LAPPEENRANNAN–LAHDEN TEKNILLINEN YLIOPISTO LUT
LAPPEENRANTA-LAHTI UNIVERSITY OF TECHNOLOGY LUT

LUT School of Energy Systems

LUT Scientific and Expertise Publications
Tutkimusraportit – *Research Reports*
113

Nadezda Belonogova, Aleksei Mashlakov, Nelli Nigmatulina, Juha Haakana, Samuli Honkapuro, Hanna Niemelä and Jarmo Partanen

# Final report: Impact of distributed energy resources (DER) on a distribution network and energy stakeholders

Lappeenranta–Lahti University of Technology LUT
LUT School of Energy Systems
Research report 113

Nadezda Belonogova, Aleksei Mashlakov, Nelli Nigmatulina, Juha Haakana, Samuli Honkapuro, Hanna Niemelä and Jarmo Partanen

# Final report: Impact of distributed energy resources (DER) on a distribution network and energy stakeholders

Lappeenranta–Lahti University of Technology LUT
LUT School of Energy Systems
Yliopistonkatu 34
53850 LAPPEENRANTA
ISBN 978-952-335-561-3 (PDF)
ISSN-L 2243-3376
ISSN 2243-3376

Lappeenranta 2020

# Preface

This report presents the key results based on the methodology, data, and publications of the project ”Impact of the distributed energy resources (DER) on a distribution network and energy stakeholders” carried out at LUT University between April 2019 and September 2020. The members of the research group were professor Jarmo Partanen, Dr. Samuli Honkapuro, Dr. Nadezda Belonogova, Dr. Juha Haakana, Aleksei Mashlakov, M.Sc., and Nelli Nigmatulina, M.Sc. The research was funded by the Finnish Electricity Research Pool (ST-Pooli), the Promotion Centre for Electrical Engineering and Energy Efficiency (STEK ry), Helen Electricity Network Ltd, Nivos, and Suur-Savon Sähkö Oy. The steering group meetings were held four times face-to-face and four times online in Teams, in addition to which the study was complemented by e-mail and Teams discussions.

The conclusions, results, and suggestions for future actions presented in this report are the authors' views only and do not tie the funding organizations in any way.

Lappeenranta September 2020

Authors

# Alkusanat

Tässä raportissa esitetään DER hankkeen metodiikasta, tulosaineistoista, ja julkaisuista koostettuja tuloksia. Tutkimushankkeen on toteuttanut aikavälillä 04/2019–09/2020 Lappeenrannan-Lahden teknillisen yliopiston (LUT) Sähkömarkkinalaboratorion tutkimusryhmä, johon kuuluivat professori Jarmo Partanen, TkT Samuli Honkapuro, TkT Nadezda Belonogova, TkT Juha Haakana, DI Aleksei Mashlakov ja DI Nelli Nigmatulina. Tutkimushankkeen rahoittivat yhteisrahoituksella ST-pooli, STEK ry, Helen Sähköverkko Oy, Nivos, ja Suur-Savon Sähkö Oy. Ohjausryhmä kokoontui selvitystyön aikana neljä kertaa kasvotusten ja neljä kertaa Teamsin välityksellä, minkä lisäksi selvitystyöhön saatiin kommentteja sähköpostitse sekä Teamsin kautta. Hankkeen raportissa esitetyt johtopäätökset, tulokset ja mahdolliset toimenpide-ehdotukset ovat tutkijoiden näkemyksiä, eivätkä sido selvitystyön tilaajia millään tavoin.

Lappeenrannassa syyskuussa 2020

Tekijät

# Abstract

The research project aimed at developing a generic methodology to quantify the impact of distribution energy resources on a distribution grid. The methodology was applied on actual distribution grids and load data that consisted of two example distribution grids in rural (15000 customers, mostly residential), urban (almost 8000 customers, mostly flats and office buildings), and suburban areas (approx. 5000 customers, mostly detached and terraced houses).

The key outcomes of the project were:

1. Models of dynamic DER profiles for EV, BESS, and new heating solutions. 'Dynamic' means that the input parameters that define the shape of the profile can be easily varied.
2. Allocation of DER profiles to the end-customers depending on penetration rate and location.
3. Model of a distribution grid topology and dimensions for power flow simulations.
4. Analysis of the grid impact for various distribution grids and DER scenarios.
5. Model of multi-objective operation of BESS for FCR-N, self-consumption, and peak shaving tasks.
6. Representation of the grid impact range as a probability of its occurrence.
7. Quantitative results for case networks.

# Tiivistelmä

Tutkimushankkeen tavoitteena oli kehittää metodiikkaa mahdollistamaan hajautettujen resurssien verkkovaikutusten analysointi. Metodiikkakehityksessä hyödynnettiin tietoja todellisista sähkönjakeluverkoista ja sen kuormituksista. Tausta-aineisto käsittää yhteensä 28 000 asiakasta koskevat kuormitus- ja verkkotiedot maaseutumaiselta alueelta (noin 15 000 asiakasta, pääosin kotitalousasiakasta), keskusta-alueilta (lähes 8000 asiakasta, kerrostaloasuntoja ja toimistoja) sekä lähiöalueilta (noin 5000 asiakasta, omakotitaloja ja rivitaloja).

Keskeisimmät tutkimushankkeessa kehitettyyn metodiikkaan liittyvät ominaisuudet ja tulokset ovat:

- Dynaamiset DER-profiilit (sähköautot, aurinkosähkö, akkuvarasto, lämpöpumput). Profiileihin liittyvä parametrisointi on vapaasti muokattavissa.
- Hajautettujen resurssien kohdistaminen asiakaskohtaisesti penetraatioasteen ja alueen sijainnin perusteella.
- Verkkomallit hajautettujen resurssien verkko- ja kuormitusvaikutusten määrittämiseksi.
- Akun monikäytön mahdollistava analysointimalli (taajuusreservimarkkinat (FCR-N), pientuotannon omakäyttö, piikin leikkaus).
- Numeeriset tulokset esimerkkitarkasteluissa olleille todellisille verkoille.

# Contents

## List of abbreviations

| | |
|---|---|
| AC | alternating current |
| BESS | battery energy storage system |
| BPM | balancing power market |
| DER | distributed energy resources |
| DG | distributed generation |
| DR | demand response |
| DSO | distribution system operator |
| EV | electric vehicle |
| PHEV | plug-in hybrid electric vehicle |
| FEV | full electric vehicle |
| FCR | frequency containment reserve |
| FCR-N | frequency containment reserve for normal operation |
| G2V | grid to vehicle |
| HV | high voltage |
| MV | medium voltage |
| LV | low voltage |
| LUT | Lappeenranta–Lahti University of Technology LUT |
| OPEX | operating expenses |
| PB | power band |
| POT | peak operating time |
| PV | photovoltaic |
| PQ | active-reactive power |
| V2G | vehicle to grid |
| RPC | reactive power compensation |
| SOC | state of charge |
| SCR | self-consumption rate |
| TOU | time-of-use |
| TSO | transmission system operator |
| UPS | uninterrupted power of supply |

# 1 Introduction

The demand for flexibility in the electricity system is growing at an increasing rate. Many changes are taking place in legislation, regulation, and political entities. The recent report of the intergovernmental panel on climate change [1] published in October 2018 provided even more tighter requirements regarding limiting the global warming to 1.5°C instead of the earlier 2°C level [1]. This further increases the role of the renewable energy production and creates a higher pressure involving distributed energy resources (DER) in the energy markets and tightening requirements for power systems regarding the power balance management and stability of the system.

While political entities have clearly recognized environmental targets that are among of the key drivers in renewing the power system (top-bottom direction), also the power system itself is facing major structural changes as a result of the tightening reliability requirements, changing end-consumption profiles, and new low-cost ICT solutions (bottom-top direction). The customer has become an active part of the power system. The end-customer consumption profiles are changing as a result of changes in heating solutions (switch to heat pumps), acquisition of rooftop solar PV, electric vehicles, stationary batteries, and even new tariff structures. For instance, the impact of the increasing penetration rates of heat pumps has been mostly analysed from the perspective of energy, while little attention has been paid to their impact on the distribution network so far. Furthermore, the complexity of the power system has been increasing as a result of the development in the ICT technology, which transforms the traditional power system into a hyper-connected one. The Internet of Energy, datahubs, home energy management systems, and various ICT-based applications enable aggregation, coordination, and control of DER in a number of ways. In the traditional power system, only DSOs and retailers have had access to the customers' energy consumption data. However, nowadays and in the near future there may be multiple other parties having access to these data through the public network (for instance, datahub). This requires a clear understanding of the roles of the TSO, DSOs, retailers, and independent aggregators in such a dynamic and ICT-focused operating environment, along with coherent and transparent cooperation between the stakeholders regarding the use of the flexible energy resources.

The main results of the Finnish Smart Grid working group (Älyverkkotyöryhmä) [2] in the context of this research area are the positive attitude towards an independent aggregator and removal of double taxation of the stored energy, which came into force on 1 January 2019. This, together with the European Commission's Clean Energy for all Europeans Package, indicates a need for the preparation of legislation on energy storages. For DSOs, the aggregator activities may create challenging events as some of the control signals may be synchronized. Furthermore, the market structures and marketplaces are under constant development. The European energy markets are also taking major steps towards harmonized market structures. This creates widespread market opportunities for many applications, but also sets new requirements.

A further ongoing change is the introduction of power-based tariffs for the residential customers. A few Finnish DSOs have already offered their customers this type of tariff, and there is a high interest in it in the distribution business. Power-based tariff creates incentives for peak load shaving at the end customer's level, and thus, in this respect, the role of DER is emphasized.

All these factors create motivation to study the impact of DER on a distribution grid.

# 2 Objective of the research

The main objective of the research was to develop a methodology to define the impact of DER on a distribution grid. This requires:

1. Defining a demand profile with integrated DER (passive usage)
2. Developing the principles of DER allocation to single customers
3. Identifying potential applications for DER active usage to construct relevant DER aggregation scenarios
4. Defining a demand profile with aggregated DER (active usage)
5. Application of the methodology to actual distribution grids and AMR load data

In order to achieve the specified objectives, the following tasks have to be carried out:

1. Identification of DER time series profiles for different DER types and sizes, grid points (single customer, connection point, secondary and primary substations) and usage type (passive and active)
2. Development of a method to allocate DER to single residential, commercial, and industrial customers
3. Analysis of the flexibility potential of DER taking into account technical restrictions and customer comfort preferences
4. Selection of the potential applications for DER based on available electricity markets and distribution grid needs
5. Establishment of a model to assess the impact of passive and active DER on a distribution grid

The main contributions of the research work are:

1. A simulation tool that allows to carry out various analyses, such as sensitivity analysis and investigation of the conflict of interests, with various input parameters
2. Definition of the nature of conflicts between various applications and quantification of the strength of the conflicts
3. Quantitative assessment of the impact of DER on a distribution grid, a DSO, a retailer/aggregator, a TSO, and a single customer
4. Outlining of further research questions

# 3 Methodology description

The methodology established in the project is described and illustrated in this section. It contains the algorithms and methods to solve the research questions that are set to achieve the objectives of the project. The core topics of the project are illustrated in Figure 1.

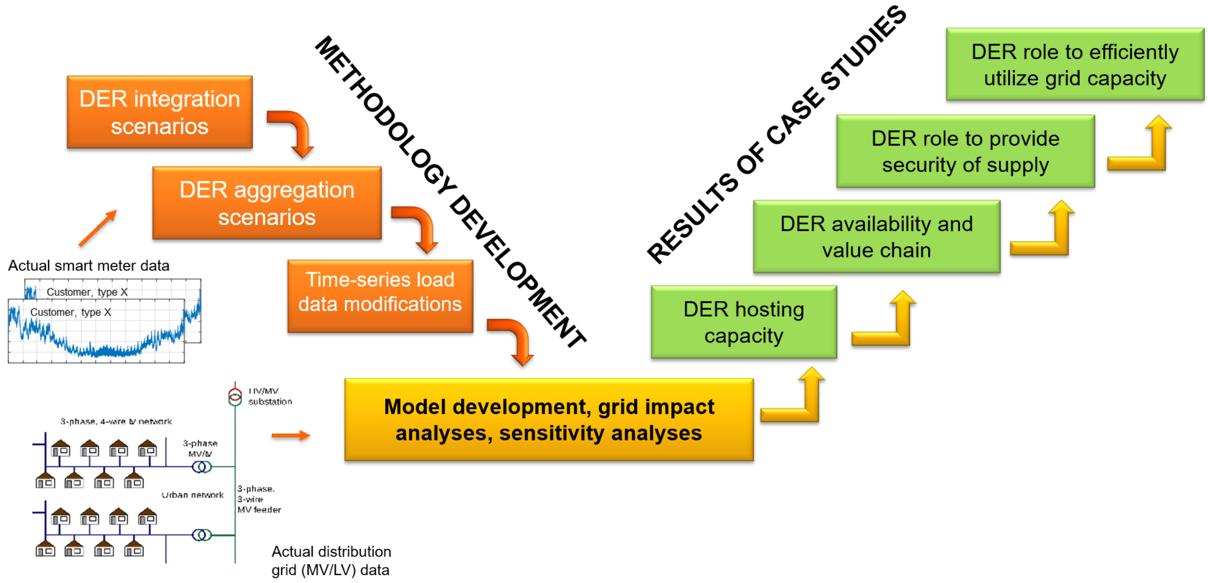



Figure 1: Main topics in the project

Based on the methodology, a model was built and applied to the case distribution networks to quantitatively assess the grid impact. The model and simulations were written in the Python programming language. Furthermore, high-performance computing resources were used in some simulations, and the C programming language was used to speed up the calculations in Python.

The structure of this section follows the order presented in Figure 1. First, the DER profiles are provided and allocated to residential customers, resulting in time series load data modifications. Next, the DER integration (passive DER usage) and aggregation (active DER usage) scenarios are explained and the algorithm to generate them is presented. By using the three main building blocks, i.e., the DER integration and aggregation scenarios, and the DER profiles and their allocation to customers, a model is built that provides answers to the research questions set in the study. In various DER scenarios and grid points, for instance, a single customer, connection point, secondary and primary substations, the main research questions are:

1. What is the DER hosting capacity in various distribution grid points? Which DER scenarios cause capacity and/or voltage problems?
2. What is the DER availability for different applications/tasks?
3. What is the DER capability and role to provide security of supply?
4. What is the role of DER to efficiently utilize grid capacity?

These topics are covered in the following subsections. Finally, in the last subsection, the limitations and challenges of the methodology are discussed.

## 3.1 DER profiles

The approach to build DER profiles is described for all the DER types; solar PV, EVs, stationary BESS, and heat pumps. All the DER are assigned primarily to residential customers, but some simulations are also carried out for commercial customers, for instance when investigating the impact of EV workplace charging on the grid.

The DER profiles are presented below.

### 3.1.1 Electric vehicles

The applied model simulates a charging profile of an individual EV using a time step of 15 min. The following input parameters are used (flexible variables):

1. Charging power rate [kW]. In this project, three charging rates were assumed: 1) one-phase charging at 16 A and a nominal voltage of 230 V resulting in 3.7 kW; 2) three-phase charging at 16 A, and 3) 32 A current levels at the nominal voltage of 230 V resulting in 11 kW and 22 kW charging powers.
2. Arrival and departure times. For the residential customers, the arrival times were roughly estimated according to the AMR load profiles (see Figure 2) as the most frequently occurring daily peak power hour during one year. Although the daily peak power hour does not illustrate the hour of home arrival, allocation of charging to the peak power hour illustrates the worst-case scenario for that particular customer. Furthermore, the probability of all residents being at home is highest during the daily peak power hour. For the rest of the non-residential customers, the arrival times were assumed to be normally distributed around 8 o'clock, the typical work arrival time. However, this hour can be easily varied in the model.
3. Size of the battery [kWh], which depends on whether full electric vehicles (FEV) or plug-in hybrid electric vehicles (PHEV) are simulated. The usable battery capacity of FEVs is above 40 kWh, and for PHEVs 8, 9, or 10 kWh. The proportion of FEVs and PHEVs per simulated area can be varied freely. However, in the presented simulations, the size of the battery did not affect the charging profile, but instead, the driving distance had an impact on the duration of charging.

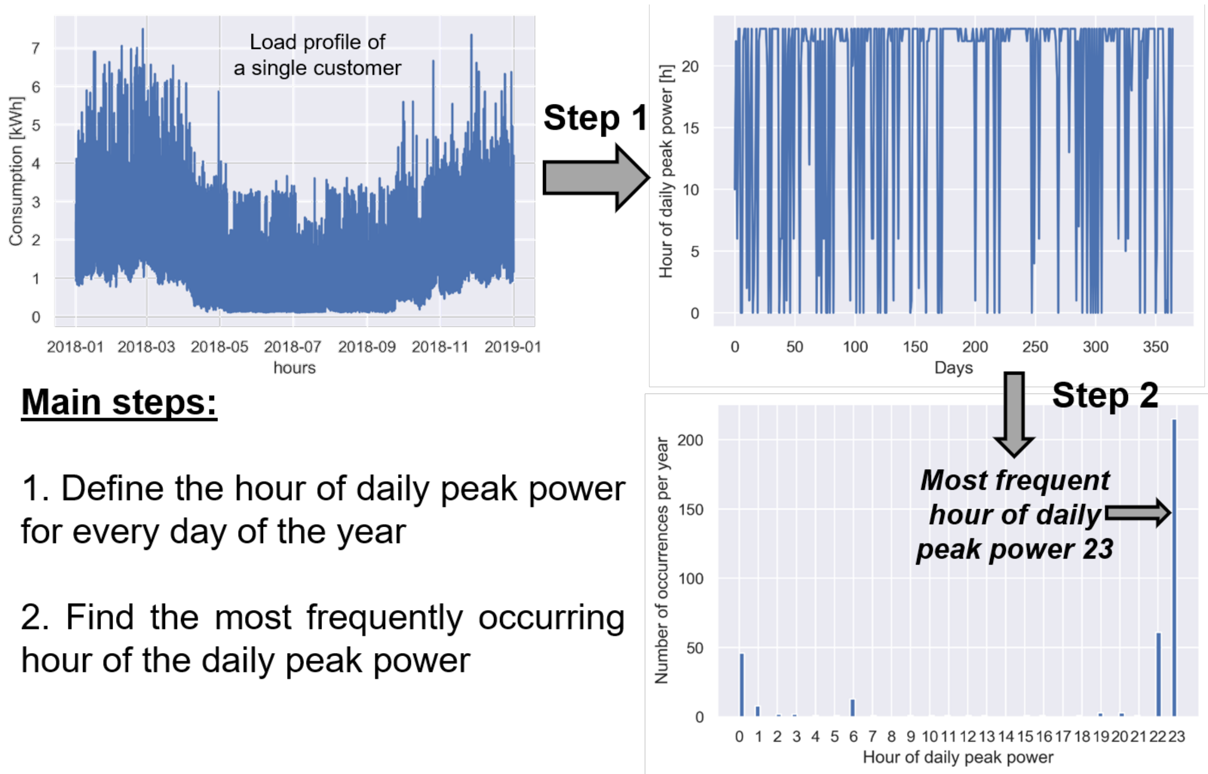



Figure 2: Definition of the most frequently occurring hour of the daily peak power

The following assumptions were used (fixed variables):

1. Energy consumption 180 Wh/km $E_{consumption}$
2. Average daily driving distance $DD_{avg}$38.4 km/day (according to [3]). Every EV driver has the same annual travel distance, but the daily travel distance varies to reflect the stochasticity of the driving behaviour. For that purpose, driving distance multipliers are used for each weekday (Mo–Su) $F_{weekday}$ and month (Jan–Dec) $F_{month}$ . The daily charging need is then calculated as follows:

$$E_{charging[kWh/day]} = DD_{avg} \cdot F_{avg} \cdot F_{weekday} \cdot F_{month} \cdot E_{consumption} \tag{1}$$

   where $F_{avg}$ is a multiplier for the specific EV and reflects its annual driving distance compared with an average driving distance of 38.4*365 = 14052 km/year. For instance, if an EV driver covers 10 000 km/year, the multiplier will be 10000/14052 = 0.7. This means that the EV driver covers 30% less annual distance than an average EV driver.
3. Charging efficiency 90%, and thus, the power loss during EV charging is 10%

The presented approach allows to simulate an EV charging profile not only for a single customer, but also for any group with any number and type of customers (residential and non-residential). For this, one has to know or make assumptions of such issues as arrival times of multiple EV drivers, charging power, and daily driven distance (charging energy need), see Figure 3.

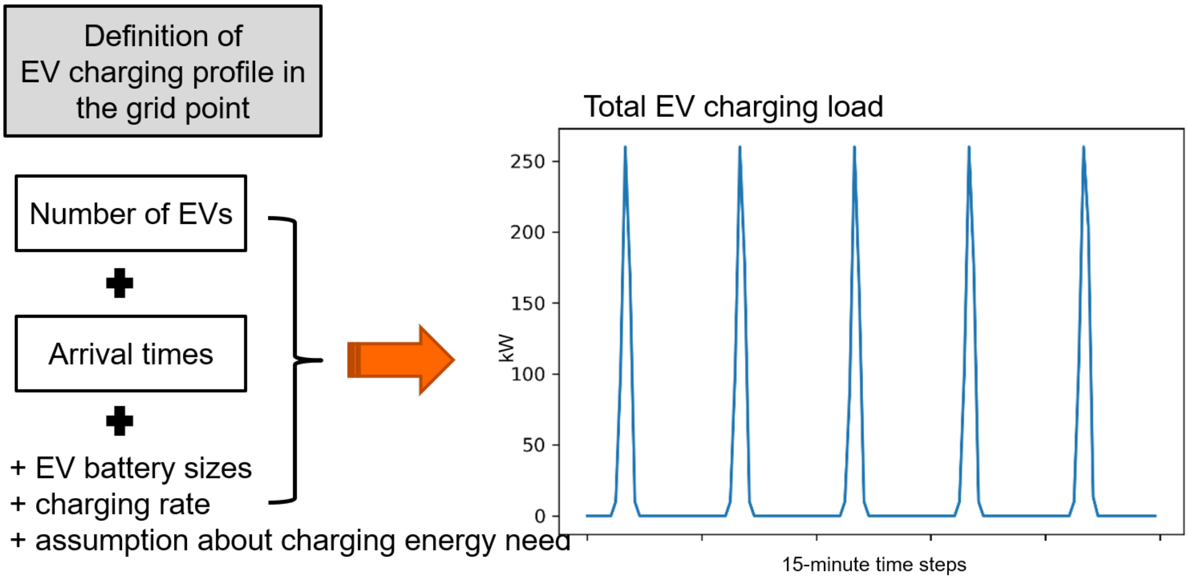



Figure 3: Definition of the EV charging profile in the grid point

The figures below illustrate how flexible parameters affect the EV charging profile. For instance, the impact of charging rate and simulation resolution on the charging profile is presented in Figure 4. For comparison, both EV drivers arriving at 16:00 (charging rate 11 kW) and 19:15 (charging rate 3.7 kW) have the same charging need. It can be seen that the charging at 11 kW lasts for a shorter time than the charging at 3.7 kW. Therefore, at the one-hour resolution, the hourly peak power is only above 8 kW (less than 11 kW peak power at 15 min resolution), but reaches 3.7 kW when charging at the 3.7 kW rate.

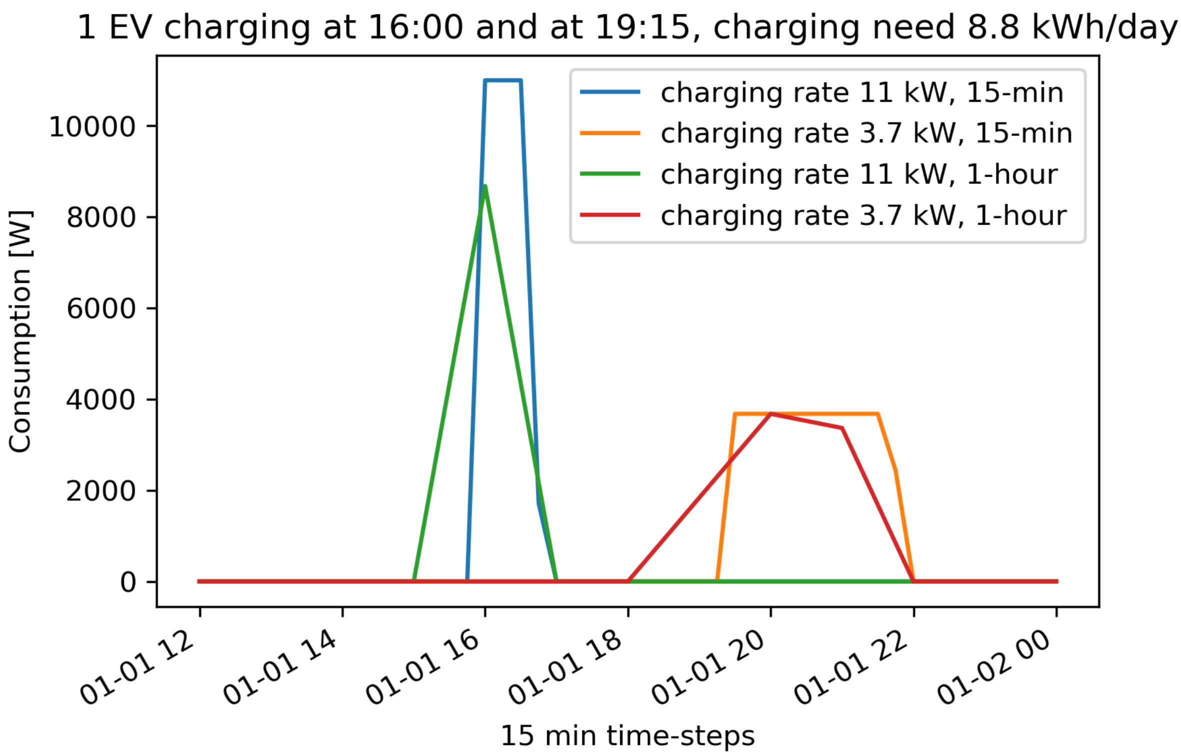



Figure 4: Simulated charging profile of one EV for the 11 kW and 3.7 kW charging rates

The impact of the length of the driving distance and charging need on the EV profile is illustrated in Figure 5, where two profiles at two resolutions, 15 min and one hour, are presented. The charging rate is 11 kW. The figure shows how the driving distance changes during an example week in January, from Monday to Sunday. Again, it can be seen that at the 15 min resolution level, the difference in charging energy is seen in the duration of charging (shape of the curve), while at the one-hour resolution level, it can be seen in the value of the hourly peak power level. For a single EV, the peak power value drops from 11 kW at the 15 min resolution down to 7 kW at the one-hour resolution level, depending on the driving distance, resulting in 36% less peak power at the one-hour resolution for a single EV. This difference should be kept in mind when analysing the impact of EV charging on a distribution grid using a one-hour resolution dataset.

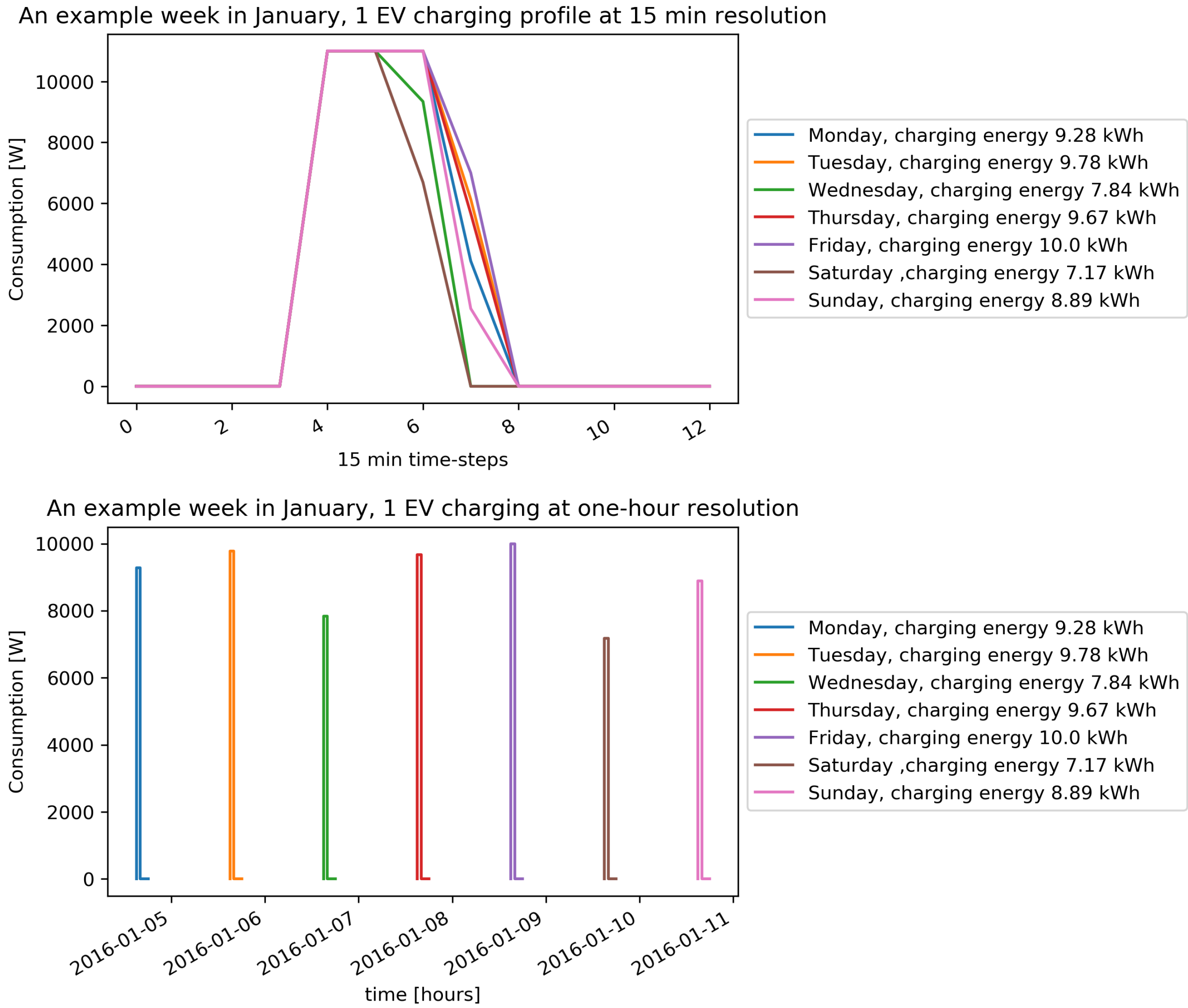



Figure 5: Impact of variation in the daily driving distance on the charging need during an example week in January

Next, the charging profile of multiple EVs is illustrated in Figure 6. Here, ten EVs arrive at the parking places one after another in 15 min time steps. One group of ten EVs charge at 11 kW (blue curve) and another group of ten EVs charge at 3.7 kW. For comparison, in both groups, the EV drivers' behaviour is identical, i.e., they have driven the same daily driving distance and arrive in the same order at the parking places. It can be seen that the 11 kW EV charging profile has a valley around 18:00. This is because the EV driver who came around that time has driven only a few kilometres and thus, has a low charging need, as a result of which their charging lasts only about 15 min. However, in the 3.7 kW EV charging profile, no valley is seen. This is because the charging lasts longer, and thus, overlapping of multiple charging profiles occurs often.

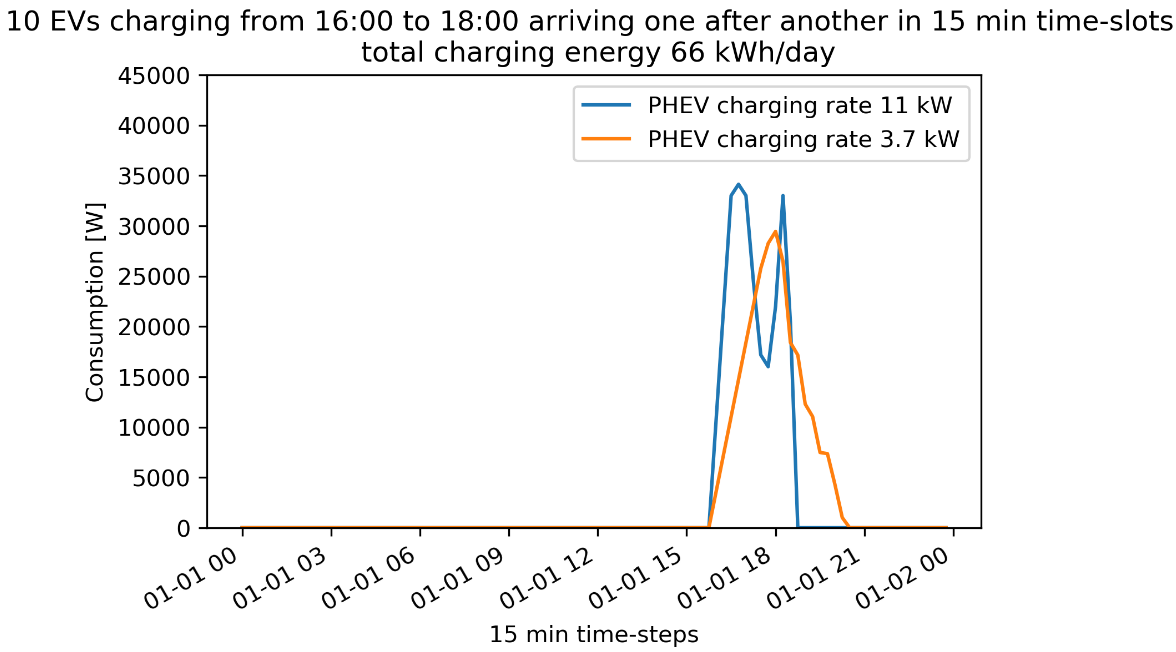
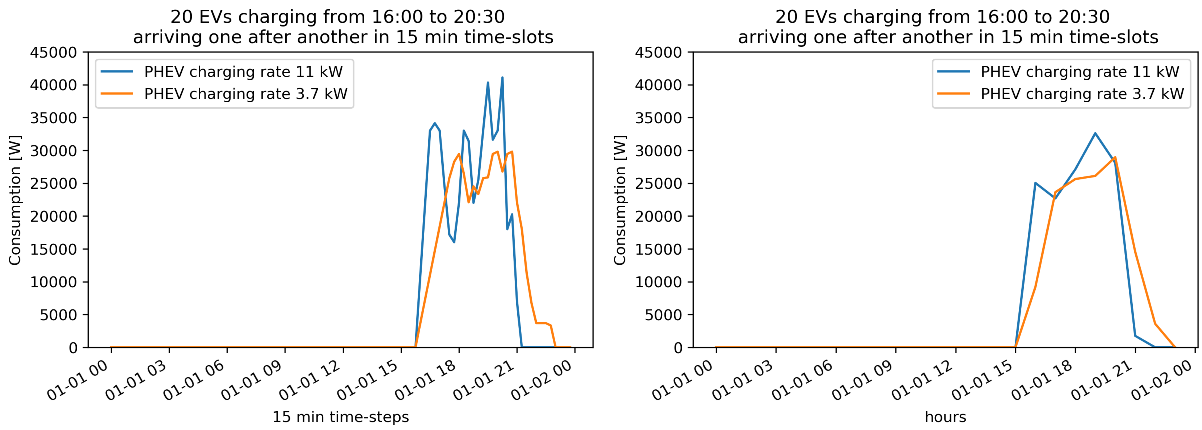



Figure 6: Simulated charging profile of ten EVs for the 11 kW and 3.7 kW charging rates

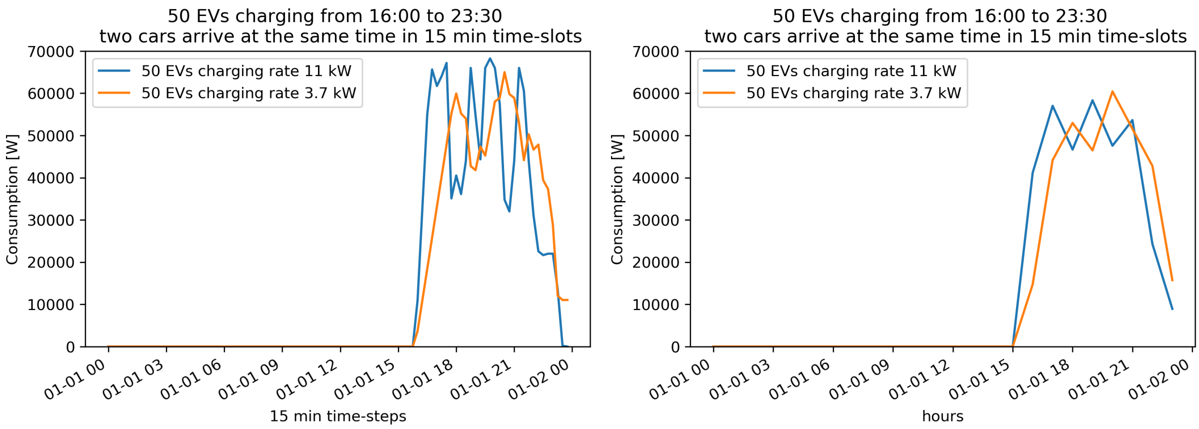
To study the impact of time resolution and the size of the EV fleet on the peak power, more examples have to be given. Below, an EV fleet of 20 and 50 cars is charging at the 3.7 kW and 11 kW rates. In both charging rates, the EV fleet has an identical driving behaviour, and thereby an identical arrival sequence and charging need, which makes both charging rates comparable. In Figure 7a, the peak power of the charging profile at 11 kW (40 kW) is higher than the one at 3.7 kW (30 kW) by about 25%. However, when shifting the simulated dataset to one-hour resolution as in Figure 7b, the peak powers at both charging rates are very close to each other, the peak power at 11 kW still slightly exceeding the one at 3.7 kW.




