Party
DER	Distributed Energy Resources
DG	Distributed Generation
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution System Operator
EV	Electric Vehicle
FO	Flexibility Operator
FR	Flexibility Reserve
LV	Low voltage
MIP	Mixed Integer Problem
MILP	Mixed Integer Linear Programing
NLP	Nonlinear Programming
NPV	Net Present Value
OPF	Optimal Power Flow
PV	Photovoltaics
RES	Renewable Energy Sources
SOC	State Of Charge
ToU	Time of Use

Executive summary

The deployment of batteries in the distribution network can provide an array of flexibility services to integrate renewable energy sources (RES) and improve grid operation in general. Capturing and quantifying the value of storage for different flexibility services require models that can represent the technological detail of battery-RES-load interactions to provide scheduling strategies for real-time operations. For this purpose, deliverable 5.3 focuses on models and algorithms for: 1) battery capacity and location planning, 2) daily operations and 3) real-time control.

Battery sizing has different implications and benefits for distribution system operators (DSO), balance responsible parties (BRPs) and prosumers, respectively. In this document, the issues and approaches related to siting, capacity planning and investment analysis are discussed. A simplified planning strategy that leverages the control strategies of battery charging and discharging to find the optimal location and size of batteries in distribution system is presented. A general planning algorithm from both prosumer and DSO perspectives are presented. This is complemented with illustrative examples on battery-PV sizing analyses for prosumers. The simplified sizing methods are tested for the pilots in Albena Hotel (Bulgaria) and small houses in the Netherlands. According to D 4.2 [1], in order to implement flexibility services progressively, the INVADE implementation has been divided in two phases. Here, phase 1 includes the implementation of prosumer services for ToU optimization, kWmax control and Self-balancing plus the DSO service congestion management. Note that in a separate document (D5.3-Flexibility operations algorithms-phase 1), the details of the simplified model intended for phase 1 are fully described. This model will be implemented in the platform of the INVADE flexibility cloud as part of T8.3.

1 Introduction

INVADE deliverable D5.3 “Simplified Battery operation and control algorithm” is divided into two documents: 5.3-first part and 5.3-second part. D5.3-first part presents design and program the flexibility management operation algorithm as part of 5.4, whereas the D5.3-second part presents energy storage units allocation/positioning and sizing algorithm as part of task 5.3. This document describes simplified models and methods for siting and sizing of batteries. In this deliverable, a simplified model means that the representation of batteries are assumed to have linear charging and discharging power characteristics, which is irrespective of its state of charge (SOC). The charge/discharge efficiency of the battery are assumed to be constant and not depend of their SOC, cell operating temperature and charging/discharge power. The battery and EV models will be extended in WP6 (T6.4 “Advanced Battery techno-economic model”) by including more technical parameters and economics of second life batteries. Another example of simplification is that adjustable loads like thermal loads are modelled with an assumption of linear relation between their energy consumption and temperature.

1.1 INVADE Flexibility Services: siting and sizing considerations

Proper sizing of the flexibility resource (i.e. batteries) is important for investment planning decisions and siting is key for its effective operation. The siting and sizing decision differs based on the flexibility services required and the user cases (mobile, distributed, centralized and hybrid). INVADE defined possible flexibility services for prosumers, DSOs and BRPs. In this document, we focus on the prosumer and DSO perspectives.

There are three flexibility services in consideration for prosumers. First, the Time of Use (ToU) flexibility service uses a battery for the effective utilization of local RES production and to avoid high tariffs by managing high peak demand. That is, the prosumer demand is adjusted in such a way (due to battery presence) that the consumption from the grid at peak hours will be moved to off-peak hours. In this case, the battery sizing algorithm will decide the battery capacity by considering the demand and local RES production. The second flexibility service from the prosumer perspective is kWmax control. This service limits the maximum amount of power imported or exported to the grid at any time at the prosumer level. If the kWmax is linked to a physical limitation, it becomes an additional constraint for optimization problem on both battery sizing and load shifting on day-to-day operation. However, if it is linked to a tariff structure, it can model as a penalty for maximum purchase. The third flexibility service is self-balancing in which the battery supports possible zero import and export of energy from the grid. A proper battery size would allow to optimally balancing demand and local RES production. The detailed operation strategy for day-to-day operation for prosumer services are given in the 5.3 first document. In D5.3 second document, through a simplified operational model, we illustrate and test how different battery sizes affects the integration of PV capacity under kWmax control restrictions. This illustrative example is applied to the pilots in The Netherlands and Bulgaria (see chapter 3). Note that for prosumers, only the sizing part of the problem is relevant there is usually one single location: the prosumer and its on-site RES.

Regarding the DSO perspective, there are three flexibility services considered: 1) congestion management, 2) voltage/reactive power control and 3) controlled islanding. D5.3 focuses on congestion management since it has be considered as a DSO service included in phase 1 of the INVADE implementation. For this flexibility service, the DSO sends requests to a flexibility operator (FO) to activate or call for available flexibility sources. Then, the FO schedules the batteries charge/discharge operations at the neighbourhood and prosumer levels to meet the requirement of the DSO. For example, the storage at the neighbourhood level could be one large array of battery bank located near the substation or multiple arrays of battery banks located at different nodes. In this situation, battery siting and sizing plays an important role specially to increase RES penetration in the distribution network without violating the network power flow limits. The siting of batteries might be constrained by the electric distribution network topology and their power flow capacities. Poor siting of batteries may bring underutilization of the resources as well as they could create new voltage and congestion problems in the distribution network. Therefore conducting optimal power flow (OPF) analyses for the different siting options in the distribution network is essential to determine the most beneficial locations. The Optimal Power Flow (OPF) problem for alternating current (AC) circuits concerns the problem of determining the voltage magnitude, the voltage angle, the real power injection, the reactive power injection at each given grid node to minimize a cost function. Typical objective functions used in OPF problems are the total generation. The constraints for OPF include (i) the AC power flow constraints, (ii) bounds on power generation, (iii) bounds on bus voltage magnitudes, (iv) bounds on thermal losses, and (v) limits on power transfer on lines. Unlike the transmission systems, the nodal voltages of the distribution systems are influenced by the active and reactive power flows and their directions. Moreover, it is the responsibility of the distribution system operator to maintain the voltages within the allowable limits. On the other hand, if the battery storage is included due to the multi-period time dimension introduced by the battery storage, a few consecutive and coupled optimal power flows are needed to simulate the charge/discharge battery cycle over given operating horizon [2].

The siting problem, using multi-period OPF is a mixed nonlinear integer program due to nonlinearity of AC power flow equations, which might become computationally intractable for large-scale optimization problems [3-6].

1.2 Siting and sizing consideration for pilots

There are five pilots planned in the project INVADE as described in D4.2[1]. The details of the different pilots and their association with the different DSO and Prosumer services are detailed here.

1) Norwegian pilot: The Norwegian pilot will demonstrate 3 different prosumer service. They are ToU optimization, kWmax control and Self-balancing. For Norwegian pilot, the problem is more focused around the sizing of storage rather than siting.
2) Dutch pilot: The Dutch pilot has both DSO and prosumer service in their demonstration. This pilot will demonstrate congestion management and voltage / reactive control as DSO services and ToU optimization, kWmax control and Self-balancing as prosumer services. Both DSO and prosumer services of this pilot are provided from the prosumer flexibility and mobile batteries of EV. Therefore, sizing is the primary problem and siting problem will focus on OPF for providing DSO services.
3) Bulgarian pilot: The Bulgarian pilot is a large prosumer case to demonstrate 3 prosumer services and the 4^{th} prosumer service “Controlled islanding” maybe included based on the feasibility at the time of implementation. Therefore, the Bulgarian pilot exposes the sizing problem only.
4) German pilot: The 3 prosumer services ToU optimization, kWmax control and Self-balancing and the DSO service congestion management are planned for the German pilot. The source of flexibility for this pilot is from both distributed and centralized storage. Therefore, both siting and sizing are equally important for German pilot.
5) Spanish pilot: The Spanish pilot primarily demonstrate the DSO services namely congestion management with centralized storage. Therefore, the siting problem is as important as the sizing problem.

2 Simplified planning model in Sizing and Siting problems

The main objective of this section is to develop a simplified planning strategy that leverages the control strategies of battery charging and discharging acting on control horizons to find the optimal location and size of batteries in distribution system. The planning strategy links the operational domain with the planning domain to find an optimal investment decision.

