*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*

Deliverable nº:	**D5.2**
Deliverable name:	**Methods for assessing the value of flexibility in distribution grids**
Version:	**1.0**
Release date:	**08/09/2017**
Dissemination level:	**Public** (Public, Confidential)
Status:	**Peer-reviewed** (Draft, Peer-reviewed, Submitted, Approved)
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This project has received funding from the European Union's Horizon 2020 Research and Innovation programme under Grant Agreement No 731148.

Document history

Version	Date of issue	Content and changes	Edited by
0.1	08.08.2017	First draft, describing the main methodology	M. Korpås
0.2	27.08.2017	Adding chapter on value of flexibility services for DSO	M. Korpås
0.3	03.09.2017	Adding chapter on value of flexibility services for BRP, adding chapter on combining different services, adding references, formatting	M. Korpås
0.4	04.09.2017	Added draft chapters on flexibility models	P. Olivella
0.5	05.09.2017	Final draft sent to review	M. Korpås (based on updates from all contributors)
1.0	08.09.2017	Peer-reviewed version sent for approval	Korpås, Olivella

Peer reviewed by:

Partner	Reviewer
Smart Innovation	Jayaprakash Rajasekharan
VTT	Ari Hentunen

Deliverable beneficiaries:

WP / Task
WP4, T4.3
WP5, T5.3 & T.5.4
WP6, T6.3
WP8, T8.3

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Abbreviations and Acronyms

Acronym	Description
BRP	Balance Responsible Party
DSO	Distribution System Operator
FO	Flexibility Operator
EV	Electric Vehicle
SP	Shiftable Profile
NPV	Net Present Value
PV	Photovoltaic
V2X	Vehicle to Grid, Vehicle to Home, Vehicle to Building..
SOC	Battery State of Charge
DER	Distributed Energy Resources

Nomenclature

Symbol	Description
$\alpha_{N,r}$	Annuity factor
η_{ch}	Charging efficiency
η_{dch}	Discharging efficiency
$p_{sm,t}$	Spot-market price at time-step *t* (Equivalent to Day-Ahead price)
r	Discount rate
Δt	Simulation/optimization time-step
E_{init}	Initial energy storage level
E_{rat}	Rated energy capacity
N	Number of years
O	Annual operating cost
$O_{BRP,yr}^{ref}$	Annual operating costs of the BRP for a reference case without flexibility
$O_{BRP,d}^{ref}$	Daily operating costs of the BRP for a reference case without flexibility
$O_{BRP,yr}$	Annual operating cost of the BRP, including flexibility options
$O_{BRP,d}$	Daily operating cost of the BRP, including flexibility options
P_{ch}	Charging power
P_{dch}	Discharging power

Symbol	Description
P_{rat}	Rated power capacity
$P_{BRP,d,h}^{ref}$	Net power purchase of the BRP in hour *h* of day *d*, for a reference case without flexibility
$P_{BRP,d,h}$	Net power purchase of the BRP in hour h of day d, including flexibility options
R	Annual revenue
R_{op}	Annual operating revenues
R_{fixed}	Annual fixed revenues
T	End time-step of simulation/optimization

1 Introduction

1.1 Background

The purpose with this document is to describe and discuss possible methodologies and models that can be used for estimating the value of flexibility from mobile and stationary storages in distribution grids. The document serves as a basis for the modelling and assessments that is carried out in Task 5.2, 5.3 and 5.4 of the INVADE project.

Chapter 1 gives a brief overview of the flexibility services defined as part of the INVADE concept. Chapter 2 covers the mathematical models of flexibility from electric vehicles and stationary batteries, as well as the main objective functions for their optimal operation. Chapter 3 describes the method for estimating flexibility potential, while Chapter 4 continues with describing the principles used for cost-benefit analysis of different flexibility options. In Chapter 5, the most important factors that determine the value of each of flexibility service are discussed, focusing mainly on the DSO services, while Chapter 6 suggests a method for estimating the combined value of two or more services which will be further explored in the continuation of Task 5.2.

1.2 Flexibility services

From the initial work in WP4 [1] and WP5 [2], the INVADE concept comprises several flexibility services to be provided from stationary and mobile batteries, as shown in Table 1.

Table 1: Flexibility services added value to each Use Case identified in WP 4 (H:high; L:low; N:no). Copied from [1].

Flexibility customer	Flexibility services INVADE	Use cases (UC)			
		UC1: Mobile storage	UC2: Centralized storage	UC3: Distributed storage	UC4: Hybrid
DSO	Congestion management	H	H	L	H
	Voltage / Reactive power control	H	H	L	H
	Controlled islanding	N	H	N	H
BRP	Day–ahead portfolio optimization	L	L	N	L
	Intraday portfolio optimization	L	H	L	H
	Self-balancing portfolio optimization	H	H	L	H
Prosumer	ToU optimization	L	N	H	H
	kWmax control	H	N	H	H
	Self-balancing	L	N	H	H
	Controlled islanding*	N	N	H	H

It should be noted that “Controlled islanding” differs fundamentally from the other services, both with respect to technical requirements and economic evaluation. It is not covered by the methods described in this document.

2 Flexibility modelling

This chapter explains the flexibility models needed to evaluate their potential. First, the battery and EV models are explained. Later on, the objective functions for optimal operation are given for the three flexibility consumers: DSO, BRP and prosumers. Finally, last section is a remark about different tariff structures and the corresponding objective functions.

2.1 Flexibility distributed energy sources models

This section focuses on the electric vehicle and stationary battery modelling only, since these are the main sources of flexibility covered by the project. Flexible load and generation models are explained in detail in [3],[4],[5].

2.1.1 Battery model

Electricity storage units can provide up- and down-regulation by discharging or charging energy respectively. This model divides the energy charging and discharging decision variables in $\sigma_{b,t}^{in}$ and $\sigma_{b,t}^{out}$ correspondingly. They represent the amount of energy charged and discharged respectively for battery unit b at time t. $\sigma_{b,t}^{soc}$ is the battery state-of-charge of unit *b* during period *t*. These variables define the energy setpoint of each battery unit *b* during each period *t*. The state-of-charge equations shown below considers the one-way efficiency each time that battery unit *b* delivers (A_b^{out}) or stores electricity (A_b^{in}):

$$\sigma_{b,t}^{soc} = \sigma_{b,t-1}^{soc} + \sigma_{b,t}^{in} * A_b^{in} - \frac{\sigma_{b,t}^{out}}{A_b^{out}}, \qquad t \geq 2$$

$$\sigma_{b,t}^{soc} = s_b^{soc,start} + \sigma_{b,t}^{in} * A_b^{in} - \frac{\sigma_{b,t}^{out}}{A_b^{out}}, \qquad t = 1$$

$$0 \leq \sigma_{b,t}^{soc} \leq O_b^{max}$$

$$0 \leq \sigma_{b,t}^{in} \leq Q_b^{in}$$

$$0 \leq \sigma_{b,t}^{out} \leq Q_b^{out}$$

Since the base case for the energy profile is assumed to be constantly zero, the flexibility provided from the batteries at the time *t* is simply. The battery contribution in the flexibility balance equation is as follows:

$$\sum_b (\sigma_{b,t}^{out} - \sigma_{b,t}^{in})$$

It is assumed that the batteries are completely adjustable in terms of power input and output up to the maximum power specified $Q_b^{B,in}$ and $Q_b^{B,out}$.

Moreover, the efficiency of charge $A_b^{B,in}$ and discharge $A_b^{B,out}$ is assumed to be constant. This implies that the relation between the power input or output and the state of charge

is linear. The state of charge is assumed to be known as well as the maximum capacity of the batteries O_b^B, which is assumed to be constant.

Finally, the lifetime of the batteries in terms of battery cycles is assumed to be known and to be constant. This means that in this analysis the strategy for the optimal lifetime of the batteries is not considered.

2.1.2 Electric vehicle model

2.1.2.1 Illustrative example

The Electric Vehicle (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 1. 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.

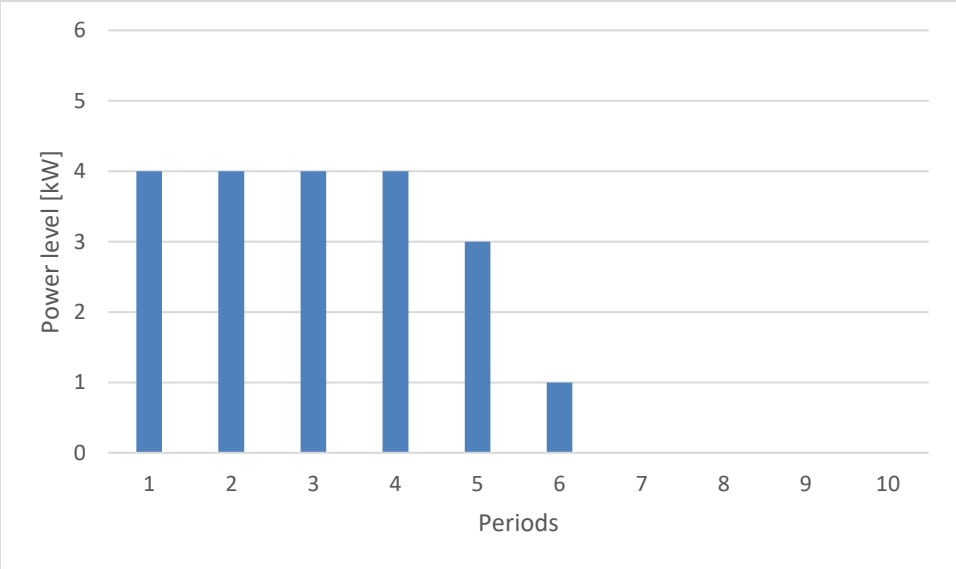

Figure 1. Original charging schedule

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 2, where the profile from Figure 1 is shifted 4 periods.

