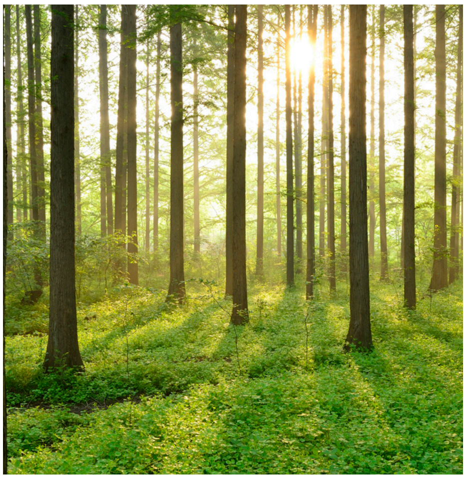
END-USER SCENARIOS AND THEIR IMPACT ON DISTRIBUTION SYSTEM OPERATORS

REPORT 2018:508



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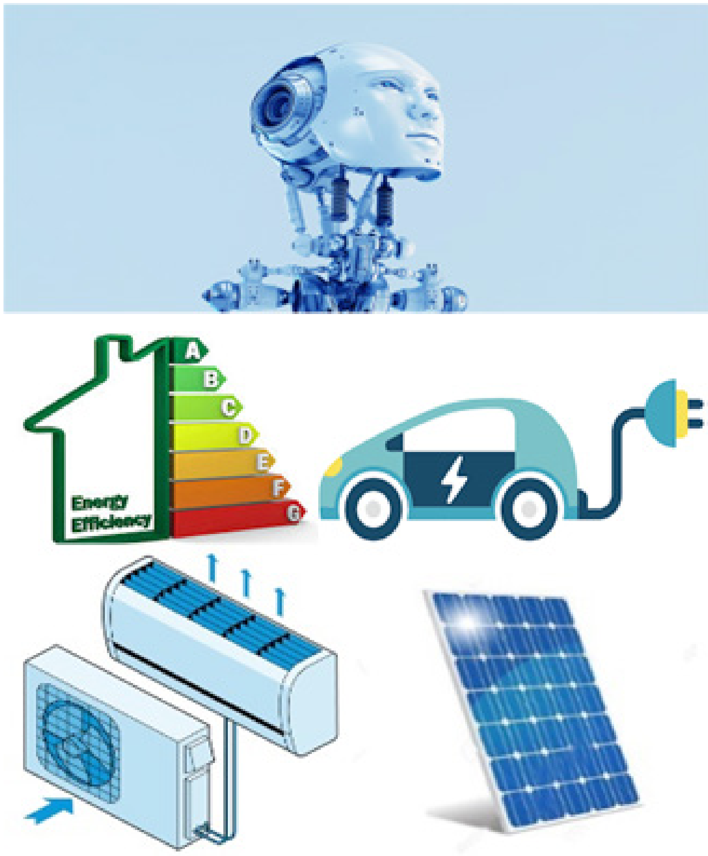

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End-User Scenarios and Their Impact on Distribution System Operators

A techno-economic analysis

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Förord

Projektet, som drivits av programmet Smarta Elnät, har analyserat problem för DSO:er i system där kunder styr sin förbrukning från samma prissignal. Förändringarna kan leda till högre nätdriftkostnader (energiförluster, effektabonnemang mot överliggande nät, etc.), lägre elkvalitet samt fler nätavbrott för DSO. Analyserna är utförda i en simuleringsmodell som tagits fram i tidigare forskningsprojekt. Simuleringsresultat baserat på verkliga användarfall visar att landsbygdsnäten är känsligt för underspänningsproblem i ett elektrifieringsscenario och tätortsnät är mer sårbart för överbelastning. Lastfaktorn tenderar att försämras i alla scenarier jämfört med basfallet, vilket är negativt då nätägarens intäkter har koppling till lastfaktorn. Kunder i landsbygdsnät bör energieffektivisera så att elnätet kan hantera en elbilsintegration. Kunder i tätortselnät bör öka elektrifieringen för att öka nätägarens intäktsströmmar.