The methods to be used is based on calculating the Net Present Value (NPV) of a battery investment, which is the difference between the present value of cash inflows and the present value of cash outflows. For a battery investment (and installation) at the start of the analysis period is cash outflows and operational net benefits are deemed as cash inflow. Hence, the NPV is in its simplest form given as Eq. (2.1) [7].

$$NPV(P_{rat}, E_{rat}) = [\sum_{n=1}^{N} \frac{R(P_{rat}, E_{rat}, n) - O(P_{rat}, E_{rat}, n)}{(1+r)^n}] - C(P_{rat}, E_{rat}) \qquad \text{(Eq. 2.1)}$$

Where, *R* is the annual revenue, *O* is the annual operational costs and *C* is the equivalent annual installation cost, which is dependent of the rated power and energy storage capacity of the battery. By assuming that each year is equal and neglecting maintenance costs of the battery, we obtain

$$NPV(P_{rat}, E_{rat}) = [R(P_{rat}, E_{rat}) - O(P_{rat}, E_{rat}, n)] - \alpha_{N,r} \cdot C(P_{rat}, E_{rat}) \qquad \text{(Eq. 2.2)}$$

Where, α is the annuity factor[1]. The annual revenue can be expressed as Eq. (2.3).

$$R(P_{rat}, E_{rat}) = \sum_{t=1}^{T} R_{op}(P_{rat}, E_{rat}, t) + R_{fixed}(P_{rat}, E_{rat}) \qquad \text{(Eq. 2.3)}$$

The resolution of the time step *t* depends on the market conditions and technical requirements for activation of services. The time step size *t* can, e.g., be one minute, 15 minutes or 1 hour. In this document, we use several terminologies about planning horizon, and we have explain them in the following bullets:

- The shortest planning horizon is the operational planning horizon represented by *T* in Eq. (2.3), e.g. 6 hours, 12 hours, or 24 hours

[1] $\alpha_{n,r} = \frac{r}{1-(1+r)^{-n}}$ where, r is discount rate

- The medium planning horizon is related to how many operational situations we will base our investment decision on. This can be one year (or more, depending on long-term uncertainties regarding spot prices, load development etc). Usually we use "one representative year", but a realistic model should cover more
- The long-term planning horizon is at least as long as the economic lifetime of the investment option, i.e. the battery in our case represented by *N* in Eq. (2.1)

In general, the economic optimal size of the battery is the size that maximizes the NPV, taking into account all technical constraints and market possibilities. This is a trade-off between operational benefit – given the battery's technical capabilities - and investment cost.

2.1 A planning algorithm from the prosumer perspective (Sizing problem)

We introduce a planning algorithm from different grid user perspectives. First, we focus on the prosumer perspective, where the operating objective function refers to the electricity bill minimization problem. In this problem, the primary objective is to find the optimal sizing of the battery that maximizes the NPV. Hence, *R* is operational cost savings due to flexibility that the battery will provide to the prosumer compared to a system without the battery. The annual revenue is the sum of revenues obtained from prosumer services. The prosumer model is similar to the model illustrated in D5.3-first part, "Design and program the flexibility management operation algorithm". The prosumer is equipped with the main meter, which is placed at the border of connection point to the network, and may have sub meters (at the resource level). The prosumer can have one or several flexibility resources as following:

- Generator resources
- Load resources
- Electric vehicles (EVs)

The detailed model of the above flexibility sources is presented in D5.3-first part. The model is shown in Figure 1.

Figure 1

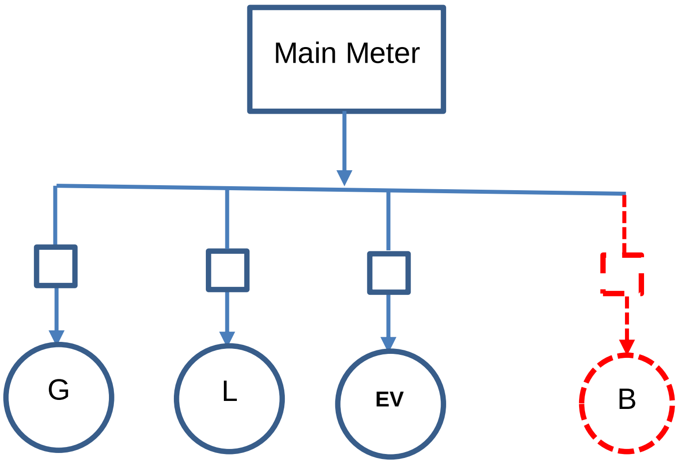

Figure 1. Prosumer model

2.2 A planning algorithm from the DSO perspective (Sizing and Siting problem)

In contrast, one of the planning objectives of the DSO is to maximize the distributed generation (DG) hosting capacity at the lowest cost with minimal grid congestion and overvoltage. From DSO point of view, the conventional way of integrating considerable amounts of DGs and electric vehicles would require significant investments for the network reinforcement and expansion. The installation of battery storage in the low/medium voltage level is an interesting alternative for solving the aforementioned technical problems and could therefore avoid or at least reduce or postpone the need for extensive conventional network reinforcements. Hence, the planning strategy includes both an optimal placement and sizing problem complying with grid constraints and storage constraints. In order to reach this goal, we need to implement multi-period OPF problem to solve an optimal placement and sizing problem for an infinite operating horizon. The objective of this optimization problem is to calculate revenues from activation of the battery and find a break-even point in battery investment.

The low/medium voltage grid model included in this algorithm is shown in Figure 2. The grid consists of a group of prosumers that might have DG, e.g., PV generators and flexible/inflexible load. Each prosumer has a meter placed at the connection point to the network. Moreover, it is assumed that each bus is a candidate to install battery shown with dotted red circle in Figure 2.

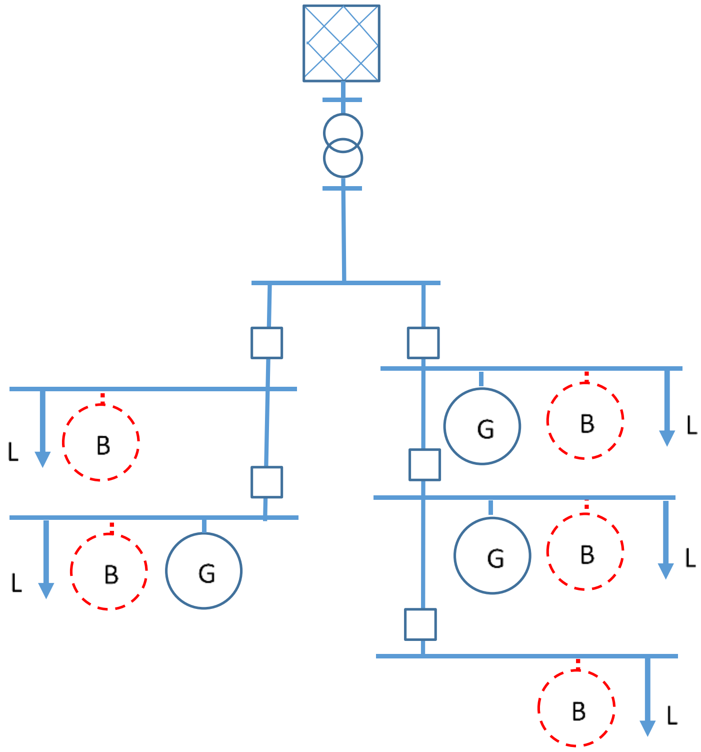

Figure 2: low/medium voltage grid

2.3 Bi-level Optimization Model

As we have already discussed, the optimal sizing and placement of battery requires the resolution of a temporal and spatial problem. The temporal problem implies a coupling of multiple time steps to ensure coherence of the battery state of charge (SOC) between each consecutive time step, which is typically one hour. One the other hand, in order to find the investment decision that is economic viable we need to compare annual benefit with equivalent annual investment costs. The long planning horizons and intertemporal coupling (storage) lead to an intractable planning problem. Hence, in this sub-chapter we will explain how we can solve this issue. A typical solution is to decompose the problem with respect to time. The decoupling for battery management algorithm could be chosen to be done on different operational time horizons, e.g., 6 hours, 24 hours, and the time granularity for the battery management model can range from 15 minutes to one hour. These timing horizons are shown in Figure 3. The coupled time steps of the battery management algorithm is then simulated for each planning horizon in order to successfully complete an annual analysis. Hence, the problem is split into a bi-level optimization problem [8] .

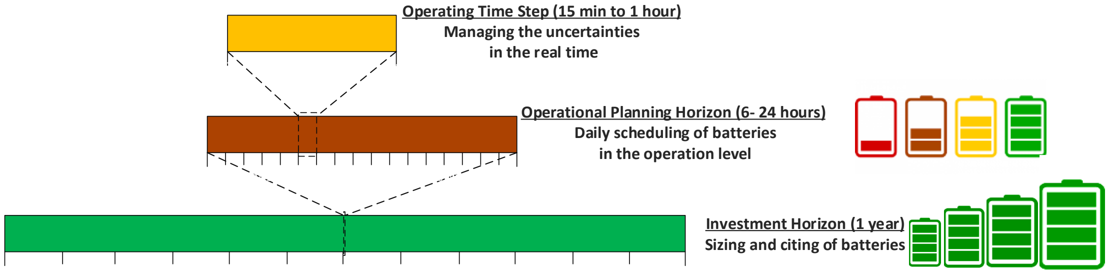

Figure 3. The different time horizons in planning model of battery sizing and siting

Bi-level optimization is characterized as a mathematical program with two levels of optimization, i.e., master and slave optimization problems. The master is commonly referred to as the upper level optimization problem and the slave problem is commonly referred to as the lower level optimization problem.

In this respect, the sizing and siting problem can be split into a storage planning master problem, where we decide about economic viable of battery investment, i.e., NPV maximisation, and sequentially-solvable sub-problems reflecting the operational strategy. Further process of splitting the problem will be explained in the following sub-chapters.

2.4 Simple investment model from the prosumer point of view

As we have already explained, the primarily objective for planning algorithm from prosumer perspective is to find the optimal sizing of the battery. The sizing algorithm focuses on evaluating the ideal battery size, i.e. maximum charging /discharging power and energy capacity, at prosumer side in order to maximize the NPV, while satisfying technical constraints.