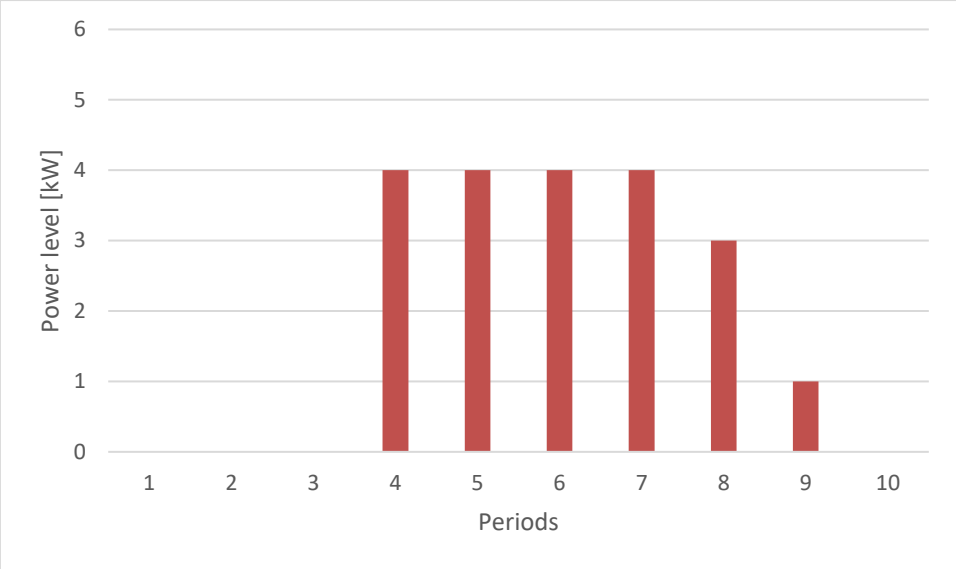

Figure 2. Shiftable charging.

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 3.

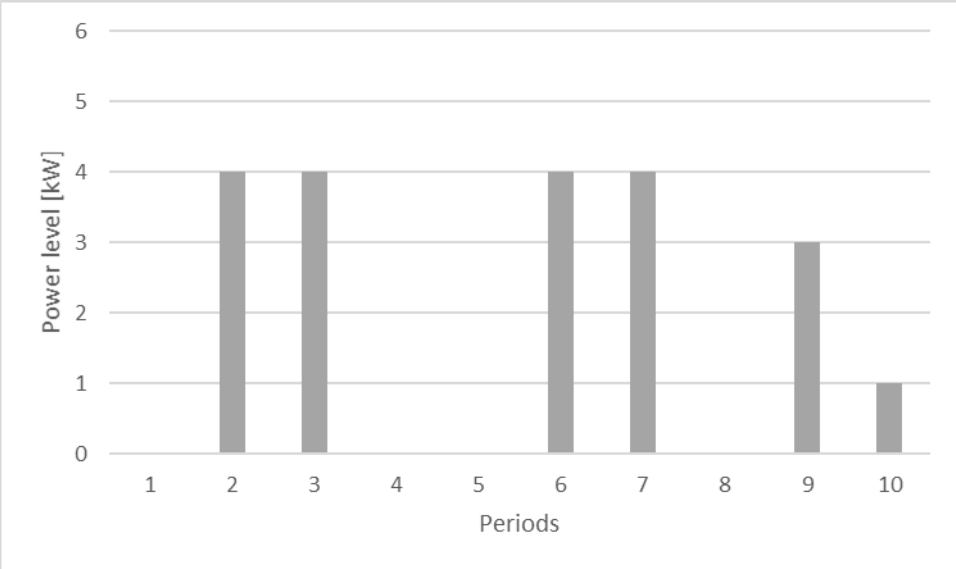

Figure 3. Shiftable and interruptible charging.

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 4, where the total charged energy volume is the same as in Figure 1.

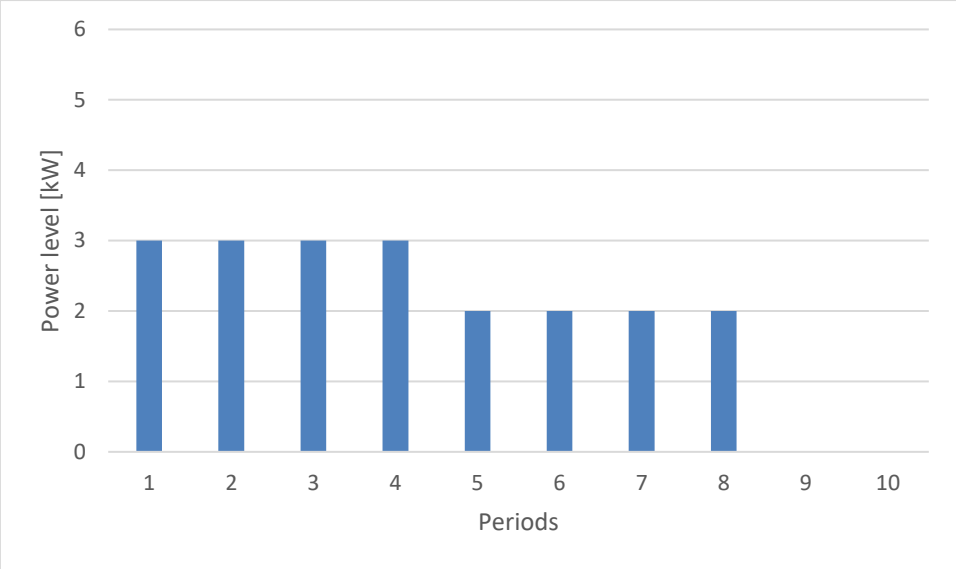

Figure 4. Controllable power level charging.

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 5, 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 1.

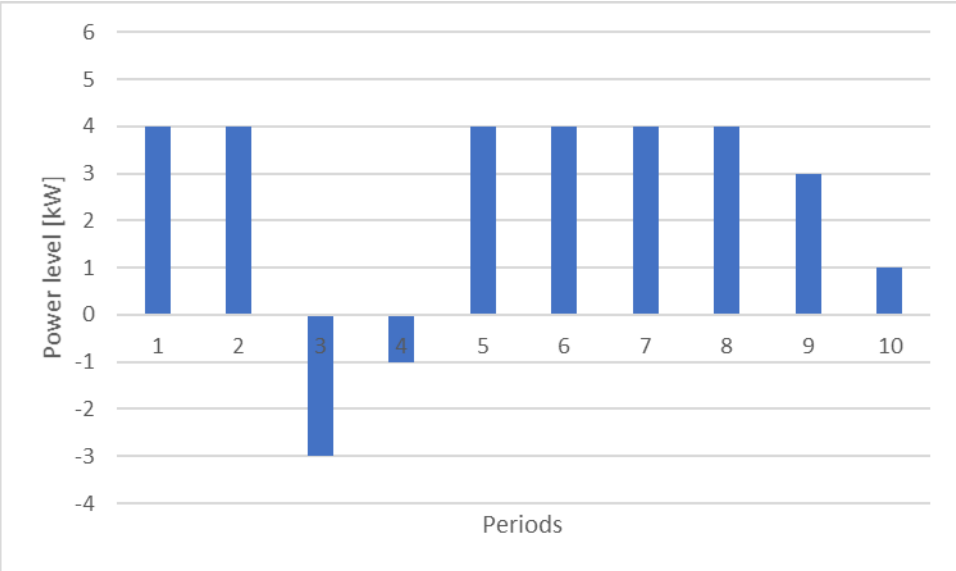

Figure 5. Charging with V2X capabilities.

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

2.1.2.2 Mathematical formulation

As seen from the previous section, electric vehicles can be modelled as shiftable profile loads. Alternatively, one can adapt the battery model from section 2.1.1 to the EV characteristics. This section proposes a EV model based on the battery model and it has been developed by Damiano Fraizzoli and Pol Olivella in Damiano's Master Thesis [6].

The EV model has been developed with the purpose of finding the optimal dispatch for the charging of the EV under the constraints given both by the owner of the EV and external agents like the Distribution System Operator (DSO) or the Balance Responsible Party (BRP).

This model is considered for scheduling EV charges in private stations, typically at home. Public EV charging stations are not considered flexible, and therefore they cannot be controlled[1].

The flexibility that an EV can provide is defined as the ability to postpone the EV charging without affecting the usability for the owner. The EV can be used and charged several times during the day.

This model considers all trips and charging processes within the simulation periods. Therefore, the present model enables to postpone an EV charging process if the driving needs are satisfied. Hence, the EV charging processes can be cheaper. For instance, at home if the energy is coming from EV driver's photovoltaic (PV) panels at midday.

The state of charge equations are given below. Notice that the equation given for t ≥ 2 could be applied in the general battery model in section 2.1.1 as well.

$$\sigma_{e,t}^{EV,soc} = s_e^{EV,start} + \sigma_{e,t}^{EV,in} * A_e^{EV.in} - s_{e,t}^{EV,out}, t = 1$$

$$\sigma_{e,t}^{EV,soc} = \sigma_{e,t-1}^{EV,soc} + \sigma_{e,t}^{EV,in} * A_e^{EV.in} - s_{e,t}^{EV,out}, t \geq 2$$

The following symbols are used:

- $\sigma_{e,t}^{EV,soc}$ is a variable representing the state of charge of the battery in kWh, where *e* indicates which particular vehicle is considered and *t* refers to the time-step;
- $\sigma_{e,t}^{EV,in}$ is a variable representing the energy input to the EV battery measured in kWh. The meaning of the subscripts is the same;
- $A_e^{EV,in}$: charging efficiency:

$s_{e,t}^{EV,out}$ is an input parameter that contains information about the forecasted use of the vehicle. The FO is in charge to forecast this energy consumption. It contains the energy output (or input) in all the regions where for the operator it is not possible or allowed to operate. Since it is not useful or realistic to know the exact pattern for the discharge of the EV outside the operator's control, the total consumption of the batteries that has occurred during a trip is concentrated in the last time-step of the trip;

$$0 \leq \sigma_{e,t}^{EV,in} \leq Q_e^{EV,in} * a_{e,t}^{EV}$$

[1] However, this might change in the future.