Claes Sandels från RISE har varit projektledare för projektet och han har arbetat tillsammans med Joakim Widén från Uppsala Universitet. Stort tack också till referensgruppen, som på ett mycket givande sätt har bidragit till projektet:

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- Thomas Larsson, Sundsvall Elnät AB

Programmets Smarta Elnät programstyrelse, som initierat, följt upp och godkänt projektet, består av följande ledamöter:

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- Luleå Energi AB
- ABB AB
- Akademiska Hus
- NKT Cables AB
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- Trafikverket
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Susanne Olausson
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Sammanfattning

Syftet med den här rapporten är att uppskatta hur olika kundrelaterade scenarier (bl.a. solel, elbilar och lastflexibilitet) påverkar lokalnätsföretagens (DSO) verksamhet. Rapportens huvudmål är att: (i) presentera ett simuleringsramverk som gör det möjligt att genomföra kvantitativ analys av scenarierna, (ii) definiera möjliga framtidsscenarier samt nyckeltal som är beskrivande för DSO:s verksamhet, och (iii) redovisa simuleringsresultat från svenska tätorts- och landsbygdsnät i Herrljunga Elektriska AB:s elnät. Detta är rapportens huvudslutsatser:

1. Det är möjligt att simulera komplexa framtidsscenarier hos slutkunderna med simuleringsramverket. Simuleringarna kan replikeras för andra elnät och DSO:er om deras elnätdata formateras och matas in i ramverket på ett korrekt sätt. Modellerna är öppet tillgängliga via GitHub.
2. Simuleringsresultat från fallstudierna visar att landsbygdsnäten är känsliga för solelintegration. Tätortsnätet gynnas av vidare elektrifiering (elbilar etc.) eftersom DSO:ns intäkter från kunderna ökar, medan nätet är dimensionerat för den ökade förbrukningen. Om dock kunderna skaffar snabbladdning så kan överbelastningsproblem introduceras.

Elnäten håller på att transformeras från traditionella centraliserade system med storskaliga produktionsanläggningar som producerar el på höga spänningsnivåer, till decentraliserade system där slutkunderna på lågspänningsnivå producerar sin egen el och är aktiva i sin förbrukning. Dessa kundutvecklingar kan introducera nya risker och utmaningar för DSO på både en teknisk och ekonomisk nivå. Bland annat kan fler elbilsladdningar leda till större lasttoppar i nätet, egenproducerad solel innebär att DSO säljer mindre energi till kunderna samt att det kan bli spänningsproblem när solelproduktion sammanfaller med låg elefterfrågan.

Den här rapporten presenterar ett simuleringsramverk som gör det möjligt att analysera och utvärdera hur olika kundrelaterade scenarier påverkar den teknoekonomiska verksamheten för en DSO. Simuleringsramverket innefattar ett flertal aspekter när det kommer till kunderna och elnätet. Till att börja med så har en klustringalgoritm utvecklats som gör det möjligt att kategorisera slutkunder baserat på deras timvisa förbrukningsdata. Denna information matas in i en botten-upp simuleringsmodell som kan generera lastprofiler i småhus baserat på väder och slutanvändarbeteenden. Lastprofilerna innefattar förbrukning från apparater, varmvatten, uppvärmning, elbilar och solelproduktion. Modellen kan även ta hänsyn till lastflexibilitet hos elbilar och uppvärmningssystem baserat på elpriser. De simulerade lastprofilerna matas in i en elnätsmodell som matar ut spänningar, effektflöden och energiförluster på timnivå.

För att kunna genomföra simulering så har kund och elnätsdata samlats in för två olika lokalnät (tätort och landsbygd) i Herrljunga Elektriska AB:s elnät. Fyra huvudsakliga kundrelaterade scenarier, och tre kombinerade scenarier har identifierats i rapporten. Huvudscenarierna är:

- *Energieffektivisering*: Kunderna isolerar sina hus och köper energieffektiv apparatur (LED-belysning etc.)
- *Elektrifiering*. Kunderna köper elbilar och ersätter sina biopannor med värmepumpar
- *Småskalig produktion*. Kunderna sätter upp solel på sina tak
- *Digitalisering och flexibilitet*. Kunderna skaffar avancerade styrenheter till sina uppvärmningssystem och elbilar som kan kommunicera med elmarknaden. De skaffar även timpriskontrakt med sina elåterförsäljare

Vidare så har sex nyckeltal definierats som gör det möjligt att utvärdera scenariernas teknoekonomiska påverkan på DSO:er. Nyckeltalen innefattar daglig lastfaktor, spänningskvalitet, intäkter från kundtariffer och kostnader för regionalnättariff.