(a) 15-min resolution (b) one-hour resolution

Figure 7: EV fleet of 20 cars

Furthermore, taking the EV fleet of 50 cars, the observation changes so that at the 15 min resolution, the peak powers of the both charging rates are very close to each other (Figure 8a), and at the one-hour resolution, the peak power at 3.7 kW exceeds the peak power at 11 kW, illustrated in Figure 8b.




(a) 15-minute resolution

(b) 1-hour resolution

Figure 8: EV fleet of 50 cars

The analyses of the EV profiles indicate that the charging at 11 kW is close to the charging profile at 3.7 kW at the one-hour resolution level. This can be explained by the fact that at the 11 kW rate, the charging event lasts for a shorter time and thus, there is less overlapping than at 3.7 kW, when the charging lasts longer and overlapping of individual charging events is more likely to occur, resulting in a high total peak power.

Still, the results are case-specific and depend on the driving behaviour of EVs. In particular, the charging need and the time of arrival of a particular EV will have an impact on whether there will be overlapping of individual charging profiles or not.

In the project, EV charging was simulated throughout the whole year and summed up with the AMR load of single customers. In that way, a time-series-modified load profile was obtained. One assumption was that the charging occurred at the same time every day throughout the year. This is not a realistic assumption, though. This is not a problem as long as a large number of Monte Carlo simulations can be performed to generate as many modified time series profiles as possible and obtain a grid impact range. More detailed information of the EV simulation model can be obtained from [4].

### 3.1.2 New heating solutions

The profiles for the new heating solutions are taken from the customers who have changed their old heating system to a new one. For this purpose, the algorithm was built to identify those customers from the AMR dataset who had changed to another heating solution. This topic will be covered in more detail in Section 3.3.

After identifying the customers with ground heat pump solutions, the next phase is to estimate what kind of heat pump solution there is behind the load profile, i.e., whether it is a partial or full load capacity heat pump. In the case of the partial load heat pump solution, the nominal capacity of the heat pump is not enough to cover all the heating demand throughout the year. During the coldest time of the year when the heating demand is high, part of it is covered by the heat pump, and the rest is provided by using electrical resistors. This kind of solution represents a combination of direct electric heating with a heat pump. The characteristic features of such a profile are high and sharp peaks during the cold time periods. Instead, in the case of the full load ground heat pump, the load profile is smoothly following the outdoor temperature without any sharp peak powers. The examples of the two GSHP solutions are illustrated in Figure 9 and 10. The vertical y-axis represents the consumption in kWh and the horizontal x-axis is the time in hours. It can be seen that the annual consumption and peak powers are at about the same level for both groups, so it is not possible to distinguish the two customer groups from each other based on those parameters.

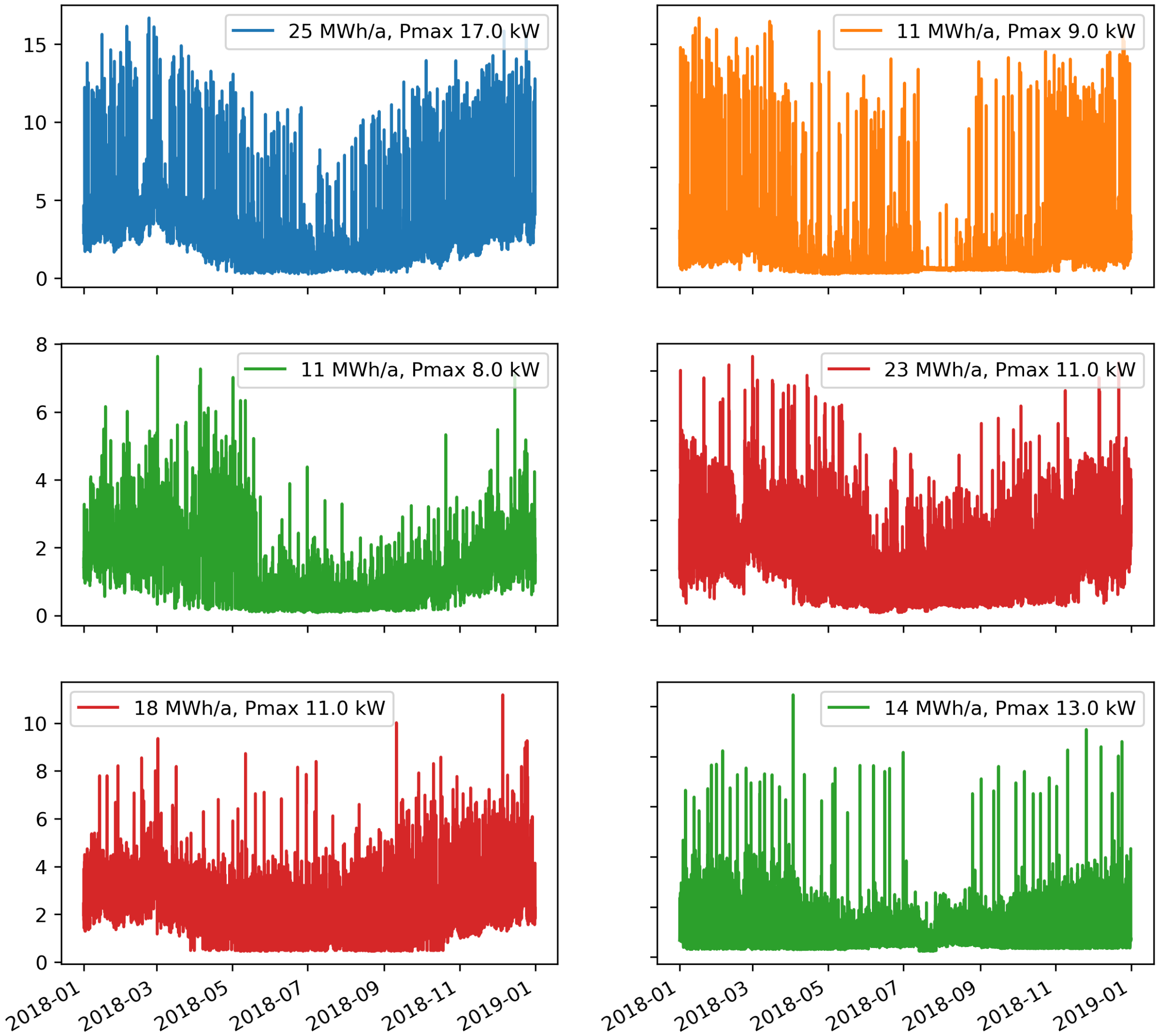


Figure 9: Example load profiles of customers with a partial load capacity GSHP

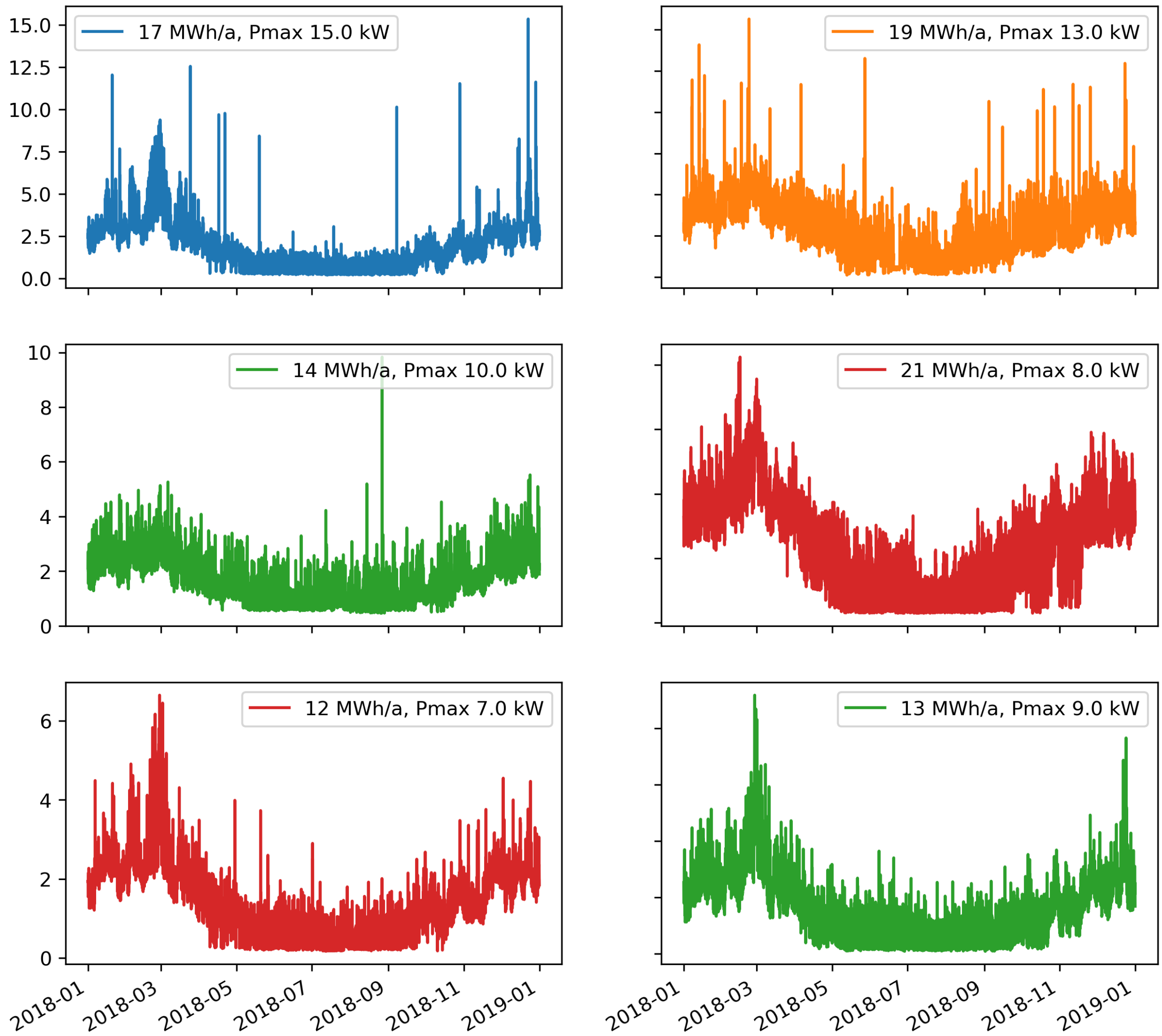



Figure 10: Example load profiles of customers with a full load capacity GSHP

In the suburban area, the information of the GSHP customers was available from the DSO. Of the group of 56 GSHP customers, about 60% of the customers had a full load GSHP solution and the rest 40% had a partial load solution.

In the rural area, the GSHP customers were identified from the AMR dataset by using a two-step algorithm explained in Section 3.3.2. In the analyses, six-year AMR data were used. Out of 46 customers identified, about half of the customers had a partial load heat pump solution, and the rest had a full load GSHP solution.

These are approximate estimations of the type of GSHP solution. More background information of the customers and analyses are required to distinguish the type of the customer's heating load.

In the framework of the project, the heat pump is used passively. This means that it is operated according to the outdoor temperature, without a goal to minimize the energy cost or the peak power of the customer's load profile. To illustrate passive operation of a heat pump, the research reported by VTT [5] is used. The operation of a heat pump was modelled at VTT, and it is illustrated in Figure 11 for three example houses with different insulation levels. The figures show that the older the house is and the worse the insulation level is, the higher the heating demand is (because of high heating losses of the building) and hence, the higher the consumption of electrical resistors. A detailed information on modelling principles and assumptions behind these load profiles can be found from [5].

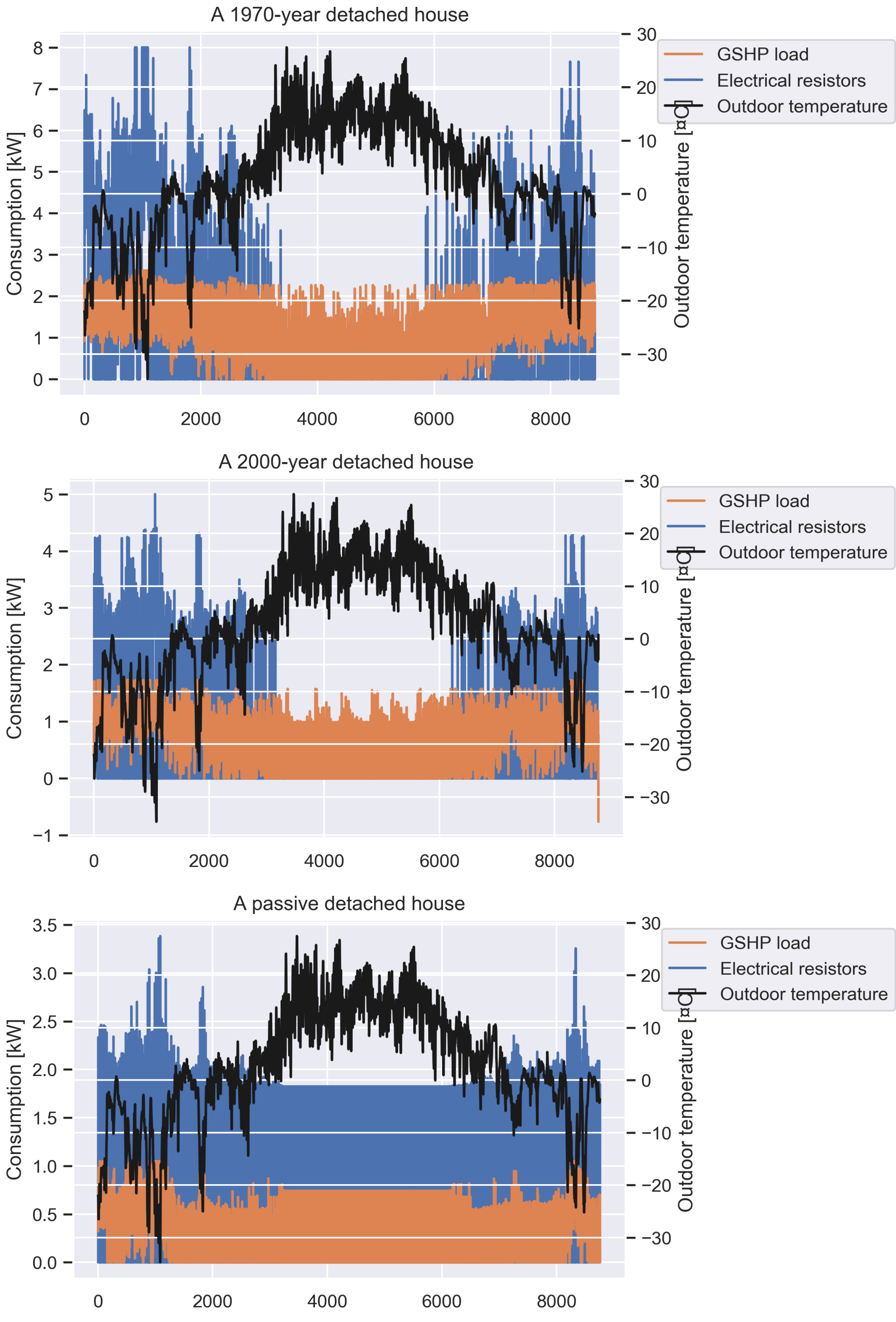



Figure 11: Impact of insulation levels on the load profile of a partial load GSHP and electrical resistors

### 3.1.3 Solar PV

For the rural case area, the profiles for solar PV generation were taken from the open-source database in [6]. The web portal enables to download a 1 kWp solar PV system generation profile at the one-hour resolution at given geographical coordinates.

For the urban and suburban case areas in Helsinki, open-source measurements from the solar PV power plant in Helsinki were applied. The measured generation profile is first downscaled to the 1 kWp size, and then upscaled from the 1 kWp profile according to the desired PV system size.

### 3.1.4 BESS

The profiles for BESS units strongly depend on the application for which they are used and the load profile of the grid point where they are installed. In the project, such applications as maximization of the self-consumption rate, peak power shaving, and frequency regulation in the FCR-N hourly market were used as examples.

The model to generate a BESS profile enables to dynamically change technical and economic parameters of the battery, such as capacity, round-trip efficiency, unit cost of the battery, and tariff component cost. The BESS is assumed to be a lithium iron phosphate (LFP) battery. The price of energy stored in BESS is defined based on the unit cost of the battery $Cost_{\mathrm{kWh}}$[€/kWh], the number of cycles over the battery lifetime period $N_{\mathrm{cycles}}$, and its round-trip efficiency $\eta_{\mathrm{RT}}$:

$$price_{\mathrm{kWh}} = \frac{Cost_{\mathrm{kWh}}}{N_{\mathrm{cycles}}\eta_{\mathrm{RT}}}, \tag{2}$$

### 3.1.5 Discussion on DER profiles

The most challenging profiles to simulate are the EV charging profiles and the ground source heat pump profiles. The challenge of the EV simulation is due to the dynamic nature of using an EV. The EV driving behaviour can vary depending on social, technical, and economic factors. On the other hand, the challenge of modelling the heat pump solution is related to the numerous factors that affect its usage, for instance weather conditions, indoor comfort requirements, domestic water usage, and living schedule. Therefore, it is impossible to take a single heat pump profile and just sum it up with the AMR profile of any potential customer who is likely to switch to the heat pump solution.

Instead, the solar PV generation profile is relatively easy to model especially at the one-hour resolution level, and in the same geographical area, many simplifications can be made. In this project, the assumption was that all customers have the same generation profile, modified only by the size of the solar PV system. In practice, this is of course not true, but for the objectives of the model, namely grid impact assessment from the viewpoint of peak power, this is enough. For instance, if the objective was the voltage quality assessment, such a simplification would not be suitable.

Although numerous flexible parameters are listed in this study and shown how they affect the DER profiles, in the real world, there are many more potential variations of DER profiles. Basically, there can be as many profiles as there are DER owners. It is impossible to model and simulate all those profiles in such a detail and variety. However, this obstacle can be overcome by using a machine learning technique called data augmentation. The idea behind the technique is to generate artificial profiles using a set of given profiles by varying them slightly and randomly in various attributes. Such a technique is often used in the machine learning area in case of lack of data. The usage of this technique is outside the scope of this project.

## 3.2 Time series load data modifications

The modification of the load profile as a result of DER integration and aggregation represents one of the major building blocks of the methodology (see Figure 1). The load data modification can be done at several levels: load modification at a single customer, connection point, secondary or primary substation level. The larger the customer group is, the more alternatives can be created regarding the DER type, size, uptake rate, and usage (passive/active). Within the scope of the project, the objective is to create a model that can use any scenario. This means that the above-listed parameters are made flexible and can be easily varied depending on the scenario to be simulated. Throughout the whole project, the idea was to simulate ”what-if” scenarios instead of a particular scenario forecast for a particular year, decade, in particular circumstances, or by a specific organization. There are many organizations that provide such scenario forecasts, but rather at a country level, not at a distribution grid level, which is a more challenging task because of the higher level of stochasticity.

The ”what-if” scenario approach allows to carry out a sensitivity analysis that identifies those input parameters that have a strong impact on the results and those input parameters that have less influence. This is a very important step towards model simplification as it allows to neglect the parameters that affect the outcomes only slightly and instead, focus on the parameters that have a strong impact.

The main challenge in this task is to select the customers to which a particular DER type will be allocated. The customer selection can be done based on various criteria, for instance the type of housing, heating solution, feasibility of the choice, and socio-economic factors, such as salary levels and feasibility of the choice. In these studies, the type of housing and heating solution is chosen as the example criteria. The information about those criteria was provided by the DSO, but it can also be obtained as a result of data pre-processing (for instance, clustering) using open-source databases or other statistical sources.

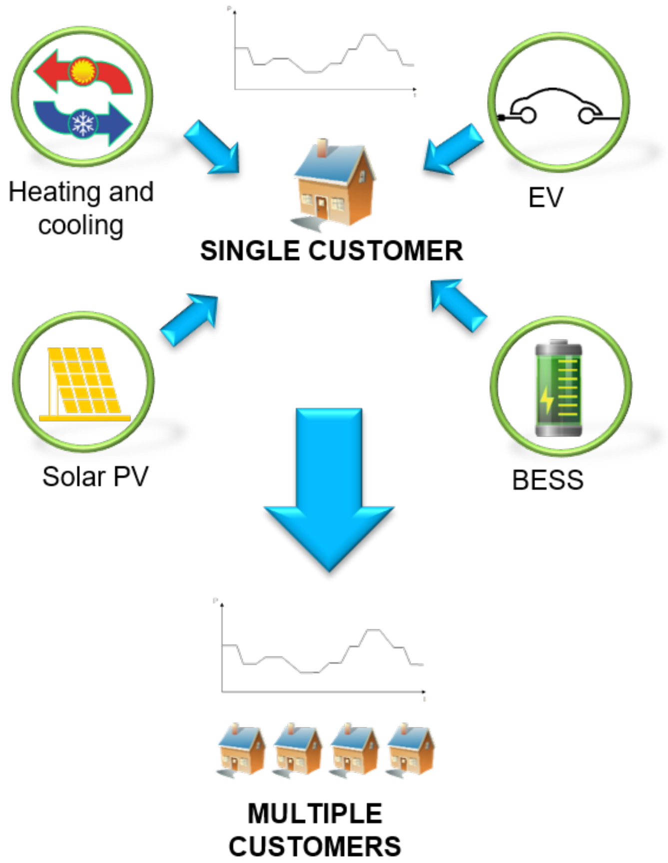



Figure 12: DER allocation to single customers and multiple customers

After the DER types and sizes are allocated to single residential customers according to certain criteria, the load data modification is achieved by adding a DER profile to a single residential customer's load. The AMR data are used as a base load of the customers, i.e., without DER.

For the single customer level, the following parameters have to be assumed:

- type of DER, such as EV, solar PV, BESS, and heat pump
- size of DER
- usage: passive/active, e.g. peak shaving, FCR, self-consumption of solar PV

For a group of customers, for example belonging to a connection point, either at secondary or primary substation levels, the following parameters have to be assumed:

- type of DER, such as EV, solar PV, BESS, and heat pump
- grid point: connection point, secondary and primary substation
- penetration rate
- size of DER
- usage: passive/active, e.g. peak shaving, FCR, self-consumption of solar PV

For example, EVs were allocated to the customers according to the assumption about car ownership in different types of houses. Thus, in urban areas, all customers who live in detached and terraced houses had EVs in the 100% penetration rate scenario, while only 20% of customers who live in blocks of flats had EVs. Heat pumps were allocated to customers with electric storage heating and non-electric heating loads.

In the project, the DER were allocated to the following customers:

1. EVs to customers living in terraced and detached houses and blocks of flats, for which the annual energy consumption stays between 1 MWh/a and 50 MWh/a. Criteria: type of house and size of customer;
2. heat pumps to customers having electric storage heating and non-electric heating. Criteria: type of customers;
3. solar PV were allocated randomly to residential customers, living in terraced and detached houses. Criteria: type of house;
4. BESS were allocated to those customers who have solar PV installed.

After DER profiles are built and allocated to customers according to some criteria, the DER integration (passive usage) and aggregation (active usage) scenarios and their implementation are carried out. In the integration scenarios, no intelligent control is performed for DER. In the aggregation scenarios, DER is controlled by some third party (aggregator) against some incentive. The modelling is presented in detail in the next subsections.

## 3.3 Modelling of DER integration

The DER integration scenario takes as the input information the type of DER, their penetration rate, size or size range, and customers to which DER are allocated. The penetration rate is calculated in per cent as the share of customers possessing DER in relation to the total number of customers. For instance, the penetration rate can be set for the customers behind a connection point, a distribution transformer, or a main transformer. Depending on the objectives of the analyses, the appropriate customer group is chosen. For example, in the grid impact analyses on a distribution transformer, the penetration rate is set for the customers supplied by that transformer.

The size of DER is expressed in terms of:

- capacity of BESS in kWh
- capacity of the battery of an EV in kWh, charging power in kW
- installed capacity of a solar PV system in kWp
- nominal power of a heat pump, kW

In the DER integration scenarios, the DER usage is assumed to be passive. This means that the DER usage is uncontrolled and not controlled against the signals coming from the distribution grid, electricity market, and/or retail tariff. Thus, the EV charging starts immediately when the customer arrives at home/work. The heat pump is operating only according to the outdoor temperature, without optimized energy management. The solar PV in its passive usage only produces active power and does not participate in the reactive power compensation task. Instead, the BESS is always operated against a certain control algorithm, so it is by default in active usage.

### 3.3.1 Methodology for EV integration

The methodology is illustrated in Figure 13. The input data required for the methodology are AMR loads, distribution grid topology and dimensions, and information on customer types (residential house types, non-residential). These are the obligatory input data, i.e., the minimum set needed to carry out the simulations. However, other data sources can be included, for instance driving statistics for the area under consideration or socio-demographic information. Such additional information will improve the accuracy of the results obtained.

The flow of the methodology comprises six steps. In the first step, data filtering and preprocessing is executed. For instance, the zero-load customers (missing customers) are removed. Furthermore, if EV home charging is simulated, only residential customers are selected for further studies. Too small residential customers living in flats can be also filtered out of the studies. Such customers can be for instance students or some retired people. In case EV workplace charging is simulated, commercial and industrial customers are selected.

In step 2, the EV simulation scenario is defined. Factors like penetration rate, charging strategy, and charging rate are defined here. In this project, ”what-if” scenarios are modelled, so at this step one can input any scenario of interest.

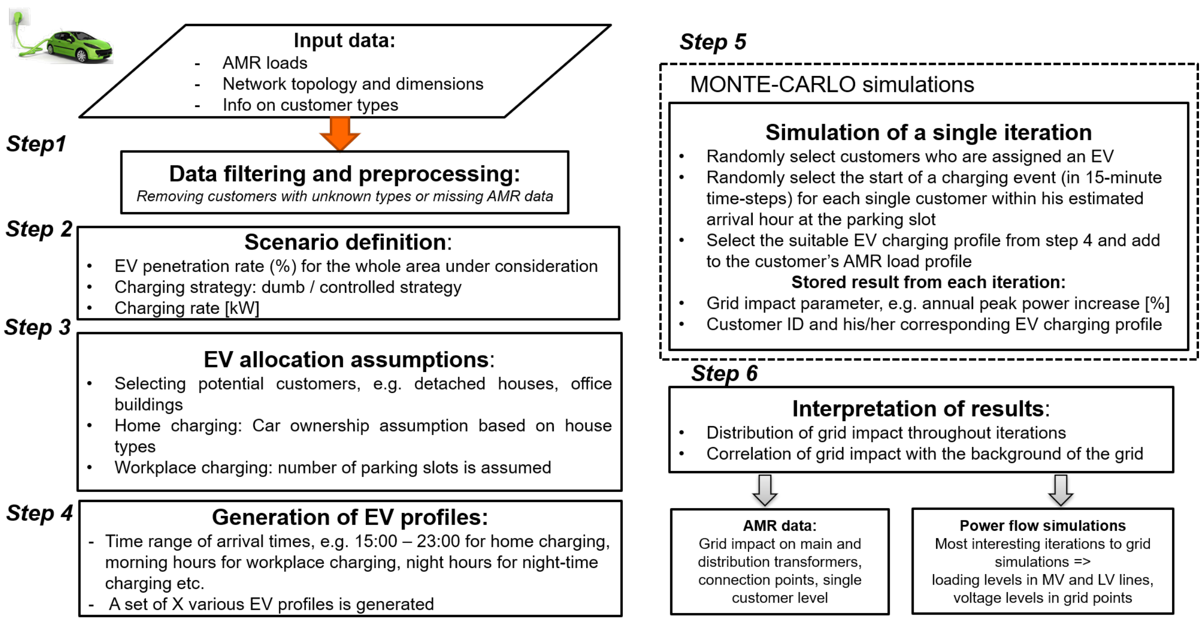



Figure 13: Methodology to integrate EVs into the distribution grid and assess their grid impact

In step 3, EVs are allocated to customers according to the assumptions made. First, potential customers who are likely to have an EV for home charging or charge at workplace are identified from the AMR data. In this methodology, it is considered that the EV charging occurs either at home or at work. Hybrid charging, partly at work and partly at home, is not simulated. However, it is possible to add also this element to the model. Secondly, car ownership is assumed. In this research work, a 100% ownership rate in a detached house and a flat in a terraced house (1 car per electricity customer) and a 25% ownership rate in a block of flats (one-fourth of the customers living in flats have a car) are assumed. This will give the number of cars in the area. Then, in the 100% penetration rate, the number of EVs is equal to the number of cars. In step 4, the idea is to generate the EV charging profiles before they can be allocated to single customers in the Monte Carlo simulations in step 5. EV charging profiles are simulated according to the given parameters: charging rate [kW], arrival time [in 15 min time steps], and charging need [kWh/day]. These can all be set by the user. In the case of the workplace charging scenario, the arrival times of the EV drivers are normally distributed around some morning hour, for example 8:00 or 9:00, or depending on the objective of modelling. If the objective is to find the worst-case loading scenario, the arrival times of EVs are distributed around the peak morning hour at the workplace.

In the case of the home charging scenario, the EV profiles are generated for the arrival times from 15:00 to 23:00 in 15 min time steps, resulting in a total of 36 EV profiles, each arriving at a different time slot. An example of the input information for generating EV profiles is presented in Figure 14.

| | | EV1 | EV2 | EV3 | EV4 | EV5 | EV6 | EV7 | EV8 | EV9 | EV10 | EV11 | EV12 | EV13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Charging rate (W) | | 11000 | 11000 | 11000 | 11000 | 11000 | 11000 | 11000 | 11000 | 11000 | 11000 | 11000 | 11000 | 11000 |
| EV distance multipler | | 1,171875 | 1,09375 | 1,640625 | 0,807292 | 0,677083 | 0,911458 | 0,208333 | 1,276042 | 1,015625 | 0,625 | 0,859375 | 1,510417 | 0,989583 |
| | | | | | | | | | | | | | | |
| Weekday: | Departure | 08:00 | 08:00 | 08:00 | 08:00 | 08:00 | 08:00 | 08:00 | 08:00 | 08:00 | 08:00 | 08:00 | 08:00 | 08:00 |
| | Arrival | 16:00 | 16:15 | 16:30 | 16:45 | 17:00 | 17:15 | 17:30 | 17:45 | 18:00 | 18:15 | 18:30 | 18:45 | 19:00 |
| | | | | | | | | | | | | | | |
| Weekend: | Departure | 12:30 | 12:30 | 13:45 | 13:30 | 15:15 | 12:15 | 11:45 | 11:00 | 10:45 | 17:00 | 11:15 | 10:45 | 11:45 |
| | Arrival | 19:00 | 18:00 | 21:45 | 19:45 | 16:15 | 18:00 | 12:30 | 12:00 | 20:00 | 19:00 | 17:00 | 14:00 | 13:30 |

Figure 14: Example of input information for simulation of 13 EV profiles

In step 5, the Monte Carlo simulations are executed. Each single iteration is different in the following parameters:

1. Customers to whom EVs are allocated. For instance, in the case of the 50% penetration rate and the home charging scenario, half of all the potential customers are assigned an EV in each iteration in a random way. For instance, out of ten detached houses with ten EVs in total in the area, five will be allocated an EV in one iteration. In the next iteration, some other five customers out of ten will be allocated an EV. Some of them can be the same as in the previous iteration, and others can be different.

2. Start of a charging event, which will be the same for the EV driver throughout one year. After the single customer's average daily peak power hour is defined based on the AMR load profile (see Figure 2), it is further analysed. If the daily peak power hour is at 15:00, then the start of charging for that customer is randomly selected from 15:00 to 18:00 in 15 min time steps. Four 15 min time steps during one hour and for four hours (15, 16, 17, and 18) makes 16 possible 15 min charging start times for that particular customer. One of those 16 different EV profiles is randomly selected in each iteration and added to the customer's AMR load profile. In practice, this means that in one Monte Carlo iteration, the customer charges the EV at 16:15 and in another iteration, the charging starts at 15:30, and so on. The time range from 15:00 to 18:00 is arbitrarily selected and can be easily changed.
3. Annual driving distance is varied between 2803 km/a to 21000 km/a in a random order.

As a result of step 5, a time-series-modified load profile is obtained for each grid point where the EVs are modelled, from the single customer level, to the connection point, distribution transformer, and the main transformer level. Here, the grid topology is used to define which customers are connected to which distribution transformer.

In this step, the CSC supercomputer resources are taken advantage of. The simulations can be parallelized at least in two ways: 1) the Monte Carlo iterations can be calculated in parallel because they are not dependent on each other, and 2) the EV charging scenario for each distribution transformer can be set independently, and thus, each distribution transformer can also calculated in parallel.

Both ways were tried in this project. The first one was used when the EV scenario was defined for the primary substation level. The second one was used when the EV scenario was defined for each distribution transformer. For instance, the case of the 50% penetration rate of EVs for the primary substation level would mean that in some iteration some distribution transformers may have no EVs at all, whereas the other ones will have a 100% penetration rate. When setting the penetration rate at the distribution transformer level, it will be always fulfilled in every single iteration.

After each iteration, the modified load profiles for every single customer were stored remotely in the supercomputer memory. Usually, it took several hundreds of GB of memory for 1000 Monte Carlo iterations. In each iteration, several grid impact criteria were stored for the later analysis. The criteria were annual peak power changes, changes in peak operating time, and load rate. These criteria took much less memory than the modified load profiles and could thus be copied to the local computer for further analyses.

In step 6, the results from the Monte Carlo simulations are presented as the probability distribution of the grid impact. The probability distribution shows how often the grid impact value occurred over 1000 iterations. For instance, if in 500 iterations out of 1000 the annual peak power changes were 20% (the new annual peak power caused by EV charging was 20% higher than before EVs), the probability of its occurrence is 50% (=500/1000). Out of the 1000 iterations presented in the histogram for the probability of the distribution of the grid impact, two iterations are selected for further analysis corresponding to the most frequently occurring grid impact value and the worst-case grid impact value. From these two iterations, the modified time series load profiles are selected from the supercomputer memory storage and used for the power flow simulations to make analyses of line loading and voltage profiles.