The state of charge is subject to the following constraints

$$\sigma_{e,t}^{EV,soc} \geq s_{e,t}^{EV,soc,min}$$

$$\sigma_{e,t}^{EV,soc} \leq O_e^{EV,max}, \forall\, t$$

$$\sigma_{e,t}^{EV,soc} = s_e^{EV,soc.end}, t = T$$

$s_{e,t}^{EV,soc,min}$ is the minimum EV battery energy that the EV driver determines at specific period *t*. For example, this could be used to ensure that the EV is fully charged at the early morning. In a similar way, $s_e^{EV,soc.end}$ defines the energy at the end of the operation horizon *T* if it is needed.

Capabilities of the model:

- The model assumes that the EV should be fully charged at the early morning if it is possible. If it is not possible, the model cannot schedule it and it should be removed for the flexibility portfolio because it cannot be controlled. Otherwise, the optimization problem is infeasible. However, this can be tuned through parameters $s_{e,t}^{EV,soc,min}$ and , $s_e^{EV,soc.end}$.
- It can manage full control and on/off control EV chargers (curtailable).

The cost of flexibility provided by the EV becomes:

$$\sum_t P_{e,t}^{EV} * a_{e,t}^{EV} * \left(\frac{s_{e,t}^{EV,soc} - \sigma_{e,t}^{EV,soc}}{O_e^{EV,max}} \right) \;\; \forall\, e \;\in EV$$

The following symbols are used:

- P_t^{user} is the flexibility price contracted with the EV owner and agreed with the FO
- $a_{e,t}^{EV}$ binary variable = 1 if the EV *e* is available to be plugged and charged during period *t*, else 0.
- $s_{e,t}^{EV,soc}$ forecasted state of charge if the EV *e* during period *t* is charged when it is plugged
- $O_e^{EV,max}$ is an input parameter that represents the usable capacity of the EV battery

2.2 Objective functions

This section introduces different objective functions related to different flexibility services. First of all, the prosumer flexibility service and its objective function refers to the electricity bill minimization problem. Some researchers refer to this problem as the home energy management problem.

In contrast, offering flexibility services to DSO and BRP are different types of problems because all flexible assets can participate by aggregation groups. Those groups can be generated according to their grid connection point or BRP membership.

2.2.1 Flexibility for prosumers

The value of flexibility for prosumers is dependent on the tariff/contract setup, capacity limitation, cost for different types of flexibility and other parameters. This is briefly described in section 5.2. For these reasons, the objective function for prosumers will vary from case to case, including from pilot to pilot, but probably also within pilots.

However, in general terms, we can state that the objective most likely will be a cost minimization function, subject to a set of constraints, where some are technical and some more related to commercial/contractual terms.

This objective function reflects the Flexibility Operator (FO) activation cost for executing flexibility and the minimization cost for prosumers during periods without DSO/BRP requests. Other prosumer's economic compensations like the availability fee should be considered in the settlement process but they are not included in the operation phase.

Furthermore, the objective function reflects the total cost per period (*t*) that a prosumer (*y*) during each scenario (*s*). Scenarios represent a possible realization of the uncertain parameters.

This objective function can be different in each country or even region according to the electricity tariff structure. Tariff structures are exposed in section 2.3. This document presents a generic equation that should be adapted to each pilot.

The first term is the cost of importing energy from the grid ($P_{y,t,s}^{grid-import}$) [€/kWh] and the energy imported during period *t* ($\chi_{y,t,s}^{grid-import}$) [kWh/period].

The second term is the energy payments for supplying energy to the grid in a similar way.

The third and fourth terms are compensation for curtailing photovoltaic generation ($\chi_{y,g,t,s}^{Gr}, \chi_{y,g,t,s}^{Gd}$).

The fifth and sixth are the economic compensations for charging ($\sigma_{y,b,t,s}^{in}$) or discharging ($\sigma_{y,b,t,s}^{in}$) batteries (*b*) during period (*t*) and scenario (*s*) respectively. Additionally, the seventh term is a cost for discharging the battery related to the battery life reduction in [€/kWh]. This needs to be discussed in more detail with WP6.

The eighth is the cost for delaying the EV charge measured as the difference between the business-as-usual case ($S_{y,e,t,s}^{EV,soc}$) and the optimized scenario ($\sigma_{y,e,t,s}^{EV,soc}$).

The last term is the economic compensation for shifting a load (k) *n* time periods.

$$
\begin{aligned}
min f_{obj}^{PRO} = \sum_{t \in T} \Bigg(& P_{y,t,s}^{grid-import} \chi_{y,t,s}^{import} - P_{y,t,s}^{grid-export} \chi_{y,t,s}^{export} + \\
& \sum_{g \in G^r(y)} P_{y,g,t}^{Gr} \chi_{y,g,t,s}^{Gr} + \sum_{g \in G^d(y)} P_{y,g,t}^{Gd} \chi_{y,g,t}^{Gd} + \\
& \sum_{b \in B(y)} (P_{y,b,t}^{B,in} \sigma_{y,b,t,s}^{in} + P_{y,b,t}^{B,out} \sigma_{y,b,t,s}^{out}) + \frac{\sigma_{y,b,t,s}^{out}}{O_{y,b}^{max}} \cdot K_{y,b}^{Cb} + \\
& \sum_{e \in EV(y)} P_{y,e,t}^{EV} \cdot a_{y,e,t,s}^{EV} \cdot \frac{(S_{y,e,t,s}^{EV,soc} - \sigma_{y,e,t,s}^{EV,soc})}{O_{y,e}^{EV,max}} \Bigg) + \\
& \sum_{k \in K^{SP}(y)} \sum_{c \in C(y)} \sum_{n=0}^{T_{k,c}^{end} - V_{k,c}^{end}} P_{y,k}^{SP} \cdot \gamma_{y,k,n,c} \cdot n
\end{aligned}
\qquad \forall y \in Y
$$

2.2.2 Flexibility for DSO or BRP

In contrast to the previous case, the optimization cost function during periods with external requests is as follows:

$$
\begin{aligned}
min f_{obj}^{LFM} = \sum_{t \in T} \Bigg(& \sum_{g \in G^r} P_{g,t}^{Gr} \chi_{g,t}^{Gr} + \sum_{g \in G^d} P_{g,t}^{Gd} \chi_{g,t}^{Gd} + \\
& \sum_{b \in B} (P_{b,t}^{B,in} \sigma_{b,t}^{in} + P_{b,t}^{B,out} \sigma_{b,t}^{out}) + \sum_{k \in K^{CD}} P_k^{CD} \cdot (\delta_{k,t}^{start} + \delta_{k,t}^{run}) \Bigg) + \\
& \sum_{k \in K^{SP}} \sum_{c \in C} P_k^{SP} \cdot (\rho_{k,c} - V_{k,c}^{start})
\end{aligned}
$$

Notice that the sets *y* and *s* are not included in this formulation as all flexible assets are not grouped by prosumer and only one scenario is considered. However, this will be discussed during next development stages of the models and this objective function could be changed according to pilot specifications.

During DSO flexibility services, the segregation by grid zones during DSO requests could be needed according to the grid topology. This will be included in further versions of the modes. In contrast, this is not necessary when the BRP needs to activate flexibility if all members belong to the same BRP.

Finally, external constraints represent the request for fulfilling upward and downward regulation. There are two possible approaches to define the external need: control or capacity based. Control-based signals specify the minimum required amount of active energy variation with respect to the forecasted baseline scenario and are denoted as D_t^{CON}. Positives and negative values of D_t^{CON} mean upward and downward regulation respectively.

In contrast, capacity-based signals define the maximum amount of consumption or generation for a specific group of customers. These customers have to be placed in the same grid zone defined by the DSO. Capacity-based signals are denoted as $D_t^{CAP,max}$ and $D_t^{CAP,min}$ for the maximum or the minimum value that the community is allowed to consume or produce.

Additionally, the control-based request can be formulated as a regulation bandwidth between the maximum and minimum flexibility requested. Hence, the maximum flexibility request could avoid a possible rebound effect. This could be critical after a regulation period with many disconnections. For instance, the maximum boundary could avoid the simultaneous reconnection of loads after an up-regulation period.

$$D_t^{CON,min} \leqslant \sum_{b\in B} \sigma_{b,t}^{out} + \sum_{k\in K^C} W_{k,t}^{CD} \cdot (\delta_{k,t}^{start} + \delta_{k,t}^{run}) + \sum_{e\in EV} (s_{e,t}^{EV,in} - \sigma_{e,t}^{EV,in}) + \sum_{k\in K^{SP}} (W_{k,t}^{SP} - \omega_{k,t}) - \sum_{g\in G^r} \chi_{g,t}^{Gr} - \sum_{g\in G^d} \chi_{g,t}^{Gd} - \sum_{b\in B} \sigma_{b,t}^{in} \leqslant D_t^{CON,max} \quad \forall t \in T$$

In case of capacity-based control requests, the total amount of energy consumed and produced must be kept within certain limits. The following equation ensures that the total amount of energy is kept within a certain upper and lower limits.

$$D_t^{CAP,min} \leqslant \sum_{b\in B} \sigma_{b,t}^{in} + \sum_{k\in K^C} W_{k,t}^{CD} \cdot (1 - \delta_{k,t}^{start} - \delta_{k,t}^{run}) + \sum_{k\in K^{SP}} \omega_{k,t} - \sum_{b\in B} \sigma_{b,t}^{out} - \sum_{g\in G^r} (F_{g,t}^{Gr} - \chi_{g,t}^{Gr}) - \sum_{g\in G^d} (F_{g,t}^{Gd} - \chi_{g,t}^{Gd}) \leqslant D_t^{CAP,max} \quad \forall t \in T$$

2.3 Prosumer tariff structures

The profitability and operation possibilities of DER, home batteries and EVs depend on the tariff structure at the point of connection. The tariffs vary from country to country and also between different grid companies within a country. This section aims to highlight these differences with examples from Norway and Spain. The tariff structures in all INVADE areas will be assessed in the later stages of Task 5.2.

2.3.1 Norwegian cases

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.

The main purpose of the grid contracts is to cover the DSO's expenses in operating, maintaining and reinforcing the distribution grid. Furthermore, the grid contracts aim at distributing the expenses between the grid users in a fair manner. In the Norwegian regime, the grid contracts are normally based on a two- or three-part tariff, dependent on how the consumer is metered. For periodically metered consumers the payment consists of two components: A fixed fee, which might be based on main fuse size, and an energy fee, which normally is based on metered electricity consumption paid according to a fixed price per kWh. For larger consumers with hourly metering, a third part may exist, based on one or a limited number of the highest metered hourly consumptions within a month. This element is paid according to a fixed price per kWh/h per month and is often denoted power charge.