The optimal battery size is obtained such that a battery with minimum size is able to store surplus energy produced by the prosumer. The term surplus energy refers to the amount of energy that has to be curtailed or stored, and used later in order to minimise prosumer's operating cost. In principle, we can formulate the objective function as the sum of operating cost over one year plus the equivalent annual battery installation cost. The algorithm then minimizes the objective function such that all technical constraints are meet. The inputs to the algorithm consist of the technical parameters of flexibility sources at prosumer side, i.e., load, generator, EV, and the equivalent annual battery installation cost per kWh. The output is the optimal size of the battery.

A comprehensive formulation of flexibility operation algorithm has been presented in the first document of this deliverable, i.e., "Flexibility operation algorithms – phase 1". In the first document, the objective function of flexibility operation has been presented from different pilot perspectives. Typically, the objective for the prosumer is to minimize the total expected operating costs, which in return may result in minimizing the peak load. This can be presented by the Eq. (2.4).

$$
\begin{aligned}
& J = \min \sum_{\tau \in T} F_\tau(\chi_\tau) \\
& \text{s.t.} \\
& \text{(a)}\ \ \mathrm{A}^{eq} \begin{bmatrix} \psi_\tau \\ \chi_\tau \end{bmatrix} = b^{eq} \\
& (b)\ \mathrm{A}^{in} \begin{bmatrix} \psi_\tau \\ \chi_\tau \end{bmatrix} \le b^{in} \\
& (c)\ A_s.\omega \le b_s
\end{aligned}
\qquad \text{(Eq. 2.4)}
$$

Where χ_τ represents the amount of electricity bought/sold in the period t [kWh] or a basis for calculation of the peak fee depending on the grid tariff structure. ψ_τ is representing control variables of available flexibility services. A^{eq} and A^{in} are matrices representing technical constraints of procuring flexibility from the flexibility sources. A_s is an intertemporal battery coupling matrix, and ω is a battery energy capacity. In principle, this constraint (Eq. 2.4-c) represents the coupling between the SOC on battery.

In order to find the economic optimal investment of the battery, the sizing algorithm can be written in Eq. (2.5), where the battery is assume to be optimised over 24-h operational horizon.

$$
\begin{aligned}
& J^* = \min \sum_{d \in D} \left(\sum_{\tau \in T} F_\tau(\chi_{d,\tau}) \right) + c_s.\omega \\
& \text{s.t.} \\
& \text{(a)}\ \ \mathrm{A}^{eq} \begin{bmatrix} \psi_{d,\tau} \\ \chi_{d,\tau} \end{bmatrix} = b^{eq} \\
& (b)\ \mathrm{A}^{in} \begin{bmatrix} \psi_{d,\tau} \\ \chi_\tau \end{bmatrix} \le b^{in} \\
& (c)\ A_s.\omega \le b_s
\end{aligned}
\qquad \text{(Eq. 2.5)}
$$

Where, D is a total number of days in one year, and c_s is the equivalent annual battery installation cost. Consequently, the first term represents the sum of operating cost over one year. The objective function consists of two terms representing:

- Operational cost
- Battery investment cost

As we have already discussed, this problem can be decomposed with respect to time in order to solve the optimization algorithm in a reasonable computational time. Hence, we can decompose the problem using Benders Decomposition (BD); accordingly, the sizing problem is split into a tractable master problem and sub-problems. The outline of the proposed algorithm is shown in Figure 6.

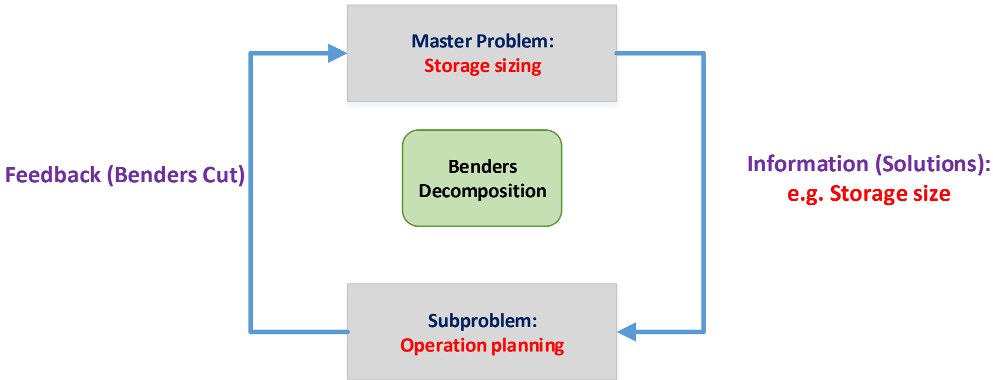

Figure 4. Using BD to find the optimal sizing of the battery from prosumer perspective

BD is a popular optimization technique. J. F. Benders initially introduced the BD algorithm for solving large-scale MIP problems [9]. The basic idea is to separate integer variables and real variables or relax the tough constraints in the optimization model and treat larger optimization problem via decomposition in order to accelerate the calculation speed. The BD algorithm has been successfully used in different ways to take the advantage of underlying problem structures for various optimization problems, such as network design, optimal transportation problem, plant location and stochastic optimization.

In applying the BD algorithm, the original problem will be decomposed into a master problem and several sub-problems, based on the LP duality theory. The sub-problems are the LP problems. The process of solution of the master problem begins with only a few or no constraints. The sub-problems are used to determine if optimal solutions can be obtained under the remaining constraints based on this solution to the master problem. If feasible, we will get an upper bound solution of the original problem, while forming a new objective function (feasibility cut) for the next calculation of the master problem. If infeasible, a corresponding constraint (infeasibility cut), which is most unsatisfied, will be introduced to the master problem. Then, a lower bound solution of the original problem is obtained by re-solving the master problem with more constraints. The final solution based on the BD algorithm may require iterations between the master problem and the sub-problems. When the upper bound and the lower bound are sufficiently close, the optimal solution of the original problem is achieved. We use the same decomposition procedure and notation as recently published by Fortenbacher, Ulbig and Andersson in [10].

2.4.1 Master Problem

The problem formulated in Eq. (2.5) can be split into a storage planning master problem and sequentially-solvable sub-problems reflecting the operational strategy. The master problem is presented in Eq. (2.6) [11].

$$
\begin{aligned}
& J_p^* = \min \; c_s.\omega + \alpha \\
& \text{s.t.} \\
& \quad \text{(a)}\, J_{sub}^{(l)} + \lambda_s^{(l)}\left(\omega - \omega^{(l)}\right) \le \alpha \\
& \quad \text{(b)}\; \alpha \ge \alpha_{down} \\
& \quad \text{(c)}\, 0 \le \omega \le \omega_{\max}
\end{aligned}
\qquad \text{(Eq. 2.6)}
$$

Where l denotes the iteration of the master problem, α is a proxy for the sub-problem costs, and the vector λ_s is the weighted sum of the dual variables from the sub-problems that are associated with the equalities in ω (see Eq. (2.7)). The variable J_{sub} denotes the sum of the sub-problem objective values. Constraint (2.6a) represents the Benders cut at stage l and constraints (2.6c) specify the bounds of the optimization variables.

2.4.2 Sequential Sub-problem

Following up the master problem the resulting sub-problem using BD can be written in Eq. (2.7), which is the sum of sequential optimal operation model over the planning horizon.

$$
\begin{aligned}
& J_{sub}^* = \min \sum_{d \in D}\left(\sum_{\tau \in T} F_\tau(\chi_{d,\tau})\right) \\
& \text{s.t.} \\
& \quad \text{(a)}\;\; \mathrm{A}^{eq}\begin{bmatrix}\psi_{d,\tau} \\ \chi_{d,\tau}\end{bmatrix} = b^{eq} \\
& \quad (b)\;\; \mathrm{A}^{in}\begin{bmatrix}\psi_{d,\tau} \\ \chi_{\tau}\end{bmatrix} \le b^{in} \\
& \quad (c)\;\; A_s.\omega \;\le b_s \\
& \quad (d)\;\; \omega = \omega^{(l)} \quad \left(\lambda_s^{(l)}\right)
\end{aligned}
\qquad \text{(Eq. 2.7)}
$$

$\lambda_s^{(l)}$ is a dual variable associated with the equality constraint of Eq. (2.7d). Note that battery degradation impact has been neglected in this formulation. We expect that it has an impact on the overall battery profitability, since the battery revenue decreases over time due to the capacity loss [reference]. It is planned that this effect will be considered based on inputs from WP6 in advanced version of the sizing algorithm of the battery.

In this algorithm, if the proposed problem has not converged $|\alpha| \geq \varepsilon$, (where ε is BD convergence tolerance), the Benders cut is added to the master problem which is reformulated as Eq. (2.6a). This process is continued until the problem has converged ($|\alpha| \leq \varepsilon$). The flowchart of implementing BD for the proposed problem is shown in Figure 5.