Simuleringsresultat för Herrljungas lokalnät visar att landsbygdsnäten är känsligt för underspänningsproblem i elektrifieringsscenariot, och tätortsnät är mer sårbart för överbelastning. Lastfaktorn tendererar att försämras i alla scenarier jämfört med basfallet. Detta är ett negativt utfall då DSO:ns intäkter delvis är kopplat till lastfaktorn. Slutligen ökar kundtariffintäkter i elektrifieringsscenarierna medan de minskar i solelscenarierna. Detta resultat är logiskt då den genomsnittliga förbrukningen ökar i det tidigare scenariot, och sjunker i det senare.

Det diskuterades att DSO:er med landsbygdsnät bör stödja sina kunder att energieffektivisera så att det befintliga nätet tekniskt kan hantera en framtida elbilsintegration på ett bättre sätt. En tätorts-DSO bör stimulera deras kunder till en utökad elektrifiering så att intäktsströmmarna ökar. Tätortsnäten är generellt överdimensionerade och klarar därmed en sådan utveckling utan att problem skapas. Det diskuteras även om vad som krävs av andra DSO att göra liknande analyser för deras elnät med simuleringsramverket (indata, kompetenser, etc.).

Summary

The purpose with this report is to assess how various changes at the customer premises related to new behaviors and technologies can impact the business of the Distribution System Operators (DSO). The main objectives are: (i) presenting a simulation model framework that makes it possible to conduct such analysis, (ii) define possible future customer pathways and key performance indicators to measure the impact on DSO:s, and (iii) present simulation results from both rural and urban distribution grid cases in Sweden. The key conclusions for the report are:

1. It is possible to simulate complex future scenarios with the simulation framework. In addition, the simulations can be replicated for other DSO:s in Sweden if their grid data is properly input to the model. The models are openly available through the software collaboration platform GitHub.
2. The simulations show that the rural grid is sensitive to voltage issues in the solar PV integration scenarios. The electrification scenario (electric vehicles) is beneficial for urban DSO as the revenue stream increases. However, fast charging can pose challenges with overload in the grid, and thus, drive grid investments requirements

The electric power systems are currently being transformed from the traditional centralized systems with large production facilities that produce bulk electricity at high voltage level, to a decentralized system where the customers are active in their consumption and have their own solar PV production. These developments are driven by increased electrification, digitalization and market liberalization. The customer developments can introduce new risks and challenges for the Distribution System Operator (DSO) at both a technical and economic level. Among other things the challenges entail more severe peak loads due to integration of electric vehicles, less sold kWh's to customers, and voltage issues with high PV production and low load during summer.

This report presents a simulation model framework that makes it possible to analyze and evaluate the impact of various customer-related scenarios on the techno-economic operation of DSOs. The model framework covers several customer and distribution grid aspects. First of all, a cluster algorithm is developed which can categorize customers based on their hourly load data. This information is input to a bottom-up simulation load model which can emulate load profiles in detached houses based on end-user behavior and weather situations. The load model includes electricity use from; appliances, domestic hot water, space heating, electric vehicles, and also production from local PV installations. With the model it is also possible to simulate load flexibility from space heating and electric vehicles with respect to variation in electricity prices. The load profiles are input to a low voltage grid model which outputs voltages and power flows at an hourly time resolution.

Customer and grid-related data from one rural and one urban low voltage grid in Herrljunga Elektriska's distribution grid are used as input for simulation studies. Four main scenarios which are believed to be possible pathways for the future

distribution grids in Sweden are proposed in the report. In addition, three combinations of these scenarios are also considered for simulations. The main scenarios are:

- Energy efficiency. Customers are improving the isolation of their homes, and are buying energy-efficient appliances
- Electrification. The customers buy electric vehicles and are replacing bio fueled boilers with heat pumps
- Small scale production. Customers install PV units on their roof tops
- Digitalization and flexibility: The customers are procuring advanced controllers to their space heating and electric vehicle loads, and have hourly pricing contracts with their retailers

Further, six Key Performance Indicators (KPI:s) are defined to evaluate the scenarios' techno-economic impact on the DSO business. The KPI:s include daily load factor, frequencies of under or over voltage levels, customer tariff incomes, and regional tariff costs.