The advantage of the methodology is that it can incorporate various EV charging strategies, and it is suitable also when considering active EV usage, such as nighttime charging, peak shaving, and/or participation in frequency regulation. These applications can be incorporated into EV profiles generated in step 4. The additional inputs needed are the flexibility potential or range and electricity markets/tariffs/other economic incentives against which the EVs are controlled. These are discussed in more detail in section 3.4.

### 3.3.2 Methodology for heat pump integration

The methodology is illustrated in Figure 15. It consists of 5 steps, including collecting the input data in step 1 and analysing the outcome results in step 5. The advantage of this methodology is that only AMR data and outdoor temperatures of the area under consideration are required to carry out the simulations. However, the methodology can take in other data sources, for instance physical characteristics of buildings (e.g. size of houses, insulation level), socio-demographic statistics, or information of the type of heating system (water-based or resistor-based), that further improve the accuracy of the results. Without those additional inputs, there is still high uncertainty related to the switching behaviour of the customers. This is mitigated by again applying Monte Carlo simulations, like in the EV integration modelling.

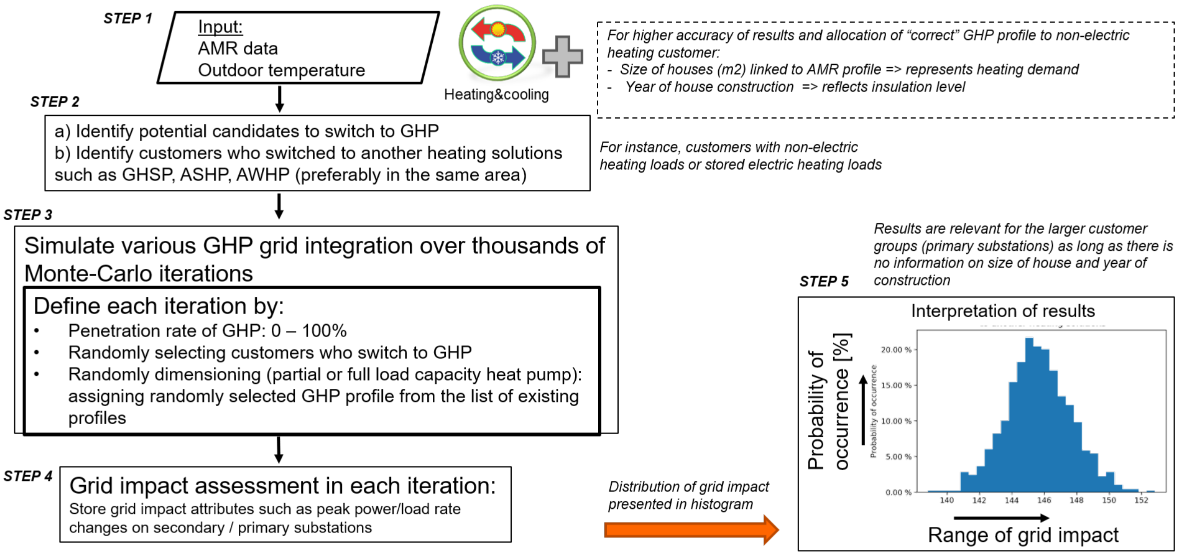



Figure 15: Methodology to integrate heat pumps into the distribution grid and assess their grid impact

In step 2, the customers who have already switched to a GSHP solution should be identified from the AMR dataset. In the suburban case area, the DSO provided information about the customers who had switched to the GSHP. For the rural case area, the DSO did not have this information, and hence, those customers were selected whose annual energy consumption changed from year to another. The changes of annual consumption were further analysed using temperature dependence regression in order to distinguish changes related to new heating solutions and not to the other non-heating issues. The algorithm is illustrated in Figure 16.

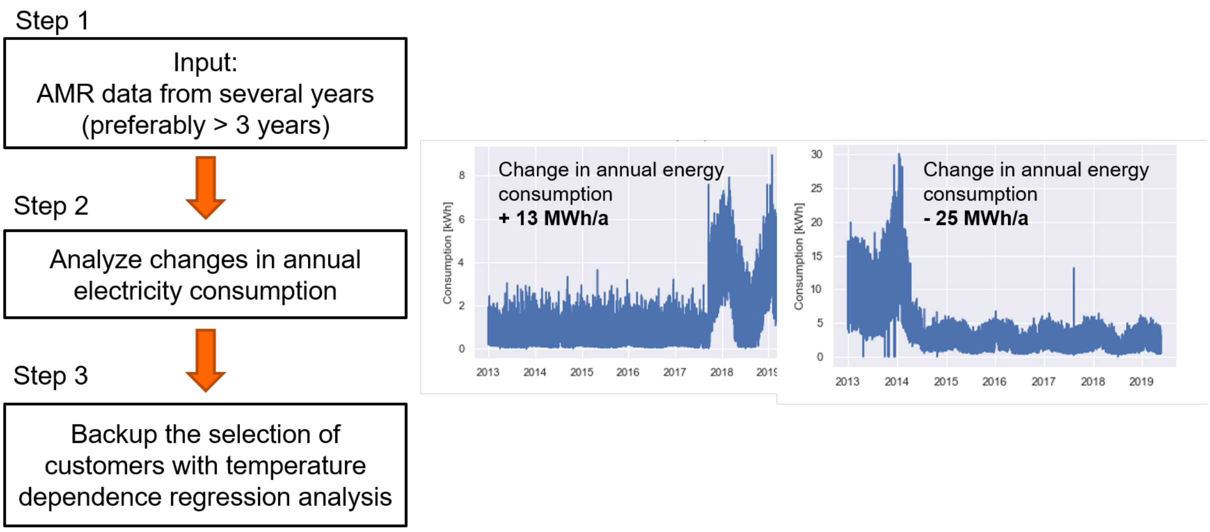



Figure 16: Method to identify customers who have already switched to another heating solution

A temperature-dependence analysis is needed to distinguish changes related to heating solutions from changes related to other issues, such as birth of children, change of residents, and other factors (Figure 17).

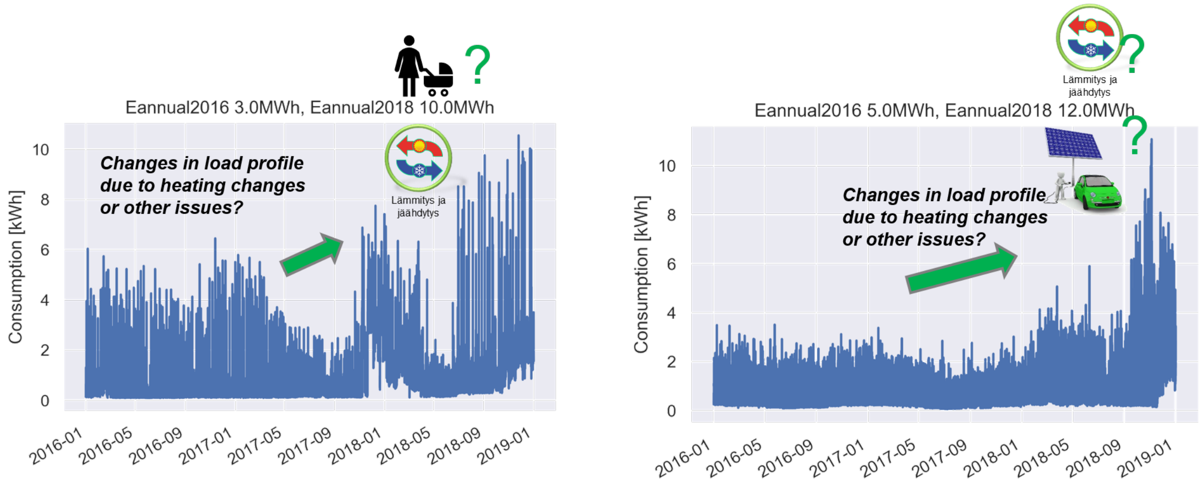



Figure 17: Temperature dependence analysis to distinguish heating changes from non-heating-related changes in the load profile

A temperature dependence analysis represents linear regression analysis where the load and outdoor temperature values are located on the same chart to search for linearity. The slope of the curve obtained in the analysis reveals whether the customer's electricity consumption depends on the outdoor temperature or not. Mathematically, the slope of the curve is a coefficient in the linear equation of the curve:

$$Load_{\mathrm{kWh}} = a + Slope * T_{\mathrm{outdoor}}. \tag{3}$$

The hourly load profiles of two example residential customers are presented in Figure 18. The annual energy consumption and peak power are similar for both customers. However, the temperature dependence analysis shows that one of them is a non-electric heating customer and another one is an electric heating customer.

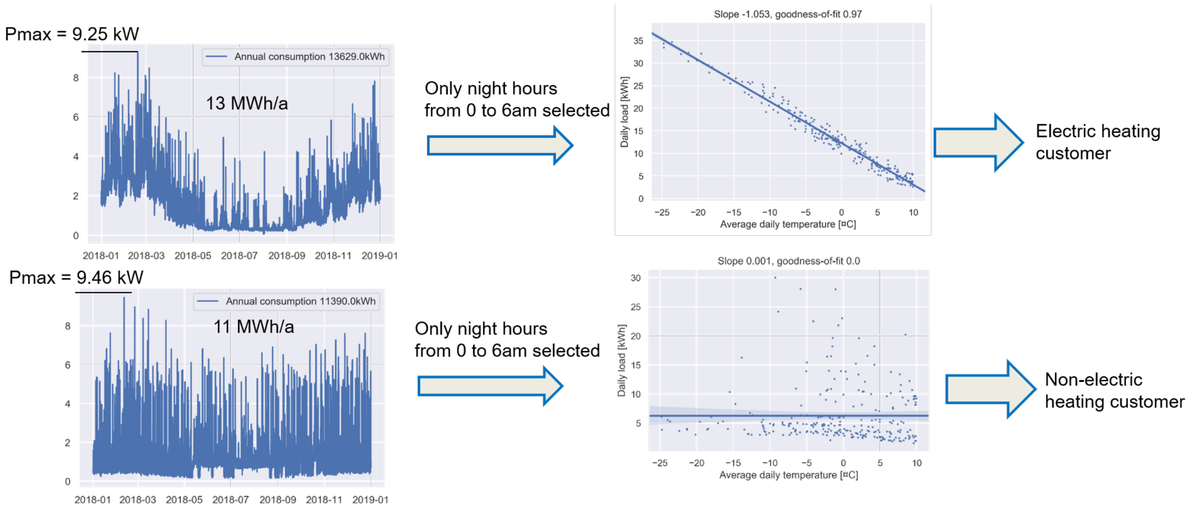



Figure 18: Temperature dependence analysis to distinguish an electric heating customer from a non-electric heating customer

Coming back to step 2, potential customers have to be identified from the AMR dataset. The assumption was that customers with non-electric heating (oil-based) and electric storage heating are likely to switch to a GSHP solution. The customer database provided by the DSO contains information on the present heating solution and helped in identifying those potential customers.

Step 3 combines the knowledge obtained from the existing customers with GSHP with the potential customers. In particular, to model changes in electricity consumption within heating transitions to GSHP, a data-driven approach was applied. This implies that the switching behaviour is learnt from present cases and applied to potential customers. Here, the two parameters learnt are information of how much the annual energy consumption changes after the switch and what type of new GSHP solution is likely to be selected by the potential customer. For instance, when customers with electric storage heating switch to a GSHP, their annual consumption may decrease by 2–30 MWh/a, based on the switching examples available. When non-electric heating customers switch to a GSHP, their annual consumption may increase by 8–25 MWh/a. Owing to the high uncertainty associated with which GSHP solution a customer is likely to switch to, a Monte Carlo simulation was applied to simulate a large number of possible switching variations. In the project, as an example, 500–1000 different combinations of switching behaviour were simulated for each distribution transformer. In each Monte Carlo iteration, the penetration rate was set fixed for every transformer, the potential customers were selected randomly from the set of potential customers identified in step 2, and the GSHP profile was allocated randomly to those potential customers. The old load profile of the selected potential customer was removed first and then replaced by the new GSHP customer's load profile. For instance, if the annual consumption of a potential customer with the present heating solution is 4 MWh/a (non-electric heating), then the customer's new annual consumption can be somewhere between 4+8 and 4+25, making it between 12MWh/a and 29 MWh/a. Taking this into account, the suitable load profiles of the present customers with GSHP are selected from all the available profiles, and one load profile is randomly selected from that set. During the next iteration, that same potential customer may get another GSHP customer's profile. In the case suburban area, 56 GSHP customers' profiles were allocated to 306 potential customers. In the rural area, 56 GSHP customers' profiles from the rural area were allocated to 1100 potential customers. The GSHP customers and the potential customers were always used from the same area, in order to avoid the need for outdoor temperature correction measures.

In step 4, in the same way as in the EV simulation, the grid impact criteria, i.e., annual peak power changes, load rate, and changes in peak operating time, are calculated from the modified time series profile at the distribution transformer level and stored for each iteration. After that, the grid impact procedure is repeated in the same way as in the modelling of EV integration.

The established methodology enables to create scenarios of heat pump integration into a distribution grid having information of hourly load measurements and outdoor temperature. The absence of the building characteristics (size of the building, year of construction, insulation level) and socio-demographic statistics of the area results into high uncertainty of which customers are likely to change to which type of heat pump solution, and hence, Monte Carlo simulations are required to generate hundreds of different combinations. However, when such information will be available, a lower number of Monte Carlo iterations will be required to obtain the reliable results.

### 3.3.3 Solar PV and BESS integration

This section presents the principles of solar PV allocation to the single customers. After defining the solar PV profile described in section 3.1.3, the next question is what size of PV-BESS system should be assigned to a single customer.

The modelling of solar PV and BESS integration into distribution grids depends on the objectives of the study. If the grid impact is analysed for a larger customer group, for instance a primary substation supplying thousands of customers, detailed modelling of solar PV allocation and sizes is not relevant, and an average approach will suffice. For instance, it is not necessary to define which customers will get a solar PV system of 3 kWp, 5 kWp, or 10 kWp, but instead, it is enough to assume that all customers will get a solar PV system of 5 kWp.

However, when analysing the grid impact at the distribution transformer level with a small number of customers, detailed modelling is required. The decision-making process of deciding to which customers solar PV systems should be allocated and what size of the system should be selected can be executed in two ways.

The first method applied to the rural area in the project, assumes that we have information about customers who already possess a solar PV system. Then, the installed capacity of the PV panels for the customers without solar PV can be selected based on the linear regression model. The model is built by applying the data on the customers with the PV panels and their mean daily energy consumption from all days in a year. First, the data was processed for revealing of the outliers. These are the customers with the PV panels, which installed capacity is several times more than thee mean daily energy consumption of the customers. Figure 19 below illustrates the results of the data processing.

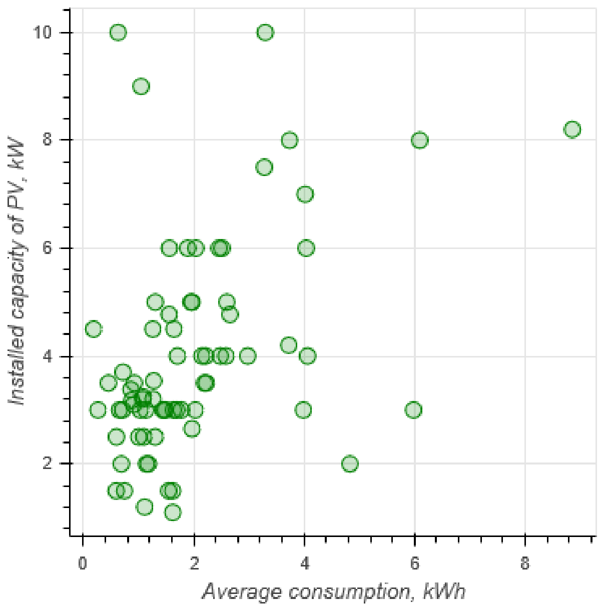



Figure 19: The correlation of the PV panel installed capacity from the customers' mean daily energy consumption

The mean absolute error of the predicted values is around 1.3 kWp. In the analysis, several battery capacities were examined:

- battery capacity equal to the installed capacity of the PV panels
- battery capacity twofold the size of the PV panels

The second method that was applied to the urban and suburban case areas in Helsinki, assumes the usage of open-source databases. In particular, the information on the annual solar generation potential [kWh/a] was provided by the DSO in the form of kWh/a/connection point. Combining the annual potential with the average number of sunshine hours in Finland 800 h/a, the size of the solar PV system can be obtained for a connection point.

## 3.4 Modelling of DER aggregation

The DER aggregation refers to the active usage of DER against various control signals. It is assumed that an aggregator collects flexibility resources from different DER and trades them in the electricity market or offers them to a DSO, who uses them for distribution grid needs, for instance congestion management or reactive power compensation. Within the scope of the project, the objective is to model a possibility to construct a DER aggregation scenario and assess its impact on the distribution grid. Thus, identification of particular DER aggregation scenarios of the future is outside the scope of the project. Again, such an approach enables a sensitivity analysis that allows to simplify and/or specify the model by focusing on the major influencing factors and neglecting the minor ones.

Figure 20 illustrates the principle of modelling the DER aggregation based on an assumption of the share of DER selected for active usage, definition of the applications for which DER are used, and finally, identifying the grid impact. The grid impact is analysed in the form of load profile changes, namely peak power changes over a specific period of time.

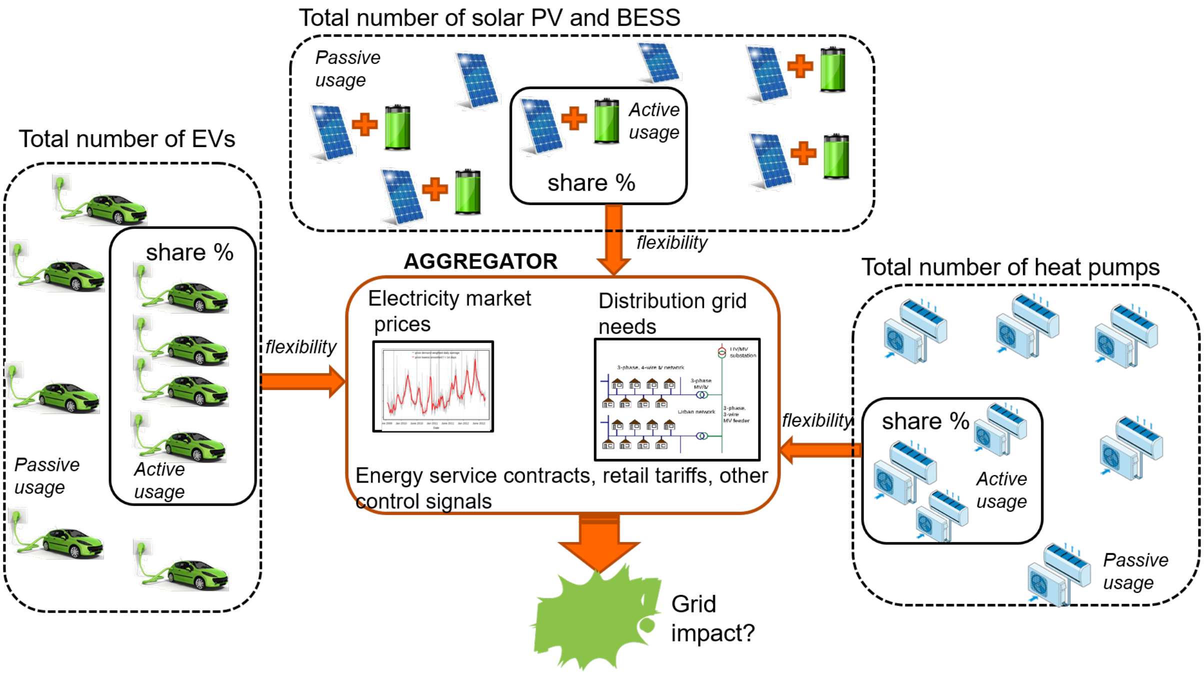



Figure 20: DER aggregation scenarios

The DER aggregation scenarios can be identified by the two major aspects:

- Selected applications for which DER are used, i.e., control signal coming from the electricity market prices and/or distribution grid needs
- Flexibility potential of DER and the share of customers providing their energy resources for the selected application(s)

These two aspects are presented in more detail in the following subsections.

### 3.4.1 Flexibility of DER

Flexibility is a wide concept, and therefore, the objective of this section is to concretize the term. In this study, we define flexibility attributes as a way to measure flexibility. These attributes are active power and energy up- and down-regulation, reactive power up- and down-regulation, duration of the control event, reaction time as a speed at which DER reacts to a control signal, and other attributes such as time of control event and location as a point in the grid where flexibility is required (see Figure 21).

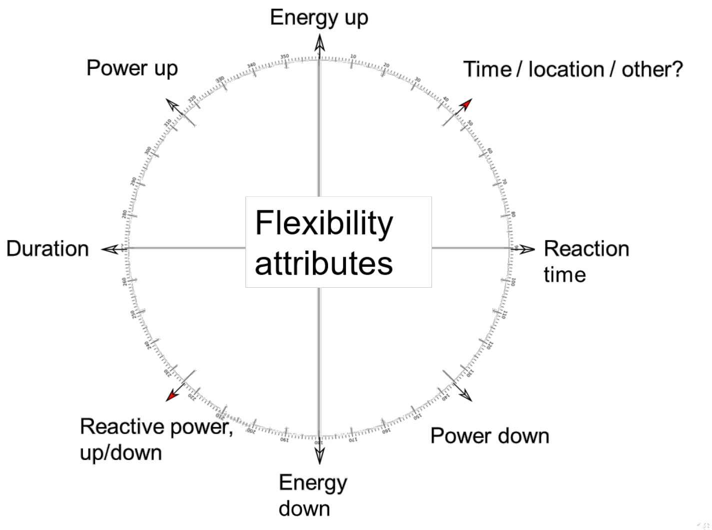



Figure 21: Flexibility attributes

The basic assumption in DER aggregation modelling is that DER can be clustered into groups according to their flexibility attributes. For instance, in the scenario of active usage of an EV fleet where EV battery capacities are offered to the FCR-N hourly market, the aggregator collects the information of those EVs whose power is available in a particular hour of the day. Hence, only those EVs participate in the frequency regulation task which are parked and whose SOC levels allow to provide active power in both up- and down-direction (attribute: active power up and down) during a pre-defined hour (duration attribute).

The flexibility potential of DER is determined by several factors, such as technical restrictions of DER units, customers' comfort preferences, and weather conditions.

### 3.4.2 Applications for DER aggregation

The applications can be divided into electricity market-based and grid-based ones. The market-based ones refer to participation in electricity markets, such as energy-based markets (€/MWh) Elspot day-ahead and intra-day balancing power markets and a power-based FCR-N hourly market (€/MW). Grid-based applications can refer to activation of DER in order to relieve congestion management in the grid, provide reactive power compensation or voltage control, and serve other needs.

## 3.5 Interpretation of the results

Interpretation of the results obtained from the model and simulations is the last step of the methodology. The results of the simulations are modified time series load profiles in various grid points. Next, the grid impact has to be analysed based on some criteria.

### 3.5.1 Concept of grid impact

The grid impact depends on two factors; the characteristics of the DER and the grid as illustrated in Figure 22.

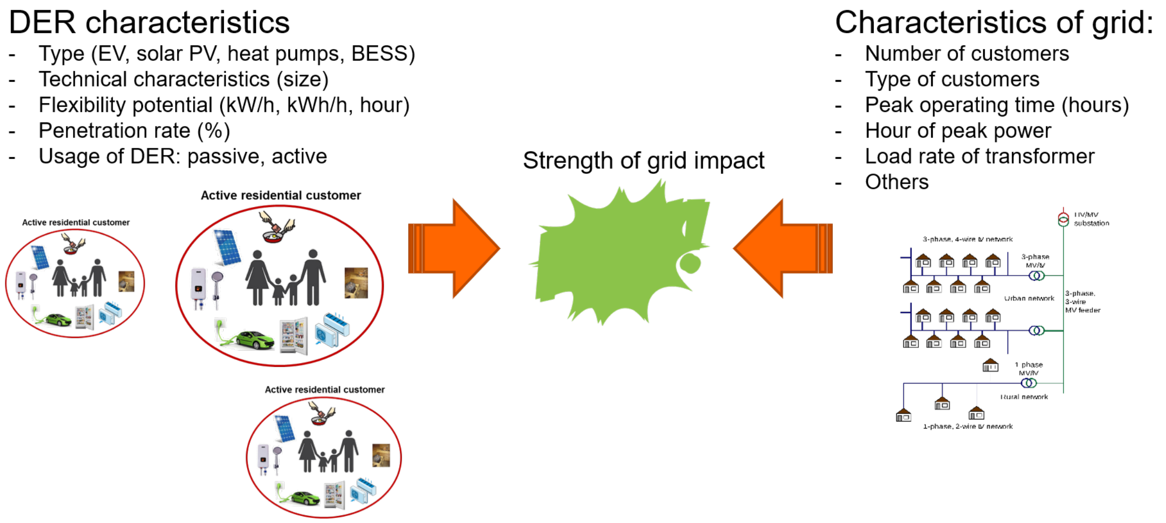



Figure 22: Concept of grid impact

It is important to analyse both parts, the DER and the grid, in order to be able to make more general conclusions from the obtained case-specific results. For example, one of the tasks of the established methodology and calculation tool is to be able to state that a particular type of transformer (e.g. low installed capacity, short peak operating time, low number of customers) will most probably experience a high grid impact (large peak power, load rate changes, voltage quality problems) if X% of customers behind it acquire EVs.

In this project, the peak operating time (POT) and the number and type of customers were considered characteristic attributes of the grid element, for instance a distribution transformer. POT is calculated by the equation

$$POT\,[hours] = \frac{E_{\text{annual}}\,[kWh]}{P_{\max}\,[kW]} \tag{4}$$

A long POT means a high capacity utilization rate of the grid element in question, i.e., peak powers occur often (on a regular basis) and are thus close to the average power consumption. This is typical for the MV network and large customers. Because the peak powers are close to the average loading level and the capacity utilization rate is high, there is little free capacity left, and hence, the probability of new peak powers is high.

A short POT means a low capacity utilization rate, i.e., peak powers are rare and/or sharp, in other words, much higher than the average power consumption. This means that there is a lot of free capacity left, and hence, if a new peak power arises, the probability of exceeding the already existing peak power is low.

The DER characteristics are not dependent on the grid but on the decisions that the customers of that grid will make. The model enables to dynamically apply and simulate numerous DER scenarios of interest as presented in Figure 23.

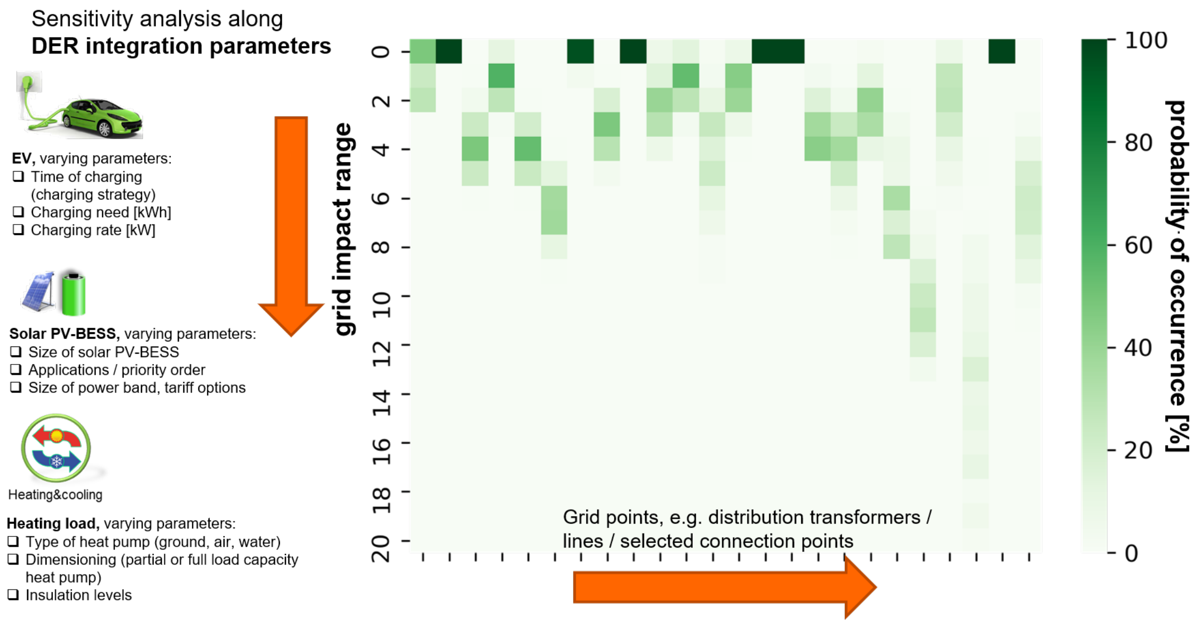



Figure 23: From input to output: illustration of results

Because of the numerous parameters and the uncertainty of DER characteristics, a Monte Carlo approach is used in the studies. This means that a large number of combinations (hundreds) are simulated, and the grid impact is calculated for each combination. All the grid impact values are then combined into one chart as in Figure 23 in the form of probability of grid impact occurrence. Thus, one outcome of the simulation tool is a modified time series profile in the grid point of interest that corresponds to the most probable scenario (highest probability of occurrence) and the worst-case scenario (highest grid impact value). The question of how close to the near-future years either of those two scenarios is remains outside the scope of this project.

### 3.5.2 From case-specific to general conclusions

Another outcome of the project is generalization of the obtained results in a broader perspective. The main research question is how the obtained case-specific results can be beneficial in other distribution grids. Can we say that a certain type of distribution transformer will be only slightly or very heavily overloaded if a certain DER scenario takes place? Which kinds of DER scenarios are more likely to overload the transformers and lines in an urban and a rural network? Do DER pose challenges to the present dimensions of a rural and an urban grid?

For this purpose, the analysis of the grid impact has to be performed together with the grid characteristics as discussed in the previous subsection.

To conclude, the same procedure of grid impact analysis will be performed for the scenarios of EV and heat pump integration following the methodologies presented in Section 3.3.

## 3.6 Advantages and limitations of the model

The advantages of the methodology are:

- Various DER scenarios can be simulated with variations in the type of DER, penetration rate, location, and size.
- Only AMR data and grid topology and dimensions are needed to obtain a range of grid impacts in a particular DER scenario.
- The results present the probability distribution of the grid impact range with the probability of the most frequently occurring grid impact and the worst-case grid impact and its values.
- The model can take in other input parameters, such as socio-demographic background information of the customers and physical characteristics of the buildings, and take advantage of open-source databases describing the electricity customers' behaviour and environment.
- The impact of DER in any grid point can be assessed from the main transformer, through an MV feeder, a distribution transformer, an LV feeder, a connection point, and down to a single customer level.
- Indications of whether the flexibility options are sufficient or a grid investment is required to mitigate the DER impact on the grid.

The limitations are:

- Some simulations require a lot of computational memory (challenging without supercomputing resources).
- The impact of asymmetrical loading caused by uneven distribution of load after DER integration in three phases is not considered.
- The low number of possible DER profiles limits the possible outcomes. For instance, if there is a low number of customers with heat pumps present in the grid but the number of potential customers to switch to a heat pump solution is high, the accuracy of the obtained results may suffer. The same is valid not only for heat pumps but also for EV charging profiles and solar PV profiles. Such lack of data can be compensated by artificially creating

new profiles from the DER profiles, for example by using machine learning techniques. This method is called data augmentation.

- The obtained results are sensitive to initial assumptions and have to be analysed accordingly. For instance, the assumption that all EV drivers arrive at a workplace and start charging around 8 o'clock, or that EVs are parked for eight hours and their battery capacity is available during that time for flexibility-related activities. These fixed assumptions also have an impact on the results. In some cases, such fixed assumptions represent the worst-case scenario from the grid perspective, while in other cases, they represent the best-case scenario from the perspective of the availability of flexibility. Therefore, analyses have to be done carefully keeping the initial assumptions in mind.

# 4 Distribution Network Modelling

This chapter presents the case networks modelled in the project, describes the modelling tool in brief, and demonstrates the modeling process used for the networks and the results of the process.

## 4.1 Distribution network

The function of the distribution network is to deliver electricity from the primary substations fed by the transmission system to the consumers. The main components of the network include primary substations, feeders, distribution transformers, distribution cabinets, and switching devices (breakers, switches, fuses). The role of distribution networks in power system operation has been emphasized in recent years as a result of challenges arising from the increased penetration of DER in these networks. The network modelling is one of the crucial approaches for an in-depth analysis and planning towards future development scenarios in distribution systems. Typically, network modelling means building of a mathematical model of the network to simulate its physical behaviour.

In this project, the raw network data accompanied by the AMR data was provided by the project DSOs to investigate the effect of DER on the networks in different locations, population density, and parameters of electric equipment. The raw data contained information about the DSO distribution networks in part or as a whole. The basic raw data included the grid topology referenced using geolocation or node identification (ID) and electric parameters of power lines and transformers, and the status of switches and breakers. In some cases, the raw data contained more detailed information, for instance the network location of installed DER and their parameters, but they were not used directly in the network modelling.

In total, the data on three distribution networks were given. The case networks from Helen Electricity Network included one urban and one suburban area, and the Nivos network consisted of a mix of rural, suburban, and urban areas. The Nivos network is the largest among the studied cases. It has five primary substations, around 1000 distribution transformers, and approximately 15000 customer points. The Helen case networks have only one primary substation and about 40 distribution transformers each with the number of connection points equal to approximately 1000 and 300 for the suburban and urban areas, respectively. Besides the overall network size, the line infrastructure is different for the Nivos and Helen cases. The Nivos network has a mix of overhead lines and underground cables, whereas the Helen networks are constructed almost completely underground.

## 4.2 pandapower description

In this project, the distribution networks were modelled by using open-source `pandapower` software. `pandapower` is a Python-based power system analysis tool that has been successfully applied for grid studies and educational purposes [7]. The primary target application of `pandapower` is automation of the static and quasi-static time series analyses and optimization of power systems, especially focusing on active distribution networks with high proliferation of DER. The functionalities of `pandapower` include power flow, optimal power flow, state estimation, topological graph searches, controller simulation, time series simulation, and short-circuit calculations, but they can be extended with third-party libraries.

An element-based model is used in `pandapower` to simulate electric networks. In this model, the network is formed as a collection of buses and elements connected to one or multiple buses. The elements can be for instance lines or transformers, and they are defined with characteristic parameters that are handled with a tabular data structure based on a Python library `pandas`. The mathematical model of the electric network is derived by converting the elements with equivalent circuit models. More information about `pandapower` software can be found in [7] and on the website https://www.pandapower.org/.

In this project, the following functionalities of `pandapower` were used for network modelling:

- AC Power flow calculation
- Customized time series simulation
- Network diagnostic
- Interactive and static network plotting
- Controller simulation
- Generic coordinates modelling

The networks were modelled from the external grid supplying primary transformers to the customer loads with the following elements in `pandapower`: bus, line, transformer, switch, external grid, load, and static PV generator.