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.

For prosumers, the surplus electricity which is fed into the grid, will have a different cost for the energy fee. This is very small or even negative.

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.

For retail contracts the variation is larger. In addition to free choice of retailer, the consumer can also select the contract type according to preferences. For consumers with periodically metered consumption, the most common are fixed or variable prices. The latter may be one specified price for a period, for instance a month, or it may follow the Day-ahead market prices. However, although the price varies from hour to hour, the consumption is only metered as an accumulated consumption for a long period, and is distributed according to a pre-defined profile to be able to settle hourly prices. For larger consumers with hourly metered values, the real consumption can be settled according to the market prices, hour by hour.

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 word, 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.

Assume that a prosumer generates 1 kWh in a specific hour. If this kWh is consumed at the prosumer’s premise, the value (saving) has three components: The grid cost, the retail cost and the taxes. If this kWh hour on the contrary is exported, the only compensation is the retail price. This is the reason why self balancing may be a target.

However, lately also other pricing models have emerged, where the compensation for selling back surplus is higher than the corresponding price for buying.

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.

The main point here is that the pricing regime is very much influencing what actions that are optimal, and thus the value of flexibility for the prosumer.

2.3.2 Spanish case

Since 2009, with the liberalization of the Spanish electricity market, the consumer has the possibility of choosing the retailer company and between three types of electricity tariff. These types are:

- Voluntary Price for Small Consumer (PVPC):

  The PVPC (previously called the Last Resort Tariff, TUR) is a regulated electricity rate, which prices are fixed by the State. It is only valid for domestic consumers with a contracted power that does not exceed 10 kW. Energy prices are hourly based and reflect the prices of the energy wholesale market. They are published the previous day around 20.00h at the REE website (www.esios.ree.es/en/pvpc).

- 12-month fixed contract:

  This type of contract has an annual fixed energy price and it also belongs to the regulated market. The annual fixed contract offers greater price stability because it is fixed for twelve months and is useful for those consumers who wish to know at any time what they will pay for their electrical consumption.

- Bilateral recruitment:

  In this case, the consumer contracts the supply of electricity with any retailer in the free market according to the price and the conditions that the consumer agrees with the electricity retailer. They tend to offer discounts in terms of power and/or energy in order to attract more consumers. Instead, unlike what happens in the regulated market, these include additional services, permanence or special clauses that must be taken into account when assessing the total of the offer.

The regulated PVPC and 12-month fixed contracts can only be offered by the biggest utilities, clustered in a group called Utilities of reference (Comercializadoras de referencia, COR). Currently, the utilities of reference are:

- Endesa Energía XXI, S.L.U.
- Iberdrola Comercialización de Último Recurso, S.A.U.
- Gas Natural S.U.R., SDG, S.A.
- EDP Comercializadora de Último Recurso, S.A.
- E.ON Comercializadora de Último Recurso, S.L.
- CHC Comercializador de Referencia S.L.U.

All these contract types have the same 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.
- 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 that sense, the tariff structure includes two main components, a per kW charge (contracted power) and a per kWh charge (energy consumption). In general, around 35% of the energy bill corresponds to the energy term, around 40% to the power term or fixed costs and around 25% to taxes.

In addition, tariffs can have several periods with different energy prices. According to that, the available tariffs for domestic consumers with a contracted power of less than 15 kW are:

- 2.0A with 1 time period for energy and power

  This tariff only has one period with a single rate applied to the energy term for 24 hours a day.

- 2.0DHA with 2 energy time periods and 1 power time period

  This tariff has two periods. It is based on peak and off-peak periods (P1 and P2) in which the valley has a reduced rate and the peak a higher rate.

- 2.0DHS with 3 energy time periods and 1 power time period

  This tariff has three different periods. It is based on the peak, off-peak and valley periods (P1, P2 and P3) where the valley period has even lower rates than the off-peak period. It is intended for those customers who have intensive consumption during night hours and it is designed to make charging electric vehicles more economical.

Table 2 shows the schedule of the time periods for 2.0 DHA and 20DHS tariffs, and Table 3 gives an example of yearly-fixed rates for the domestic tariffs 2.0A and 2.0DHA offered by Mercator.

Table 2: Schedule of the time periods of 2.0 DHA and 2.0 DHS tariffs.

Tariff	Periods	Winter	Summer
2.0DHA	P1 (Peak)	12h to 22h	13h to 23h

	P2 (Off-peak)	22h to 12h	23h to 13h
2.0DHS	P1 (Peak)	13h to 23h	
	P2 (Off-peak)	23h to 1h and 7h to 13h	
	P3 (Valley)	1h to 7h	

Table 3: Example of yearly-fixed rates for 2.0 DHA and 2.0 DHS tariffs.

Tariff	Periods	Power term	Energy term
2.0A	P1 (Peak)	0,121649 €/kW/day	0,135948 €/kWh
2.0DHA	P1 (Peak)		0,159423 €/kWh
	P2 (Off-peak)		0,075550 €/kWh

As an example, Figure 6. PVPC rates for the 2.0 A, 2.0 DHA and 2.0 DHS tariffs the day 01/09/2017 (source eSIOS). shows the PVPC rate values of the 2.0 A, 2.0 DHA and 2.0 DHS tariffs the day 01/09/2017.

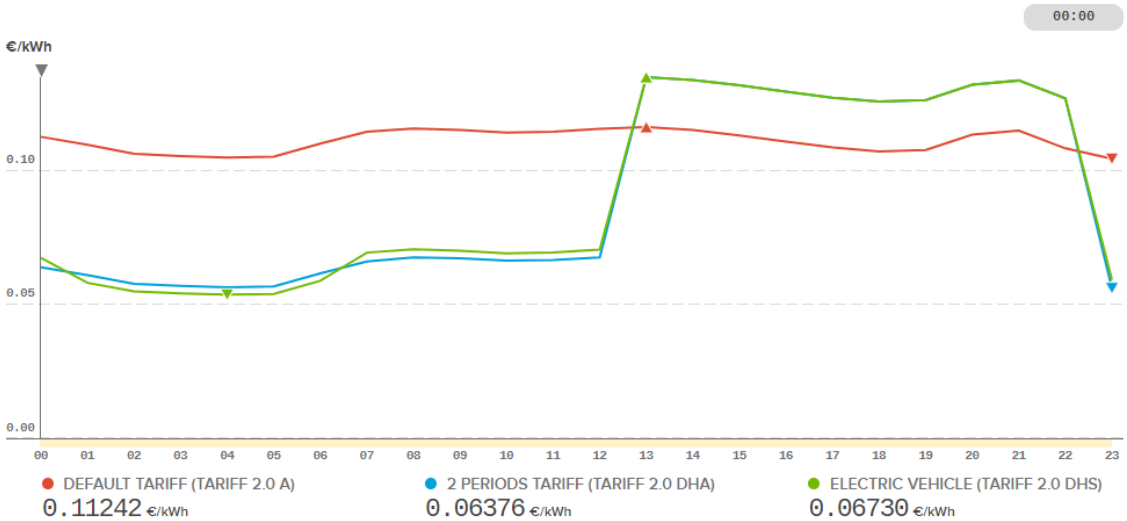

Figure 6. PVPC rates for the 2.0 A, 2.0 DHA and 2.0 DHS tariffs the day 01/09/2017 (source eSIOS).

3 Flexibility potential analysis methodology

This chapter aims to quantify and describe the flexibility potential of a portfolio composed of common distributed energy resources (DER) in residential distribution grids. Those DER are photovoltaic generators, batteries, EVs and loads with a shiftable profile.

The work presented in this chapter is based on Fraizzoli' Master Thesis submitted in UPC and supervised by Andreas Sumper and Pol Olivella [3].

There are certain typologies of analyses needed to evaluate the potential of a flexibility portfolio. Those analyses are:

1. Instantaneous analysis
2. Consecutive periods analysis

The methodology developed can be interesting for carrying feasibility studies for flexibility operators.

3.1 Case study portfolio

The portfolio case study is composed by:

- 4 reducible generators (5 kWp each)
- 1 battery (6 kWh and 4 kW)
- 4 Electric vehicles (41 kWh and 3.2 kW)
- 12 loads with a shiftable profile (4 dishwashers, 4 washing machines and 4 tumble dryers)

The proportion of each device was decided with the rationale that the flexibility potential of the different categories should be comparable in order of magnitude. On the other side, the total number of devices should be high enough to show at the same time some different configurations, but small enough to keep all the parameters under control.

The next figure is an example of flexibility provided by the portfolio during an entire day under a DSO request for up and down regulation. Positive flexibility means up regulation (increase generation or decrease consumption). Negative flexibility is down regulation. The DSO request is a control-based request and the FO is the central entity executing an optimization problem to schedule all flexible resources for the following day. Details of the optimization problem executed in this case can be found in [2].