The results from the simulations show that the rural grid is sensitive to under-voltage problems in the electrification scenarios (i.e., more heat pumps and EV:s), and the urban grid is more prone to overloading issues. In all scenarios, the load factor tends to decrease as compared to the base case. This is a negative for the DSO as their revenue is dependent on the load factor. Lastly, the income from customer tariffs increased in the electrification scenarios, and decreased in the PV scenarios, which is logical as the former increases the average consumption, and the latter decreases the consumption.

It is discussed that a DSO with rural grids should promote their customers to lower their electricity-use so that the existing grid can better cope with an anticipated EV integration. An urban DSO:s should stimulate an increased electrification of their customers as their revenue goes up, while the grid can handle it technically due to extra grid capacity. It is also argued that the model framework can be used by other DSO:s to assess the techno-economic impact of the scenarios in their distribution grid.

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1 Introduction

The electric power systems are currently being transformed through the integration of intermittent renewable energy resources and new types of electric loads at customer premises. Increased digitalization of the society and economy by integrating solutions for smart homes and smart meters, make it technically possible for end-users to be flexible in their electricity usage. These developments realizes the potential for end-user loads (e.g. space heating (SH), dishwashers, electric vehicles) to communicate with the electricity market and be controlled in an automatic and intelligent fashion, which can result in cost savings while maintaining indoor comfort. Today, end-users have the possibility to take advantage of hourly price variations on the electricity market. And due to the fact that the share of intermittent weather-dependent power generation (mostly in the form of wind power) has increased in Sweden recent years, the requisite for demand response (DR) is foreseen to increase in the near term future. Increased mismatch between supply and demand will result in a higher price variation (e.g., occasionally very low or negative prices, which has happened in Denmark (1)), which may provide additional economic incentives for end-users to move electricity usage between hours of the day. However, note these prices are not yet exposed to the end-customers. There are other markets where DR could offer value as well, e.g. the balancing markets. However, the current balancing markets are not designed for receiving control power from a large number of small end-users. It is possible that future market designs will offer such opportunities.

If the loads at the end user premises will be controlled based on the price signals from the energy markets, the consumption patterns of the individual customers will coincide in time to a larger extent, and, thus, create more severe peak loads in the local distribution grids. This will have a negative effect on the business of Distribution System Operators (DSOs) as their distribution grids have power flow constraints related to overload of components and acceptable voltage levels (will drive grid investment needs and thus costs). The situation will get extra troublesome for the DSO if new load categories are introduced at the customer sites, such as heat pumps (HP), electric vehicles (EV), and stationary batteries. This is because these load categories will increase the average load level of the distribution grid or create new peak loads. These kinds of developments (smart homes, new load categories, and DR) may occur faster than the investment speed and expansion of the distribution grid.

Because of these likely developments it is important to make scenario analyses related to changes of the end-users driven by, among other things, new technologies, customer behaviors, business, and market models. Such analyses will increase the awareness and knowledge for DSOs how these developments impact their business and responsibility to ensure electricity deliveries. This understanding makes it possible for DSOs to be proactive in their risk management of the grid operation, and identify feasible solutions for the future problems that might appear. The possible solutions could be either technical (energy storage) or economic (power tariffs), or combinations thereof.

1.1 AIM OF THE REPORT

The aim of the report is to analyze how various scenarios at the customer premises change their load profiles, and, consequently, how this affects the business of a DSO.

Given the aforementioned background and aim, the three following goals can be concretized:

1. Present validated simulation models that can be used by DSOs to assess the impact of DR and new loads on their business and operation (both technical and economic).
2. Describe plausible scenarios regarding future electricity usage. In addition to this, a number of Key Performance Indicators (KPI:s) that are useful to assess the business of DSO are defined.
3. Present simulation results for a case study, which is representative for a typical Swedish distribution grid. The simulation results are produced based on data collected from the case study.

1.2 DELIMITATIONS

In order to make a focused analysis, proper delimitations need to be introduced. In the report, the following assumptions and delimitations have been made:

- The report will not cover aspects related to specific technologies used in the buildings for realizing the flexibility, such as standards and information models for smart homes, communication protocols used for DR, etc.
- Network tariffs for solving distribution grid related issues will not be simulated. However, tariffs will be discussed in qualitative terms in the discussion section.
- All analyses are performed on the distribution network of Herrljunga Elektriska AB. Although it is unclear how representative this network is for other grids in Sweden or elsewhere, it was chosen because of the availability of hourly meter data for a large number of customers.