## 4.3 Modelling process

The network modelling included the processes from obtaining the raw network data to simulating and visualizing the case study scenarios. This process consisted of the following steps:

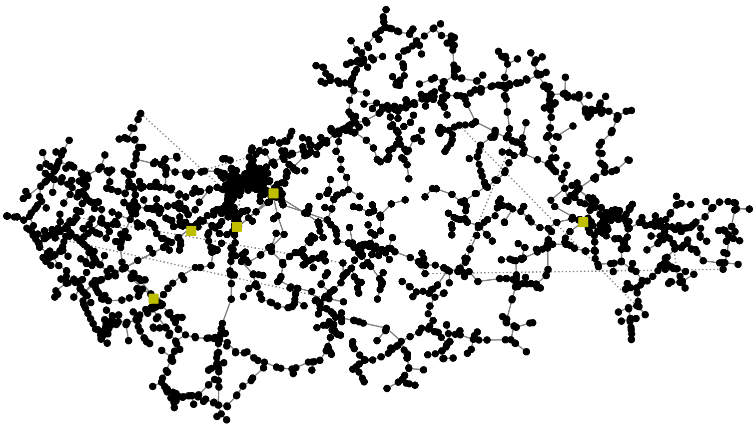
1. Data cleaning and preprocessing
2. Data mapping
3. Topology modelling
4. Network diagnostic
5. Power flow validation

6. Case study application
7. Visualization of results

The *data cleaning and preprocessing* step consisted of the initial readings of the raw data into a tabular `pandas` form, analysis of the data on the subject of electric components available and missing data, relabeling of the parameters, and filling of missing parameters. The next step was used for *data mapping* from the created tabular form into `pandapower` elements and related sub-steps, such as modifying the standard line libraries in `pandapower` for new conductor types. In the *topology modeling* step, the network elements and buses were created and connected. In many cases, the given topology data were corrupted, which required automated (and manual) *network diagnostic* to re-create the topology in the best way. In that case, visual analysis using network plotting with real or artificially created coordinates was helpful. In the validation step, real AMR time series were used to test the power flow results based on convergence, voltage amplitudes, losses, and aggregated power profile. The final step included a power flow analysis for the *case studies* at different distribution levels: customer connection, distribution transformer, and primary transformer. Finally, the results of the case studies were presented by different forms of *visualization* including network diagram, voltage profiles, and transformer and line loadings.

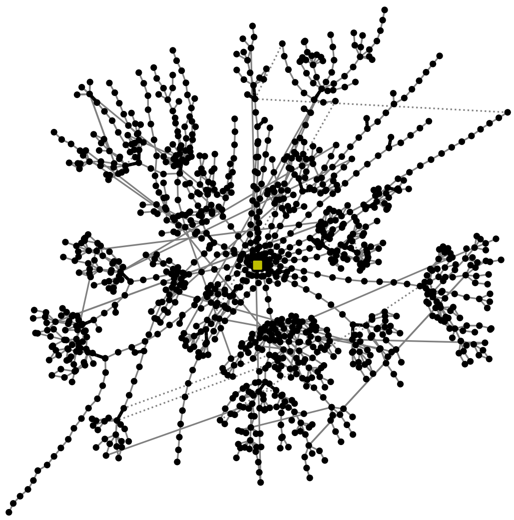
The modelling approach, however, varied between the networks in some steps. For example, the topology modelling for Helen case networks was implemented by linking the electrical equipment with the connection IDs. However, for the Nivos case, direct linking was not possible. Therefore, the geolocation of the equipment and connection assumptions were used to create the correct topology. These assumptions were derived based on the network diagram available. Moreover, the LV network was not modelled in the Nivos case because of the complexity of the topology building based on component geolocation. In this case, all LV loads were connected directly to the distribution transformer.

The resulting characteristics of the modelled case networks implemented in `pandapower` are given in Tables 1–3, and the networks are visualized in Figure 24. The case networks and their characteristics are not an ideal representation of the real networks but a very close approximation of the actual case. The difference is primarily caused by the quality of the raw network data. As it can be seen from the characteristics, the modelled grids can be distinguished by the total line length and their parameters and the number of customers and distribution transformers. Therefore, they provide a good basis for drawing generic conclusions of DER penetration scenarios in different cases.



(a) Nivos network

(b) Helen suburban network



(c) Helen urban network

Figure 24: Topological graphs of the Nivos (a) and Helen (b)–(c) case networks visualized in `pandapower`. The black dots represent network nodes, the yellow squares indicate external grid connections, and the grey solid and dashed connectors are the connected and disconnected distribution lines, respectively.

Table 1: Summary of the parameters for the modelled distribution network: case Nivos

| Element | Parameter | Value |
|---|---|---|
| Network | Voltage levels, kV | 110/20/0.4 |
| | Primary substations | 5 |
| Load | Customer points | 14738 |
| MV lines | Total length | 891.64 km |
| | Section length, km | [0, 0.30, 3.77][a] |
| | Total length by type, km | [657.68, 233.96][b] |
| | Resistance, ohm/km | [0.537, 0.169][b] |
| | Inductance, ohm/km | [0.384, 0.119][b] |
| | Capacitance, nF/km | [10.05, 260.00][b] |
| LV lines | - | - |
| HV/MV transformers | Apparent power, MVA | [16, 25, 31][a] |
| | Total number | 7 |
| MV/LV transformers | Apparent power, kVA | [16, 100, 10000][a] |
| | Total number | 1013 |
| | Distance to primary substation, km | [0.22, 9.32, 26.10][a] |
| | Number of customers | [1, 7, 362][a] |

[a]Minimum, median, maximum.
[b]Overhead line, underground cable system.

Table 2: Summary of the parameters for the modelled distribution network: case Helen—suburban

| Element | Parameter | Value |
|---|---|---|
| Network | Voltage levels, kV | 110/20/0.4 |
| | Primary substations | 1 |
| Load | Connection points | 1042 |
| MV lines | Total length | 28.07 km |
| | Section length, km | [0.0001, 0.123, 1.016][a] |
| | Total length by type, km | 28.0658 [b] |
| | Resistance, ohm/km | 0.14 |
| | Inductance, ohm/km | 0.116 |
| | Capacitance, nF/km | 320 |
| LV lines | Total length | 106.172 km |
| | Section length, km | [0.0001, 0.0362, 0.3165][a] |
| | Total length by type, km | [0.0235, 106.1483] [b] |
| | Resistance, ohm/km | [0.393, 0.480][b] |
| | Inductance, ohm/km | [0.330, 0.082][b] |
| | Capacitance, nF/km | [9.5, 290.0][b] |
| HV/MV transformers | Apparent power, MVA | 40 |
| | Total number | 1 |
| MV/LV transformers | Apparent power, kVA | [315, 630, 1000][a] |
| | Total number | 41 |
| | Distance to primary substation, km | [0.013, 8.22, 12.89][a] |
| | Number of connection points | [1, 1, 17][a] |

[a]Minimum, median, maximum.

[b]Overhead line, underground cable system.

Table 3: Summary of the parameters for the modelled distribution network: case Helen—urban

| Element | Parameter | Value |
|---|---|---|
| Network | Voltage levels, kV | 110/10/0.4 |
| | Primary substations | 1 |
| Load | Connection points | 325 |
| MV lines | Total length | 29.019 km |
| | Section length, km | [0.0033, 0.0564, 1.51][a] |
| | Resistance, ohm/km | 0.14 |
| | Inductance, ohm/km | 0.116 |
| | Capacitance, nF/km | 320 |
| LV lines | Total length | 50.29 km |
| | Section length, km | [0.0002, 0.03, 0.32][a] |
| | Total length by type, km | [0.0225, 50.2655] [b] |
| | Resistance, ohm/km | [0.393, 0.182][b] |
| | Inductance, ohm/km | [0.330, 0.082][b] |
| | Capacitance, nF/km | [9.5, 280.0][b] |
| HV/MV transformers | Apparent power, MVA | 40 |
| | Total number | 1 |
| MV/LV transformers | Apparent power, kVA | [315, 630, 1000][a] |
| | Total number | 50 |
| | Distance to primary substation, km | [0.0, 0.818, 1.916][a] |
| | Number of connection points | [1, 1, 2][a] |

[a]Minimum, median, maximum.
[b]Overhead line, underground cable system.

# 5 Active DER usage

The advantages of the joint use of the PV+BESS system and the increasing number of business models motivate the current prosumers to invest in batteries and become prosumagers [8]. The more advanced term ‘prosumager’ refers to the active participation of the PV and BESS owners in trading of energy through different platforms and intermediaries. This chapter presents the results of the study of the joint use of the PV+BESS system in a series of applications. The technical analysis was conducted at three grid points, namely, a single customer and secondary and primary substations. In the simulations, all customers were provided with individual values of the PV panel installed capacity and BESS capacity. At the substation level, the change in the annual peak power was analysed for different penetration rates, namely 25, 50, 75, and 100%. The penetration rate was calculated as a share of customers having a PV+BESS system and being connected to one secondary substation. The penetration level was increased starting from the customers with the highest consumption to the lowest. The principle was based on the assumption that the customers with high consumption are willing to reduce their energy expenses, and they are the first to acquire DER. The economic analysis was carried out for every application and only for the level of a single customer. The main objective of the economic analysis was to study the cost-effectiveness of PV+BESS operation in opposition to the PV panels only. The energy expenses include:

- bill from the DSO (power-based tariff)
- energy supplier (spot price tariff)
- operational cost of the BESS (OPEX)

In the economic analysis, the real prices provided by the DSO, energy suppliers, and spot market were used. The BESS OPEX was calculated using the following assumptions:

- the number of cycles until the battery reaches the end-of-life is 3200
- the round trip efficiency is 90%
- the battery cost is 600 €/kWh [9]

It is a well-known fact that deep discharge and overcharge of battery cells accelerate ageing of the battery [10]. Therefore, 10% and 90% SOC were assumed as the minimum and maximum operational battery SOC. The economic analysis neglected the fee for solar energy fed into the grid and the payment for the supply of the generated solar energy to the grid.

## 5.1 Self-consumption of solar PV

The installation of PV panels contributes to a decrease in the energy purchase from the grid and promotes decentralization of the energy supply. However, according to the studies, the customers consume only about 20% to 40% of the total energy produced [11]. The rest of the energy is injected into the distribution grid. However, the profitability of a PV investment is lower if energy is sold instead of self-use. The replenishment of the PV panels by BESS facilitates the growth of the self-consumption rate (SCR) of the PV panels and contributes to a reduction in the energy bill. The energy generated onsite can be supplied to the customer in hours of high prices or expected high energy demand, thereby reducing the electricity expenses of the customer.

The self-consumption rate is the ratio of the consumed onsite solar energy to the total energy generated:

$$SCR_{\%} = \frac{Energy_{\text{PV consumed}}}{Energy_{\text{PV total}}} \tag{5}$$

In the context of SCR studies, the following research questions were identified:

- Which size of the BESS is economically feasible for the customers for an increase in the self-consumption rate and a decrease in the energy bill?
- How does the peak power change in different grid points with the PV-BESS system operating for the increase in SCR?

A total of 1500 load profiles of residential customers were studied. The analysis was carried out for one year. The SCR analysis was tested in two scenarios: scheduled and non-scheduled supply of energy from the BESS. The benefit of the first scenario is the reduced operational time of the battery.

### 5.1.1 Development of the operational schedule

The schedule of the battery discharging and charging events was created based on the customer's comfort and the structure of the power-based tariff. The schedule was used later as input data to conduct an analysis and create the customer's load profile with the PV+BESS system and its operation for an increase in the SCR. The traditional load profile of the residential customer was assumed for support of the customer's comfort. The battery discharges during the time frames of intensive energy use:

- from 6:00 to 8:00
- from 18:00 to 21:00.

Thereby, it secures the customer's comfort by the use of the onsite generated solar energy and affects the customer's expenses. The price in the spot market was neglected in the development of the schedule. A number of studies have shown that the energy arbitrage does not provide significant savings for the customer because of the low price volatility in the spot market [12].

During the day, the battery charges either from the surplus solar energy or from the market at night. Charging from the PV panels occurs whenever there is excess solar energy. Charging from the grid is carried out with regard to the power band value. It is the value of subscribed capacity that the customer intends not to exceed. The value of power band was determined as the difference between the maximum monthly peak power and the capacity of the battery.

Therefore, twelve values of power band were determined for the entire year. The hours of BESS charging from the grid were selected with regard to the day and night tariff components of the power-based tariff and spot price analysis. The examination of the tariff structure showed that the night-time component is cheaper than the daytime component. Moreover, the analysis of the spot market revealed that for most of the time, low prices prevail in the market in the night-time. Periodically, the price decreases in the daytime. However, the savings may not outweigh the overpayment for the daytime component of the DSO tariff. Eventually, the charging time was determined as follows:

- from 23:00 to 5:00 (if the next-day solar energy production is sufficient to charge the battery)
- from 23:00 to 7:00 (if low solar energy production is forecast)

All the customers were provided with the same time frames for battery charging from the grid. Such an assumption may result in simultaneous charging of the BESSs and a drastic increase in the peak demand at the substation level. This is the worst-case scenario for the DSO. However, such a scenario is possible and the results of the analysis will reveal its consequences.

### 5.1.2 Selection of the PV panels and BESS size

Within the analysis, every customer was provided with individual sizes of the PV panels and the battery. The installed capacity of the PV panels was determined by a linear regression model (see Section 3.3.3). The solar generation profile was obtained from the open-source database (see Section 3.1.3). Two options of battery capacity were considered in every scenario: equal to the capacity of the PV panels and twice the capacity. According to [13], the battery capacity has to be selected based on the nominal capacity of the PV panels and the average electricity demand of the customer between sunset and sunrise. The authors emphasize that the BESS capacity of 1 kWh/kWp is sufficient to significantly increase the use of energy generated onsite. The BESS capacity of 2 kWh/kWp is the limit value resulting from the constraint of the energy generated by the PV panels. Otherwise, the amount of excess solar energy may not be sufficient to fully charge the battery. Therefore, only two sizes of BESS were studied in every scenario.

### 5.1.3 Description of the operational algorithm

Figure 25 illustrates the algorithm of the scheduled BESS operation with the focus on the SCR increase applied for every customer. In the analysis, the above-described input parameters were used: the original load profile of the customer, the PV generation profile, the operational schedule, the value of the power band, and the capacity of the battery. During the day, the microcontroller of the battery follows a predefined schedule of charging and discharging events outlined above. If the present hour is selected as the time for charging from the grid, the microcontroller checks the present energy consumption and compares it with the PB value. If the consumption exceeds the power band and the SOC of the battery exceeds the minimum threshold, the battery supplies the energy to the customer. If the consumption is below the power band, the battery is charged from the grid. If the present hour is selected for the supply of energy to the customer by BESS, and the battery SOC does not reach the minimum threshold, the battery supplies the energy to the customer. If the present hour is not in the operational schedule, the microcontroller checks the presence of solar energy surplus and charges the battery if its SOC is less than the maximum threshold. For the rest of the time the battery remains idle.

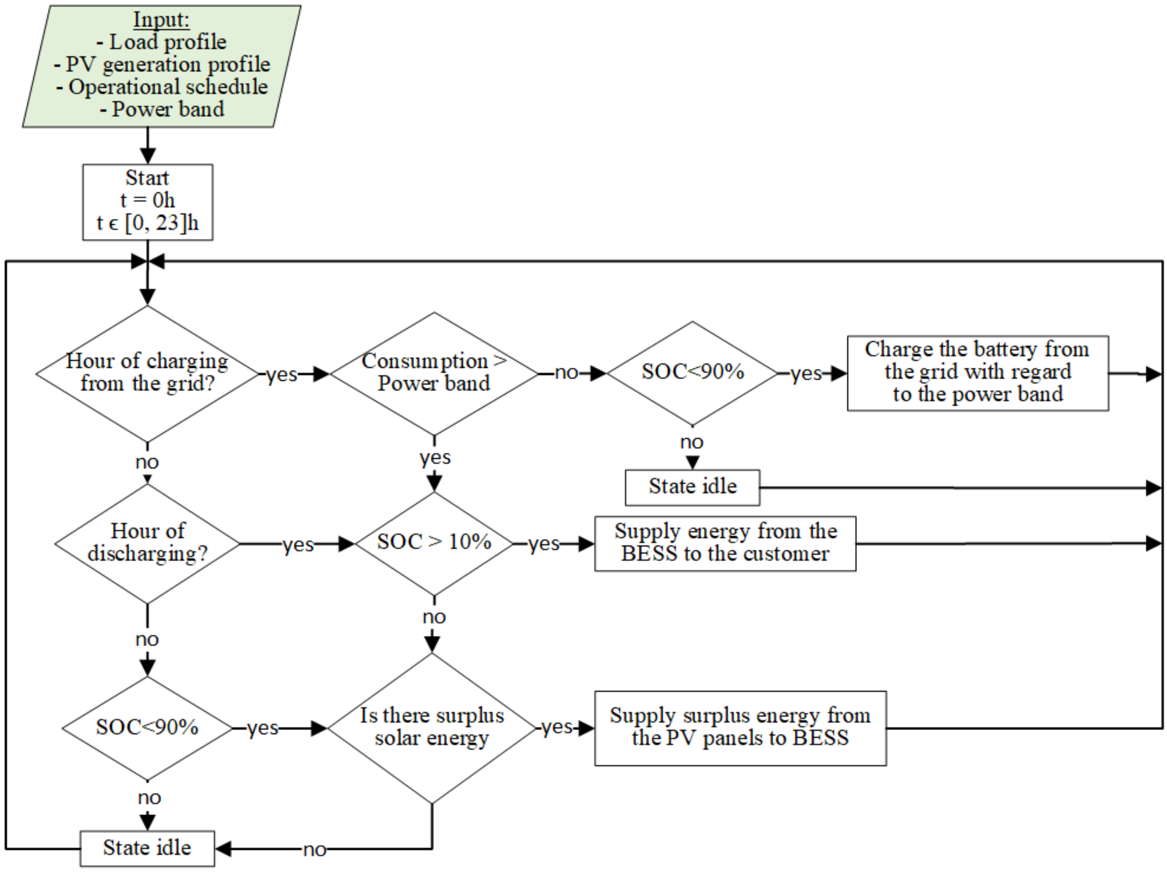



Figure 25: Operational algorithm of the self-consumption increase task, scheduled self-supply

### 5.1.4 Technical analysis

First, the SCR was studied in every scenario and for every battery size (Figure 26). The graph shows that the mean SCR increases by 7% with the connection of the BESS to the PV panels. The SCR in the scheduled scenario is slightly less than in non-scheduled BESS operation. This is due to the limited operational time of the battery; the battery supplies less energy to the customer and, consequently, needs less energy to charge. Therefore, the scheduled operation of the battery may not facilitate the SCR with a single application of the battery. However, supplementing the self-supply application with another service will facilitate the increase in the SCR of the customer.

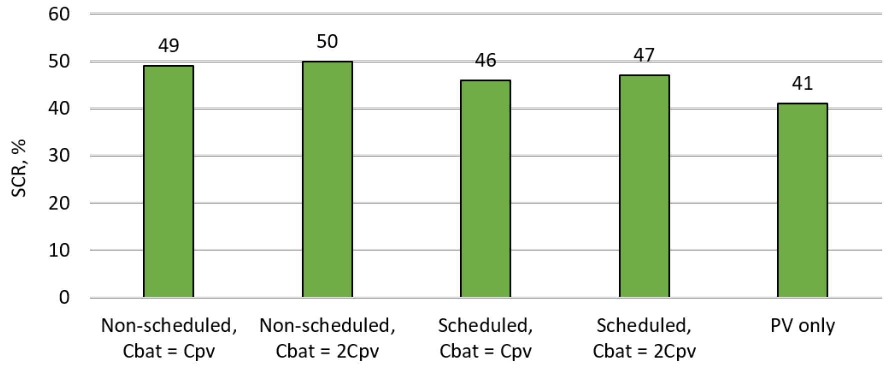



Figure 26: Comparison of the self-consumption rate, customer level

The use of the battery for self-supply may affect the customer's peak power. Figure 27 illustrates the analyses of a peak reduction change in different scenarios for one arbitrarily selected customer. According to the results, the highest reduction in peak power occurs during the time of high solar irradiance for all scenarios and battery capacities. The increase in the battery size does not significantly affect the reduction in peak demand. The main objective of the self-consumption strategy was to increase the use of generated PV energy and to use it for the reduction of the customer's energy bill.

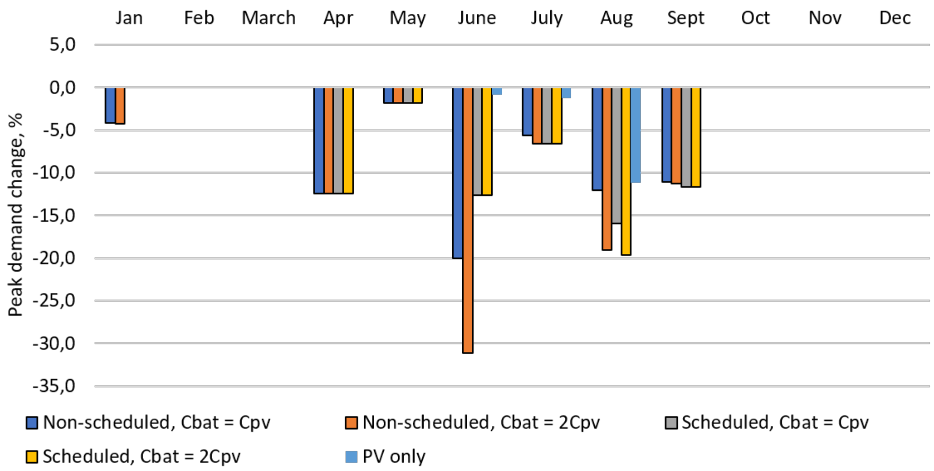



Figure 27: Analysis of peak demand change

Next, the change in the mean annual peak demand was evaluated at the single customer level. The annual peak demand was analysed for all the customers in the profile with the PV panels only and in all the scenarios with a PV+BESS system ( Figure 28). The results show the reduction in the annual peak demand in all the scenarios. Moreover, the results reveal that the selected hours for scheduled supply of energy from the battery to the customer do not match the actual hours of peak demand. The figure shows that the non-scheduled supply of energy reduces the peak demand more than the scheduled supply of energy. Later on, the economic analysis will demonstrate which scenario is more economically beneficial to the customer.

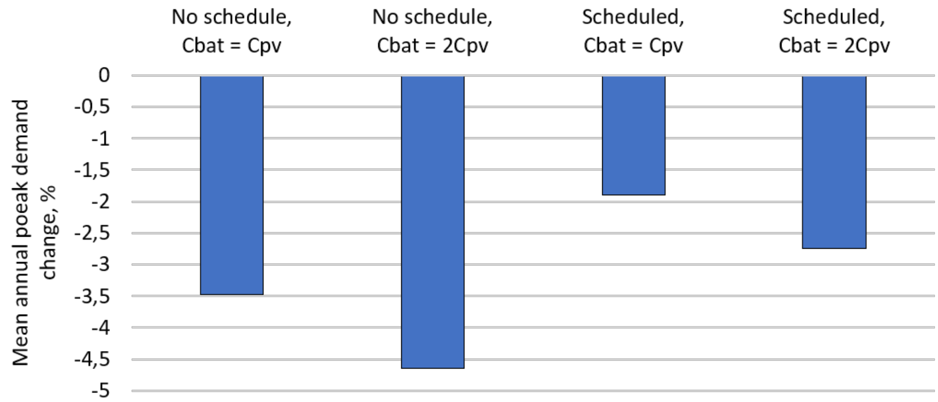



Figure 28: Analysis of the mean annual peak demand change, customer level

Further, an analysis of the secondary substation profile was conducted for 119 secondary substations. As the focus group of the study is residential customers, all the secondary substations are residential. All the industrial customers connected to the substation were neglected. The mean annual peak demand change was evaluated for all secondary substations and with different penetration rates. Figure 29 shows that the mean peak demand increases at the substation level with an increase in the penetration level. The main reason for this is the simultaneous charging of the BESS from the grid in the evening. The battery SOC analysis revealed that the batteries reached the minimum SOC or close to it by the beginning of the charging process. Eventually, it results in a growing peak demand at the level of the secondary substation. The increase in annual peak power does not vary significantly between the scenarios. The results show that doubling the battery size does not double the peak demand as well. The analysis of the SOC of the BESSs revealed that the stored energy is not used completely during the day because of the increased battery capacity. Since the battery is not discharged entirely, the peak demand did not double. The peak demand grows steadily up to the 75% penetration rate, after which the growth rate declines.

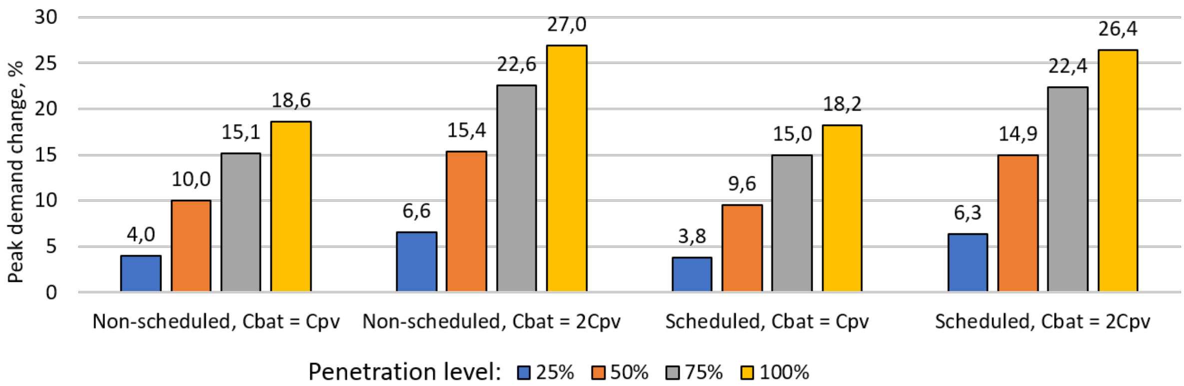



Figure 29: Change in the mean annual peak demand at the secondary substation level

Finally, the change in the peak power demand was studied at the primary substation level. In the analysis, two primary substations were considered. The change in the mean annual peak demand was evaluated for both of them and with different penetration rates. Figure 30 shows that simultaneous charging of the BESS increases the peak demand at the primary substation level more than at the secondary substation level. This is due to the high number of connected DER. Therefore, to exclude such a situation, the charging of the batteries should be controlled by a third party, such as an aggregator.

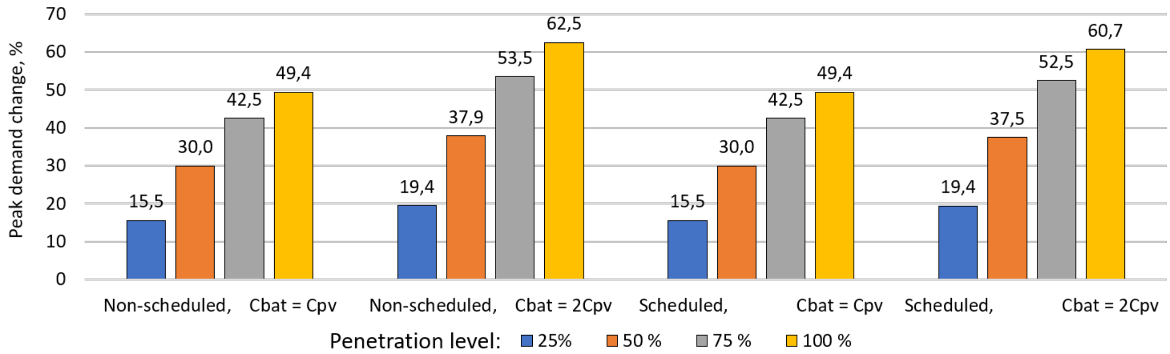



Figure 30: Change in the mean annual peak demand at the primary substation level

### 5.1.5 Economic analysis

Further, the customers' energy expenses were evaluated for every scenario of PV+BESS operation and every size of the battery. First, the energy bill was analysed for one arbitrarily selected customer in every scenario. With the assumptions made, the installation of the BESS does not benefit a specific customer—the final energy expenses are higher than in the scenario with the PV panels only (Figure 31). The main reason for this is the high operational cost of the BESS. The analysis of the operational scenarios revealed that the bills from the energy supplier and the DSO are slightly higher in the scenarios with the scheduled BESS operation in contrast to the non-scheduled operation. However, the reduction in the BESS OPEX facilitates a reduction in the final cost. Moreover, the scheduled operation of the BESS has room for improvement in the energy bill by the use of the BESS flexibility for ancillary services.

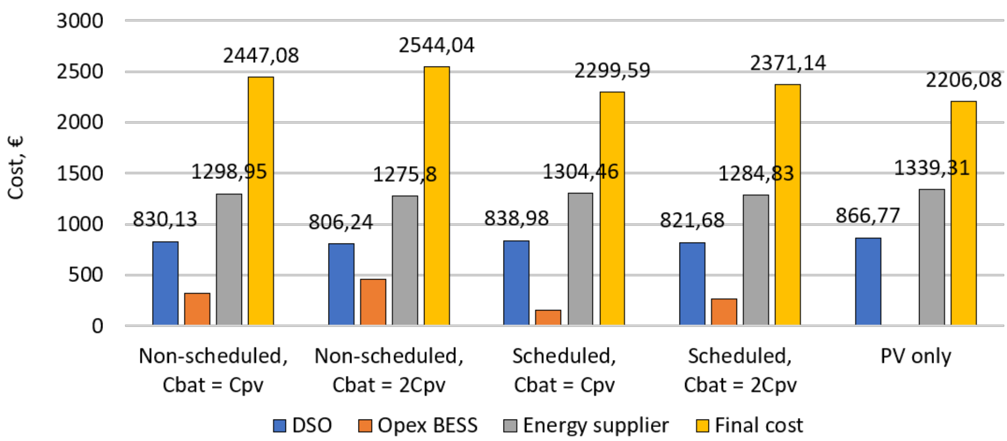



Figure 31: Single customer energy expenses

The economic analysis of 1500 customers shows that the use of the BESS for self-consumption only is profitable for less than 1% of the customers in any operational scenario. The increase in the battery capacity increases the operational cost of the battery and the final expenses of the customer. In the analysis of the scheduled BESS operation, all the customers were provided with one operational schedule of the BESS. However, the scheduled self-supply of energy did not contribute to the reduction in the energy cost from the energy supplier. The disadvantage of the operational schedule of the BESS is that the hours of BESS energy supply based on the customer's comfort are selected only once and for the entire year. In addition, the actual hours of increased peak demand may mismatch the suggested ones, and the values of peak power will remain the same. Moreover, the limited number of hours of BESS operation in the daytime increases the expenses for the day tariff component compared with the non-scheduled scenario. Further research is required to consider the change in the customer's energy expenses in the scenario with a dynamic selection of hours of self-supply for every day.

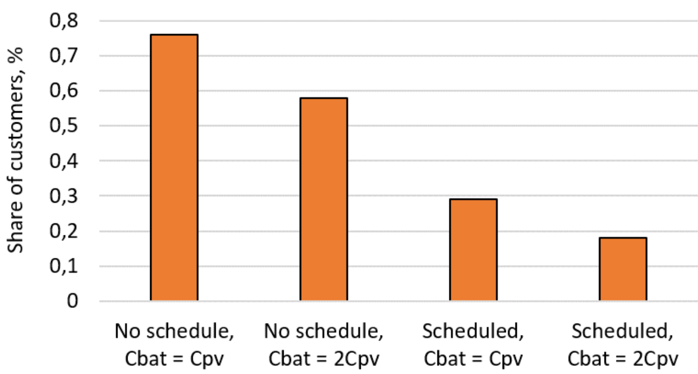



Figure 32: Profit comparison, customer level

The analysis of the price development shows the positive profit for the vast majority of the customers if the BESS operation is scheduled and the battery cost is reduced to one-third (Figure 33). The non-scheduled supply of energy from the BESS decelerates the BESS OPEX compensation because of the frequent operation. However, with the price decrease up to sixfold, the operation of the BESS becomes beneficial for DER owners.

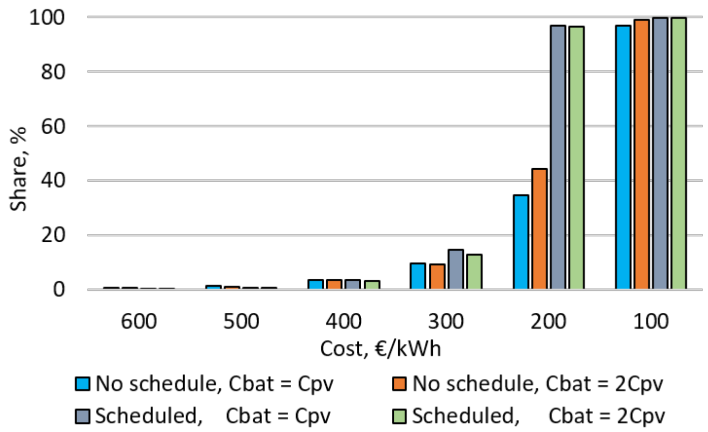



Figure 33: Customer's share with a positive profit with the BESS price development

### 5.1.6 Conclusion

In the study, the methods for an increase in the SCR rate were considered. In addition, different operational scenarios for the supply of energy generated onsite were analysed. Two operational scenarios of BESS were considered—scheduled and non-scheduled supply of energy to the customer. The results show that the SCR rate of the customer depends directly on the capacity of the battery and further operation of the BESS. The SCR rate will decrease for the scheduled operation of the battery owing to a reduction in the battery use. Moreover, for the increase in the SCR, the capacity of the BESS should be selected based on the mean energy consumption of the customer after sunset or further services provided by the battery. Otherwise, the BESS will lack the energy recipient and will not be capable of absorbing the energy generated onsite in the following day.

Further, it is worth mentioning that simultaneous charging of the BESSs in the distribution network leads to a growth in the peak demand at the secondary and primary substation levels. Moreover, the primary substations are affected more than the secondary substations. The reason for this is the greater number of connected batteries. Therefore, the charging of the BESSs from the grid should be scheduled for all the customers at different times. Currently, the Finnish day-ahead market is featured by a low price volatility, which does not make the price arbitrage beneficial to the customers. Therefore, one of the options is to establish a charging schedule for the DER within the day for instance by an aggregator.

## 5.2 Peak shaving/peak load management

With the introduction of the power-based tariff, the research interest has increased around the use of the BESS for reduction of peak power. Traditionally, the hours of peak demand of the residential customer do not match the hours of high solar energy production. Therefore, the installation of a BESS may contribute to a reduction in the peak tariff component and ultimately decrease the electricity bill. Throughout the research, the main research questions were as follows:

1. What is the mean flexibility potential of the BESS operating for the peak shaving task?
2. What is the change in peak demand with different penetration levels of PV+BESS systems operating for the reduction of peak demand?
3. How do the energy expenses of the customer change under different values of power bands?

The term of flexibility potential indicates the number of hours when the battery remains idle and has a SOC exceeding the minimum value. In the study, the flexibility potential was evaluated for ancillary services, requiring upward and downward regulation (e.g. FCR-N market) and the overall potential. The upward and downward regulations require the BESS owners to provide a reserve with a SOC in the range of 40% to 60%.

### 5.2.1 Power band selection

In the study, the consumers were provided with a power band (PB) to decrease the peak demand. A PB is the value of subscribed capacity that the customer intends not to exceed. The energy consumption beyond the power band is provided by the BESS if its SOC is within the predetermined minimum and maximum operational limits (10% and 90%). In the study, four power bands were considered:

- 70PB; 70% of the monthly maximum peak power
- 3rdPB; third highest monthly peak power
- MonthPB; monthly maximum peak power
- YearPB; annual maximum peak power

Of the above-mentioned parameters, three are based on selection of monthly power band values and the latter on a yearly value (one PB for a year). The values of the PB are based on the monthly and yearly values of the customer's peak demand for the previous year. Therefore, individual monthly and yearly PB values were assigned to every customer. The PB parameters were considered in four operational scenarios of the PV+BESS system.