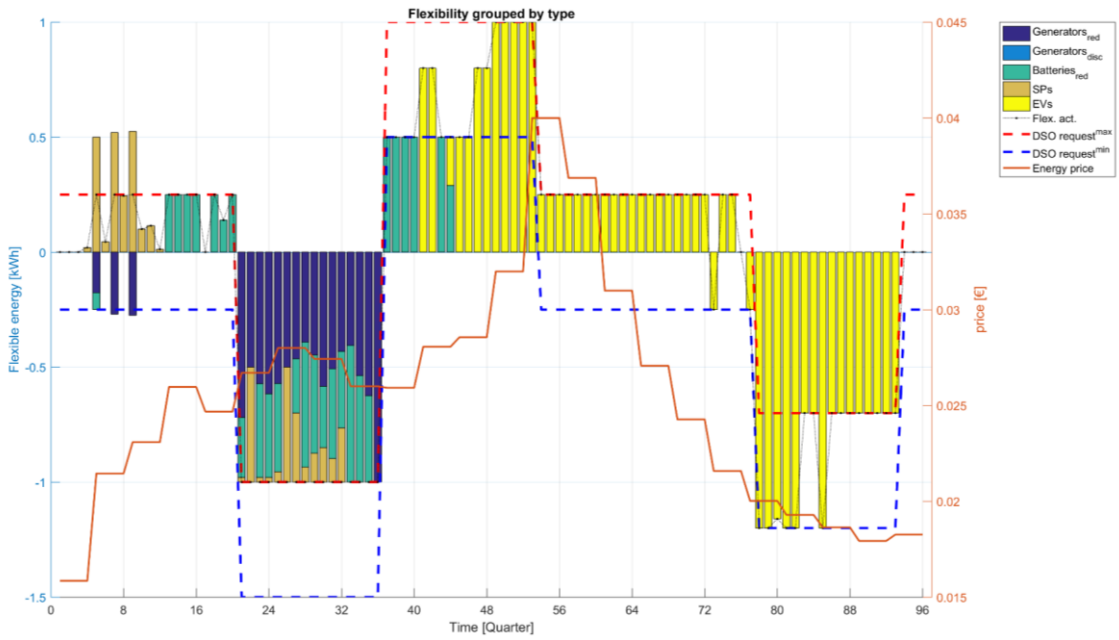

Figure 7. Solution of the custom problem for the reference portfolio. Source: [6]

3.2 Combined instantaneous flexibility analysis

Figure 7 shows up the maximum flexibility provided by a certain portfolio using all kind of DER. As it was seen, the distribution of the potential is quite irregular and depends heavily on whether the regulation considered is up- or down-regulation. The cumulative distribution of the different instantaneous flexibility analyses can be seen in Figure 8.

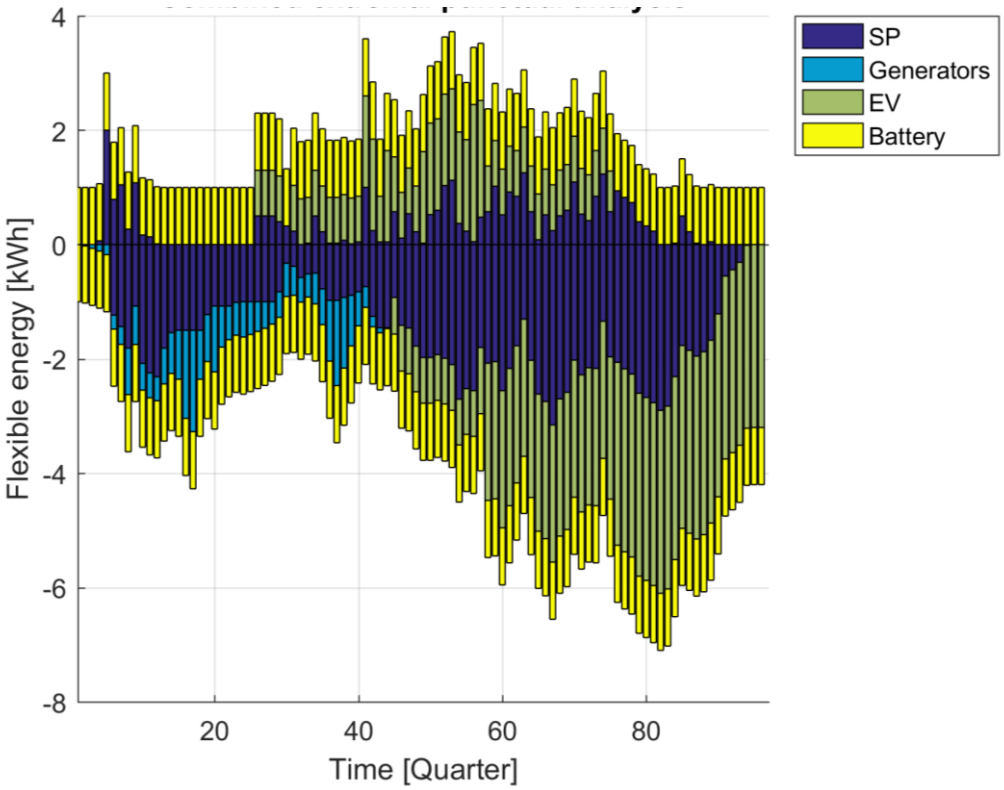

Figure 8. Combined instantaneous analysis. Source: [6].

One of the main issues to be considered during flexibility analysis is the interdependence effect in DER. This effect is the influence of activating flexibility in a period, over future availability of flexibility.

For instance, the number of periods that a shiftable profile (SP) can be shifted determines the up- and down-regulation simultaneously. Once the SP is shifted 'n' periods for providing up-regulation, the down-regulation service is limited to the shifted consumption periods. Therefore, the potential and the feasible flexibility can vary. The same happens with EV and batteries. In contrast, photovoltaic generators providing down-regulation have no interdependence effect because the energy disconnected during a period does not compromise the flexibility during forthcoming periods.

The conclusions of Fraizzoli' master thesis [6] in instantaneous flexibility analyses showed different results for the up- and down-regulation even of the same device type.

In the consecutive periods analyses, it was possible to see a correlation between the length of the period considered and the reduction of average regulation that is possible to provide in the period. This is explained by the limited flexibility capacity of the devices.

Additionally, the distribution of the potential depends heavily on the type of device considered and the kind of regulation that is investigated. In general, the potential for down-regulation seems to be higher than the one for the up-regulation. The devices with the best distribution of the potential for flexibility are batteries, while the worst are the generators.

4 Method for cost-benefit analysis

4.1 Net Present Value

The methods to be used is based on calculating the Net Present Value (NPV) of a project, which is generally 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, the NPV is in its simplest form given as:

$$NPV(P_{rat}, E_{rat}) = \sum_{n=1}^{N} \frac{R(P_{rat}, E_{rat}, n) - O(P_{rat}, E_{rat}, n)}{(1+r)^n} - C(P_{rat}, E_{rat})$$

where the annual revenue *R*, the annual operational costs *O* and initial installation cost *C* of the are 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

$$NPV(P_{rat}, E_{rat}) = \alpha_{N,r} \cdot R(P_{rat}, E_{rat}) - C(P_{rat}, E_{rat})$$

where *α* is the annuity factor[2]. The annual revenue is the sum of revenues obtained from the services listed in Table 1. This comprises of fixed annual contracts (e.g. from a DSO to provide flexibility for congestion management and voltage control) and revenues from activation of the battery at different time steps (e.g. from the BRP for spot price optimization). For prosumer services, *R* may not consist of cash inflows as such, but rather operational cost savings compared to a system *without* the battery (or antoher flexible asset). In general, the annual revenue can be expressed as:

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

where the resolution of the time step *t* depends on the market conditions and DSO requirements for activation of services. The time step size *dt* can e.g. be one minute, 15 minutes or 1 hour.

4.2 Optimal storage sizing

4.2.1 Analytical formulation

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 storage's technical capabilities - and investment cost, which is illustrated in Figure x for a battery system where the energy storage capacity is (for simplicity) the only free variable.

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[2] $\alpha_{n,r} = \sum_{n=1}^{N} (1+r)^{-n} = \frac{1-(1+r)^{-n}}{r}$

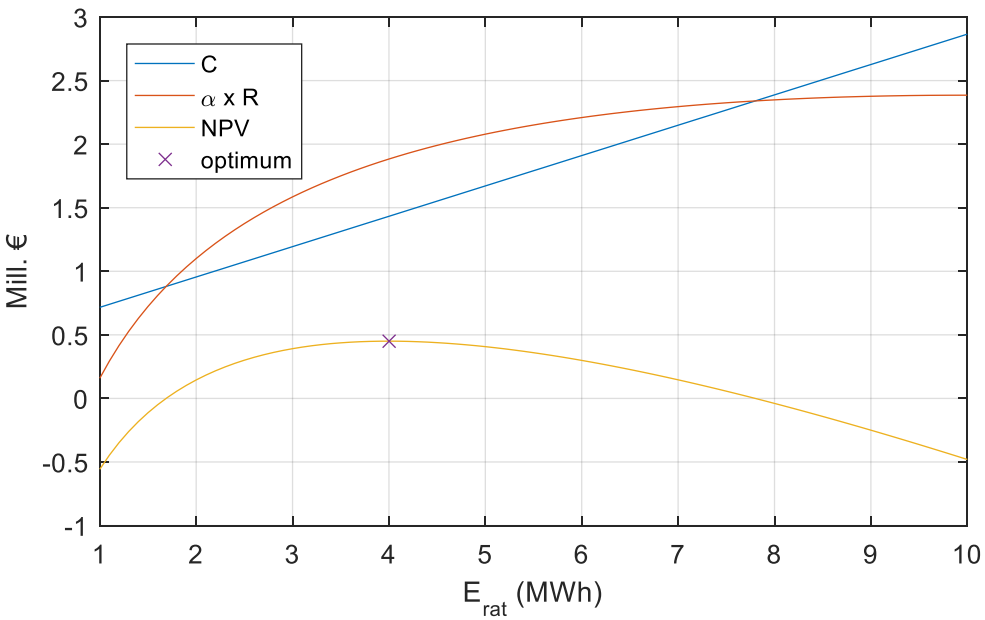

Figure 9. Illustration of how investment costs (C), annual revenue (R) and the net present value (NPV) depends on the rated energy capacity of a battery. NPV=α×R-C, where α is the annuity factor.

An analytical solution of the maximum NPV can in principle be found by setting the partial derivative of the free variables (the power and energy capacity of the storage) to zero:

$$\frac{\delta NPV}{\delta E_{rat}} = \frac{\delta}{\delta E_{rat}}(\alpha_{N,r} \cdot R(P_{rat}, E_{rat}) - C(P_{rat}, E_{rat})) = 0$$
$$\frac{\delta NPV}{\delta P_{rat}} = \frac{\delta}{\delta P_{rat}}(\alpha_{N,r} \cdot R(P_{rat}, E_{rat}) - C(P_{rat}, E_{rat})) = 0$$

For modular devices such as stationary batteries, the fixed cost *C* can be expressed by a linear equation (see e.g. [7]), and is therefore differentiable. However, the annual revenue is not possible to differentiate analytically for real cases, since the revenue depends on many complex factors, such as technical restrictions, storage operation strategy, market conditions and rules for connection to the grid. It is therefore common to calculate the annual revenue by some type of simulation (optimization-based [8], rule-based [9][3], monte-carlo based [10] or probabilistic [11], [9][4]). Since we deal with storage, it is necessary to take into account the time sequence.