1.3 OUTLINE OF THE REPORT

The report is structured as follows. In chapter 2, the modeling framework for analyzing the impact changes at the customer premises have on the DSO business is presented. The used case study for validating and showing the usability of the modeling framework is described in chapter 3. In this section, the anticipated end-user scenarios and the KPI:s used for assessing the simulation results are also presented. Chapter c) presents the model results, together with the model validation, and the scenarios' impact on the various KPI:s. Chapter 5 contains discussions and conclusions of the results.

2 Model framework description

In this section, the model framework that is used to simulate various end-user scenarios and their effect on the DSO business is presented. The framework consists of several modules, focusing on different aspects of the end-users and the power grid. We start by presenting an overview of the model, and then explaining the functioning of each module. Note, more elaborate description of the modules (including the mathematics, etc.) can be found in the Appendix section.

2.1 OVERVIEW OF THE MODEL FRAMEWORK

In Figure 1, a flowchart of the module interactions can be seen. The flowchart starts from the cloud symbol which is an abstract representation of all the customers in the electric grid being analyzed. Here, hourly load data from the customer smart meters are collected, and are represented by the data symbol. This data is input to a clustering algorithm which sorts the customers in different categories based on their load patterns. The cluster data reveals important characteristics of the end-users which are used as important input to the bottom up buildings simulation model. With this model, load data at a high time resolution (down to one minute time resolution) at appliance level can be generated per building. The model is based on a combined physical and behavioral approach. The load model interacts with a flexibility model which manipulates set point values of e.g. heating systems due to electricity price variation. Thus, the flexibility module will change the load patterns based on the comfort constraints and the price sensitivity of the end-users. The simulated load profiles are then input to a load flow model that computes power flows, voltages and power losses in the modelled electricity grid. This data is used to estimate various KPIs that are relevant for the business of DSOs, which is the main result from the simulation framework. Note, the scenario box to the left represents the possibility to alter various parameters values of some modules to reflect future conditions of end-users, i.e. load category setup, flexibility and small-scale production. Each module is described in more detail in the upcoming subsections.

Some further clarifications of the different terms are listed below:

- The term electricity grids are referred to as distribution grids at either a medium voltage level (10 to 20 kV) or a low voltage level (400 V).
- The future scenarios include developments in the buildings stock, such as heating solutions, the number of electric vehicles, and the share of flexible end-users. It also includes potential small scale electricity production in the form of solar photovoltaics (PV).
- Detached houses are the building types that are included in the simulations. This will include models for appliance usage, domestic hot water, and space heating. Note, models for office buildings and multi-family buildings are available as well, and can be used in future work.
- The end-user behavior is simulated with non-homogenous Markov chains, and the thermodynamics buildings are modelled with a lumped capacitance methodology.

- The price signals that are used for DR comes from the wholesale market Nord Pool spot. These price signals will not necessarily reflect the load level situation in the local distribution grid.
- PV production on rooftops and electric vehicles are included in the model to reflect future end-user scenarios.