The data sample includes around 700 residential customers located in central Finland. The capacity of the battery was assumed to be equal to the installed capacity of the PV panels. The generated solar energy was determined as the only source of battery charging. The study of the increase in the self-consumption rate revealed that simultaneous charging of the BESSs from the grid leads to a drastic increase in the peak demand at the primary and secondary substation levels. Moreover, during the charging process, the BESSs were following the predefined power bands. However, the matching charging schedules led to an escalation of the peak demand. Therefore, it is out of interest to consider the scenario where the PV panels act as the only source of energy for the batteries. Because of the small customer subset, the primary substations are outside the scope of the analysis.

### 5.2.2 Description of the operational algorithm

Figure 34 presents the operational algorithm of the peak reduction task. The following input parameters were applied: the original load profile of the customer, the solar energy generation profile, and the values of the power band. The pre-installed fictional microcontroller is dedicated to follow the load profile of the customer, the generation profile of the PV panels, and the battery SOC. At every hour, the microcontroller of the battery checks the SOC and makes the next operational decision based on the check. If the SOC exceeds the minimum limit, the BESS supplies the energy to the customer if the consumption surpasses the PB value. Otherwise, the battery checks the solar energy generation and accumulates the solar energy surplus. The battery does not charge and stays idle if its SOC has reached the maximum threshold.

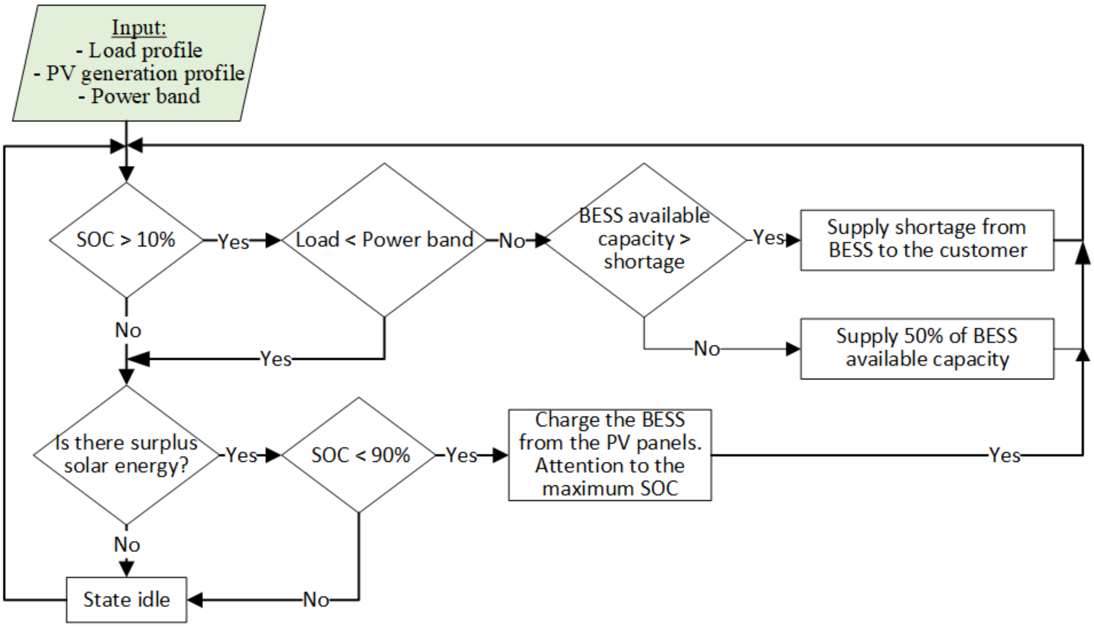



Figure 34: Operational algorithm of the peak demand reduction task

### 5.2.3 Technical analysis

First, a single customer level was studied. The analysis of the customers' energy profiles for 2018 and the values of power bands revealed the overall reduction in the customers' peak demand in 2019. Therefore, for instance, the values of the yearly power band were higher than the actual annual peak demand of the customer for half of the test sample. Thus, the reduction in the peak demand is insignificant. The analysis of the mean annual peak demand showed a reduction in the peak demand in every scenario (Figure 35). However, the power band determined as the customer's third highest peak power demonstrates the highest reduction.

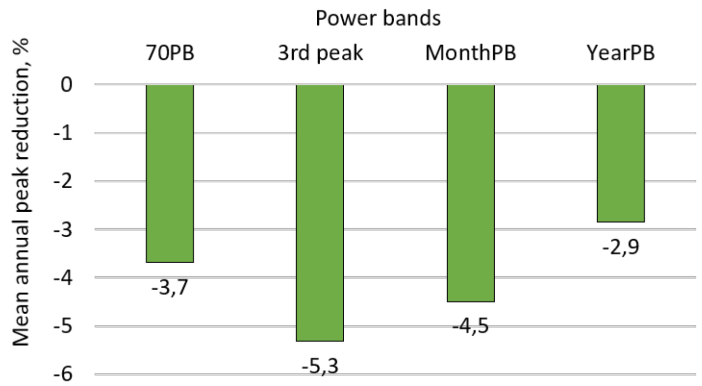



Figure 35: Mean annual peak reduction, customer level

Further, the analysis of the mean flexibility potential of the BESSs was conducted. As it was mentioned above, the comparison of the customer's energy profiles for the last two years revealed a reduction in the peak consumption. Consequently, it resulted in a significant flexibility potential of the batteries (Figure 36). The chart shows the significant mean flexibility potential of the BESSs—over 90% of the time within a year. Therefore, this potential creates a fertile ground to attract additional revenue streams for the customers and increase the cost-effectiveness of the battery.

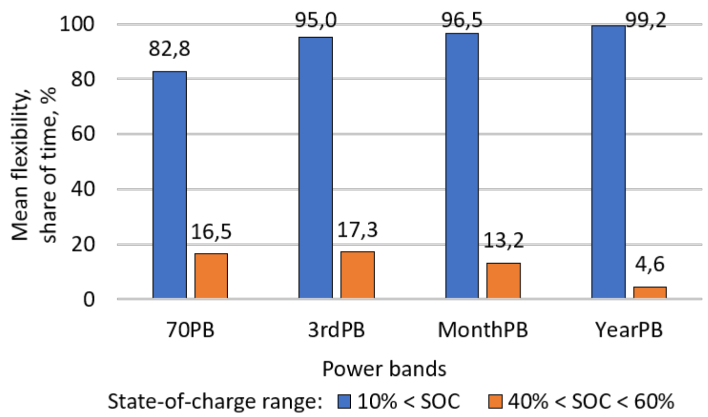



Figure 36: Mean flexibility potential of the BESSs

Next, an analysis of the mean monthly flexibility potential was conducted. As the BESS availability does not vary considerably between the scenarios, the mean monthly availability was evaluated only for a one power band parameter, 70PB (Figure 37). The graph shows an increase in the overall flexibility potential during the months of high solar irradiance. In contrast, the availability of the ancillary services decreases in the same period of time. The high production of solar energy leads to charging of the battery to the upper limit, 90%, which is advantageous for the peak reduction strategy. However, it limits the availability of the BESS for the aggregator and the use in the market of ancillary services. Because of a high SOC, the battery will not be capable of reacting to the upward regulation signal. Therefore, to attract additional revenue streams, the prosumer and the aggregator should agree on BESS operational hours in the market. Then, the battery charging events can be programmed to reach the specific SOC required for the service.

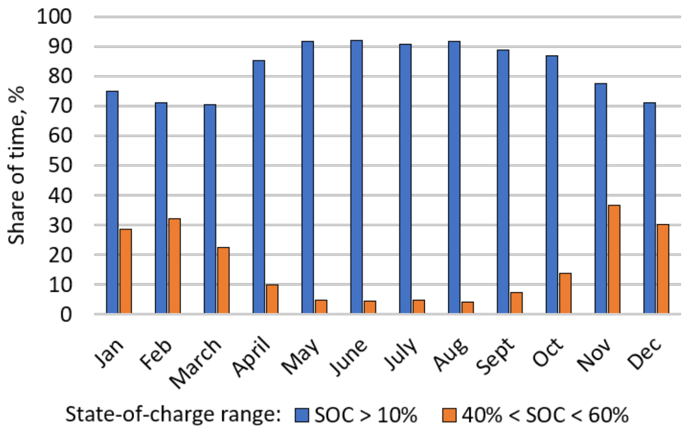



Figure 37: Mean monthly flexibility potential of the BESSs, 70PB

To evaluate the change in the peak demand at the secondary substation level, the customers were divided into groups of ten people. Thus, the change of the peak demand was evaluated for around 70 secondary substations. It was assumed that one group is connected to one secondary substation. The change in the annual peak demand was evaluated for all the customers and the mean change was calculated. The results show a boost of peak power reduction with an increase in the penetration level (Figure 38). Interestingly, at the 25% penetration level the peak demand change reproduces the illustration of the mean peak demand at the single customer level. However, with an increase in the penetration level, the most considerable reduction in the peak demand is represented by the 70PB scenario.

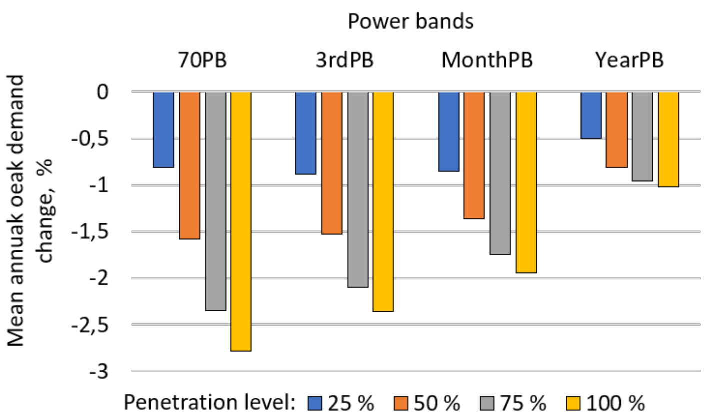



Figure 38: Mean annual peak demand change with an increase in the penetration level, secondary substation

#### 5.2.4 Economic analysis

Next, the profitability of the PV+BESS system in the peak reduction task was evaluated. Figure 39 shows that the MonthPB and 3rd PB parameters benefit the largest share of customers. 70PB has the smallest share of customers because of the high use of the battery, which results in a significant operational cost.

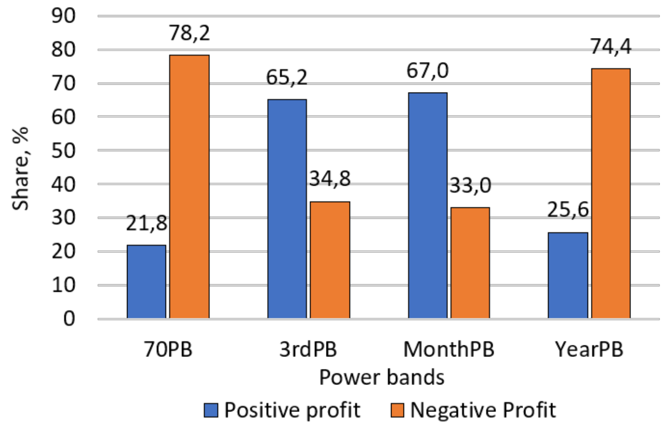



Figure 39: Profit evaluation, customer level

#### 5.2.5 Conclusion

In the project, a study of the battery use for the peak shaving task was conducted. The PV panels were determined as the only source of battery charging. The results show that the use of the battery for the peak reduction task reduces a peak demand at the secondary and primary substation levels. The operation of the BESS for peak reduction could be profitable for a considerable share of customers. Moreover, the use of the battery for a peak demand decrease leaves a significant flexibility potential for other revenues. However, depending on the second task, a proper operational schedule should be created. The schedule consists of the operational hours in the services, the charging schedule, and the SOC required for the task.

### 5.3 Frequency regulation

The support of the grid frequency requires a fast increase or decrease of power. The distinctive feature of the BESS is the fast reaction to the submitted task. Therefore, the BESSs are considered a promising technology for maintaining the grid frequency. In the study, the operation of the battery in the FCR-N market was studied as part of multifunctional operation of the BESS. The main research questions were:

1. What is the grid impact of BESS multifunctional operation? (level: single customer, secondary substation)
2. What is the economic potential of BESS multifunctional operation?
3. What is the flexibility potential of BESS multifunctional operation for the aggregator?

4. Is there a conflict of interests between multiple stakeholders?

The multifunctional operation of the battery implies the prioritization of one task over another. Within the study three operational scenarios were suggested with different priorities of tasks:

- FCR-N market and peak reduction (FCR-N + PR)
- FCR-N market and self-consumption (FCR-N + SS)
- Peak reduction and FCR-N market (PR + FCR-N)

In the first two scenarios, operation in the FCR-N market had the first priority. The prosumager focuses on maximization of the profit from the FCR-N market. This means neglect of the power band values during the operation in the FCR-N market and during charging from the grid for the implementation of the scheduled FCR-N task. In the third scenario, the prosumager aims to decrease the electricity expenses by keeping the consumption below the PB in all tasks. 50 residential customers were selected for the study. The test period was one month.

### 5.3.1 Development of the operational schedule

To carry out the analysis, an operational schedule was determined for the customers. The schedule includes the time of charging from the grid and the operational hours in the FCR-N market. It was assumed that the bids of the consumer are always accepted through the aggregator. Therefore, the battery always participates in the market if it has a sufficient SOC. The size of the bid depends on the assignment of the first priority. For instance, if the FCR-N market is the first priority task, then the size of the bid is calculated as the minimum available capacity of the battery at this hour. If the peak reduction is the first priority task, then the size of the bid is calculated with regard to the power band and the anticipated load of the customer:

$$Bid[kW] = Power\ band - Energy\ consumption_{\text{forecasted}} \tag{6}$$

The operational hours for the FCR-N market were defined based on the market price analysis for the test month. For every day in the month, three hours with the highest prices were highlighted. Afterwards, the most frequent hours with the highest prices were selected as operational in the FCR-N market. The battery always charges for an hour before the operation in the FCR-N market and only up to the 50% SOC and if its SOC is less than 50%. Otherwise, the battery remains idle for this hour. For the rest of the time the charging continues until the battery SOC will reach 100%. Two energy sources were determined for charging the battery; the PV panels and the grid. The battery charges from the grid if the PV panels do not produce a sufficient volume of energy and only for operation in the FCR-N market. The PB value was neglected during the charging from the grid in the scenarios with a priority in the FCR-N market. The power band value limits the supply of energy from the grid. Thus, the battery may not have a sufficient SOC for operation in the FCR-N market. By neglecting the PB value, the customer ensures the attraction of additional revenue streams. However, it may drastically increase the peak demand at the secondary substation level. The results of the analysis will reveal the consequences of such an assumption.

All customers were provided with individual values of PV panels and BESS size. The selection of the PV panel installed capacity is outlined in Section 3.3.3. The generation profile of the PV panels was determined by applying the open-source database (see Section 3.1.3). The capacity of the BESS is equal to the installed capacity of the PV panels.

### 5.3.2 Power band selection

In the analysis, two values of PB were determined. One was defined as a monthly maximum peak demand of the customer for the previous year; MonthPB. The second PB was determined as a difference between the monthly peak power and the capacity of the battery—BatteryPB. The MonthPB was applied in the process of BESS charging either from the grid in the scenario with the priority of the peak reduction task or from the solar panels in every scenario. The BatteryPB was used for the peak reduction task in every scenario. The value of MonthPB is higher than the value of BatteryPB. Two PBs were determined to motivate the customer to reduce the monthly peak demand values (BatteryPB) and allow the battery to charge from the grid to the full (MonthPB). A low power band value considerably limits the capability of the BESS to operate in the FCR-N market if the peak reduction task has the first priority.

### 5.3.3 Description of the operational algorithm

Figure 40 illustrates the algorithm of multifunctional BESS operation in the scenario with the focus on peak reduction. The difference between the operational algorithms between the scenarios is small. Therefore, the flow chart of only one scenario is presented for the illustration purposes. The customers were provided with PV panels, BESS, power band values, and a charging schedule. During the day, the microcontroller of the battery follows the predefined operational schedule, energy generation profile, and the consumption of the customer. The operation in the FCR-N market occurs only if the BESS SOC is between 40% and 60%. For the rest of the time, the battery follows the energy consumption of the customer and compares it with the predetermined power band value. If the consumption exceeds the PB value, the battery supplies the whole shortage if its capacity is more than the shortage. If the shortage is more than the available capacity of the BESS, the BESS supplies only 50% of the shortage. The supply occurs only if the battery SOC is more than the minimum threshold.

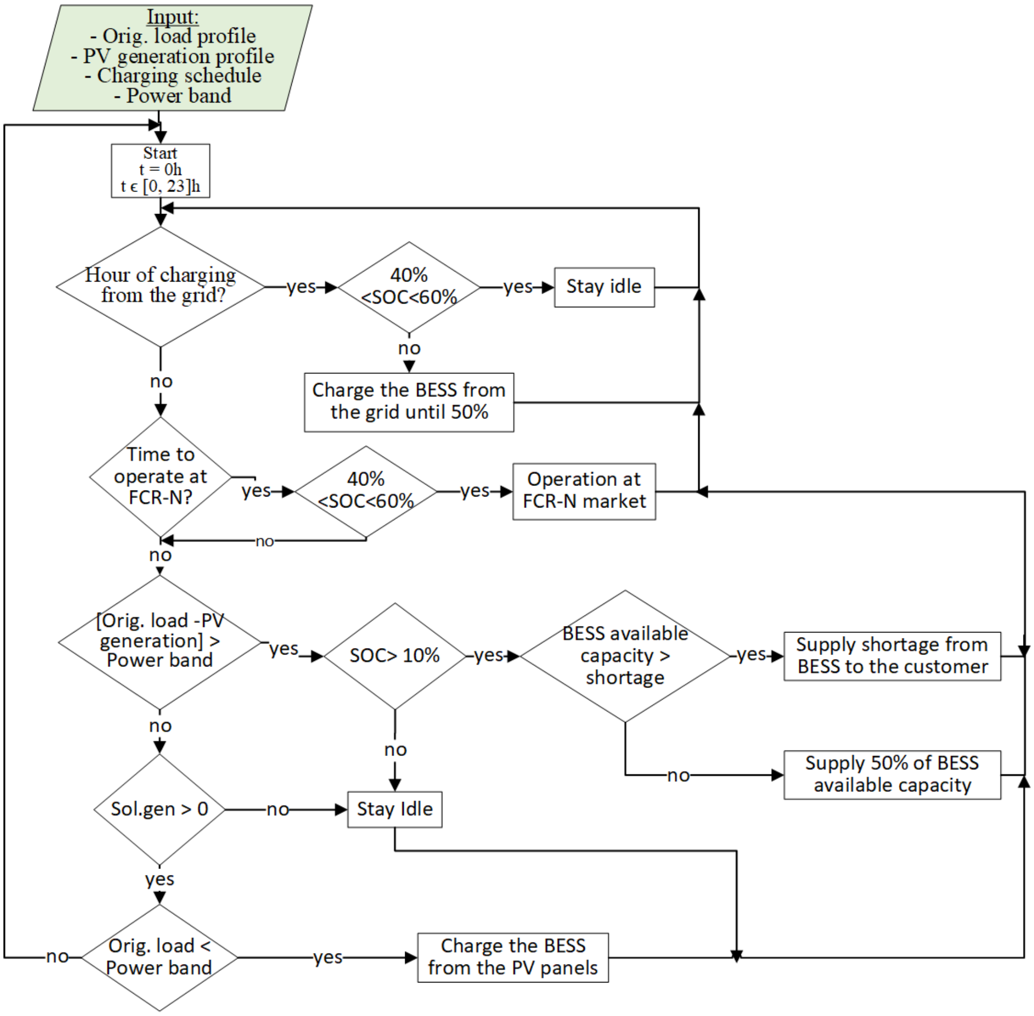



Figure 40: Algorithm of the BESS operation for the peak reduction and FCR-N tasks

### 5.3.4 Technical analysis

First, a technical analysis of the battery operation was conducted at the single customer level. Figure 41 shows that prioritization of the FCR-N market and neglect of the PB value leads to an increase in the customer peak demand during the charging process. Eventually, the month peak value increases to a double compared with the original peak.

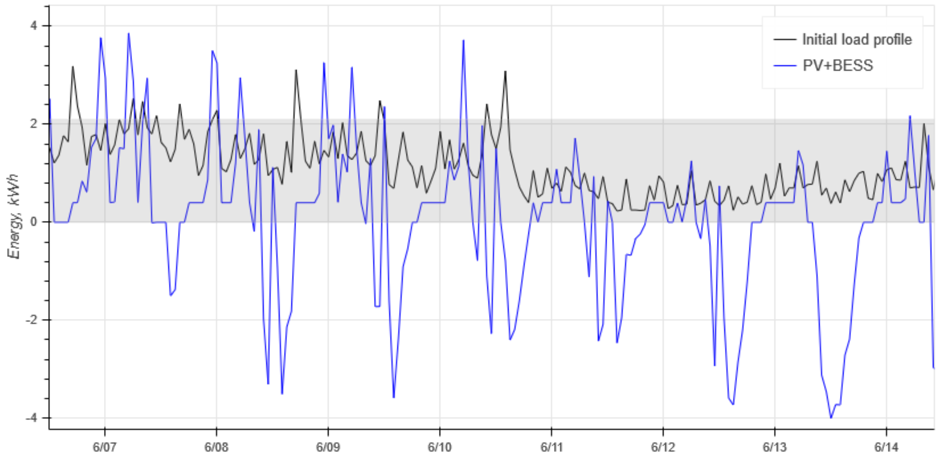



Figure 41: Load profile, FCR-N + self-consumption

As shown in Figure 42, the focus on peak reduction keeps the energy consumption of the customer below the power band. The presence of a predefined power band enables to smooth the load profile both at the customer and substation levels. Later on, the economic analyses will reveal the most beneficial scenario for the customer.

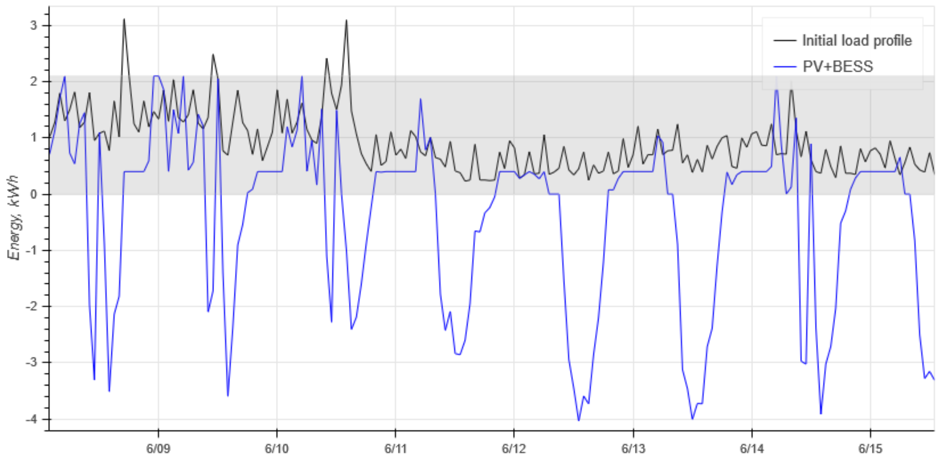



Figure 42: Load profile, Peak reduction + Self-consumption

Further, the change in the mean peak demand was evaluated a the single customer level (Figure 43). The figure depicts the increase in the peak demand if the FCR-N market is the first priority task for the customers. This is due to the neglect of the PB value. Later on, the economic analysis will reveal if the profit from the FCR-N market outweighs the cost of the peak power component.

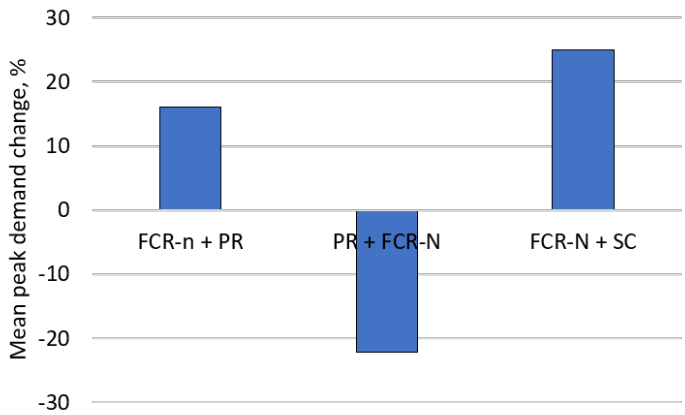



Figure 43: Mean peak demand change, customer level, one month

Next, the change in the peak demand was studied at the secondary substation level. The set of residential customers was split into a group of ten people to create artificial secondary substations. The change in the peak demand was evaluated for all the substations, and the mean change was calculated for all of them. Figure 44 shows that prioritization of the FCR-N task leads to an increase in the peak demand at the secondary substation level. This is explained by the simultaneous charging of the batteries irrespective of the power band. The PB presence restrains the peak demand growth but reduces the number of operational hours in the FCR-N market. The peak demand increases until the 75% penetration level. In other words, the peak demand grows significantly only with the installation of DER among the customers with a high energy consumption. The small-scale residential customers do not considerably affect the peak demand value.

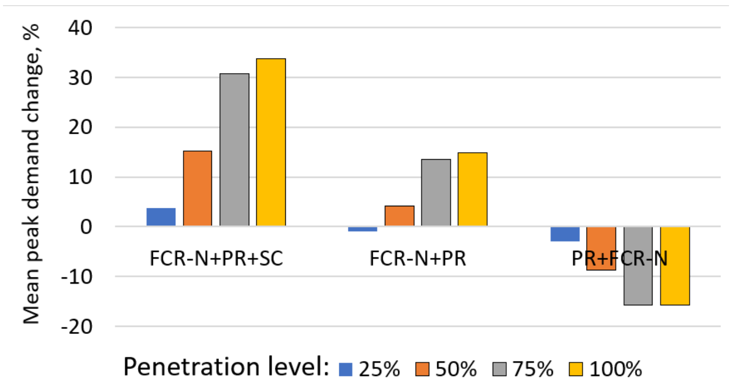



Figure 44: Mean peak demand at the secondary substation level, one month

### 5.3.5 Conflict of interests

The multifunctional operation of the BESS involves participation of multiple stakeholders; BESS owners, the DSO, and the TSO. The TSO requires the confirmed energy resources to implement both upward and downward regulations. Therefore, the SOC of the BESS has to be in the range of 40–60%. However, the owner of the battery assumes 100% battery SOC for sufficient operation in the peak reduction or self-supply tasks. For a successful increase of the SCR rate, the SOC should be as low as possible to accumulate the generated onsite energy. On the other hand, one of the objectives of the DSO is to balance the power flow in the grid and decrease the number of rapid demand spikes. The sticking point in this situation is the SOC of the battery required for various tasks. For advantageous and profitable operation of the battery, an agreement on the BESS availability should be reached. One of the solutions is the integration of another stakeholder, which will act as an intermediary between the prosumagers and the DSO or the TSO; an aggregator. The aggregator is a new entity emerging in the market for accumulation of the customers' loads or generation for a purchase or sell. Thus, the market value of the small-scale DER increases, thus bringing their owners higher revenues. The existing aggregator business models can be divided into two groups: independent or combined aggregators. The combined business models involve a market player who also operates as an aggregator. An independent aggregator is a company that acts independently of any other market participants. However, at the present, the operation of an independent aggregator and its relationship with a balance-responsible party and an energy supplier are uncertain [14]. Recently, the Finnish TSO launched its aggregation pilot project in the balancing market. The project is an extension of the previous pilot and analyses the business models of an independent aggregator. The first tests produced important results regarding the technical requirements, information exchange rules, and trading and multilateral settlements. The objective of the current pilot is to test the scalability of the solutions defined in the previous pilot before making changes in the reserve agreements [15].

### 5.3.6 Economic analysis

Figure 45 depicts an analysis of the profit for a single customer for the test period of one month. The expenses were calculated as it is described in the introduction of Chapter 5 and replenished by the revenue from the FCR-N market and OPEX of the battery during the operation in the FCR-N market. Eventually, the expenses were calculated by the following formula:

$$\begin{aligned} Final\ cost = Revenue_{\text{FCR-N}} - Cost_{\text{DSO}} - Cost_{\text{Energy supplier}} - \\ Opex\ BESS_{\text{total}} - OPEX\ BESS_{\text{FCR-N}} \end{aligned} \tag{7}$$

The figure shows that the multifunctional operation of the battery does not generate profit for this specific customer. However, with regard to the current cost of the BESS, the difference in the profit is around 30%. The reduction in the BESS cost will impact the operational cost of the battery and bring positive profit for this specific customer.


Figure 45: Profit analysis, multifunctional BESS operation, single customer

As it was mentioned above, the schedule of BESS operation in the FCR-N market was defined based on the market price analysis for the test month. In other words, this is a theoretical maximum of the customers' revenue from the FCR-N market. However, in reality, the prices and bid volume are published by Fingrid after the reserve procurement. Moreover, it is difficult to forecast the hours with high prices and the actual price of the bid because of the high price volatility. Therefore, the second approach was adopted to evaluate the customer's revenue and its difference compared with the assumed theoretical maximum. The method is based on an analysis of the market price for the previous month; i.e., it is a deterministic approach. Five hours with the highest prices in the months were selected and applied to the test. Figure 46 shows a comparison of the two approaches. The main objective of the analysis was to evaluate the profit only, neglecting the operational cost of the battery. Because of the frequency variation, the operational cost of the battery may vary drastically. Therefore, the main idea was to analyse the profit and the coincidence of actual hours with high prices with the assumed one. The figure illustrates a 30% reduction in the revenue on average. Two out of five hours did not match the actual hours with high prices. Eventually, this resulted in a reduction in revenue.

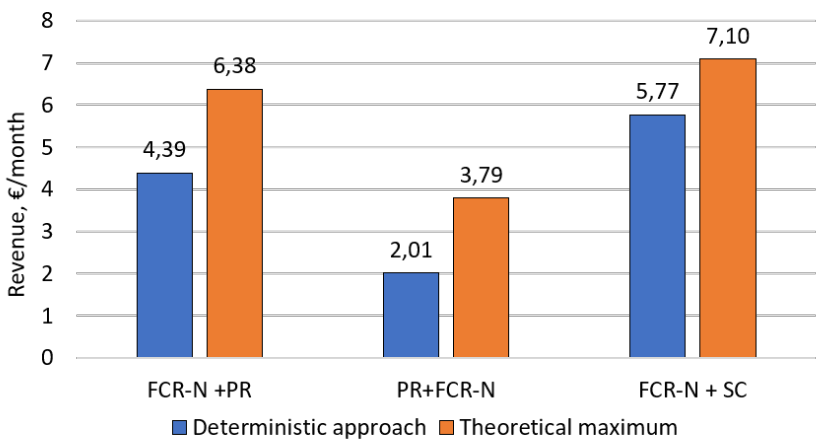



Figure 46: Comparison of the revenue from the FCR-N market in different operational schedules

### 5.3.7 Conclusion

The multifunctional operation of the battery was studied in the project. Based on the analysis, a multifunctional BESS operation validated the previous recommendations about the development of the detailed operational schedule (section 5.2.5). In addition, the outcomes show that the use of the battery for multiple services creates a conflict of interests between multiple stakeholders. The customer interest in income increases, and active participation in the FCR-N market may lead to an increase in the peak demand at the secondary substation level. Therefore, there should be an intermediary (e.g. an aggregator) in the market to negotiate the BESS operation and enable the behind-the-meter energy storages to operate in the market of ancillary services.

## 5.4 Smart charging of EV

The smart charging of EVs was illustrated for the example of workplace charging. Only commercial and industrial customers were selected for the simulations. For them, the number of parking places was estimated according to the floor area of the office buildings using the open-source database. Moreover, the solar PV size was estimated based on the annual solar generation potential obtained from the open-source database. Three charging strategies were simulated:

1. dumb charging (uncontrolled)
2. controlled charging within the peak power constraints
3. controlled charging with solar PV integrated

A detailed description of the methodology and simulation results can be found in [16].

The main findings from the obtained results are:

- EV workplace charging does not cause capacity problems in the urban network, even in the dumb charging scenario.
- Dumb charging causes high monthly peak powers and hence, high demand charges for commercial and industrial customers. The annual payments can increase even by 50% for some connection points.
- Smart charging, i.e., shifting the EV charging load equally throughout the working hours, helps to mitigate the problem. The increase in annual payments is only about 10% compared with the scenario without EVs.
- Solar PV integration did not significantly contribute to the decrease in annual payments. However, it helped to significantly decrease the summer monthly peak powers.

## 5.5 DER role in security of supply

The research questions are:

- What is the role of DER to provide security of supply?

- Which option to choose: a DER on a single customer's premises or a common DER capacity at the distribution transformer level?
- How ready is the customer to secure supply of electricity with their already installed DER capacity?
- What is the role of demand flexibility in the security of supply?
- With the DER resources available in the residential sector, dimensioned for customers' local interests, what is the readiness to provide security of supply with these resources during a grid interruption?
- What is the impact on the DSO's business if a customer can secure supply of electricity with his own energy resources during an interruption?

Below, an algorithm and simulations are presented to provide some answers to these research questions.

### 5.5.1 DER capacity requirements in various interruption scenarios

In order to answer some of the research questions listed above, the scenarios were defined by varying the length of interruption of 2 h, 4 h, and 6 h, load coverage capability of DER of 100%, 80%, and 50%, and point of electricity supply at a single customer and a distribution transformer level.

The security of supply is a relevant topic for the rural areas, where cabling rate and average number of customers per km is much lower than in the urban or suburban networks. Therefore, a group of 13 199 residential customers from a rural area was taken as an example for the analyses. For every customer, the DER capacity was calculated for each of the above-listed scenarios according to the following algorithm. An example of the DER capacity calculation for a single residential customer is illustrated in Figure 47. The energy consumption for every 2, 4, and 6 adjacent hours throughout one year were calculated. As a result, numerous values of sums during one year are obtained, and their maximum values are considered to be the DER capacity required for a single customer to provide them a continuity of supply during an interruption. In case the actual interruption of supply from the grid occurs during that high loading period, the size of the calculated DER capacity will be enough to cover 100% of a single customer's load. Such moments could occur for instance in the winter period with high snow loads on overhead lines and the simultaneous high electric heating demand.