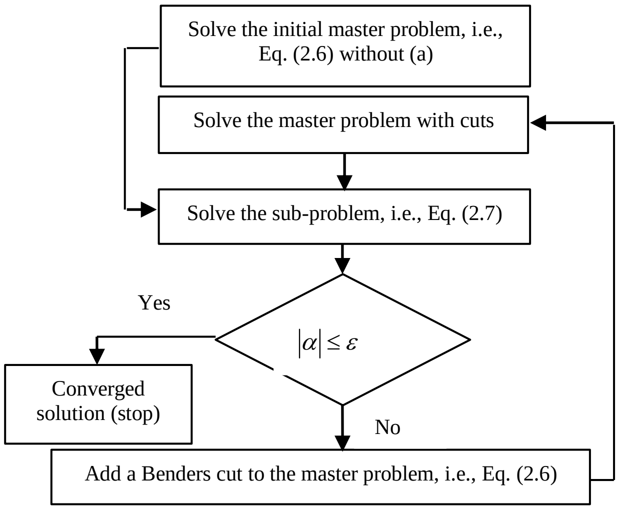

Figure 5. BD algorithm to solve proposed problem

2.5 Simple investment model from DSO point of view

As described in D 4.2 [2], congestion management and voltage control are dominated services that can be implemented in Dutch pilot, Spanish pilot and most probably in the German pilot. The appropriate size and placement of the battery system and expected operational strategy are important aspects to make economic investment decision to procure these flexibility services. The optimal location and size of the batteries can be obtained using multi-period Optimal Power Flow (OPF) over finite planning horizon. In this respect optimal sizing and placement of storage can be found by considering the investment cost of batteries weighted against the operational benefit. The inputs to the algorithm is similar to the previous planning algorithm for the prosumer in addition to the parameters of the distribution grid. Here, the outputs consist both the location and optimal sizing of the batteries.

The same framework as an investment model for prosumer, i.e., a bi-level optimisation problem can be adapted for this purpose. The decision variables for battery capacity in the master problem are now changed to Ω, which is a decision vector for battery capacities at each or subset of distribution nodes. Ω is a vector including the energy capacity of the batteries installed at each given nodes, $\omega_b^{\max}$ .The objective function for the sub-problem should be adapted to DSO perspective identified in D5.2 section 2.2.2.

The constraints identified in Eqs (2.7a-c) are adapted to include model multi-period AC OPF in a distribution system. Therefore, we can re-write Eq. (2.7) in a general form as Eq. (2.8):

$$
\begin{aligned}
& J^* = \min \sum_{d\in D}\left(\sum_{\tau\in T} F_\tau(\chi_{d,\tau})\right) \\
& \text{s.t.} \\
& \quad \text{(a)}\ \mathrm{A}^{eq}\begin{bmatrix}\psi_{d,\tau}\\ \chi_{d,\tau}\end{bmatrix} = b^{eq} \\
& \quad (b)\ \mathrm{A}^{in}\begin{bmatrix}\psi_{d,\tau}\\ \chi_{\tau}\end{bmatrix} \le b^{in} \\
& \quad (c)\ A_s\Omega \le b_s \\
& \quad (d)\ \Omega = \Omega^{(l)} \quad \left(\lambda_s^{(l)}\right) \qquad \omega_{b\in\varphi_b}^{\max} \in \Omega
\end{aligned}
\qquad \text{(Eq. 2.8)}
$$

Where χ_τ represents activated flexibility including battery in the period t [kWh]. ψ_τ is representing state variables of the distribution grid, e.g., voltage magnitude and angle at each bus. A^{eq} and A^{in} are matrices representing multi-period AC OPF equations. A_s is an intertemporal battery coupling matrix, and $\omega_b^{\max}$ is a battery energy capacity at bus *b*. The mathematical formulation of multi-period AC OPF is explained in the subsequent chapter.

2.5.1 Representation of multi-period AC optimal power flows constraints

NOMENCLATURE

1) Indices and Sets:

(b,j), t,l, k	Indices of bus, time, linearization segments of voltage magnitude term and circular constraint
φ_b, φ_t, φ_l, φ_k	Sets of bus, time, linearization segments of voltage magnitude term and circular constraint

2) Parameters:

A	Bus incidence matrix (if line existed between buses *b* and *j*, $A_{b,j}$ is equal to 1,otherwise zero)
g, b, y	Line conductance, susceptance, admittance in pu
PG, QG	Active and reactive power generation in pu
PD, QD	Active and reactive load in pu
$SL_{b,j}^{\max}$	Maximum loading of distribution line
T	Operating horizon, i.e., 6 hours, 12 hours, 24 hours or 48 hours
V^{max}, V^{min}, V_{ref}	Maximum and minimum voltage and voltage magnitude for reference bus in pu
Y	The network admittance matrix in pu
$\omega^{\max}, \omega^{\min}$	Maximum and minimum boundary of batteries state of charge in pu
η_{ch}, η_{dis}	Efficiency parameter for charging and discharging battery, respectively

3) Variables: All variables are in per unit (pu)

ID, IE, IG, IL	Load, parking lot, station and line current
PL, QL	line active and reactive power, respectively
V, ΔV, θ	Magnitude, deviation and angle of voltage

SOC_t	Batteries State of charge at time t
P^{ch}, P^{dis}	Amount of electricity charged and discharged from battery, respectively

In this sub-chapter we present a methodology to linearize AC power flow for radial low voltage grid based on [12]. These equations can represent the constraints represented in general sub-problem illustrated in Eqs. (2.8 a-c). Here, we extend our proposed methodology to account for linear approximations for voltage and branch flow as well as temporal operation constraints of batteries. The Eq. (2.9) to Eq. (2.13) represent the load flow equations that include active power balance Eq. (2.9), reactive power balance Eq. (2-10), active and reactive power flow of lines Eq. (2.11) and Eq. (2.12), and the value of the voltage angle in the reference bus Eq. (2.13) [13].

DGs are considered as PQ buses[2] in different nodes. However, if DGs are involved in the control voltage strategy, they should be adopted as PV buses [14].

$$PG_{b,t} - \sum_{j\in\varphi_b} A_{b,j} PL_{b,j,t} + \left(P^{dis}_{b,t} - P^{ch}_{b,t}\right) = PD_{b,t} \quad \forall\, b,t \qquad \text{(Eq. 2.9)}$$

$$QG_{b,t} - \sum_{j\in\varphi_b} A_{b,j} QL_{b,j,t} = QD_{b,t} \quad \forall\, b,t \qquad \text{(Eq. 2.10)}$$

$$PL_{b,j,t} = g_{b,j,1}(V_{b,t,1})^2 - V_{b,t,1}V_{j,t,1}\left(g_{b,j,1}\cos(\theta_{b,t}-\theta_{j,t}) + b_{b,j,1}\sin(\theta_{b,t}-\theta_{j,t})\right) \quad \forall b,j,t \qquad \text{(Eq. 2.11)}$$

$$QL_{b,j,t} = -b_{b,j,1}(V_{b,t,1})^2 + V_{b,t,1}V_{j,t,1}\left(b_{b,j,1}\cos(\theta_{b,t}-\theta_{j,t}) - g_{b,j,1}\sin(\theta_{b,t}-\theta_{j,t})\right) \quad \forall b,j,t \qquad \text{(Eq. 2.12)}$$

$$\theta_{b,t} = 0 \quad \forall\, b = reference\,bus, t \qquad \text{(Eq. 2.13)}$$

System operation limits:

Here, the system operation limits including bus voltage, and line power flow included in Eqs. (2.14) and (2.15) [13].The Eqs. (2.14) refers to avoiding the thermal overload of distribution lines, where failure due to overloading may occur. Voltage control is typically requested when solar PV systems generate significant amounts of electricity. This will “push up” the voltage level in the grid. However, in high load situations, there is a risk that the voltage might drop below the permissible level, which has a negative

[2] In PQ buses, the real power |P| and reactive power |Q| are specified. It is also known as a *Load Bus*.

consequence on safeguard of operating the system; therefore, Eq. (2.15) ensures that the voltage levels are maintained within the voltage permissible limits.

$$(PL_{b,j,t})^2 + (QL_{b,j,t})^2 \leq (SL_{b,j}^{\max})^2 \quad \forall\, b, j, t \qquad \text{(Eq. 2.14)}$$

$$V^{\min} \leq V_{b,t,1} \leq V^{\max} \quad \forall\, b, t \qquad \text{(Eq. 2.15)}$$

Temporal operation constraints of operating batteries:

The temporal constraints of operating batteries are presented in Eqs. (2.17) to (2.19). The temporal problem implies a coupling of multiple time steps to ensure coherence of the battery SOC between each consecutive time step. The spatial problem implies the consideration of all nodes as possible placement locations for storage devices.

As we have already discussed that, the operating time horizon can range from 6 hours to two days. The time steps of *T* are then coupled in order to successfully complete an annual analysis.

$$SOC_{b,t} = SOC_{b,t-1} + \frac{1}{\eta_{ch}} \cdot P_{b,t}^{ch} - \eta_{dis} \cdot P_{b,t}^{dis} \qquad \text{(Eq. 2.16)}$$

$$0 \leq P_{b,t}^{ch} \leq P_b^{\text{ch-max}} \qquad \text{(Eq. 2.17)}$$

$$0 \leq P_{b,t}^{dis} \leq P_b^{\text{dis-max}} \qquad \text{(Eq. 2-18)}$$

$$\omega_b^{\min} \leq SOC_{b,t} \leq \omega_b^{\max} \qquad \text{(Eq. 2.19)}$$

$$SOC_{b,0} = SOC_{b,\mathrm{T}} \qquad \text{(Eq. 2.20)}$$

The battery state of charge, i.e. the storage content, for battery unit in period *t* depends on the state of charge in the previous period, and charging or discharging in current period. These impacts are replicated by Eq. (2.16). The charging and discharging and the SOC must be within minimum and maximum limits as expressed in Eqs. (2.17) to Eq. (2.19). An additional constraint is added to avoid daily (if T is 24 hours) accumulation effects by forcing the SOC of the first and last time step of the operating time horizon be equal as stated in equation (2-20).