4.2.2 Analytical optimization

In analytical optimization, we express the objective function and constraints explicitly as analytic functions, which can be linear or non-linear. The problem formulation can in general be expressed as:

$$\text{Maximize} \quad f(\boldsymbol{x})$$

[3] Chapter 3

[4] Chapter 4

$$\begin{aligned} \text{subject to } \; & g_i(\mathbf{x}) \leq 0, \;\; i \in \{1, \dots, m\} \\ & h_i(\boldsymbol{x}) = 0, \;\; i \in \{1, \dots, p\} \\ & \boldsymbol{x} \in \boldsymbol{X} \\ & \boldsymbol{X} \subseteq \mathbb{R}^n \end{aligned}$$

where *f* is the objective function, *x* contains the decision variables, *g* are inequality constraints and *h* are equality constraints, see e.g. [12].

4.2.2.1 Example: Spot market optimization

To illustrate the method, we present here a simple, linear example for the optimal sizing of energy storage based on spot price arbitrage. The technical description of the battery, and the market operation used in the example is simplified compared to the model description in Chapter 2, since the emphasis is on the battery sizing. For the market and grid operation, the grid constraints are omitted, and each year is treated equal. Our goal is to find the rated power and energy capacity that maximizes the NPV of the project.

The NPV is given in section 2.1, and we need expressions for the total installation cost *C* and the annual revenues *R*.

The installation cost are assumed to a be linear function of the rated power and energy capacity:

$$C = a + b_1 \cdot P_{rat} + b_2 \cdot E_{rat}$$

where *a*, b_1 and b_2 are constants.

The annual revenue is in this example given by the sum of the net income from the spot market over the year:

$$R = \sum_{t=1}^{T} p_{sm,t} \cdot (P_{dch,t} - P_{ch,t}) \cdot \Delta t$$

where $p_{sm,t}$ is the spot market price in time step *t*, $P_{dch,t}$ is the average power discharge from the battery during time step *t*, and $P_{ch,t}$ is the average charging power of the battery during time step *t*.

The objective function then becomes

$$f(x) = \; NPV = \alpha_{N,r} \cdot \left(\sum_{t=1}^{T} p_{sm,t} \cdot \left(P_{dch,t} - P_{ch,t}\right) \cdot \Delta t \right) - (a + b_1 \cdot P_{rat} + b_2 \cdot E_{rat})$$

where *N* is the battery lifetime and *r* is the chosen discount rate.

The restrictions of the problem comprises the storage balance and battery operation limits:

$$\begin{gathered} E_1 - E_{init} = \left(P_{ch,1} \cdot \eta_{ch} - P_{dch,1} \cdot \frac{1}{\eta_{dch}} \right) \cdot \Delta t \\ E_t - E_{t-1} = \left(P_{ch,t} \cdot \eta_{ch} - P_{dch,t} \cdot \frac{1}{\eta_{dch}} \right) \cdot \Delta t, \qquad t \in \{2, \dots, T\} \\ 0 \leq P_{ch,t} \leq P_{rat} \,, \quad t \in \{1, \dots, T\} \\ 0 \leq P_{dch,t} \leq P_{rat} \,, \quad t \in \{1, \dots, T\} \end{gathered}$$

$$0 \leq E_t \leq E_{rat}\,, \quad t \in \{1, \dots, T-1\}$$
$$E_T \geq E_{init}$$

where the decision variables are the rated power capacity, rated energy capacity, the charge and discharge power in each time step, and the energy storage level in each time step. The last restriction is set to ensure that the final battery storage level is at least as high as the initial value at the start of the year. The problem stated above can easily be implemented and solved in a standard optimization package like GAMS, AMPL, Mosel, Pyomo etc.

The benefit of these types of model formulation is that we know the structure of the whole problem and can choose a suitable solving method based on this. The drawback is that the problem soon gets very big if we include several markets, short-term stochasticity and so on. Then it becomes more practical to split the problem in a simulation part (where the rated power and energy capacities are given) and a design part (a loop on top of the simulator to find the best combination of the rated power and energy capacities). This is called *black-box optimization* and is briefly introduced in the next section.

It should be noted that the energy storage model shown here is on generic, simplified form for illustrative purposes. For detailed battery models, see INVADE Deliverable D6.1 [13].

4.2.3 Black-box optimization

In black-box optimization, we do not know the analytical expression of the objective function. Its general form can be expressed as:

$$\text{Maximize} \quad f(\boldsymbol{x})$$
$$\boldsymbol{x} \in \boldsymbol{X}$$
$$\boldsymbol{X} \subseteq \mathbb{R}^n$$

where we know the boundaries for the decision variables $\boldsymbol{x}$, and we can obtain the numerical value of f as a function of $\boldsymbol{x}$. This optimization method can be applied "on top" of a simulator of a given energy system – the simulator being the black-box.

For our simple battery problem, we now consider that the annual revenue R is calculated inside a simulator[5], with input arguments P_{rat} and E_{rat}. The required output argument is R, but additionally the time step values of the charging power, discharging power and energy storage level can be provided although not needed for the optimization problem.

Keeping a linear investment cost function of the battery as before, the objective function becomes:

$$f(x) = NPV = \alpha_{N,r} \cdot R(P_{rat}, E_{rat}) - a + b_1 \cdot P_{rat} + b_2 \cdot E_{rat}$$

[5] If the simulator does not include annual revenue calculation, it is necessary to add an intermediate layer with revenue calculation post-simulation (based on simulation outputs).

One very simple – but potentially inaccurate and time consuming – way to solve the problem is to run the simulator for a range of feasible combinations of P_{rat} and E_{rat}, and select the one with highest NPV. There are numerous advanced methods for solving black-box problems, ranging from free Matlab functions to commercial software packages. For a throughout overview of different algorithms and techniques, see [14] and [15].

5 Value of flexibility services

5.1 Value of flexibility for DSO

The DSO can benefit from local flexibility services in several ways. As listed in Section 1.2, we focus here on congestion management and voltage control. As additional reading on the concept of using flexibility (flexible demand, in this case) as alternative to grid reinforcements, see the recent paper on the subject by Spiliotis et.al, 2016 [16].

5.1.1 Congestion Management

In this case, local flexibility is used for reveling congested situations in the DSO grid. A key question is how local flexibility can be a reliable and cost-efficient alternative to traditional grid upgrades. To assess the value of flexibility, we must establish several alternatives that should be evaluated against each other:

- Congestion case: This is the situation where congestions are occurring, but no particular action is carried out with respect to grid upgrades or flexibility. Congested situations can be solved by different immediate (emergency) procedures. For simplicity, we can here assume forced outage of costumers for power deficit situations and forced reduction of local generation for power surplus situations.
- Grid upgrade case: This is the traditional solution to the congestion problem. Depending on the congestion, the grid upgrade can be to build new lines, new transformers, replacing or adding to existing ones. A variant of this case is where the situation is uncongested, but some line segments must be renewed due to lifetime of the existing equipment. Local flexibility can then be an alternative to this replacement (i.e. a cable connection to a remote island).
- Local flexibility case 1: Congestion caused by too high load.
    - For local flexibility to be a real alternative to grid upgrades in this case, it must prove to fulfil the required reliability standards for the power grid. A main challenge with this respect is that the peak load is hard to predict both regarding time and maximum power. Contracts with EV owners to voluntarily (and automatically) stop charging in critical situations can be extended to even provide reverse power flow if the car is V2G compatible. Similarly, contracts with owners of home batteries can be made to automatically provide power in congested cases. In INVADE, we consider

that these capabilities can be made available for the DSO through an aggregator [1].

- Local flexibility case 2: Congestion caused by too high production.
    - This situation is principally easier to handle than too high load, since the consequences of stopping production for a short period is much less severe, and it is easier to compensate for the loss of produced power. In fact, automatic reduction of solar and wind production can be considered as a local flexibility option. However, with this solution, the surplus energy is “lost”, which makes shiftable loads (such as EVs) and local storage attractive alternatives, as for the case with too high load.

5.1.2 Voltage Control

In weak distribution grids, voltage violations typically occurs before violation of the thermal limits of lines and transformers [17]. Voltage variations can to some extent be suppressed by active and/or reactive power control of local loads and generators. Reactive power control requires certain grid interface for DC loads and generation, which is not mandatory in most grid areas and therefore usually omitted by providers of assets such as EVs, PV panels and stationary batteries.

For situations with too high or low steady-state voltage levels, the problem is similar to the case with grid congestions. Too high levels of distributed generation can cause too high voltage levels (See Local flexibility case 1 in section 5.1.1), and too high loads can cause too low voltage levels (See Local flexibility case 2 in section 5.1.1).

In the next section, an example is given for the case of congestion management, but it is equally relevant for a case with steady-state voltage problems, see e.g. [18].

5.1.3 Value for DSO: Example

In this section, we present a general and simplified congestion case relevant for INVADE. A radial feeder is supplying a load with electricity, initially with no congestions. The introduction of EVs results in a load increase that will cause line currents above the thermal limit if no action is taken. This is illustrated in Figure 10 and Figure 11.

The “worst case” maximum load which is indicated in Figure 11 is given by adding the maximum base load and the maximum EV load. As the 24-hour time plot shows, the “worst case” scenario can be considered as a conservative measure for the required grid capacity, since the maximum base load occurs in the evening, while the maximum EV load occurs at night.

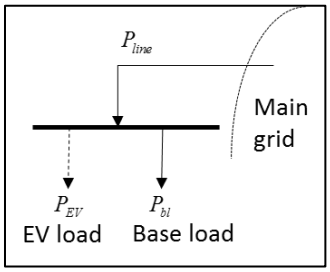

Figure 10. Local power system connected to the main grid with a single feeder.