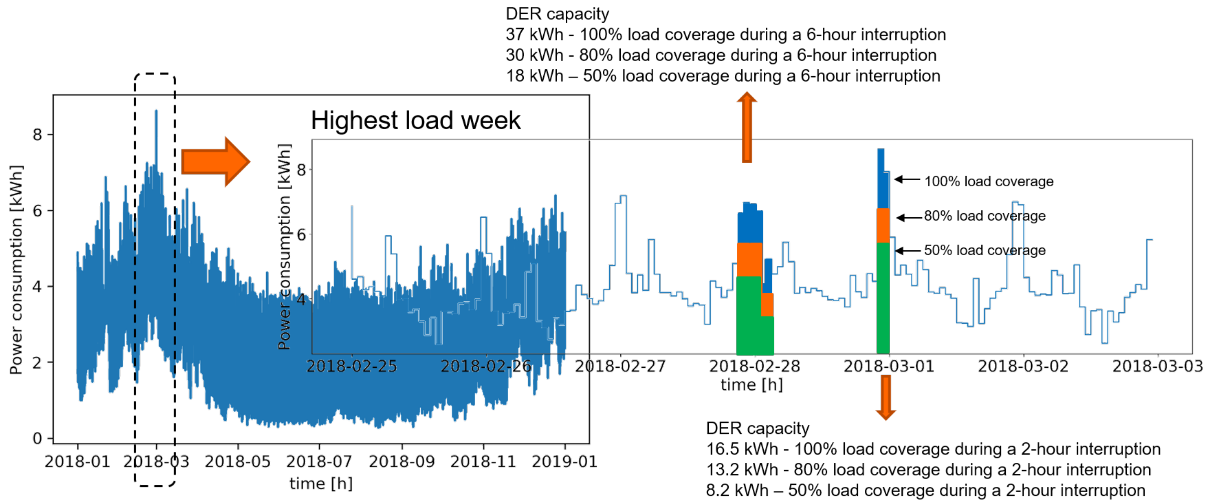
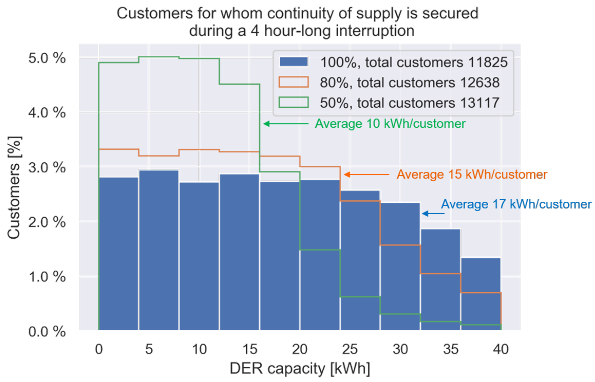


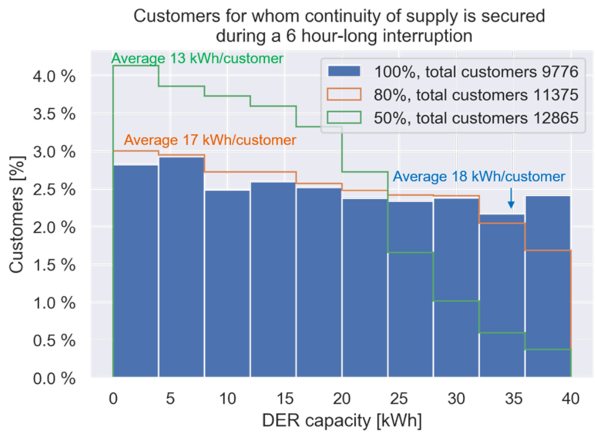

Figure 47: Calculation of the DER capacity for a single customer required for various interruption lengths and load coverage scenarios

The results for the rest of the residential customers are depicted in Figure 48, where only customers with DER capacity less than 40 kWh are presented. The rest customers require a storage capacity larger than 40 kWh to withstand a 2 h interruption. Out of 13199 customers, 13079 customers can withstand a 2 h interruption with the full 100% load coverage with under 40 kWh DER capacity, with the average DER capacity being 12 kWh/customer. 13150 can withstand a 2 h interruption if 80% of their load is covered and the remaining 20% of the load can be shifted to a later moment (load is flexible), with the average DER capacity being 10 kWh/customer. 13182 out of 13199 customers can withstand a 2 h interruption with an average of 6 kWh/customer if they shift 50% of their load during the interruption event to a later time. Three histograms presented in the same figure correspond to various load coverage rates (blue 100%, orange 80%, and green 50%). For example, Figure 48a shows that about 9% of the customers (around 1100 customers) can secure the continuity of supply during a 2 h interruption, if they have a DER capacity of 4 kWh. The same number of customers can secure their supply with the DER capacity of 5, 6, 7, or 8 kWh, resulting in a total of 5*1100 customers = 5500 customers being able to withstand that interruption with the full 100% load coverage if they have DER capacity from 4 kWh to 8 kWh. The DER capacity of 0 kWh corresponds to the customers whose measured load was 0 throughout the whole year for instance because of missing measurements.


(a) 2 h scenario




(b) 4 h scenario

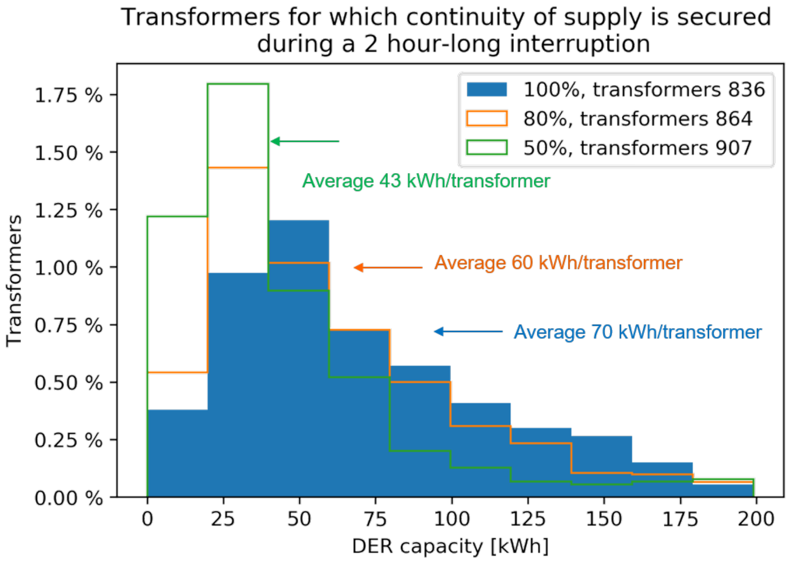



(c) 6 h scenario

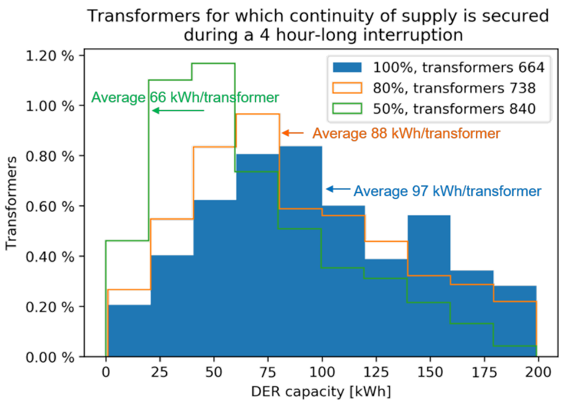
Figure 48: DER capacity needed to secure the supply of a single customer during an interruption

The calculated DER capacity is a distributed option, and thus, every single customer has a DER unit on their premises. It can be a stationary BESS or an EV battery or any other storage option. The assumption is that it is fully charged before the interruption event. This is not always possible, especially in the case of EV.

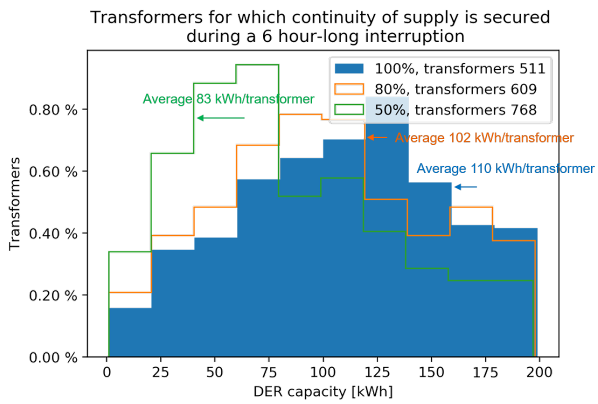
Next, the DER capacity was calculated for the distribution transformer level, as if the customers supplied by a transformer had a centralized DER capacity installed at the distribution transformer. The same algorithm as for the single customer level is applied at the transformer level. Instead of a single customer load profile, the total load profile of the transformer is used. The results are presented in Figure 49. For comparison in the further analyses, transformers supplying only residential customers were used in the analyses, 449 in total.




(a) 2 h scenario




(b) 4 h scenario




(c) 6 h scenario

Figure 49: DER capacity needed for a distribution transformer to withstand a 2 h grid interruption

After the calculations were performed at the single customer and distribution transformer levels, the difference between the sum of the distributed DER for N customers behind the transformer and the centralized DER capacity was calculated as:

$$\Delta E_{\%} = \frac{\sum_{n=1}^{N_{\text{customers}}} DER_{\text{distributed}} - DER_{\text{centralized}}}{\sum_{n=1}^{N_{\text{customers}}} DER_{\text{distributed}}} * 100\% \tag{8}$$

Figure 50 shows that for most of the transformers, the sum of the distributed DER capacity is 30–40% higher compared with the centralized DER solution, ranging from 0% to 70%. The reason for this is that the peak powers of the single customers supplied by a distribution transformer occur in different times, and thus, the peak power of a transformer is not equal to the sum of the peak powers of single customers behind it.

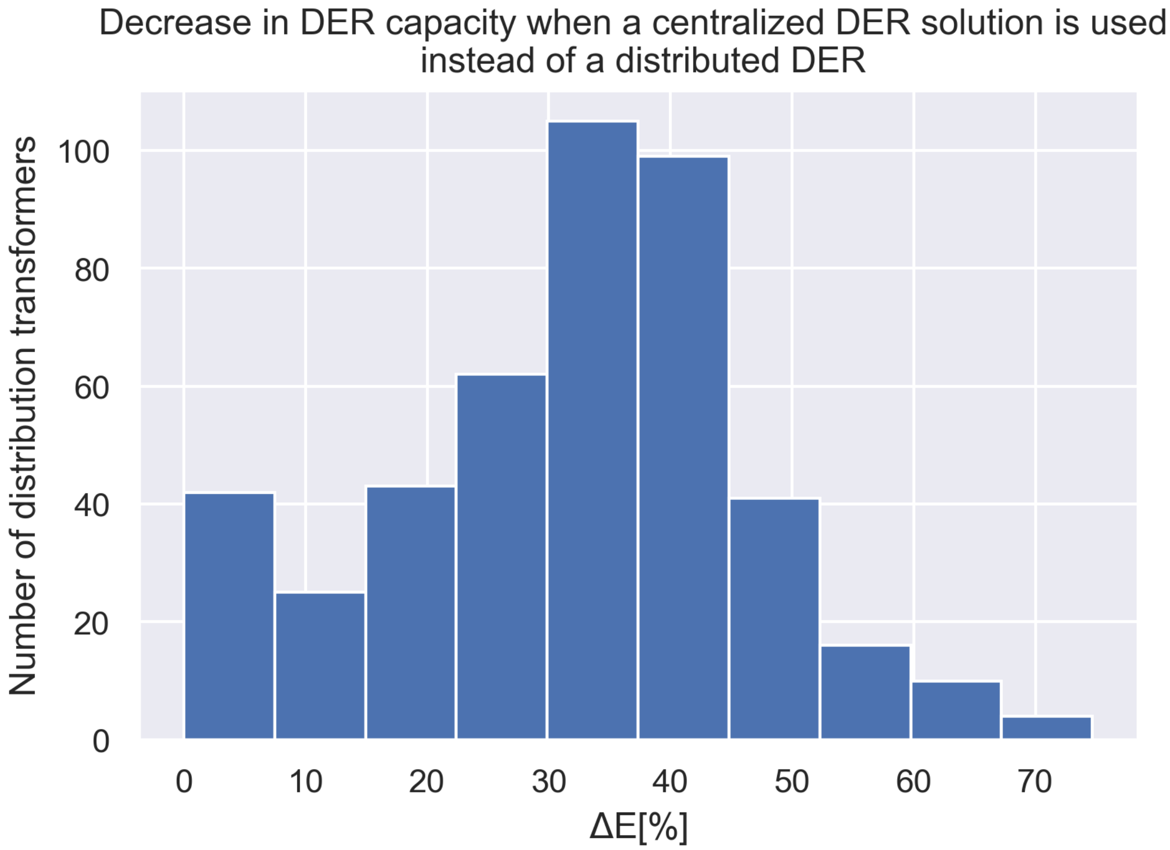



Figure 50: Decrease in the DER capacity if a centralized DER solution is used instead of the distributed DER at the distribution transformer

### 5.5.2 Economic analyses of the role of DER in the security of supply

The main objective of the economic analyses is to quantify the impact of demand flexibility in the security of supply and the economic benefit of a centralized DER solution compared with the distributed one. For this purpose, the technical results from the previous chapter were combined with the assumed price of a storage solution. As a DER option, a stationary BESS unit was considered at the price of 250 €/kWh.

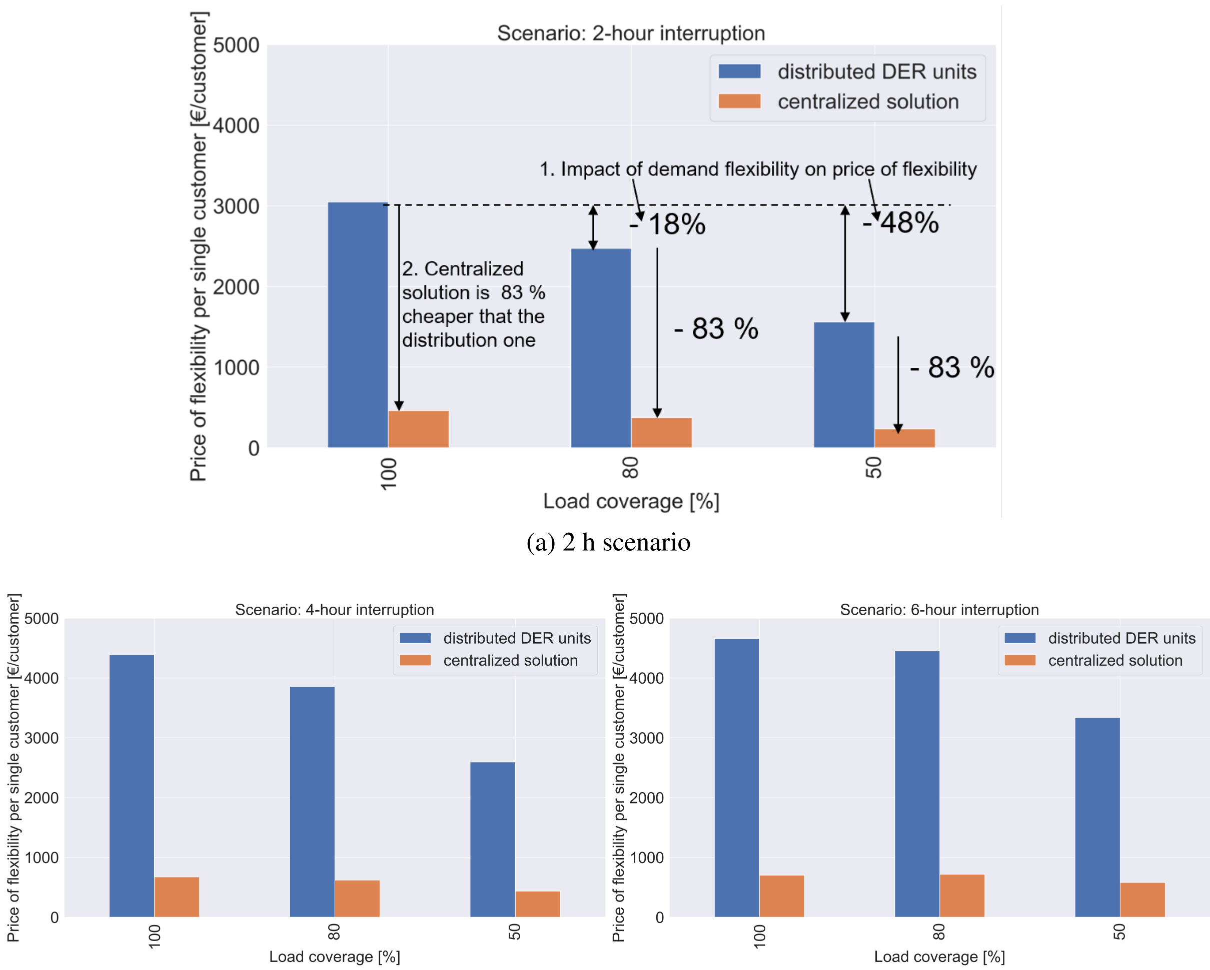
The price of flexibility was calculated per single customer and per distribution transformer as follows:

$$Price_{\text{€/customer}} = \frac{\sum_{n=1}^{N_{\text{customers}}} DER_{\text{distributed}} * Price_{\text{battery}}}{N_{\text{customers}}} \tag{9}$$

$$Price_{\text{€/transformer}} = \frac{\sum_{n=1}^{N_{\text{transformers}}} DER_{\text{centralized}} * Price_{\text{battery}}}{N_{\text{transformers}}} \tag{10}$$

Again, only the customers with the DER capacity less than 40 KWh were considered. For comparison, the centralized capacity of the transformers was calculated for the customers that can secure their supply with a less than 40 kWh energy storage. The rest of the customers were taken out of the load profile of the distribution transformer.

The calculated prices of flexibility for the centralized and distributed DER options and for various interruption scenarios and flexibility of demand are presented in Figure 51.




(a) 2 h scenario

(b) 4 h scenario

(c) 6 h scenario

Figure 51: Average price of flexibility per single customer for the centralized vs. distributed DER solution

The results presented in the figure provide answers to the questions identified at the beginning of this subsection. First, the impact of demand flexibility in the security of supply on the average price of flexibility is quantified. That is, if the customer is willing to shift 20% of their load to a later moment (80% load coverage during the interruption time), the price of flexibility decreases by 18% because the required DER capacity is then lower. With 50% of flexible load, the price of flexibility is 48% lower than with a non-flexible load.

The second outcome is the economic benefit of a centralized DER solution compared with the distributed one.

It has to be kept in mind that the results are only indicative and provided here to illustrate the idea of the methodology. The results are sensitive to the assumptions made. In both cases, the price of the battery is assumed to be 250 €/kWh, and that the DER capacity is full before the interruption event.

### 5.5.3 Capability of the existing DER to provide security of supply

After the DER capacity requirements were calculated in general for various grid interruption scenarios and with various load coverage (flexibility) levels (50%, 80%, and 100% (no flexibility)), the next research question to answer is how ready the customer is to secure the supply of electricity with their already installed DER capacity. For this purpose, as an example, a scenario is considered where the customers have 10 kWp solar PV systems together with the BESS size needed to reach the 60% self-consumption rate. The results are illustrated in Figure 52.

The results show that over 60% of 13199 residential customers will survive a 2 h interruption event with their BESS capacity with the full 100% load coverage rate (blue bar), slightly under 80% will survive with the 80% load coverage rate (green bar), (20% of their load being flexible during an interruption), and the continuity of 50% of supply will be secured for almost for all the customers with the BESS capacity and 50% flexible demand (red bar) during a 2 h interruption event, in case it will coincide with their highest load level.

The results in Figure 52 represent the best-case scenario for the customers. This means that the basic assumption is that the already installed BESS is fully charged before the interruption. This is not always possible in practice if the BESS is operated for other applications, such as peak shaving or frequency regulation, and its SOC level may not be adequate to secure the supply during an interruption. In some cases, this can be mitigated partly by letting the customers know about the potential interruption in the grid, for instance by using weather forecasts (snow, wind, outdoor temperature). In that case, the task of the security of supply will be of highest priority for the BESS unit, and it will start charging thus preparing for the possible interruption. This topic of risk management strategy is outside the scope of this project.

### 5.5.4 Discussion

The calculated distributed DER capacity for each customer represents the worst-case scenario when the interruption event coincides with the highest consumption period of the customer. This means that for many more customers than presented in Figure 48, the continuity of supply will be secured if the interruption does not coincide with the highest loading level. However, it is not a good idea to overdimension the DER.

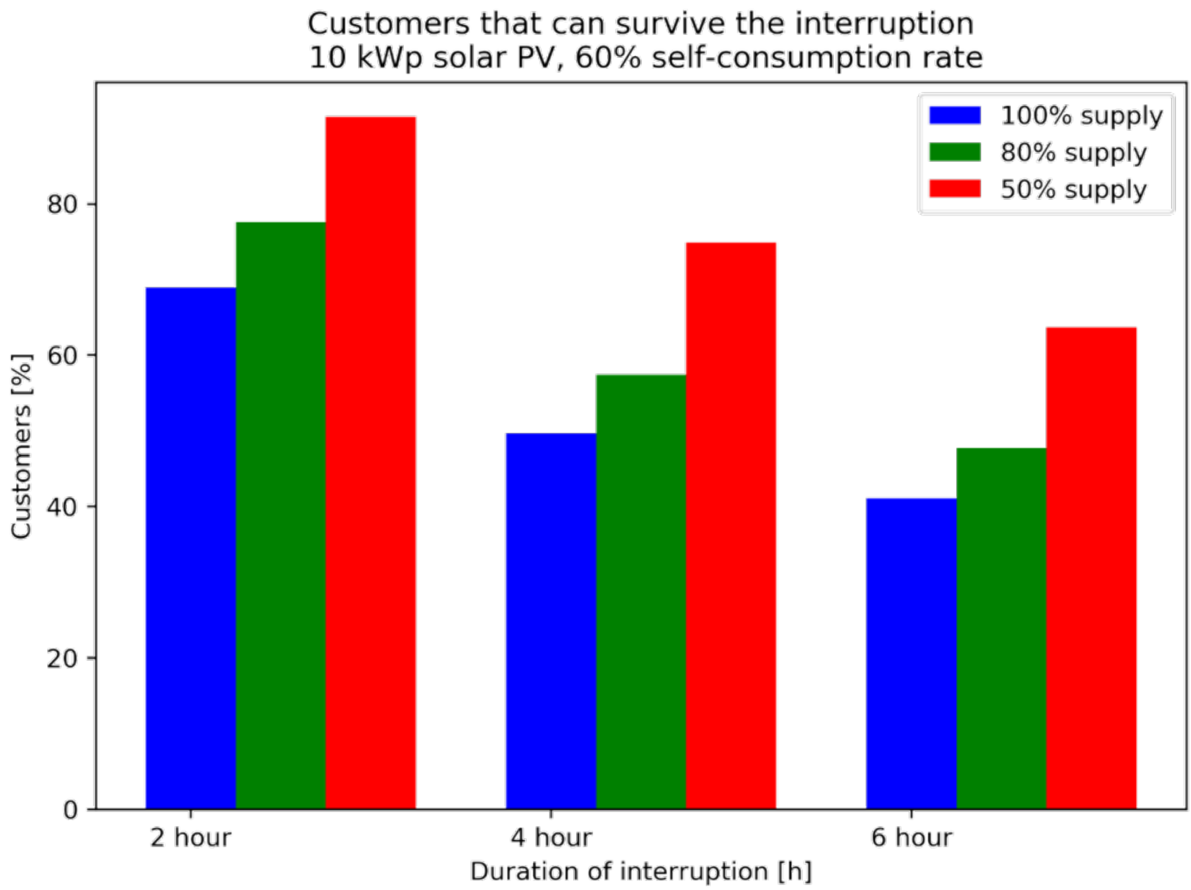



Figure 52: Share of customers for whom the continuity of supply is secured during an interruption

In practice, the probability that the interruption coincides with the annual highest loading hours of the year is rather low, and hence, the DER capacity illustrated here is overdimensioned in most of the cases. Instead, it is more advisable to calculate the DER capacity according to the second, third, or maybe the most frequently occurring loading level. In case the interruption occurs during the higher loading level than the DER capacity was dimensioned for, flexibility of demand can help to mitigate the impact of interruption on a single customer.

In addition, the results clearly indicate that from the economic perspective, the centralized DER alternative is a preferable solution compared with the distributed DER alternative. Moreover, in LV networks, the fault rates are typically lower compared with MV networks, and thus, a centralized DER choice is a more favourable solution for distribution transformer districts.

From the technical perspective, however, a centralized storage solution will not solve for instance voltage quality issues at a single customer level. This is outside the topic of the security of supply, though.

# 6 Simulation results and grid impact analyses

In this chapter, the grid impact results are presented for the EV and GSHP integration simulations. The results are assumption- and case-specific, and therefore, careful analyses are required keeping in mind the initial assumptions. The results provide only indicative answers to the research questions posed above. The main objectives in this section are to quantify the grid impacts of the DER scenarios and to identify which of the simulated DER scenarios and in which grid points cause overloading and/or voltage problems. However, the purpose is not to present all the obtained results but rather to illustrate how the methodology works and how the results can be interpreted.

For comparison, DER scenarios were created in the same way for each distribution transformer. Thus, the penetration rate, characteristics, and usage of DER were simulated in the same way for each transformer in order to make the grid impact comparable and draw general conclusions.

The chapter is divided into three subsections. In the first subsection, Monte Carlo simulations with AMR data, the grid impact results are obtained using only the AMR data and network topology and dimensions of the transformers. The probability distribution of the grid impact values in various scenarios is illustrated for the case grids. No power flow simulations are executed at this stage yet. From each histogram for the probability of the grid impact distribution, the worst-case and the most probable iterations are extracted and inserted into the grid model in order to run power flow simulations and obtain line loading and voltage levels in various grid points. This is performed in the second subsection, Power flow simulations. Finally, the obtained results are interpreted in a wider scope in the last subsection, Interpretation of the obtained results in a wider perspective.

## 6.1 Monte Carlo simulations with AMR data

Rural and urban networks were analysed using the same methodology and simulation tool. The results are presented for the EV and heat pump scenarios.

### 6.1.1 EV integration

For the EV integration scenarios, the following assumptions were used:

- 100% penetration rate behind each distribution transformer
- 100% car ownership in detached and terraced houses, 25% in flats
- start of charging is adjusted to the customer's home arrival time
- charging rates 3.7 kW and 11 kW
- 1000 Monte Carlo combinations simulated for each distribution transformer

For the primary substation level, the changes in peak power are illustrated for a rural area in various EV integration scenarios in Figure 53. The major observation from the obtained results is that the scenarios of the EV charging rate of 3.7 kW (blue bar) and 11 kW (green bar) are very close to each other in the most frequently occurring EV driving behaviour for all the primary substations. This can be explained by the overlapping phenomena described in the example of the EV fleets of 20 cars and 50 cars in Section 3.1.1. and shown in Figures 7b and 8b.

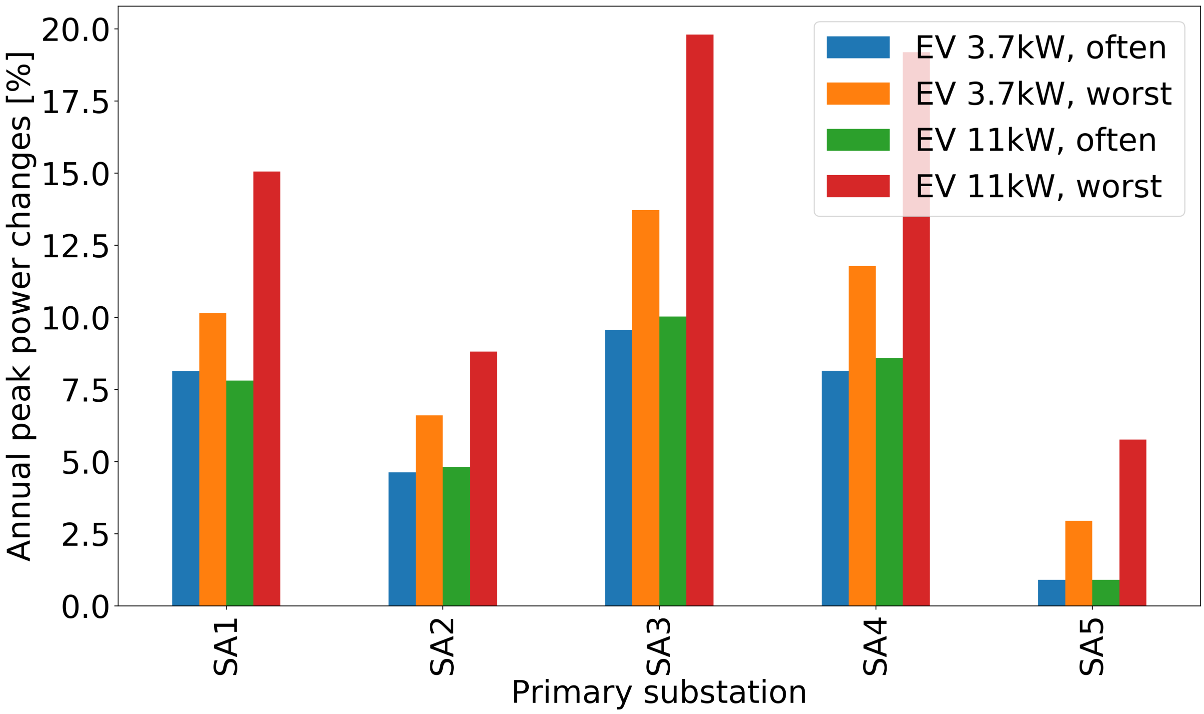



Figure 53: Impact of various scenarios of EV integration at the primary substation level in a rural area

The probability distribution of grid impact values at the distribution transformers in the rural area is presented in Figure 54. The results for approximately 900 transformers are illustrated in the figure, and hence, the readability of the data is rather poor. For this reason, the peak power changes in the most frequent EV charging behaviour (orange histogram) and the worst-case charging behaviour (blue histogram) were combined into two histograms.

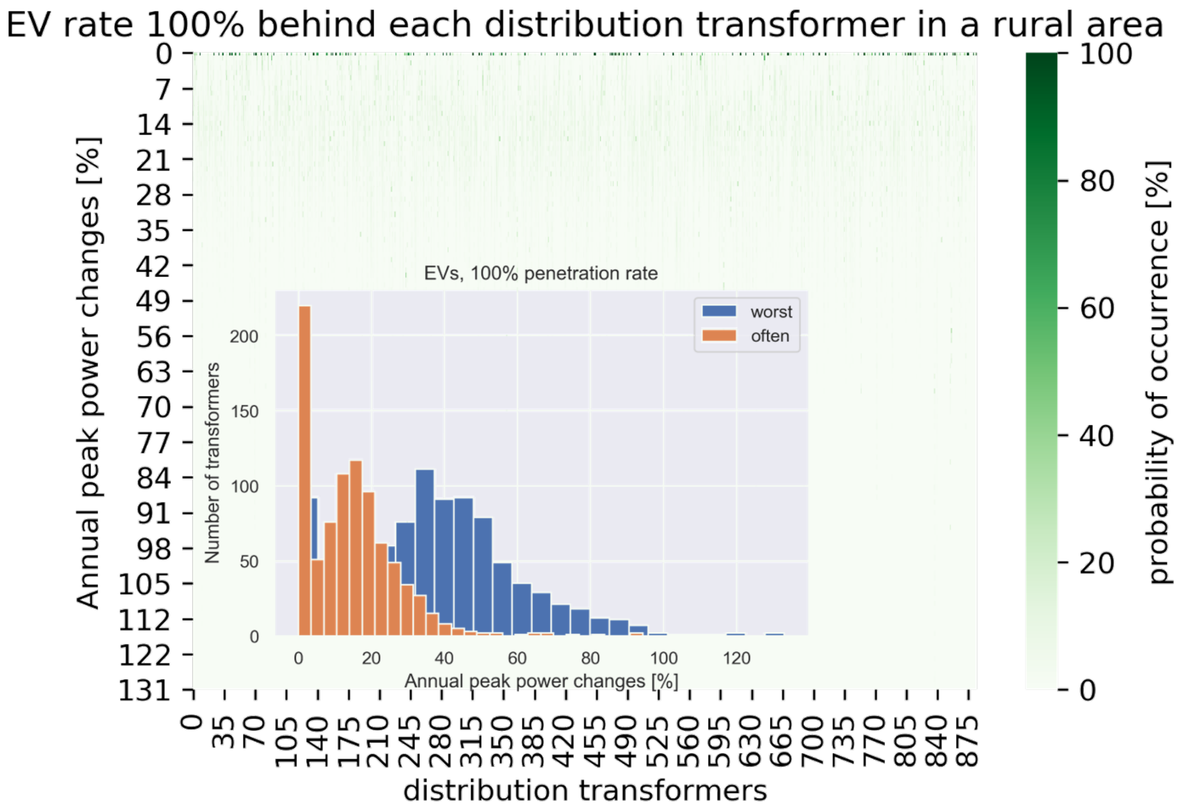
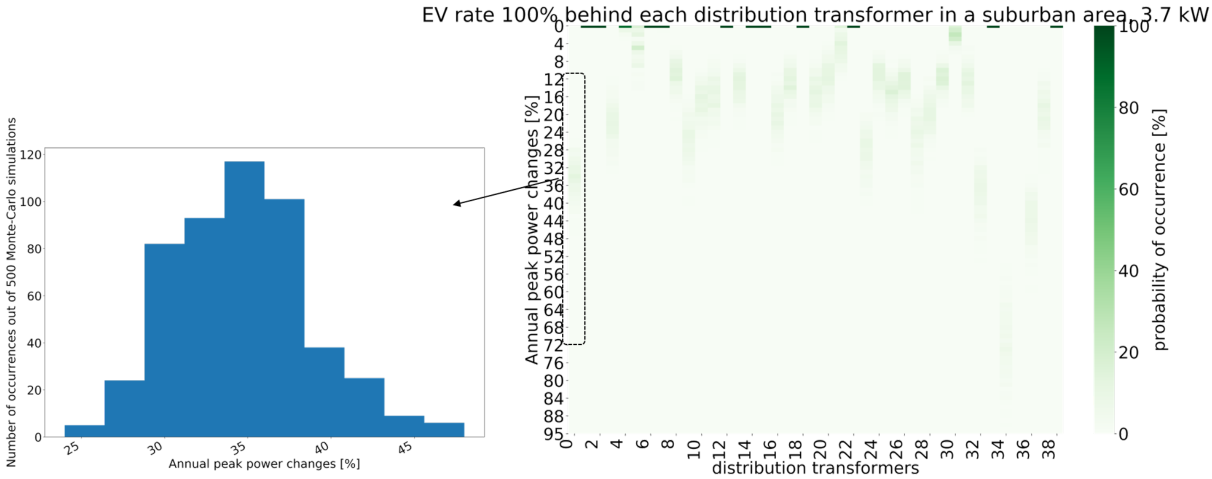
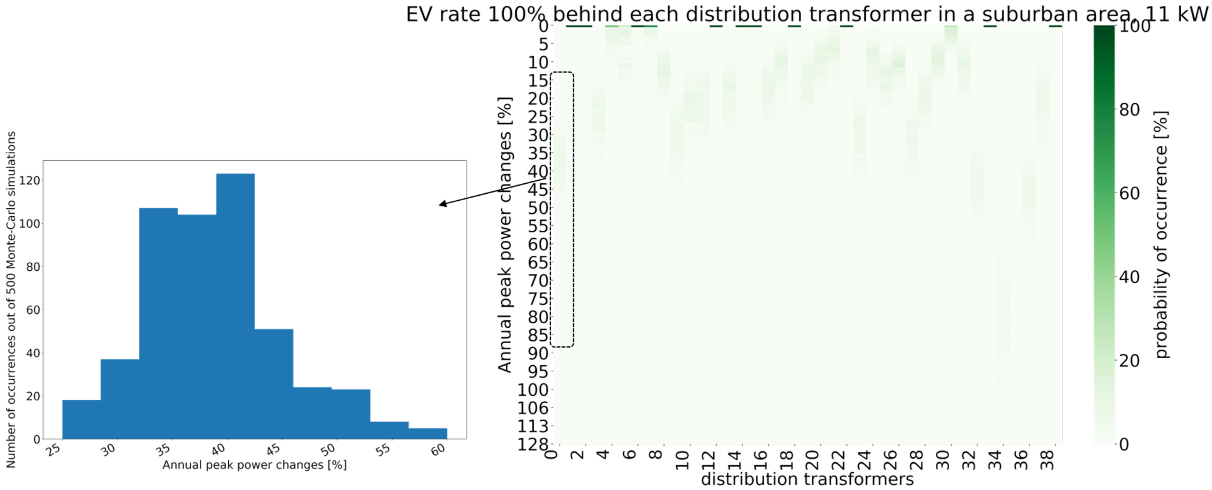



Figure 54: Impact of EV integration at the distribution transformer level in a rural area

The probability distribution of the grid impact of EV integration in the suburban grid area is illustrated in Figure 55 for the charging rates of 3.7 kW and 11 kW. For each distribution transformer, the peak power changes are organized in a probability distribution format in vertical columns in the graph; the brighter the green colour is, the more often that grid impact value was obtained in the Monte Carlo simulations. The colour bar shown on the right-hand side illustrates the colour and the associated probability of occurrence. The annual peak power changes are presented on the left-hand side axis, increasing from top to bottom. In the suburban area, most of the transformers experience under 40% annual peak power changes even in the worst-case driving behaviour. In the rural area, the peak power changes stayed below 50% for the majority of the transformers. An example transformer is selected randomly for a closer look at the grid impact. The shape of the probability of the grid impact distribution is similar for both charging rates, having the most frequently occurring grid impact in the range of 35–40 %. However, the worst-case grid impact at 11 kW is somewhat higher, reaching 60%, than at the charging rate of 3.7 kW, where the grid impact reaches about 50%.