The proposed problem is a nonlinear programming (NLP) model due to non-linear Eq. (2.11), Eq. (2.12), and circular inequality of Constraint (2.15). Moreover, NLP problems are intrinsically more difficult to solve compared to linear problems, and there is no guarantee to reach optimal solution [13]. Hence, we need to develop a linearized OPF method for redial distribution grid to reduce the computational time. This process is explained in the appendix.

3 Pilots and illustrative sizing examples for prosumers

INVADE deliverable 5.2 [7] outlined the capabilities of different models to capture the value of flexibility services. In short, D5.2 report discussed flexibility analysis methodologies, approaches for cost-benefit analysis and the value of flexibility services for prosumers with batteries and EVs. As noted earlier, for this deliverable, the objective is to describe sizing and siting approaches. In this section, we present illustrative examples for the sizing problem based on simplified prosumer models. The aim is to illustrate the effect of flexibility services on sizing decisions for the prosumer's battery. Recall that we defined three services: 1) Time of use (ToU) price, 2) kWmax control, and 3) self-balancing. For these services, the battery smooths and integrates local PV production, manages peak demand and handles imports/exports to the grid under a kWmax constraint.

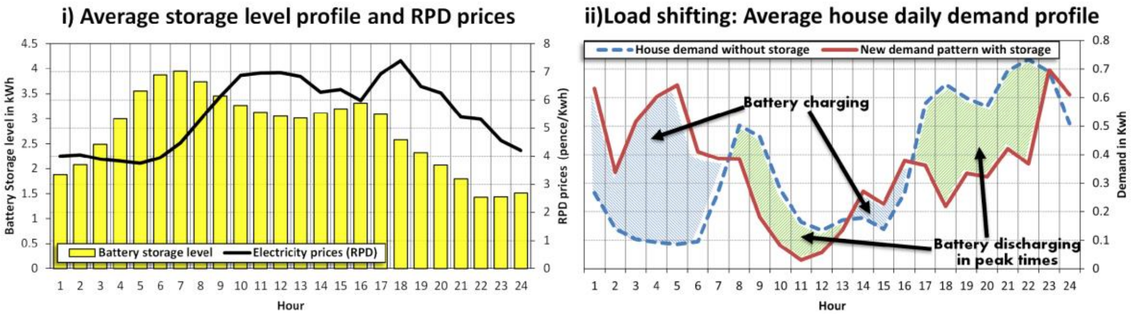

Figure 6. Example of a prosumer (house) exposed to hourly ToU price variations

For example, with ToU the prosumer is exposed to tariffs that vary in time dynamically (hourly) or in pre-defined periods (night vs day). Figure 6 depicts an example in which the battery operations determine an optimal consumption pattern for a house in Great Britain based on expected inter-temporal price variations throughout the day. Basically, at the beginning of the day (Figure 6i), the battery is being charged in the morning (when demand and prices are low) and discharged in peak times to reduce grid consumption. In Figure 6ii, the dotted blue line represents the house actual consumption pattern whereas the solid red line shows the new demand pattern (seen by the grid) created by charging the battery in off-peak times and discharging the battery in the morning and evening peak times. Hence, the sizing problem for ToU flexibility service will be a function on quantifying the energy arbitrage gains. In this house (annual demand of electricity:

3.8 MWh, no PV considered), three battery sizes were tested: 1.4kWh, 2.9kWh, and 4.3kWh which produced cost savings (reduction to the annual electricity bill) in the magnitude of 7%, 11% and 15% compared to not having the battery in the house. However, if other flexibility services are included for battery operations the value will increase and hence affect the battery size. In this chapter, we look at the kWmax service and self-balancing services impact on the prosumers PV-battery sizing decisions.

3.1 Flexibility needed due to kWmax and self-balancing

In the next sections, we discuss the prosumer sizing problem by considering the effects of flexibility services for kWmax control and self-balancing. On one hand, kWmax constraints RES exports (also grid imports) and therefore might limit installation of additional RES capacity for the prosumer. In this case, the battery provides the flexibility to manage kWmax limitations, which allows installing more solar capacity. On the other hand, flexibility for self-balancing maximizes RES utilization by better matching supply-demand operations. In short, given the limitations of kWmax, how much PV is installable based on the size of the battery? If we increase on-site solar capacity, what battery size will be required to support this deployment? These questions are discussed by simulating the installation of a battery in two INVADE pilots (following section). This preliminary analysis employs available simplified operational models previously developed by NTNU. The scope of the analysis is to show battery-solar size combinations for the prosumer and estimate the operational value of the battery. For this purpose, a sensitivity analysis on different sizes for batteries and PV is performed as follows:

1. Show PV installation subjected to a kW_{max}

   First case: No storage considered or present in the prosumer system

2. Battery supports solar PV deployment (increase capacity)

   1. Battery presence increases RES capacity

   2. Through the simplified operational model illustrate the operational value of having a battery showing the benefits

3. Different storage capacities tested (sizing problem) along with increased solar PV capacity

3.2 INVADE pilots data collection for simplified model

To implement the simplified operational models in the INVADE pilots, we attempted to collect data from the different partners involved in the INVADE project. At the moment, most of the pilots are being set up and consequently data is not yet available. However, we were able to gather some applicable information from the house pilots in the Netherlands and from the Albena hotel in Bulgaria. Based on this limited data, we illustrate and discuss the sizing problem for different battery and solar PV sizes. The details regarding data collection, assumptions and model implementation are explained in the next subsections.

3.2.1 INVADE pilot: Homes in the Netherlands

The pilot in Netherlands is split in several categories with the main goal to include as much as renewable energy possible by using on-site batteries and electrical vehicles. The pilot is divided in: 1) Small scale homes with smart charging, 2) large scale offices and parking lots containing several charge points for EVs, and 3) a large public case with thousands charge points. From these three cases, small scale homes have been chosen to illustrate the sensibility of battery sizes on PV integration and kWmax control. This is due to the availability of data provided by Elaad (Dutch INVADE partner) as well as to show the sizing problem for small prosumers (houses) while the Bulgarian case (Albena, following section) shows the case of large prosumer (a hotel). Hence, in this way, we can present and discuss two different prosumer perspectives.

3.2.1.1 Data sets used, assumptions and limitations

For the small scale home simulation of Arnhem, Elaad recommended to this deliverable the usage of some basic data sources. For example, home load data were taken from a standardized profile for Dutch houses. Actual demand data from the home pilot is not yet available or cannot be shared due to privacy limitations. In summary, the following data sets were collected:

- Load data was obtained from the Dutch organization NEDU[3]. It provides standard consumption profiles of small consumers. These profiles are used by grid operators to estimate the allocation of energy to small consumers on a daily basis. Therefore, a profile is typically used to estimate for a certain period what

[3] http://www.nedu.nl/portfolio/verbruiksprofielen/

the consumption will be. There are ten profiles for electricity. The dataset consists of 15 min demand time-steps spread over a year that together contain the entire annual consumption. The sum of all profile fractions is one. In order to represent a typical Dutch house, the sum of the profile fractions is multiplied by the annual consumption. For our illustrative sizing example, we have used two profiles: 1) the "E3A" profile in which we assume a 3.5MWh annual consumption and 2) the E1C profile in which we assume a 4MW annual consumption under ToU price regime throughout the day (7am to 9pm).

- Solar potentials: Temperature and irradiation data were downloaded from the national weather service station closest to Arnhem. Then, this dataset was converted to PV production. We used the methodology conversion noted in [15] .
- Electricity prices: spot market electricity price was taken from the APEX website and other sources. Also NEDU publishes typical electricity prices for households under different profiles. The electricity price is asset under a fix retail price of 41 €/MWh.

3.2.1.2 <u>Model description</u>

The simplified operational model implemented for the Dutch houses was based on the multi-period optimization model initially developed and implemented in Crespo del Granado et. al (2014) [15]. It is a model with emphasis on electricity storage presence in houses. The model minimizes the marginal cost of supplying energy to the house in hourly basis within the day. Wholesale spot price or day ahead market electricity prices are used as inputs for the cost of electricity (i.e. BRP application). The model objective is to minimize the total energy grid consumption cost over a finite horizon (one day discretized in hourly or finer time steps) by employing electricity storage for peak shaving and smoothing renewable generation. Therefore, the model optimizes battery operations to: 1) charge when energy spot prices are low and discharge when prices are high, and 2) saving local solar surplus. In a nutshell, the house model contains the following features: the objective function (minimizes grid consumption), a supply demand balance equation, and the storage inter-temporality equilibrium constraint along with the limits on the battery charging/discharging flow rates and capacity.