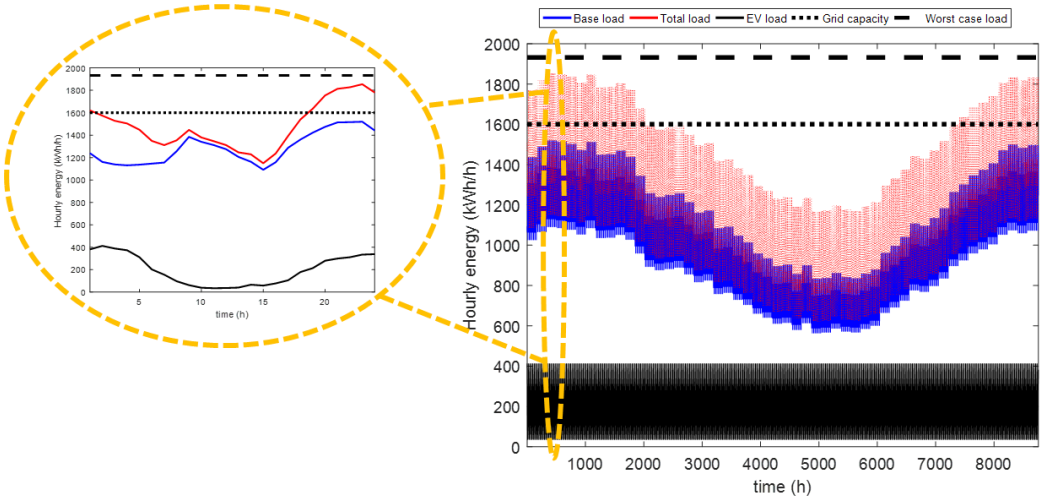

Figure 11. Time plot of the (passive) loads in the local power system shown in Figure 2. The grid capacity and "worst case" maximum load is indicated with dotted and dashed lines, respectively.

We now consider the possibility of EV flexibility, by shifting the time of charging away from critical hours. In line with the INVADE concept design, this can be achieved by an aggregator who can be assumed to control a substantial part of the connected EVs. To illustrate this case, we have constructed a simple control strategy for the EVs, which is to reduce charging in the critical hours until the total load is at its maximum allowable value (equal to the grid capacity of 1600 kW in this example). The charging is increased as soon as the grid capacity allows, for minimizing the influence on the EV batteries State of Charge (SOC).

The result is shown in Figure 12, where it is seen that the total load is kept below the grid capacity over the year (right plot). We can also see how the EV charging profile on critical days is changed, when comparing the left plot with the similar plot in Figure 12. Although heavily simplified, this example highlight a possible issue when using EVs as flexible loads. In order to keep the power flow below the grid limit, some of the charging must be moved to the morning, when many EV owners drive to work. This can result in lower SOC than expected, which can have a negative impact on some EV owners willingness to participate. However, this might be a minimal problem in practice, as long as daily driving distances are considerably lower than the EV range, or if charging possibilities exist at the workplaces.

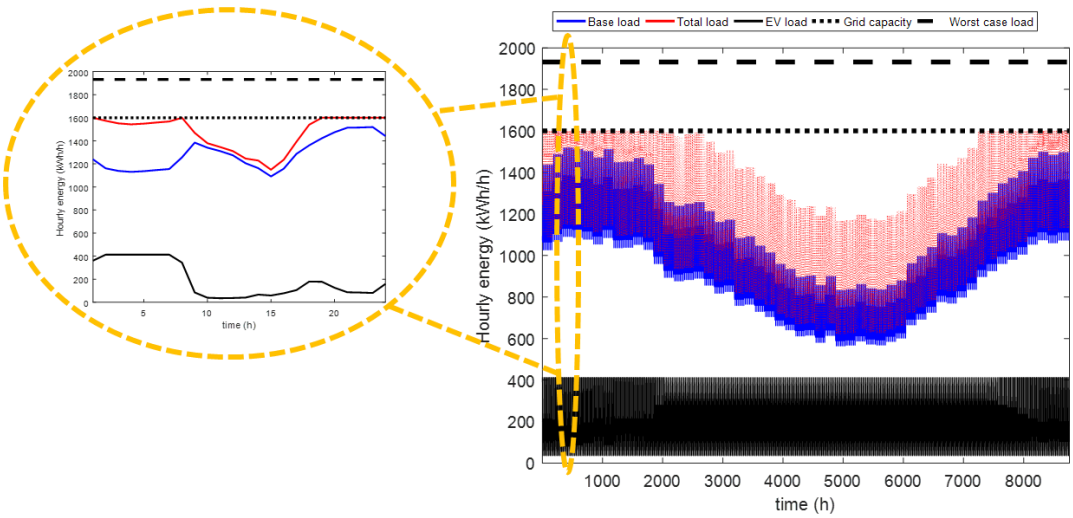

Figure 12. Time plot of the (passive) base load and flexible EV load in the local power system shown in Figure 2. The grid capacity and "worst case" maximum load is indicated with dotted and dashed lines, respectively.

5.2 Value for prosumer

As indicated in section 2.3, the value of flexibility is closely linked to the price regime and the price levels/variations. Flexibility may then be used to minimize the total cost or correspondingly maximize the total profits based on the grid tariff and the retail contract. In this context, costs may also represent disutility or loss of comfort. However, as we saw, flexibility may have other values like the possibility to avoid falling out of the plus-customer arrangement. In addition, other hard constraints might exist, like capacity limits. An example is a main fuse that limits the power flow into a house. A violation might lead to a black out, and flexibility can contribute to avoiding such a situation.

Furthermore, flexibility may help avoiding a capacity reinforcement. In the house example, a larger main fuse might be needed. In a charging station example, an expansion of the number of charging points may induce the need for a larger substation transformer, for which the charging station owner must pay (partly). Flexibility can then be used to avoid these investment costs.

A different setting is when a prosumer is a flexibility vendor, selling flexibility to a Flexibility operator. Then the value of the flexibility relates to maximizing the net profits from the sales.

Two recent Master Theses at Dept. of Electric Power Engineering at NTNU modelled and evaluated the flexibility of EV batteries [21] and stationary batteries [22] for a prosumer with PV and conventional load, under different tariff structures (See section 2.3). The methods used are based on deterministic and stochastic dynamic programming, and where employed for two Norwegian case-studies. In the further work in WP5, we will consider to use these models for the suitable INVADE pilots, focusing on the prosumer perspective.

5.3 Value for BRP

BRP is defined by [20] as "*a market participant or its chosen representative responsible for its imbalances in the electricity market*". Smaller renewable generation facilities are normally not today penalised for their imbalances, but this might change in the near future, due to the increased installation of PV-panels, and their impact on system balancing.

5.3.1 Day-ahead portfolio optimization

The BRP can utilize flexible resources to reduce their electricity purchase costs (or increasing their revenues, depending on the sign of net load) in the day-ahead market. This is done by adjusting their daily bids so that price variations are exploited in a better way according to the availability of the flexible and inflexible resources. Thus, the value of flexibility for this purpose is entirely given by the relative spot price variations within the day and not the price level itself. For example, in [19] the energy arbitrage value for house-installed batteries is about 10-15% cost savings in the electricity bills for the end-user.

To estimate the value of flexibility for day-ahead portfolio optimization, we need spot price forecasts and proper models of the flexible resources to be used in the optimization procedure. We also need to establish a reference case for the BRP portfolio optimization *without* the added flexibility.

Using a one-year forecast for the spot market price as basis, the yearly electricity purchase cost of a BRP with *no flexible assets* can in general terms be expressed as

$$O_{BRP,yr}^{ref} = \sum_{d=1}^{365} O_{BRP,d}^{ref}$$

where the daily costs are given by

$$O_{BRP,d}^{ref} = \sum_{h=1}^{24} p_{sm,d,h} \cdot P_{BRP,d,h}^{ref}$$

Here, purchased energy is given with positive sign. As the spot price is the same for sales and purchased, the equation also holds for net sales.

By adding one or more flexible assets to the portfolio, we can reduce the cost by operating the asset according to price variations within each day. The costs of the BRP now becomes

$$O_{BRP,yr} = \sum_{d=1}^{365} O_{BRP,d}$$

where the minimum possible costs in day *d* is determined by the optimization problem

$$\min_{P_{BRP,h}} O_{BRP,d} = \sum_{h=1}^{24} p_{sm,d,h} \cdot P_{BRP,d,h}$$

$$\text{subject to the technical constraints of the flexible asset(s)}$$

If the flexible assets can be operated separately from each other and from the rest of the BRP's portfolio (e.g. an energy storage), and the trading *only* takes place in the spot market, the optimization of each asset can be performed individually without any loss of value for the BRP.

5.3.2 Intraday optimization

In Nord Pool, intraday trading takes place continuously on a bilateral pay-as-bid basis up to one hour before delivery, offering the possibility to reduce costs for regulating power when the real net load (or generation) of a BRP deviates from the amount settled in the day-ahead market. The value of trading in the intraday market is somehow uncertain as it both depends on the realised BRP unbalance and the realised regulating power prices – both unknown on the time of trading. However, the uncertainty is heavily reduced compared to the spot market clearing which takes place 12-36 hours before delivery, which means that the intraday markets can significantly reduce penalties caused by e.g. wind forecast errors.

For an operator of flexible assets that does not participate in the regulating power market, the intraday market gives an opportunity to earn money by trading with operators of inflexible generators (or loads) who experience deviations due to forecast errors. The value of flexibility of this purpose is however hard to calculate exactly before the time of actual trade, since it depends on the price that the inflexible generator is willing to pay (which again depends on the expected regulating power price as explained above).

5.3.3 Self-balancing

Self-balancing after day-ahead market clearing can be beneficial when the BRP operates both inflexible generators/loads (with forecast errors) and flexible assets. Self-balancing reduces the need for intraday trading, and reduces the risks for imbalance costs for regulating power.

The preferred operating strategy for self-balancing depends on several factors:

- If regulating power prices relative to the day-ahead prices are expected to change significantly over the day
- If we know the position of the system imbalance (up- or down-regulation) during the operation. It may not be necessary to perform self-balancing if the generation/load deviation actually improves the system balance[6].