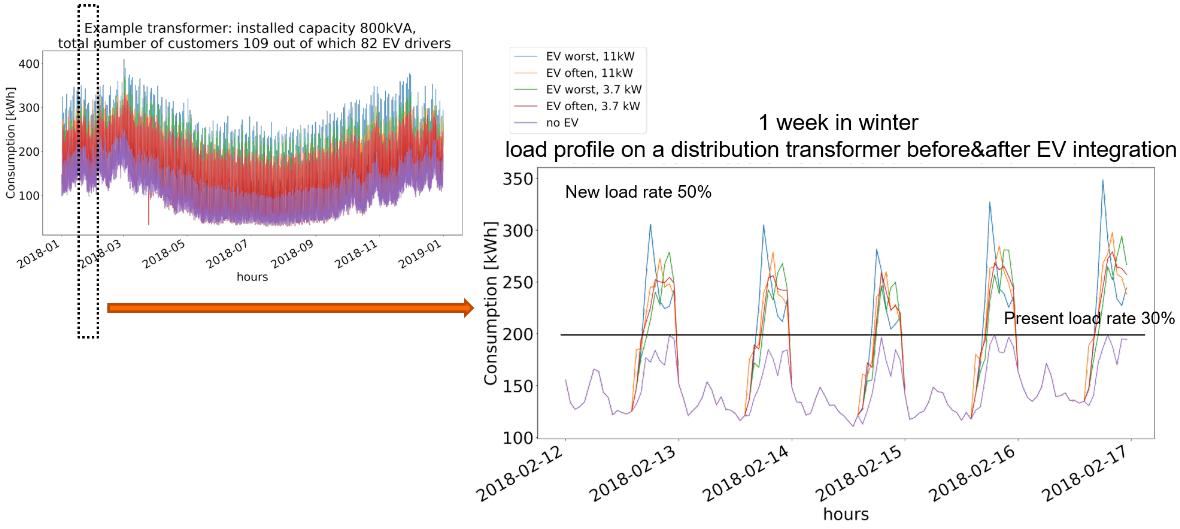

(a) Charging rate 3.7 kW



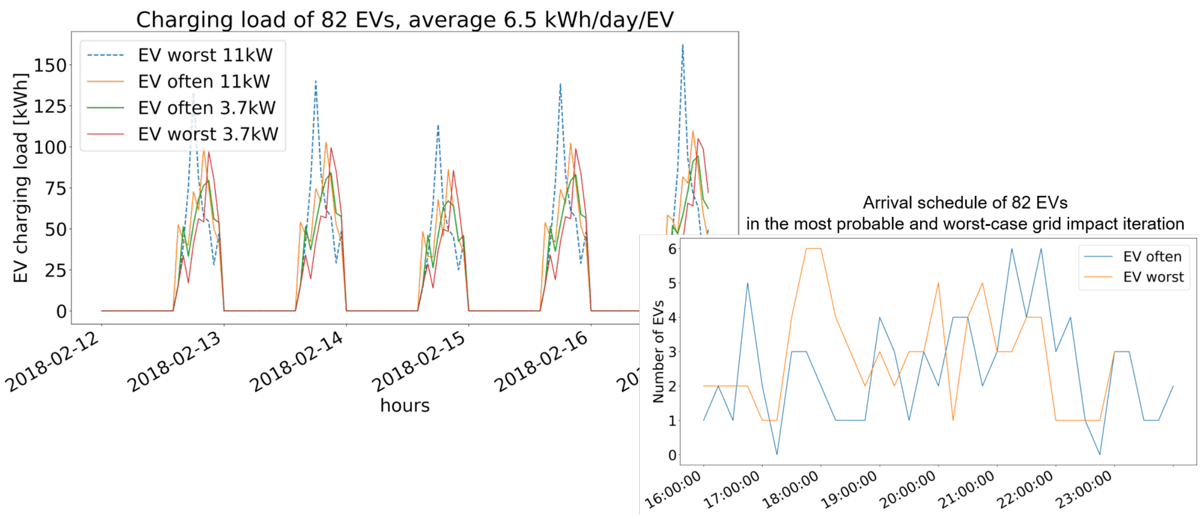

(b) Charging rate 11 kW

Figure 55: Grid impact of EV integration in a suburban area, home dumb-charging scenario

To take a closer look at the selected transformer, the time-series load profiles are illustrated for the scenarios of the most frequent and worst-case EV charging behaviour at the charging rates of 3.7 kW and 11 kW (see Figure 56). Figure 56a shows five time-series load profiles over a one-year period and a one-week period in winter. It can be seen that there is no overloading problem at this distribution transformer with the installed capacity of 800 kVA, even in the worst-case EV charging behaviour scenario where the maximum annual peak power reaches about 400 kW. Figure 56b shows that the reason for the highest peak power in the worst-case EV driving behaviour at 11 kW is the simultaneous charging of a group of six EVs at around 18 o'clock (orange line), followed by another six EVs arriving during the following 15 min. However, such a high peak power does not occur in the most often occurring EV charging behaviour when the arrival of EVs is more or less equally spread in time (blue line) throughout the time period from 16 to 23 o'clock.




(a) Load profiles at the example distribution transformer




(b) EV charging load profiles and the corresponding arrival times

Figure 56: Correlation of the load profile with EV drivers' arrival times

The next figure illustrates the impact of EV integration in a rural area.

However, based on the annual peak power changes, one cannot say whether there is an overloading problem on a distribution transformer or not. The overloading problem arises if the present load rate of the transformer is high already before the EV integration.

Figure 57 illustrates the load rate for rural and suburban areas in three scenarios: (1) no EV, (2) the most often occurring EV driving behaviour, and (3) the worst-case EV driving behaviour. The lowest green curve represents the load rate in the no EV scenario. The middle blue curve shows the load rate during the most frequently occurring EV charging combination, whereas the upper orange curve depicts the load rate in the worst-case scenario for each distribution transformer. In each of those two combinations, the distribution transformer has the same number of EVs, but their charging behaviour differs in the home arrival time and the charging energy need.

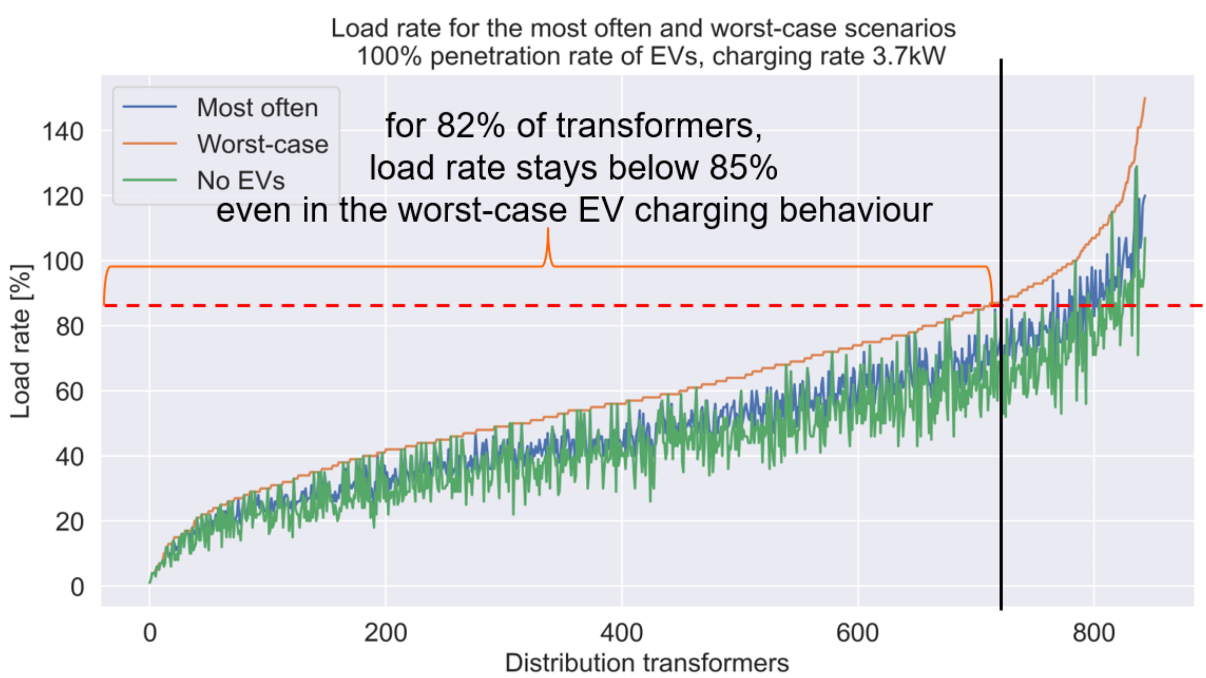
In the suburban area, EV charging at 3.7 kW does not cause overloading problems because the load rate stays below 80% for all the distribution transformers. Some transformers did not experience load rate changes at all, and for those transformers, the average annual energy consumption is higher than for the majority of the transformers. This indicates that those transformers supply large non-residential customers and hence, their daily peak powers most likely occur in the daytime. Therefore, evening dumb home charging of EVs did not cause exceeding of peak powers and thus, changes in load rate.

In the rural area, 15% of all the distribution transformers (about 120) did not experience any load rate changes. This can be seen in Figure 57b, where the green line (no EVs) coincides with the orange line (worst case). The reasons for this are at least the following:

- these transformers supplied also non-residential customers in addition to the residential customers
- there were no residential customers behind these transformers
- a customer switched from electric storage heating to a GSHP solution sometime during the year. The annual peak power was high as a result of electric storage heating, and EV charging did not exceed it.

For 82% of the distribution transformers, the load rate stayed below 85% even in the worst-case EV charging behaviour. For those transformers, the present load rate without EVs stayed below approximately 60%. This could be considered a threshold for estimating whether the overloading problem will exist or not if the EV charging occurs behind that transformer. In other words, if the present load rate of the distribution transformer is less than 60%, the probability of overloading is low when customers start to implement EV dumb charging at home at the 3.7 kW charging rate.


(a) Suburban network




(b) Rural network

Figure 57: Load rate in the EV integration scenarios

### 6.1.2 Heat pump integration

The assumptions used in the simulations are listed below:

- Penetration rate (switching rate) is set as per distribution transformer and assumed to be 100%
- Potential candidates identified based on Trimble NIS customer databases and annual energy consumption

- Only customers living in detached houses regarded as potential customers
- When customers with electric storage heating switch to GSHPs, their annual consumption may decrease by 2–30 MWh/a
- When non-electric heating customers switch to GSHPs, their annual consumption may increase by 8–25 MWh/a
- For each distribution transformer, 500–1000 different combinations were simulated (Monte Carlo)

Three main scenarios were defined:

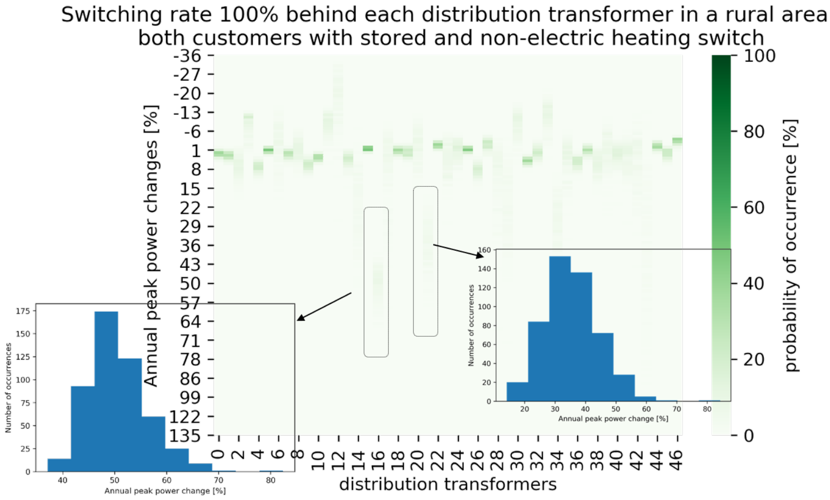
- only customers with electric storage heating switch to a GSHP
- only customers with non-electric heating switch to a GSHP
- both customers with electric storage heating and non-electric heating switch to a GSHP

For the rural area, Figure 58 illustrates the grid impact on the distribution transformers in the three scenarios.

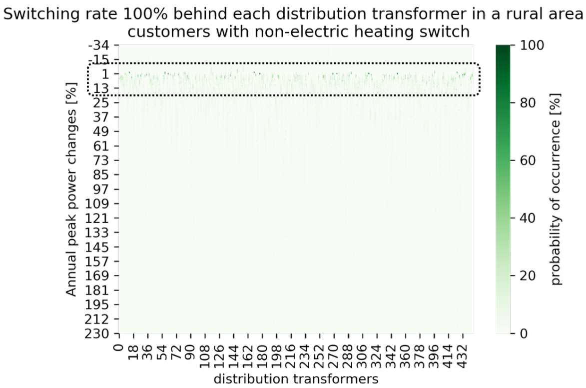
The main highlights of the results are:

1. In the scenario where only electric storage heating customers switch to a GSHP:
   - for the majority of the transformers, the annual peak powers decrease
   - the most frequently occurring grid impacts range within -3 +1% for the transformers (bright green coloured boxes)
   - for some transformers, +26% and -49% of annual peak power changes are observed, but these are rare cases (light green colour)
2. In the scenario where only non-electric heating customers switch to a GSHP:
   - for the majority of the transformers, the annual peak powers increase
   - the most frequently occurring grid impacts range within 0 +10% for the transformers (bright green coloured boxes)
   - for some transformers, +230% and -34% of annual peak power changes are observed, but these are rare cases (light green colour)
   - decreases in peak power are due to the absence of electric sauna peaks in the new load profiles and should be disregarded
3. In the scenario where both the potential customer groups switch to a GSHP:
   - for the majority of the transformers, the annual peak powers will most probably change from -10% to +10%
   - for some transformers, +135% and -34% of annual peak power changes observed, but these are rare cases (light green colour)

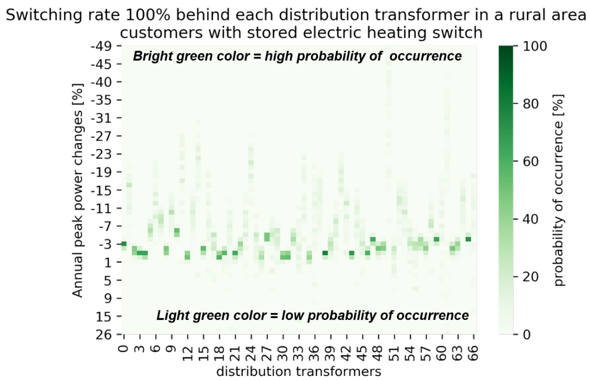
- again, decreases in peak power are due to the absence of electric sauna peaks in the new load profiles and should be disregarded




(a) Both customers to a GSHP




(b) Non-electric heating customers to a GSHP




(c) Electric storage heating customers to a GSHP

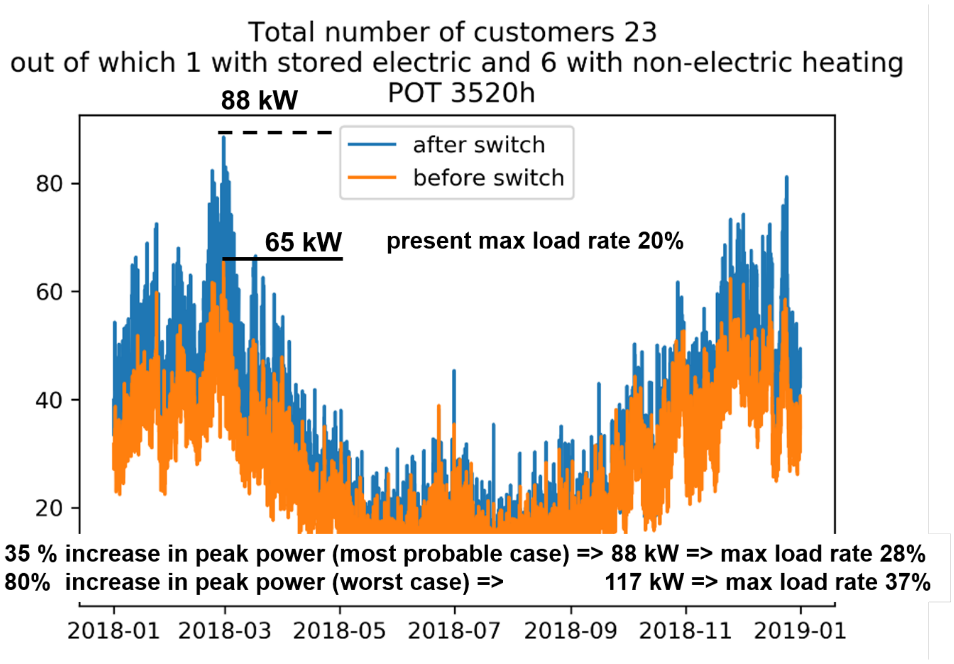
Figure 58: Grid impact of GSHP integration in a rural area

To take a closer look at the obtained results, the two example transformers were selected from Figure 58a for further analyses in the scenario where both the potential customer groups switch to a GSHP.

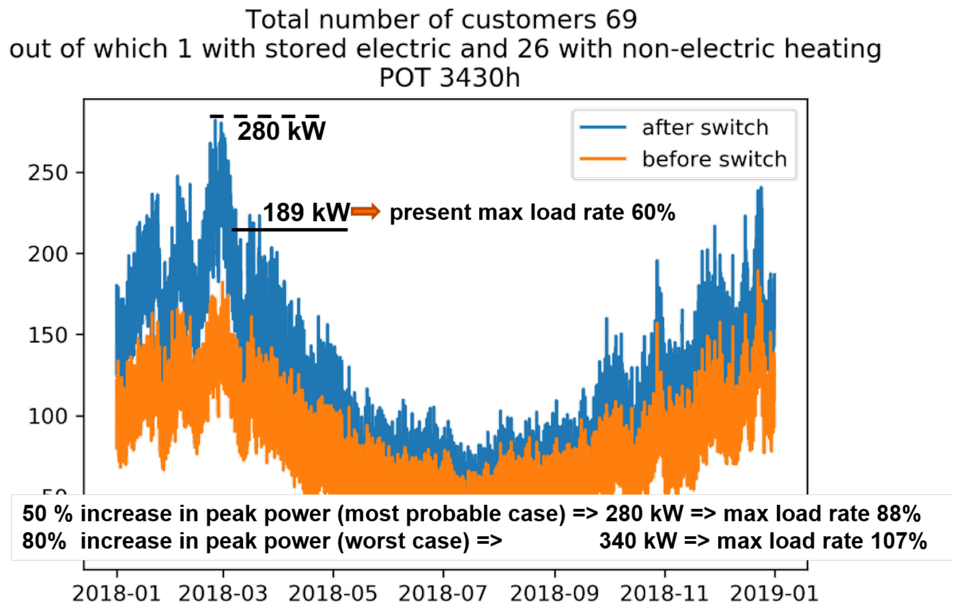
In Figure 59, the original and modified load profiles after the switch, corresponding to the most probable switching behaviour, are presented for the two transformers. The nominal capacity of the both transformers is 315 kVA, and the peak operating time is almost the same for the both transformers, around 3500 hours. The present maximum load rate for the first transformer is 20% and for the second transformer 60%. For the first transformer in Figure 59a, switching to a GSHP does not present any overloading problems, even in the worst-case scenario, where the peak power change reaches 80%. This transformer is smaller having 23 customers in total, compared with the other transformer supplying 69 customers. The number of potential customers is also smaller in the first transformer (7 out of 23, 30%) than in the second transformer (27 out of 69, 39%). For the second transformer, both the most probably occurring and worst-case switching behaviours may present overloading for the transformer. Even though the maximum load rate is 88% in the most probable case, the value is calculated at one-hour resolution, and a higher resolution may show higher peak power changes and load rate values.

The major highlights of the obtained results are:

- large changes in annual peak power do not indicate overloading problems
- the risk of overloading for the distribution transformers is higher for transformers having a high load rate and a large share of residential customers and potential customers to switch to a GSHP
- in case of overloading, the need for grid investments depends on the nature of the overloading problem, which can be described by a) time of a new peak power occurrence (winter, summer, the cooling conditions when a new peak power occurs) and b) frequency of a new peak power occurrence, changes in the peak operating time: whether the overloading occurs rarely or frequently
- in case of switching to a GSHP, the overloading occurs usually in wintertime when the outdoor temperature is low and the heating demand is high.




(a) Example transformer 1




(b) Example transformer 2

Figure 59: Grid impact of GSHPs on two example transformers

Furthermore, a closer look at the new GSHP profiles of the non-electric heating customers is presented in Figures 60 and 61. Comparing the two figures, one can say that the worst-case switching behaviour for the transformer does not necessarily represent the worst case for single customers in terms of the size of peak power. The reason for the increased peak power of the worst-case switching behaviour compared with the peak power in the most probable switching behaviour can be explained partly by the switching to the partial load capacity heat pumps. As mentioned earlier, this GSHP solution has additional electrical resistors that are turned on during the coldest time periods of the year. Since the operation of the heat pumps together with the electrical resistors follows the outdoor temperature, the switching on of the resistors takes place simultaneously for all the customers behind a distribution transformer as they are located more or less in the same geographical area with the same weather conditions. The COP of the resistors is one, and hence, they are the ones that have a larger power consumption compared with the full load capacity GSHP (COP is approx. 3) during the coldest days. This leads to a larger increase in the peak power at the distribution transformer compared with the full load capacity GSHP solution.

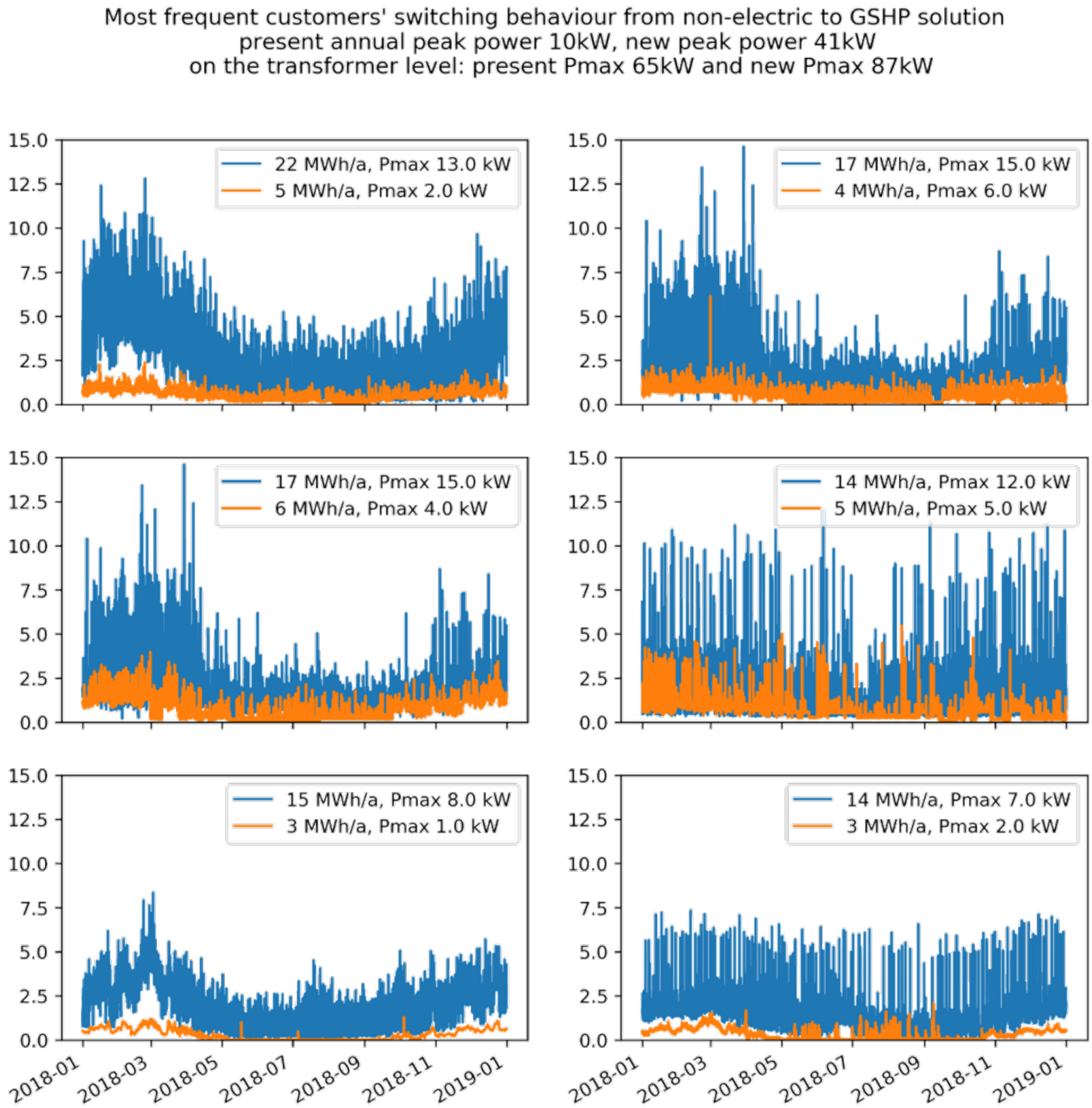



Figure 60: Switching behaviour that occurred most often in the Monte Carlo simulations

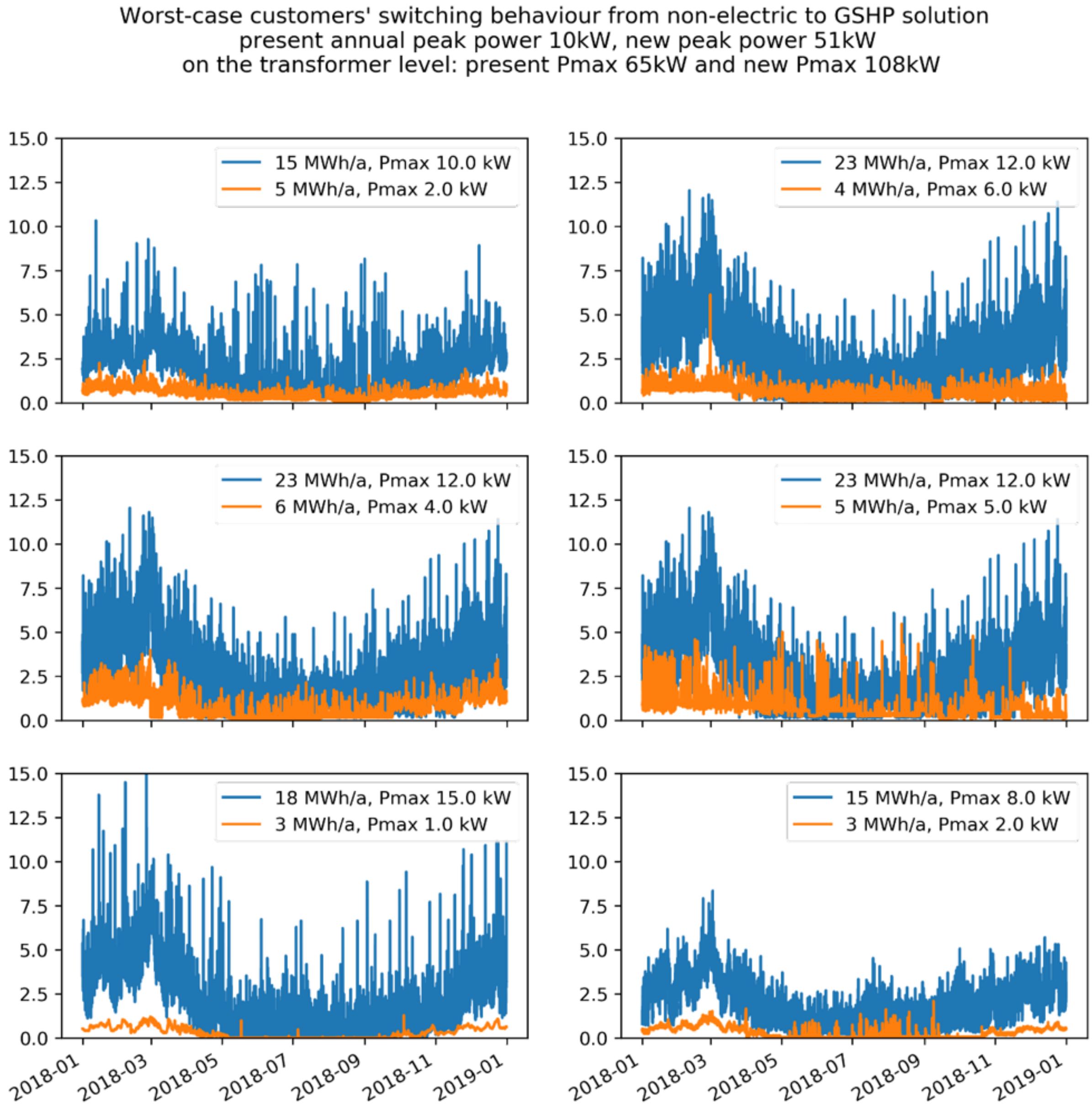


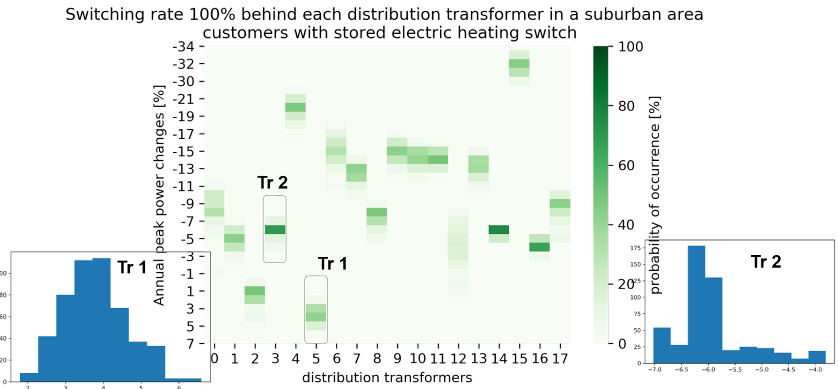

Figure 61: Switching behaviour that causes worst-case loading for the distribution transformer

For the suburban area, Figure 62 illustrates the grid impact on the distribution transformers in the three scenarios. The major highlights from the obtained results are:

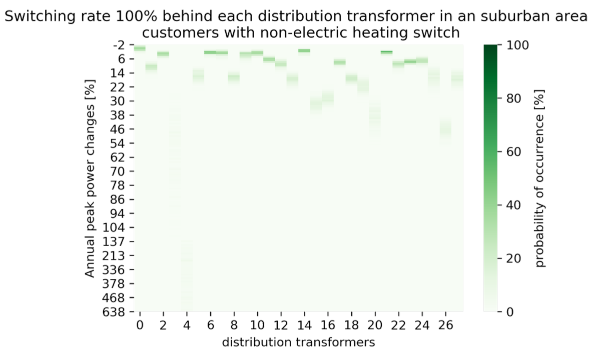
1. In the scenario where only the electric storage heating customers switch to a GSHP:
   - For a few transformers, the customers' switching behaviour causes an increase in peak power
   - For most of the transformers, the customers' switching behaviour causes a decrease in peak power
2. In the scenario where only the non-electric heating customers switch to a GSHP:

- In the most probable cases, the increase in peak power is less than 46%, varying for most of the transformers between 0% and 20%.
- In the worst-case scenarios, the peak power may increase up to 600% for a few transformers. However, this was the case of a transformer supplying a single non-electric heating customer.
- The worst-case scenario corresponds to the case where all the non-electric heating customers (small consumption) change to the largest possible heating solution ( up to +25 MWh/a)

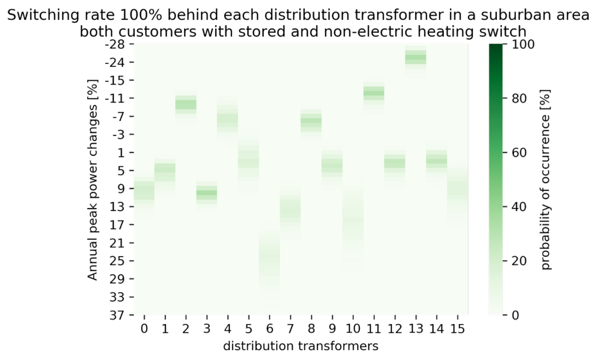
3. In the scenario where both the potential customer groups switch, the switching behaviour of electric storage heating customers compensates the peak powers caused by non-electric heating customers' switching activities.




(a) Electric storage heating customers to a GSHP




(b) Non-electric heating customers to a GSHP

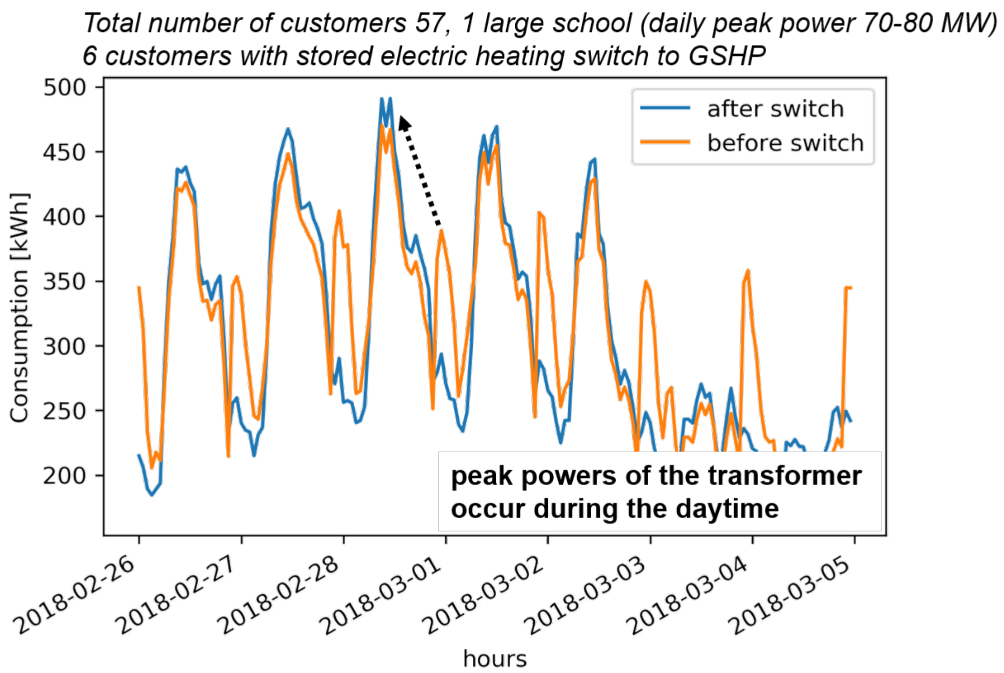



(c) Both customers to a GSHP

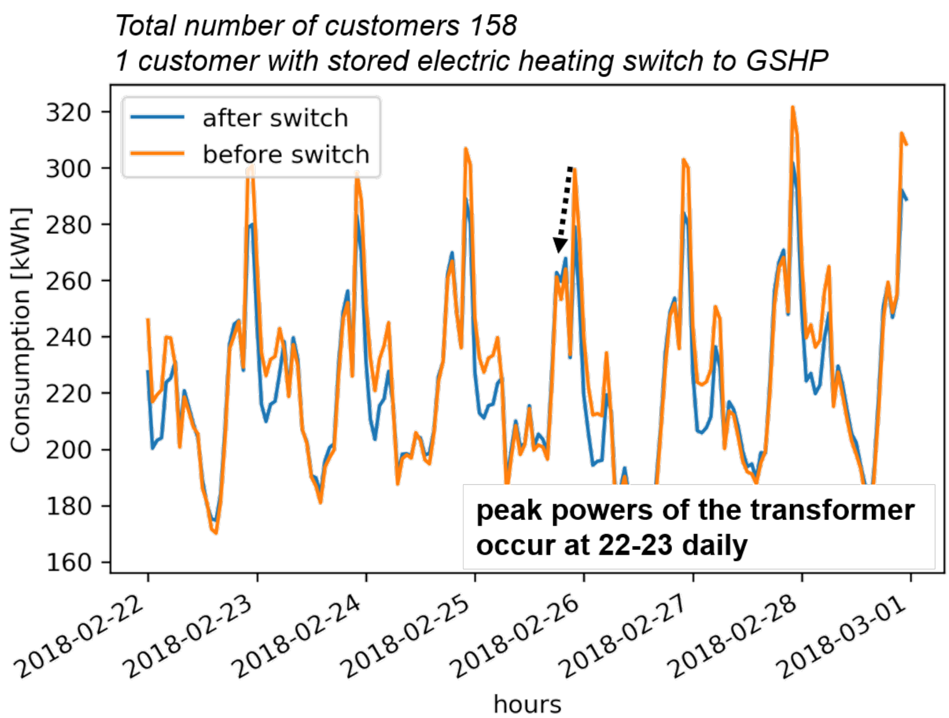
Figure 62: Grid impact of GSHP integration in a suburban area

To explain some of the obtained results, two example transformers from Figure 62a were selected in the scenario where only the electric storage heating customers switch to a GSHP. For one transformer, this switching behaviour causes an increase in the annual peak power and for the other transformer, the peak power decreases. The reason for the increase in the peak power on the first transformer is that the peak powers of that transformer occur in the daytime owing to the large school supplied by that transformer. After the switch, the consumption of the electric storage heating customers will be shifted from the night-time to daytime (see the dashed arrow in Figure 63a), which adds to the daily peak power of the transformer. However, on the second transformer, the daily peak powers occur in the evening time owing to the electric water heaters of the direct electric heating customers turning on at 22:00–23:00. After the electric storage heating customers have switched to the GSHP, their contribution to the evening peak power disappears shifting to the daytime (see the dashed arrow in Figure 63b) and hence, it decreases. Although the grid impact is slight on these example transformers and does not present any overloading risk, the purpose of these examples is to explain the main reasons behind the increase and decrease in peak power.