3.2.2 INVADE pilot: Hotel in Albena, Bulgaria

The five-star-hotel Flamingo Grand is an end-user with a high energy consumption, resulting in high savings potential by installation of a smart energy system. Their demand profile is ideal for a PV installation due to high consumption during daytime [16]. In addition, grid utility tariffs are calculated from the monthly peak load, making high peak loads very costly for the hotel. Thus, self-balancing through installation of a battery could reduce these peaks. The load profile of the hotel is season dependent, where the summer is the most power intensive period due to a high number of guests. However, if a high PV production day occurs in a day with a low amount of guests, the net load could turn negative. According to D10.1 [16], prosumers are not compensated economically for injecting power into the grid. On the contrary, it could potentially become a problem as Bulgarian DSOs are not used to prosumers. Therefore, the battery is also important in order to avoid a negative net load where power is injected into the grid.

Season use:

1. Summer – In the summer there is high PV production and high demand due to many guests. High PV production will take care of the high peak loads in the middle of the day, but the potential high evening load described in D10.1 [16] can be partially covered by the battery.
2. Autumn / Spring – Although hotel activity is reduced in the autumn and spring, high PV production could still occur. In the instance of high PV production and low consumption, the battery can be used for self-balancing to avoid injecting power into the grid.
3. Winter – Both energy consumption and PV production is low, and the battery can be operated freely in order to reduce own costs. In low activity periods, self-balancing is not as necessary as in the high season. During these periods, there is greater potential for the battery to work as a flexible resource on the day-ahead and intraday market for a FO or BRP. Note that FO/BRP perspective is not included in phase 1, and therefore not described further.

3.2.3 Data sets used, assumptions and limitations

The data used to run simulations for the hotel are load, temperature, irradiation and energy price data. In the results presented in this deliverable, load data from July to September 2017 provided by Albena was used. However, the PV data, which were provided, were from January to July 2017, which makes it hard to create correct results because the data don't correlate. Therefore, an open source satellite based service was used to find PV data for the relevant months. However, the data used is then from 2014, and correlation could therefore potentially be weak. As explained by Dimitar Stanev in Albena, the electricity price is set to 42 €/MWh (flat rate).

Because the energy bill structure in Bulgaria is a bit different, some assumptions were made. The energy price is negotiated as a result of the customer's load profile. The more load the customer is able to shift from peak load hours (8 am to 8 pm), to low load hours (8 pm to 8 am), the lower prices can be negotiated. In the summer of 2017, the peak load of the hotel was approximately 600 kWh/h. By setting a virtual upper kW max bound of 500 kW, and a lower bound of 0 kW (meaning that no energy is exported to the grid), the self-balancing optimization can be run for different PV and battery sizes to see how increasing battery size allows for higher PV installations. This virtual limit (or soft constraint) can be changed. The lower the limit is the more flexibility is needed to handle the limit.

3.2.3.1 Model description

The model by Bjarghov *et. al*. 2017 [17] was used to simulate the hourly operations of the battery in Albena. The model represents load, some PV production and a grid. The two first are considered known (deterministic model), whereas the grid is considered stiff and supplies whatever demand the system has. In addition, there is a battery which is modelled as a flexible load that can be both positive and negative, depending on whether the battery is being charged or discharged. This is shown in Figure 7.

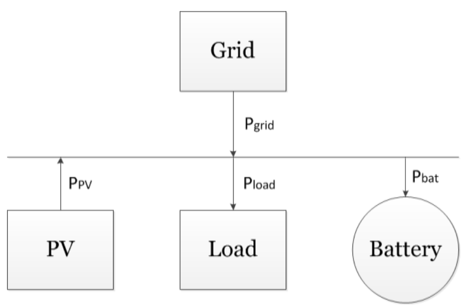

Figure 7. Model overview

The model used for this pilot employed the mentioned load, irradiation, temperature and pricing data in order to optimize costs and load profile based on a dynamic programming optimization algorithm. By defining a set of constraints, the algorithm calculates the cost of every charge and discharge decision for every time step. By calculating every single possible legal operation of the battery for every time step, a global optimum can be determined by navigating through the resulting transition cost matrix.

3.3 Implementation and illustrative preliminary results

3.3.1 Battery-PV sizing for houses in Netherlands

The simulations for the small houses in Netherlands are in one-hour resolution. The data collected allowed simulating one year. The model horizon performs this simulation for each day separately. Hence, the model is run 365 times as it assumes that is rather unrealistic to have perfect knowledge on solar-load patterns beyond 24hours (for a discussion on planning horizon, see chapter 4 in D5.3 "Flexibility operations algorithms"). Figure 8 depicts typical results on simulating supply-demand operations and taking into account the decisions for battery charge/discharge levels. In Figure 8a, observe that the battery at the begging of the day (dotted red-lines) has a low energy content. The reasoning is to have at is lowest in order to be ready for the solar surplus happening at the middle of the day (Figure 8b and Figure 8c). In this period, the battery tries to charge as much as possible, but this is still not enough for self-balancing and the surplus is exported to the grid. For this particular example, we arbitrarily set a kWmax limit of 1kWh. Throughout the year, demand exceeds this limit only in 6 days and hence the battery use for this flexibility service was not significant. However, for larger PV sizes, the solar surplus (exports) exceed 1kWh more frequently.