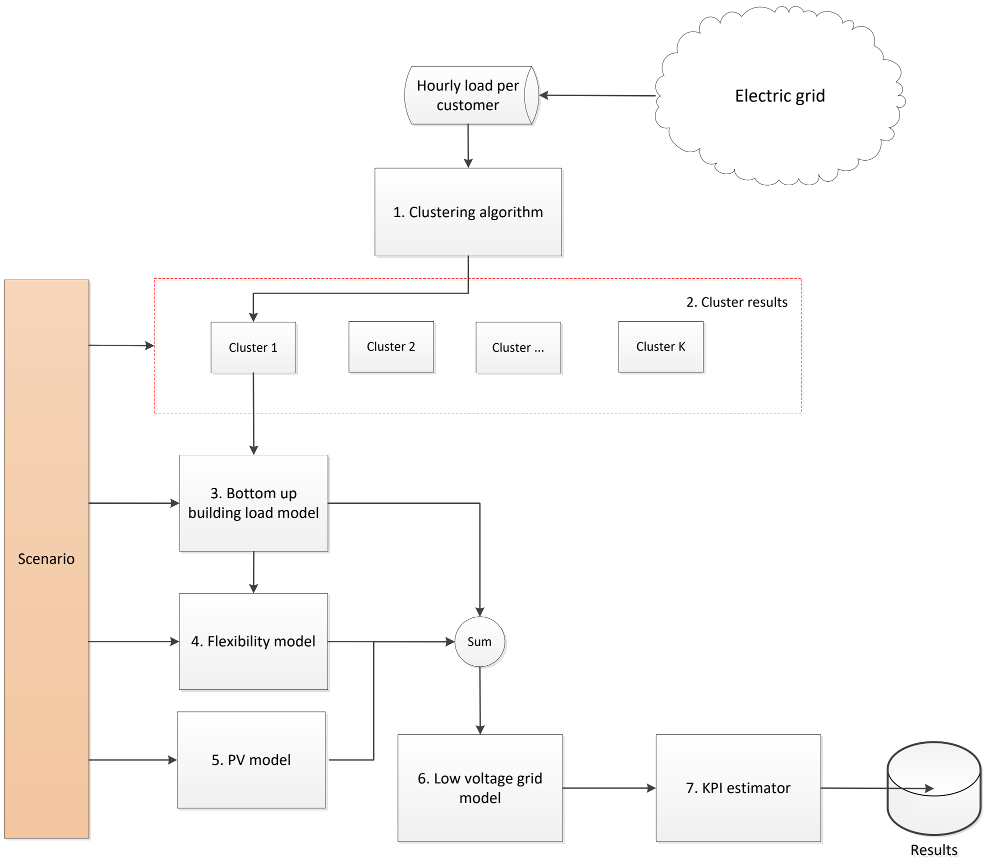

Figure 1: An overview of the model framework

2.2 CLUSTER ALGORITHM

The main purpose of the clustering algorithm is to be able to input hourly load data from all customers in a distribution network, and get the category for each customer. These insights are then used for setting the parameter values in the bottom up simulation model in the upcoming step.

The structure and method of the clustering algorithm are described in this section. The method is composed by a number of steps, namely: (i) data processing and cleaning, (ii) data transformation, and (iii) data clustering.

2.3 BOTTOM-UP BUILDING LOAD MODEL

The bottom-up building load model consists of three separate modules: (i) end-user behavior, (ii) appliance and hot water usage which are mainly driven by behavior, and (iii) HVAC system load which is primarily driven by weather dynamics and building properties. The model is also extended with electric vehicle usage and charging, along with PV generation. These two models can be used to reflect futures where the transportation sector is electrified and small scale local production at home is more common.

Moreover, with these models it is possible to simulate load profiles at a load level for a single occupant, a group of individuals in a building (e.g., a household) and an aggregation of buildings. Each individual has a stochastic occupancy behavior which will in turn correlate with an energy-use of appliances and Domestic Hot Water (DHW), along with the need to heat, cool and ventilate the building. At the bottom of the diagram, the electric vehicle and PV modules can be seen. The EV module inputs activity data from the behavioral module along with EV load parameters, e.g. driving patterns and charging pole capacity. The PV module inputs solar irradiance data and building data, such as roof top areas.

2.4 FLEXIBILITY MODELS

Two types of flexible controllers are implemented, one for thermostatically controlled loads (SH and DHW) and one for the EV charging. For thermostatically controlled loads an indoor temperature comfort interval along with price sensitivity parameters constitutes the flexible controller. The controller relates an electricity price with an allowed comfort and the price parameters specified by the end-users, and then compute a new temperature set-point for the controller to work against a higher or lower price

The flexible rule based controller for EV:s works in the same fashion as the thermostatically controller loads, except for some minor differences. In essence, the flexibility of the charging of EV:s is determined by a minimum State of Charge (SOC) level of the battery (SOC_{min}) which is specified by the end user. The SOC_{min} explains how much of the battery that is subject to flexible charging, i.e. charging that can be postponed to a later point in time.

2.5 LOW VOLTAGE GRID MODEL

Low-voltage grids are modeled as balanced three-phase networks, where all lines have constant impedance (resistance and reactance) and the secondary substation is used as slack bus. Active and reactive power for loads and generators can be defined for each bus of the grid, and the voltage in all buses and the current in all lines are calculated using three-phase balanced load flow, solved with Newton’s method (12)

2.6 KEY PERFORMANCE INDICATORS (KPI)

In this section, the KPI:s which are used to analyze how the DSO is affected by end-user scenarios are presented. The KPI:s are of technical and economical types. These set of KPI:s have been chosen to capture a wide range of DSO business and operation related issues, meanwhile making the KPI list as simple and straightforward as possible.