It is important to keep in mind that the results are sensitive to the customer switching behaviour. For that, two factors are significant: which customers are likely to switch to a GSHP and to which GSHP solution they will switch. The results are especially sensitive for distribution transformers supplying a low number of customers, for instance in rural areas.




(a) Example transformer 1




(b) Example transformer 2

Figure 63: Grid impact of the GSHP on two example transformers

## 6.2 Power flow simulations

The objective of the power flow simulations was to analyse the grid impact of DER on loading levels in MV and LV lines and voltage levels. For this purpose, the most probable and worst-case scenarios are extracted from the Monte Carlo simulation results and the obtained time-series-modified load profiles are given as an input to the distribution grid model where the power flow simulations are performed.

### 6.2.1 Grid impact on MV feeders

Figure 64 illustrates the loading levels in the MV feeders during the annual peak power in the whole rural area for the scenario of EV charging at 11 kW in the worst-case charging behaviour. The loading level exceeds 50% slightly for a few MV feeders in that particular hour. However, a single hour does not show whether the MV line is overloaded or not, and thus, the whole year has to be calculated to be able to draw some conclusions.

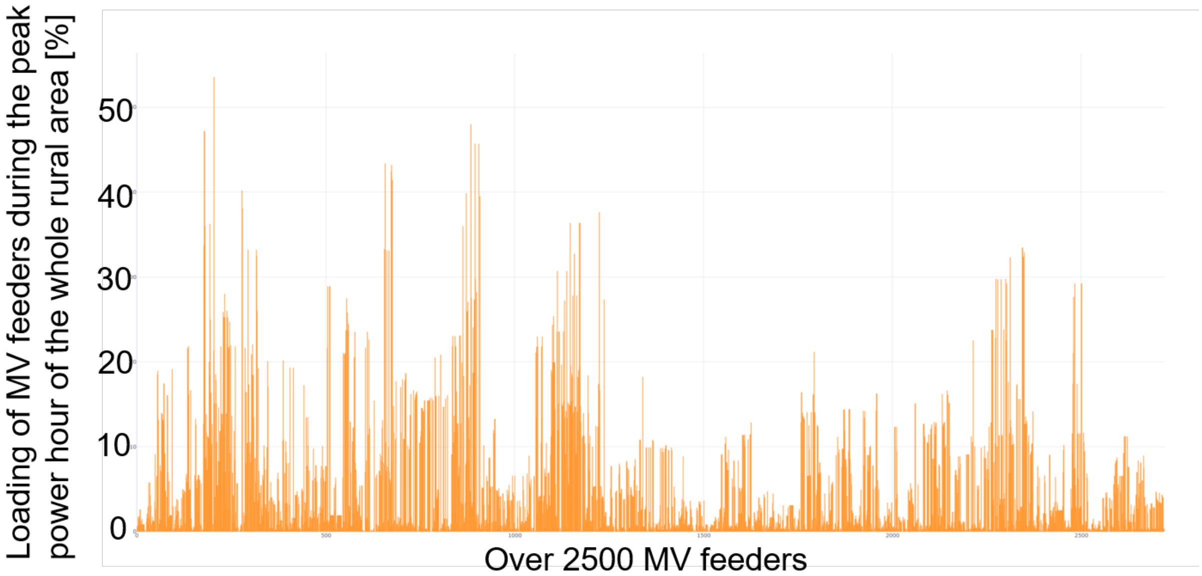



Figure 64: Loading levels in MV feeders during the annual peak power hour of the whole rural area. EV charging at 11 kW, worst-case scenario

Figure 65 shows the variation in loading levels on 10 MV feeders leaving from the main transformer of the primary substation. For each MV feeder, the loading levels are presented for the whole year in the form of boxplots. The boxplot shows the distribution of loading levels on each MV feeder, combining all the loading values for 8760 hours. The major element of interest is the blue dots in the upper part of the boxplot, which represent the highest loading levels during the year. The figure shows that for all the MV feeders, the loading does not exceed 16%. Therefore, there are no overloading problems on the MV feeders in the suburban area.

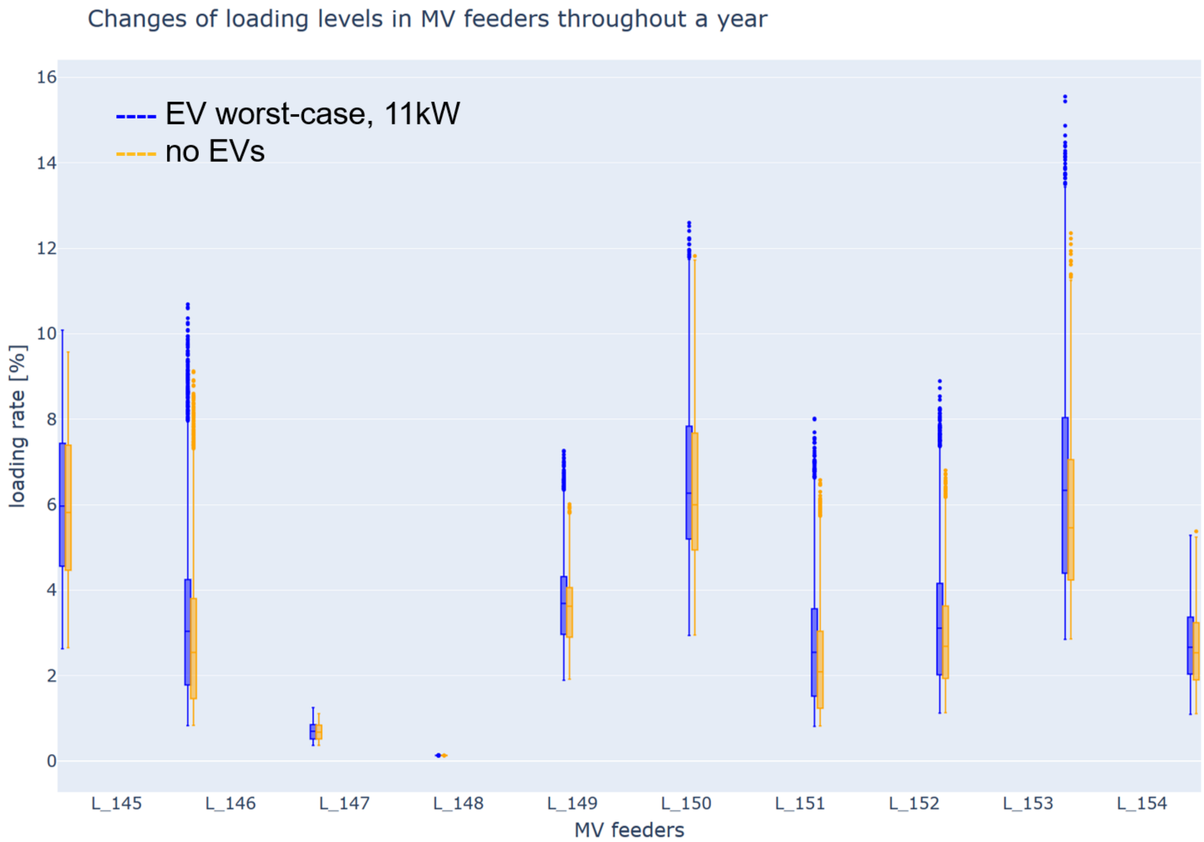
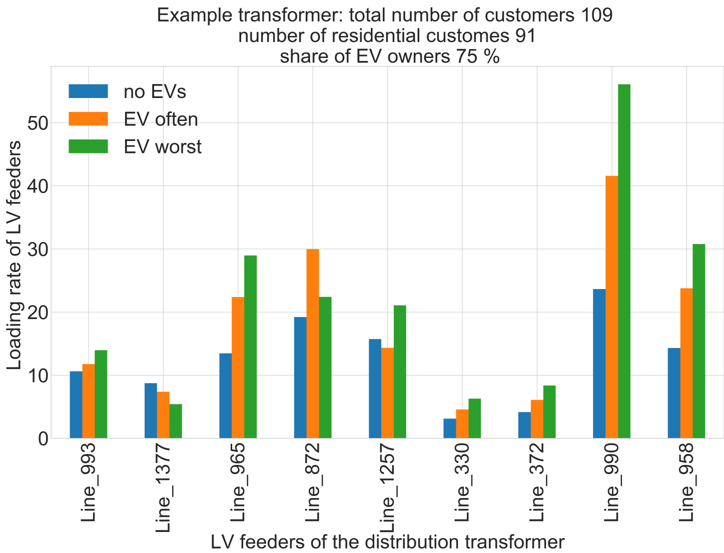


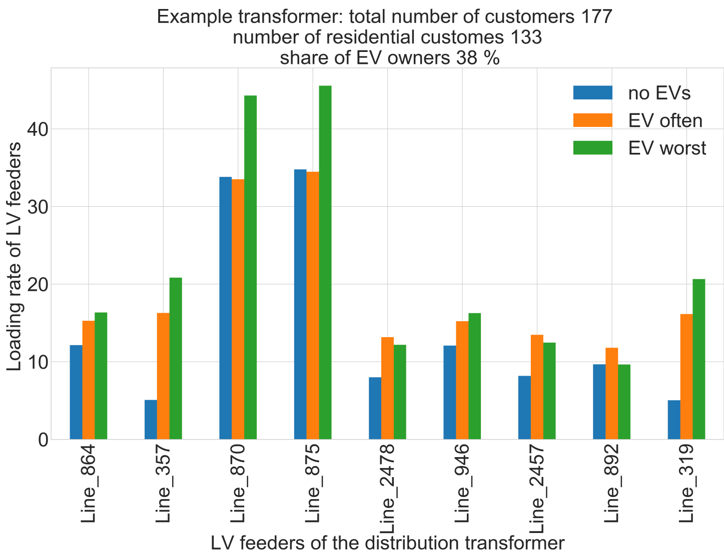

Figure 65: Loading levels in the MV feeders during the whole year in the suburban area. EV charging at 11 kW, worst-case scenario

### 6.2.2 Grid impact on LV feeders

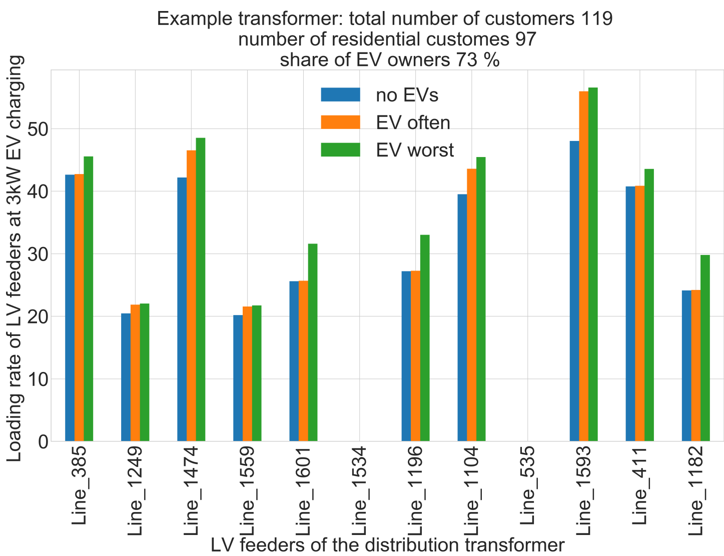
The objective here was to identify overloading problems on LV feeders. As an example, loading on the LV feeders of the three case distribution transformers are calculated for the annual peak power hour of the distribution transformer for three scenarios: (1) no EVs, (2) the most probable EV charging behaviour, and (3) the worst-case EV charging behaviour. The charging rate is 3 kW. The results are given in Figure 66. In most cases, the annual peak power hour is different in the three scenarios for the same distribution transformer. Furthermore, the annual peak power of a distribution transformer does not reflect the peak loading rate of the LV feeders. Therefore, sometimes, the loading rate in the ”EV often” scenario is higher than in the ”EV worst” scenario. Similar to the previous section, the loading rate of the LV feeders during the annual peak loading of the distribution transformer does not necessarily reflect the maximum annual loading level.




(a) Example transformer 1




(b) Example transformer 2




(c) Example transformer 3



Figure 66: Loading levels on LV feeders of the example distribution transformers during their annual peak power. EV charging at 3 kW rate

To determine the maximum annual load rate, power flow simulations are to be run for the whole year. The variations in the LV feeder loading for the example transformer from Figure 66c are illustrated in boxplots in Figure 67. For instance, the LV feeder line 1474 reaches the maximum load rate of 54%, while its loading was below 52% during the annual peak loading hour of the distribution transformer.

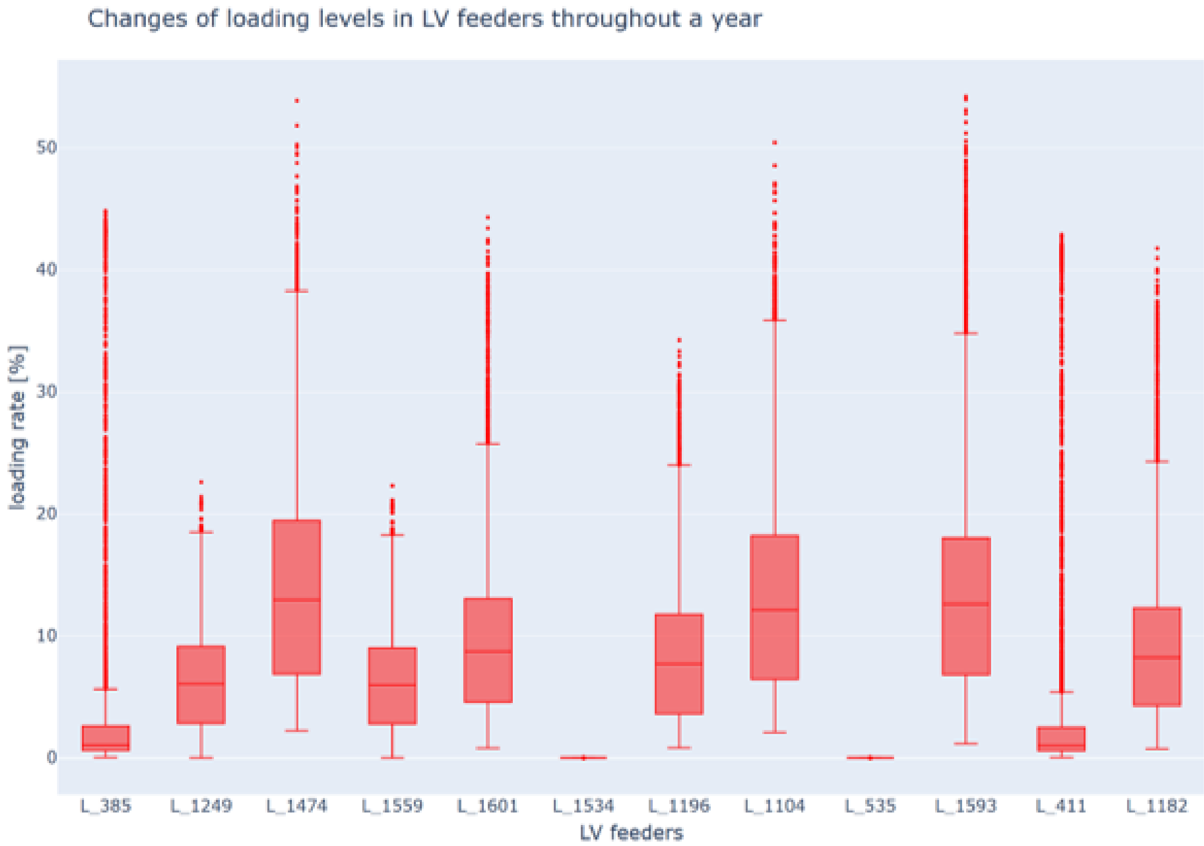



Figure 67: Loading levels on the LV feeders of an example transformer during the whole year in the suburban area. EV charging at 3.7 kW, worst-case scenario

## 6.3 Interpretation of the obtained results in a wider perspective

### 6.3.1 From case-specific to general conclusions

The analyses are presented only for the grid impact caused by EV integration. The main idea is to combine the grid characteristics with the obtained grid impact results. The main target is, under a certain EV scenario, to be able to determine the types of transformers that are prone to grid impacts, and whether the impacts on these transformers are mild or strong. For this purpose, the background information of each distribution transformer is combined with the grid impact results. The background information includes:

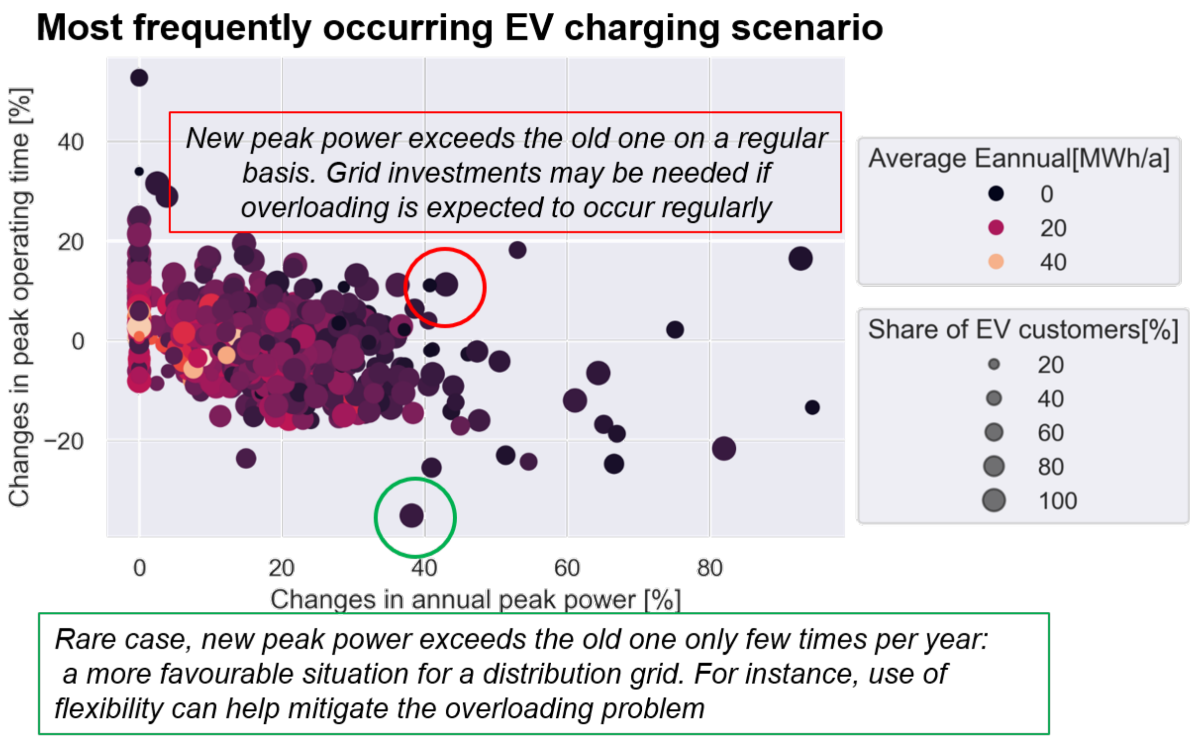
- average size of a customer supplied by the transformer and
- the share of EV owners of the total number of customers behind that transformer.

The grid impact criteria comprise changes in the annual peak power together with changes in the peak operating time.

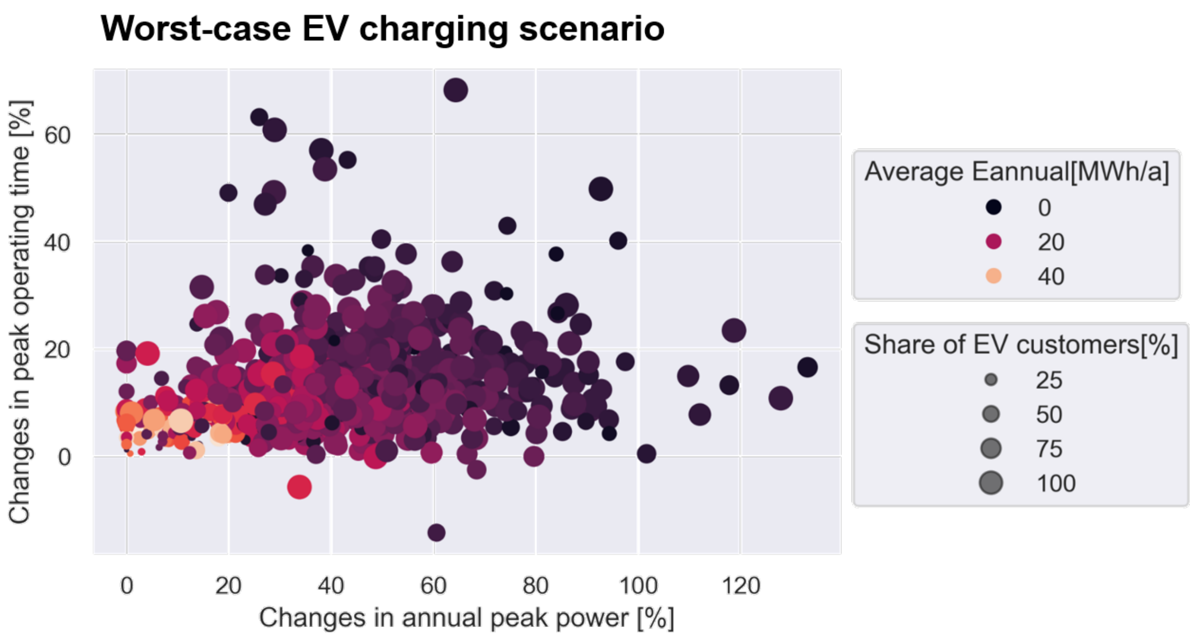
The results for the rural area are presented in Figure 68 for the EV charging rate 3.7 kW and the most probable and the worst-case EV charging behaviour.

The figure shows that the larger the average size of the customer is (light dots in the figures), the fewer grid impacts the EV charging causes for that transformer (dots are located closer to the left-hand side of the figures). The large average size of the customer may indicate that there are other non-residential customers supplied by that transformer. The load pattern of the non-residential customers with morning and/or day peak powers is usually opposite to the residential customer profile, which typically has evening peak powers. This explains why the EV evening dumb charging does not cause much stress on the transformers with non-residential customers.

Another observation that can be made from the figures is that the share of EV drivers behind the transformer does not correlate with the strength of the grid impact (the value of peak power changes). Transformers with a large EV share (large dots) can experience both large and small peak power changes. The reason for the high stochasticity of the obtained results is due to the fact that many distribution transformers in the rural area have a low number of customers, and thus, the grid impact is sensitive to the load profile of the customers.



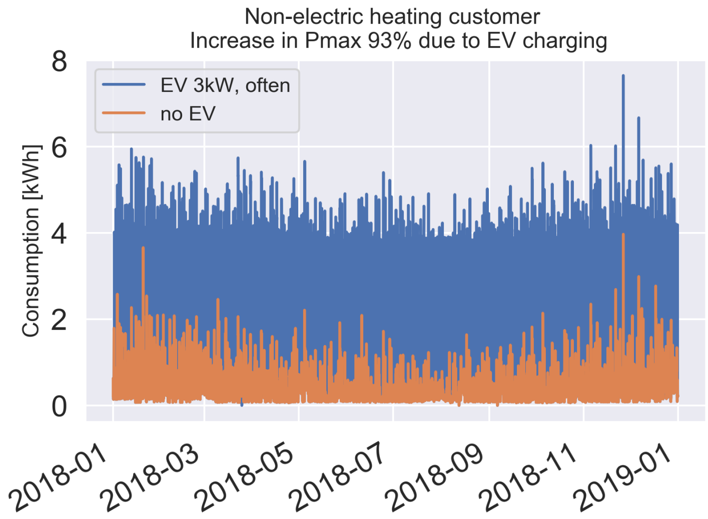

(a) Most probable EV driving behaviour



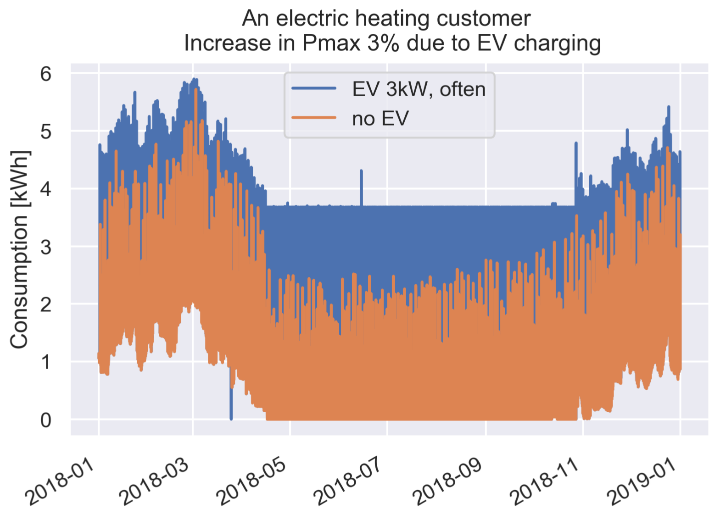

(b) Worst-case EV driving behaviour

Figure 68: Generalizing the grid impact results of EV integration in a distribution grid in a rural area

For instance, customers with non-electric heating have usually a larger increase in the annual peak power compared with customers with an electric heating load (see Figure 69).




(a) Non-electric heating customer




(b) Electric heating customer

Figure 69: Impact of EV charging on a distribution transformer with a single customer

Hence, the grid impact on distribution transformers supplying a low number of customers, like in rural areas, can take a large variation from the lowest to the largest increase in annual peak powers, which finally depends on the type and number of customers. For instance, transformers supplying non-electric heating customers may experience a higher grid impact than transformers supplying electric heating customers.

#### 6.3.2 Major outcomes of the project

The project focused on establishing a methodology and building a simulation tool upon it to quantitatively assess the grid impact of DER on distribution networks. The major outcomes of the project are:

1. Modelling of dynamic DER profiles for EV, BESS, and new heating solutions

2. Allocation of DER profiles to the end customers depending on penetration rate and location
3. Distribution grid topology and dimensions are modelled for power flow simulations
4. Grid impact analysed for various distribution grids and DER scenarios
5. Multi-objective operation of the BESS is modelled for the FCR-N, self-consumption, and peak shaving tasks
6. The grid impact range is represented as probability of its occurrence to deal with uncertainty

The obtained quantitative results were not the primary objective of the project, but rather, they were used to illustrate the width and functionality of the developed methodology and research simulation tool. Therefore, in order to achieve some reasonable and practical results, many more different DER scenarios should be simulated and grid impacts analysed using multiple criteria. In this regard, further research needs are formulated regarding development of the research tool and the purpose of usage of the tool.

The main conclusions drawn based on the quantitative results are:

For the EVs:

- The grid impact observed was similar in the scenario of EV charging at 3.7 kW and 11 kW in the most probable EV charging behaviour.
- There were no overloading problems on the MV and LV feeders.
- The grid impact depends on the type of residential customers in rural areas and on the type of customers (residential, commercial) in suburban areas.
- EV workplace charging may dramatically increase the morning peak power and increase the demand charge. Shifting the EV charging load throughout the day may significantly reduce peak powers and bring economic benefit to the customers.

For the GSHP:

- Both an increase and a decrease in annual peak power may take place when customers with electric storage heating switch to a GSHP solution.
- The preliminary results indicate no significant differences in the grid impact between selecting a partial or full load GSHP solution. Those profiles do not differ significantly in the annual peak power and annual energies. However, more simulations have to be carried out to confirm this.

Common to all:

- Even a high penetration rate of solar PV alone with a large injection of excessive generated energy in the grid does not cause a significant grid impact, both technically and economically.
- BESS operation for multiple tasks together with solar PV may result in various grid

impacts at single customer, distribution, and primary substation levels.

- The grid impact of DER may cause overloading problems for a distribution transformer if the present load rate of the transformer is above 60%.
- A centralized option of DER capacity installed at the distribution transformer level for the security of supply is a more feasible option in rural areas compared with the distributed DER option when each customer has a DER unit of their own. Moreover, the economic value of demand flexibility is high during interruption events.

# 7 Further research needs

The development needs are:

1. Multiple grid impact criteria should be considered as a single criterion may not be enough to illustrate the strength of the grid impact. For example, an increase in annual peak power does not reveal whether it occurs in winter or summer, whether the new higher peak power occurs frequently, or it is a rare event (e.g. once per year). For this purpose, changes in the peak operating time as well as the time of year when these peaks occur most often should be added to the grid impact criteria.
2. Grid impact of multiple DER types. The results of the project showed that the scenarios of a particular DER type cause grid impacts of different strength and direction (increase/decrease in peak powers) depending on the type of DER and grid area. However, the impact of multiple DER can be very different from the results presented in this study owing to the varying nature of different DER types and their individual impacts on the grid.
3. An in-depth sensitivity analysis should be carried out to identify the least- and most-influencing input parameters and simplify/develop the model accordingly.
4. A higher time-step resolution of simulated DER and input load data could be considered to estimate the grid impact more accurately.
5. Simulation of 1-phase loading of DER, such as charging of EVs, operation of a heat pump, solar PV, and BESS.
6. Implementation of DER grid impact analyses in the grid planning tools.

The developed research tool:

1. represents the infrastructure needed to simulate market- and non-market-based solutions for congestion management in distribution grids;
2. enables testing of various designs of local flexibility markets, remuneration schemes, and aggregator business models;
3. may provide recommendations for the long-term planning of distribution grids when choosing between flexibility and grid investment options with the help of life-time cost analysis;
4. identifies conflicts of interests when the TSO, the DSO, and/or the aggregator request for flexibility resources;
5. allows to test various tariff designs to incentivize the end customers to provide/activate their flexibility;
6. enables to simulate and quantify the techno-economic potential of sector coupling and synergy: synergy between various DER types, for example EV + solar PV, heat pumps and solar PV, and vehicle-to-home (V2H);

7. quantifies the value of flexibility to a DSO;
8. can be used to test various tariff designs for end customers to activate/incentivize their flexibility; and
9. can be applied to analyze the capability of distributed DER units, such as solar PV, to compensate reactive power in the distribution grid.

# References

[1] IPCC. Global warming of 1.5c: summary for policymakers. Available at https://report.ipcc.ch/sr15/pdf/sr15_spm_final.pdf.

[2] TEM. Joustava ja asiakaskeskeinen sähköjärjestelmä; Älyverkkotyöryhmän loppuraportti. Available at http://urn.fi/URN:ISBN:978-952-327-346-7.

[3] Statistics Finland, "Henkilöautoilla ajettiin edellisvuosien lailla – maanteiden tavarankuljetukset tehostuivat,(In Finnish), Article.

[4] Toni Simolin, Antti Rautiainen, and Pertti Järventausta. Assessment of prediction uncertainties in EV charging management. *accepted for IREE journal 2020.*

[5] Ari Laitinen, Maija Ruska, and Göran Koreneff. Impact of large penetration of heat pumps on the electricity use. Available at https://www.vttresearch.com/sites/default/files/julkaisut/muut/2011/VTT-R-03174-11.pdf.

[6] Renewables.ninja. https://www.renewables.ninja/.

[7] Leon Thurner, Alexander Scheidler, Florian Schäfer, Jan-Hendrik Menke, Julian Dollichon, Friederike Meier, Steffen Meinecke, and Martin Braun. pandapower—an open-source python tool for convenient modeling, analysis, and optimization of electric power systems. *IEEE Transactions on Power Systems*, 33(6):6510–6521, 2018.

[8] Fereidoon Sioshansi. *Consumer, Prosumer, Prosumager: How Service Innovations Will Disrupt the Utility Business Model*. Elsevier, 2019.

[9] IRENA. Electricity Storage Valuation Framework. Assessing system value and ensuring project viability, 2020.

[10] Evelin Wikner. *Lithium ion Battery Aging:Battery Lifetime Testing and Physics-based Modeling forElectric Vehicle Applications*. PhD thesis, Chalmers University of Technology, 2017.

[11] The self-consumption bonus. https://www.sma.de/en/partners/knowledgebase/the-self-consumption-bonus.html. Accessed: 2010-6-22.

[12] Frida Berglund, Salman Zaferanlouei, Magnus Korpås, and Kjetil Uhlen. Optimal Operation of Battery Storage for a Subscribed Capacity-Based Power Tariff Prosumer—A Norwegian Case Study. *Energies*, 12(23):4450, Nov 2019.

[13] Johannes Weniger, Tjarko Tjaden, and Volker Quaschning. Sizing of esidential PV battery systems. *Energy Procedia*, 46:78–87, 2014.

[14] Simon De Clercq, Daniel Schwabeneder, Carlo Corinaldesi, Odilia Bertetti, and Achim Woyte. How to create value through aggregation: A business model review for multiple regulatory environments in europe. 10 2018.

[15] Fingrid Oyj. Aggregation pilot project in the balancing energy markets. Available at `https://www.fingrid.fi/en/electricity-market/market-integration/the-future-of-the-electricity-markets/aggregation-pilot-project-in-the-balancing-energy-markets/`.

[16] Belonogova N. et al. Assessment of EV hosting capacity in a workplace environment in different charging strategies. *CIRED*, 2020.

ISBN 978-952-335-561-3 (PDF)

ISSN-L 2243-3376

ISSN 2243-3376

Lappeenranta 2020