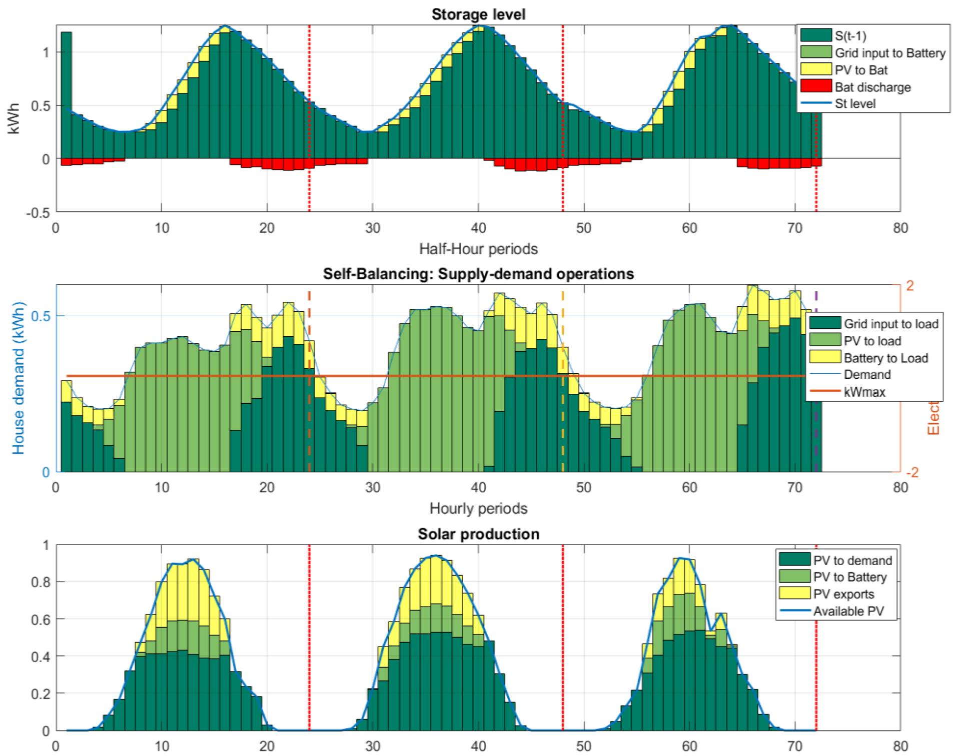

Figure 8. Three-day (in summer) example of supply-demand dynamics in the house

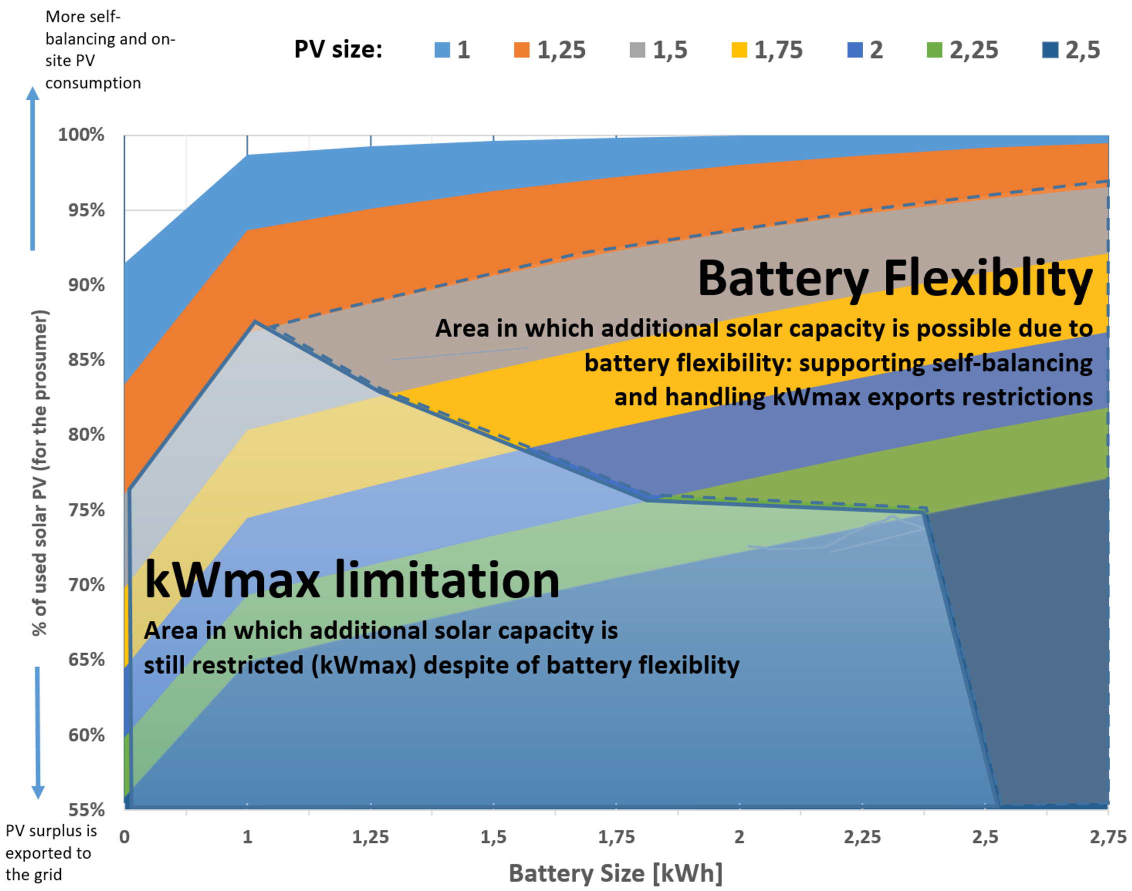

Figure 9. Example of testing different PV sizes related to battery capacity

As described and noted in Figure 8, the battery shifts some of the solar surplus to the evening peak (or to other periods) in which PV leaves unfulfilled demand (i.e. discharge the battery to avoid grid consumption). This shifting of PV surplus is limited to the battery capacity. Therefore, if a small house wants to increase its PV capacity, it will be up to how much the battery helps circumvent exceeding the kWmax export limitation. Figure 9 illustrates this premise by testing different PV sizes against battery capacities, the main insights are as follows:

- How much PV does the house consumes? The area chart presents different PV sizes. Note that for smaller PV sizes the closer to 100% on-site PV consumption is, the easier is to be able to install bigger PV capacities. For example, the PV case of 1kW (top light blue area), solar production is almost fully consumed by the end-user and hence not violating kWmax exports (below 1kW). The same applies for the 1.25kW solar PV case, which makes the two cases “needless of battery flexibility”. That is, the house can handle these capacities.
- When does battery flexibility facilitate installing larger PV sizes? As the PV size increases, the harder it becomes to integrate PV into the system (violating

kWmax). This is illustrated in the chart area “Battery Flexibility”. Consider the 1.5 PV size (grey area), here the solar production is exceeding the pretended 1kW control limit, hence PV this size could not be installed in the house. This is the case when there is no battery presence (kWh=0). However, once the battery size is 1kW, there is enough flexibility in the system and hence the solar PV can be increased. Similar trend occurs for larger PV sizes based on the increase of battery size.

- How kWmax and self-balancing limit greater PV capacities? Under the kWmax limitation area in the chart, we observe that for larger PV capacities (>1.5), it becomes increasingly difficult to self-balance PV. Despite of having a battery, the PV surplys overcomes the possible flexibility provided by the battery. For instance, a 1kWh battery along with a 1.75kWh solar PV will be charged in couple of time steps and hence the solar surplus will start exceeding the kWmax limitations. Therefore, this PV size is not suitable for installation in the house. However, as the battery size increases, observe that the possibilities to increase PV capacity improves.

Based on Figure 9, we calculate the savings on installing the possible PV-battery combo sizes. That is, the value of having a battery compared to not having the battery installed. This is calculated as savings (in %) on the energy bill. Figure 10 shows these results in which the values with greater PV size produce the larger savings. The size of the battery plays a major role since, as more PV surplus will occur, the more the battery will support self-balancing the additional PV capacity. Hence, the higher the savings.

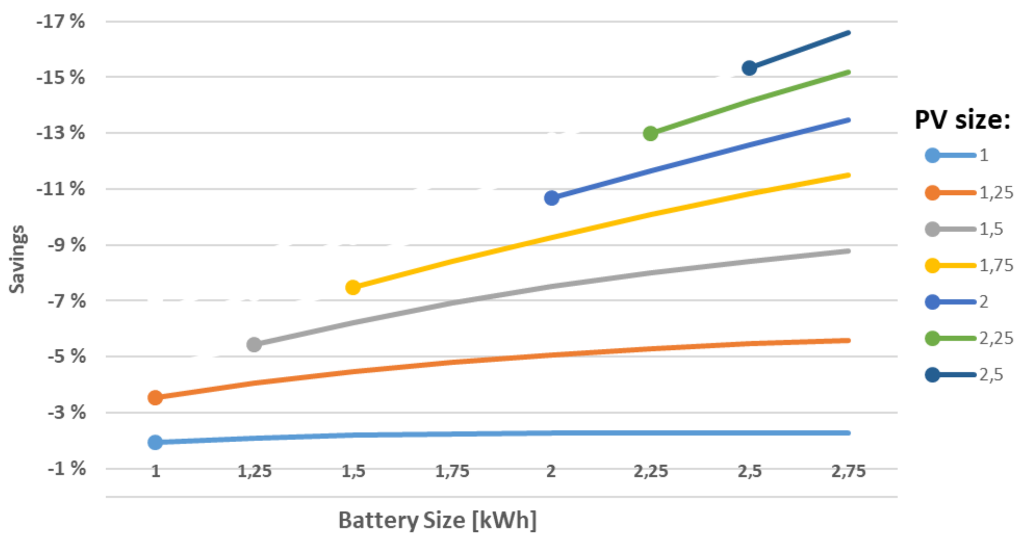

Figure 10. Cost savings for different Batter-PV six combinations

3.3.2 Battery-PV sizing for Albena

As we know that the energy tariff in Bulgaria is flat and by moving the demand from peak hour to off-peak hours, a new lower flat energy tariff can be negotiated with the retailer. The value of flexibility is calculated by simulation with the load data available from 08th June 2017 till 18th September 2017. The hotel base load is 344 kWh/h on average and peaks at 595 kWh/h. It is to be noted that this period of the year has maximum demand compared to the rest of the periods of the year. For the given load data, to respect the 500 kW grid import limit a 250 kWh battery is needed without any local PV generation. The minimum PV generation capacity required to minimize the investment cost of battery is 100 kW and the corresponding battery capacity is 75 kWh. Further addition of battery capacity will not add any value to the flexibility as shown in the figure. The value of this additional flexibility can be calculated only if the relation between the normal and reduced tariff are known. As there is a strong correlation between the PV generation and the demand, the electricity bill can be further reduced by adding more PV generation capacity. The maximum PV capacity the 75 kWh battery can handle is 425 kWp. Further addition of PV is possible with additional battery capacity. Otherwise, part of the PV production has to be curtailed in real time to avoid the energy export to the grid, as the grid code in Bulgaria might not support (and certainly does not promote) RES injection from the consumers. The battery capacity required to support 500 kWp PV installation is 250 kWh without curtailment of PV generation. Figure 11 shows the associated energy cost for the grid import for every installed capacity of PV generation from 25 to 475 kWp. The maximum saving is 34% (~8000 €) for the period of 10 weeks with 475 kWp PV installation. It is to be noted that the additional battery capacity beyond the minimum battery capacity (75 kWh) for every installed kWp of PV generation do not add any value for its flexibility. This scenario may change for the rest of the period of the year, as the demand will be low and the excess PV generation with the 475 kWp generation capacity may balance the lower demand with this additional battery capacity without any energy import for the grid.

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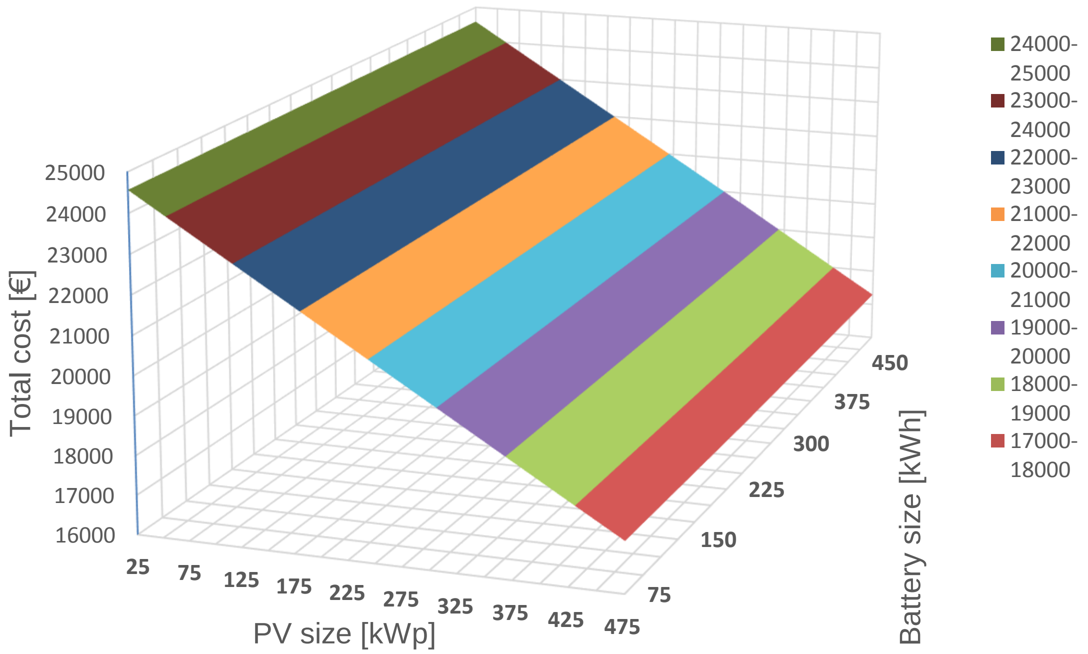