A simple, but effective, method to estimate the potential value of flexibility for self-balancing is to use historical or forecasted data for spot prices and regulating power

[6] The operating strategy of the flexible asset of course depends on the rules of the regulating market, and whether imbalances are penalized independent of the system balance or not.

prices, and assume ideal[7] performance of the flexible asset. To illustrate the method, we create an example based on [23] for a wind power producer in Western Denmark:

- The yearly wind power forecast errors averages to 39 % of the actual production for 12-36 hours ahead (corresponding to the Nord Pool spot market)
- The forecast error caused additional regulating power during 31 % of the year (meaning that the wind forecast error worsened the system balance)
- The regulating cost, averaged over the whole year, were estimated to be 2.3 €/MWh, based on historic time series for spot market prices, regulating prices and wind production.

Assuming a wind power plant of 10 MW with 2500 utilization hours, the yearly production would be 25 000 MWh. The maximum value of flexibility for self-balancing in this case would then be 25 000 MWh/year * 2.3 €/MWh = 57 500 €/year. The real value of flexibility would of course be lower, depending on the power rating, energy capacity and energy conversion efficiencies.

In the same article [23], Holttinen estimated the value of trading in the Nordic intraday market. It was calculated that the total net balancing cost (intraday + regulating power) of wind power production in the example was reduced from 2.3 €/MWh to 1.4 €/MWh, compared to the situation were all wind power imbalances were settled in the regulating power market. Thus, the balancing cost was reduced by almost 40 % by trading in the intraday market, without the use of flexibility.

In [24], a community based battery within a micro grid models stochastically wind uncertainty to demonstrate that the deterministic case (simple average forecast) underestimates the value of the battery by around 30%.

6 Combining DSO flexibility with other services

In the previous chapter, we have discussed the value of flexibility for different services separately from each other. A flexible asset such as a grid-scale battery, distributed home batteries or a fleet of EVs with smart-charging capability, can be used for several purposes over time. In Figure 11, it can be seen that the need for EV flexibility for congestion management is limited to the winter season due to the shape of the load profile. This gives - in principle – room for an aggregator to optimize the EV fleet charging for other purposes in the rest of the year, such as day-ahead and intraday trading. However, in practice this opportunity can be limited by different requirements from the DSO on one hand (e.g. a guarantee that flexibility is available when congestions occurs) and the EV owners on the other (e.g. an expectation that the aggregator's influence on the charging pattern has negligible impact on the driving range when they need the car).

[7] Ideal performance refers to an flexible asset with no energy losses and infinite capacity in both directions.

To estimate the value of combining different flexibility services, we propose here to use a two-step procedure, where step 1 will determine whether it is necessary to proceed to the more complicated assessment in step 2 and onwards:

- Step 1: Calculate the value of utilizing the *full flexibility* for each of the services separately. If the total value is higher than the expected costs of flexibility (e.g. installation of a grid-scale battery), proceed to Step 2.
- Step 2: Decide the high-level operating strategy of the flexible asset for the combined services. The choice of operating strategy depends on requirements for the different services.
- Step 3: Simulate the operation of the flexible asset for a suitable range of realistic situations (e.g. a full-year simulation with 15 min resolution), both when conflicts between the services can occur and not.
- Step 4: Based on the simulation results of Step 3, calculate the total value of flexibility and compare with the expected costs, similar to Step 1.

As shown in the previous chapters, the calculation in Step 1 can be simulation-based (5.1.3), optimization-based (Section 4.2.2.1) or rule-of-thumb based (Section 5.3.3) depending on the complexity of the system, and whether we are performing a first screening or detailed assessment. The method will be tested and further developed in the continuation of Task 5.2.

Looking beyond todays structures, the development of electricity market design for prosumers and distributed batteries will be crucial for the possibility of offering several flexibility services simultaneously or sequentially. Current intra-day and day-ahead markets structures are mainly tailored for conventional power plants. To jointly exploit and combine different flexibility services, future work might consider the study of new market designs that are more complementary to other battery flexibility values.

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Annex A: Symbol list for flexibility models in Chapter 2

Notice some sets, parameters and variables are not included in the battery or EV models because they belong to generator and flexible load models. For more information about generator and flexible load models, see [5].

T	Set of periods, indexed by t
T^+	Subset of periods with DSO requests for upward regulation
T^-	Subset of periods with DSO requests for downward regulation
K	Set of non-buffered flexible loads, indexed by k
K^{CD}	Subset of flexible load units of type curtailable disconnectable
K^{SP}	Subset of flexible load units of type shiftable profile
C	Set of shiftable load periods, indexed by c. It depends on each k
G	Set of flexible distributed generators, indexed by g
G^r	Subset of reducible distributed generators
G^d	Subset of disconnectable distributed generators
B	Set of storage units, indexed by b
EV	Set of electric vehicle units, indexed by e
EV^r	Subset of reducible electric vehicles
EV^d	Subset of disconnectable electric vehicles

D_t^{CON}	Control-based request in the local flexibility market during period t [kWh/period]
$D_t^{CON,max}$	Maximum flexibility control-based request during period t [kWh/period]
$D_t^{CON,min}$	Minimum flexibility control-based request during period t [kWh/period]
D_t^{CAP}	Capacity-based request in the local flexibility market during period t [kWh/period]
$D_t^{CAP,max}$	Maximum flexibility capacity-based request during period t [kWh/period]
$D_t^{CAP,min}$	Minimum flexibility capacity-based request during period t [kWh/period]

$P_{g,t}^{Gr}$	Price in local flexibility market contract for curtailing the reducible generator unit $g \in G^r$ during period t [NOK/kWh]
$P_{g,t}^{Gd}$	Price in local flexibility market contract for curtailing the disconnectable generator unit $g \in G^d$ during period t [NOK/kWh]
$P_{b,t}^{B,in}$	Price to charge the battery unit b during period t [NOK/kWh]
$P_{b,t}^{B,out}$	Price in local flexibility market contract for discharging the battery unit b during period t [NOK/kWh]
P_k^{CD}	Price in local flexibility market contract for disconnecting the load unit $k \in K^{CD}$ during period t [NOK]
P_k^{SP}	Price in local flexibility market contract for shifting the load unit $k \in K^{SP}$ one period [NOK]
$P_{e,t}^{EV}$	Price in local flexibility market contract for reducing the energy stored in the EV battery of EV unit e during period t

O_b^{max}	Maximum storage capacity of the storage unit b [kWh]
Q_b^{in}	Maximum charging capacity of the storage unit b [kWh]
Q_b^{out}	Maximum discharging capacity of the storage unit b [kWh]
A_b^{in}	Efficiency factor for charging the storage unit b [p.u.]
A_b^{out}	Efficiency factor for discharging the storage unit b [p.u.]

$S_{e,t}^{EV,in}$	Forecasted energy charged in the baseline scenario of EV unit e during period t [kWh]
$S_{e,t}^{EV,out}$	Forecasted energy consumption in the baseline scenario of EV unit e during period t [kWh]
$S_{e,t}^{EV,soc}$	Forecasted battery state-of-charge in the baseline scenario of EV unit e during period t [kWh]
$S_e^{EV,start}$	Forecasted battery state of charge at t=*1* of EV unit e [kWh]
$S_e^{EV,end}$	Forecasted battery state of charge at t=T of EV unit e [kWh]
$Q_e^{EV,in}$	Maximum charging capacity of the EV battery unit e during a single period [kWh]
$O_e^{EV,max}$	Maximum storage capacity of the storage unit b [kWh]
$a_{e,t}^{EV}$	Binary parameter = 1 if the EV unit e can be controlled during period t, else 0

$\chi_{g,t}^{Gr}$	Total amount of electricity generation curtailed of reducible the generator unit g during period t [kWh]
$\chi_{g,t}^{Gd}$	Total amount of electricity generation curtailed of disconnectable the generator unit g during period t [kWh]
$\delta_{g,t}^{G}$	Binary variable = 1 if curtailment of the disconnectable the generator unit g is applied during period t, else 0
$\sigma_{b,t}^{in}$	Energy charged by the storage unit b during period t [kWh]
$\sigma_{b,t}^{out}$	Energy discharged by the storage unit b during period t [kWh]
$\sigma_{b,t}^{soc}$	State of charge of the storage unit b during period t [kWh]
$\delta_{k,t}^{start}$	Binary variable = 1 if curtailment of the disconnectable load unit k starts during period t, else 0
$\delta_{k,t}^{run}$	Binary variable = 1 if curtailment of the disconnectable load unit k is running in time period t, else 0
$\delta_{k,t}^{end}$	Binary variable = 1 if curtailment of the disconnectable load unit k ends during period t, else 0
$\omega_{k,t}$	Delivered energy to the shiftable load unit k during period t [kWh]
$\gamma_{k,t}$	Binary variable = 1 if the shiftable load k begins consuming at period t, else 0
$\rho_{k,c}$	Time period when the shiftable load k for load shift interval c begins consuming [#]
$\sigma_{b,t}^{EV,in}$	Energy charged by the EV unit e during period t [kWh]
$\sigma_{b,t}^{EV,soc}$	State of charge of the EV unit e during period t [kWh]

$W_{k,t}^{CD}$	Curtailable load consumption forecast for the load unit k during period t [kWh]
$W_{k,t}^{SP}$	Shiftable load consumption forecast for the load unit k during period t [kWh]
N_k^{max}	Maximum number of disconnections for the load unit k during the planning horizon T [#]
D_k^{min}	Minimum time duration between two curtailments of the load unit k [# of periods]
D_k^{max}	Maximum curtailment duration of the load unit k [# of periods]
$V_{k,c}^{start}$	Start-period of forecasted consumption of the load unit k during shift time interval c [#]
$V_{k,c}^{end}$	End-period of forecasted consumption of the load unit k during shift time interval c [#]
$T_{k,c}^{start}$	Earliest possible start period for shifting the load unit k during time interval c [#]
$T_{k,c}^{end}$	Latest possible end period for shifting the load unit k during time interval c [#]
$F_{g,t}^{Gr}$	Forecasted generation of reducible generation the unit g during period t [kWh]
$F_{g,t}^{Gd}$	Forecasted generation of disconnectable generation the unit g during period t [kWh]