Figure 11. Energy costs (08. July – 18. September) for different PV-Battery sizes

4 Concluding Remarks

This part of the report focusses on placement and sizing of batteries in low voltage grids. The initial sections of the report explains the importance of siting and sizing of batteries for delivering flexibility by considering OPF. The present approach focusses only on prosumer and DSO perspective. The simplified planning model presents the method to calculate net present value (NPV) and explains the trade-off in maximizing NPV. The difference between prosumer's perspective and DSO's perspective are detailed. Further sections explains the solution to the siting and sizing problem considering it as a bi-level problem. The method of separating the siting and sizing problem as a master and sub problem, the iterative approach by adding benders cut to the master problem to achieve optimal solution are detailed in the next section. Next section details the problem in DSO perspective, the nonlinearity associated with the OPF problem and the method of mixed linear programing approach to solve the problem with piece-vise linearization. Further section describes investment analyses for storage and RES with illustrative examples showing analysis for two pilot sites at Bulgaria and The Netherlands. The Bulgarian example shows the battery sizing, PV sizing and the savings related to energy import from the grid for different combination of batteries and PVs for a large prosumer. The Netherlands example shows similar calculations for small homes.

The focus of the next deliverable D5.4 will be on extended operational model with an elaborate battery and flexible load models to deliver flexibility services.

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Appendix I

The Mixed Integer Linear Programing (MILP) Model

1) **Linear approximation of power balance equations**: constraints (2.11) and (2.12) in the model are non-linear equations. For linear approximation of these constraints, this paper considers the following assumptions [13]:

- The difference of voltage angle between two buses (across a line) is less than 0.105 radian.
- The voltage magnitude at the fundamental frequency can be written as $V^{\min} + \sum_{l \in \varphi_l} \Delta V_l$ based on the piecewise linearization method in [18] and Figure 12, wherein $\Delta V \ll 1$.

It is expressed that the difference of voltage angle across a line is less than 0.105 radian based on power flow results of different distribution networks [19, 20] that is shown in Table 1. Therefore, based on the first assumption, **sin** $(\theta_b-\theta_j)$ and **cos** $(\theta_b-\theta_j)$ are equal to $(\theta_b-\theta_j)$ and 1, respectively. In addition, based on the second assumption, V^2 and V_bV_j are respectively equal to:

$$V^2 = \left(V^{\min}\right)^2 + \sum_{l \in \varphi_l} m_l \Delta V_l \qquad \text{(Eq. 2.21)}$$

$$V_b V_j = \left(V^{\min}\right)^2 + V^{\min} \sum_{l \in \varphi_l} \Delta V_{b,l} + V^{\min} \sum_{l \in \varphi_l} \Delta V_{j,l} \qquad \text{(Eq. 2.22)}$$

Where, m is the line slope. It is noted that ΔV^2, $\Delta V \times (\theta_b-\theta_j)$ and $(\theta_b-\theta_j)^2$ are negligible, and these terms are considered to be zero in this paper. Therefore, the linear approximation of Eqs. (2.11) and (2-12) are as follows:

Table 1. Maximum difference of voltage angle across a line

Network	33-Bus	69-Bus	123-Bus
Maximum value of $(\theta_i-\theta_j)$	-0.004	-0.006	-0.009

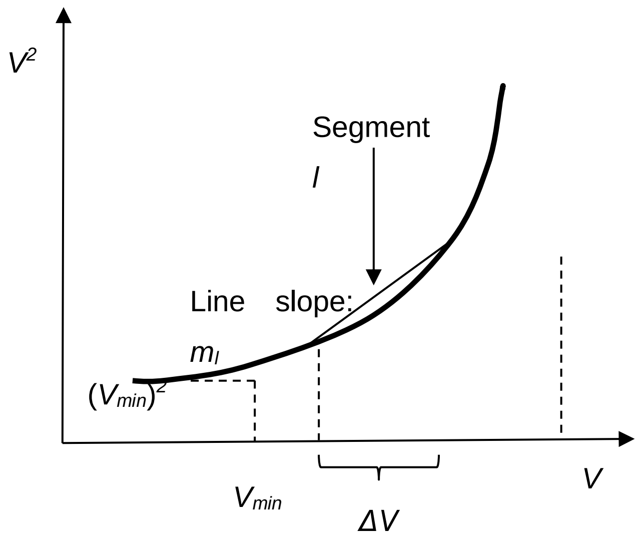

Figure 12. The piecewise linearization method [18]

$$PL_{b,j,t} = g_{b,j,1}\left(\sum_{l\in\varphi_l}\left(m_l - V^{\min}\right)\Delta V_{b,t,1,l} - V^{\min}\Delta V_{j,t,1,l}\right) - \left(V^{\min}\right)^2 b_{b,j,1}(\theta_{b,t} - \theta_{j,t}) \quad \forall b,j,t \qquad \text{(Eq. 2.23)}$$

$$QL_{b,j,t} = -b_{b,j,1}\left(\sum_{l\in\varphi_l}\left(m_l - V^{\min}\right)\Delta V_{b,t,1,l} - V^{\min}\Delta V_{j,t,1,l}\right) - \left(V^{\min}\right)^2 g_{b,j,1}(\theta_{b,t} - \theta_{j,t}) \quad \forall b,j,t \qquad \text{(Eq. 2.24)}$$

Linear approximation of voltage limits, i.e., constraint (2.14) is re-written as Eq. (2.25).

$$\Delta V_{b,t,l} \le \Delta V^{\max} \quad \forall\, b,t,l \qquad \text{(Eq. 2.25)}$$

Where, ΔV is positive variable based on Figure 12, and ΔV^{max} is equal to $(V^{max}-V^{min})/N_l$, where N_l is the number of linearization segments of the voltage magnitude term. The constraints (2.15) is a circular inequality. Based on idea presented in Figure 13, the linear approximation equations of these constraints are written as follows:

$$\cos(k\Delta\alpha)\times PL_{b,j,t} + \cos(k\Delta\alpha)\times QL_{b,j,t} \le SL_{b,j}^{\max} \quad \forall\, b,j,t,k \qquad \text{(Eq. 2.26)}$$

$$\cos(k\Delta\alpha)\times PG_{b,t} + \cos(k\Delta\alpha)\times QG_{b,t} \le SG_{b}^{\max} \quad \forall\, b,t,k \qquad \text{(Eq. 2.27)}$$

Based on the above equations, the circular constraint is approximated by a polygon. Each edge of the polygon is a straight line and their equations are obtained from the tangents to the circle at different points depicted in Figure 13 [21]. In other words, these equations linearized based on the method presented in Figure 13, but it should be noted that we need enough piece-wise linear sections, in order to avoid high error. Therefore, the number of piece-wise linear sections with different angles from horizontal axis should be increased to reduce the linearization error. Hence, the 360 degrees of circle perimeter are divided into equal parts $\Delta\alpha$. Then, the line equation is linearized for each $k\Delta\alpha$, where k is the linearization segments index. Finally, the calculated line equation is integrated into a circle with a radius less than or equal to S.

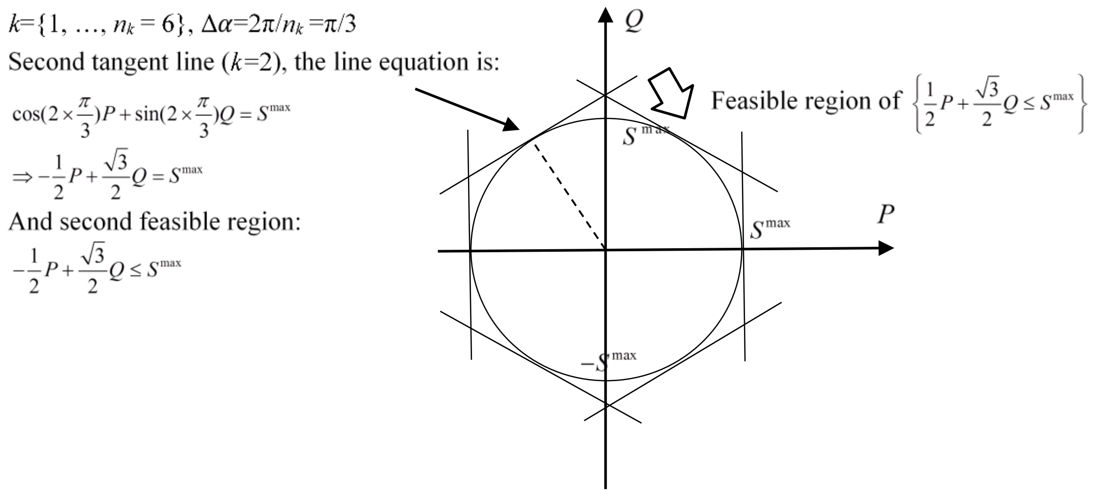

Figure 13. Linearization of circular constraint