2.6.1 Technical KPI:s

Three technical KPI:s are defined below.

KPI1a – Average daily load factor

The average daily load factor is the average of 365 load factors, one for each day. It is defined as

$$LF = \frac{1}{365}\sum_{d=1}^{365}\frac{L_{\mathrm{mean}}(d)}{L_{\max}(d)}$$

where L_{mean} is the average daily load and $L_{\max}$ is the daily peak load.

Data requirements: The load data is hourly energy use averages collected for at least a full year for the customer base within the system boundary, e.g. low voltage grid.

KPI1b – Average yearly load factor

Definition: The load factor is defined as the ratio of the average load and maximum hourly load over the year. The load data is collected for the electric power system of interest, e.g. the low voltage grid under a secondary substation which serves 20 detached houses with electricity.

KPI2a: probability of undervoltage

The operational performance of the grid in terms of voltage is described by the probability for undervoltage, calculated over all customers and all hours of the year:

$$P(V < 0.95V_{\mathrm{nom}}) = \frac{\sum_{i=1}^{N}\sum_{t=1}^{8760} n_{V_{i,t}<0.95V_{\mathrm{nom}}}}{8760N}$$

where V_{nom} is the nominal voltage (400 V in the low-voltage networks), N is the number of customers, and $n_{V_{i,t}<0.95V_{\mathrm{nom}}}$ indicates whether the voltage dip at customer i is below 5% of the nominal voltage at hour t:

$$n_{V_{i,t}<0.95V_{\mathrm{nom}}} = \begin{cases} 1 & \text{if } V_{i,t} < 0.95V_{\mathrm{nom}} \\ 0 & \text{otherwise} \end{cases}$$

Data requirements: hourly voltage values per bus j for a whole year, along with the nominal voltage value.

KPI2b: probability of overvoltage

Analogously, the probability for overvoltage is calculated as

$$P(V > 1.05V_{\mathrm{nom}}) = \frac{\sum_{i=1}^{N}\sum_{t=1}^{8760} n_{V_{i,t}>1.05V_{\mathrm{nom}}}}{8760N}$$

KPI3 – Power system component overloading

Probabilities for overloading of cables are defined similarly to the probabilities for under- and overvoltage above:

$$P(I > I_{\max}) = \frac{\sum_{i=1}^{N} \sum_{t=1}^{8760} n_{I_{i,t} > I_{\max,i}}}{8760N}$$

with *N* here denoting number of cables $I_{i,t}$ and $I_{\max,i}$ are, respectively, current at hour *t* for cable *i* and maximum line current rating of cable *i*. The probability for overloading of secondary substation transformers is likewise defined as:

$$P(S > S_{\max}) = \frac{\sum_{t=1}^{8760} n_{S_t > S_{\max}}}{8760}$$

where S_t and $S_{\max}$ are apparent power flow through the transformer at hour *t*, and rated capacity of the transformer, respectively.

Data requirements: power system component data (maximum capacities for transformers, lines, cables), and hourly power flow data for a full year.

2.6.2 Economic KPI:s

Three economic KPI:s are proposed below.

KPI4 – The monthly tariff income per customer (energy vs. power tariffs).

Definition: the monthly income for the customers within the defined system boundary, which include: (i) the number of transmitted kWhs to the customers for the whole month, and (ii) the average of the two highest hourly peak loads per customer and month.

Data requirements: hourly load data from the customers for a whole year, and customer tariff design,

KPI5 – Monthly expenditures from regional network tariffs [SEK/month]

Definition: the monthly expenditures for imported energy from the overlaying regional network to the defined system boundary. This includes: (i) the number of imported kWhs to the customers for the whole month, and (ii) the average of the two monthly highest hourly peak loads for the network. Assume relative contribution

Data requirements: hourly load data from the customers for a whole year, and a regional tariff design,

KPI6 – Capital cost on network expansion [SEK/month]

The capital cost of network expansion is calculated as an annuity

$$A = C_0 \frac{p}{1 - (1 + p)^{-n}}$$

where p is the interest rate, n is the investment period, and C_0 is the investment cost for network reinforcement, calculated as

$$C_0 = C_c L_c + C_s P_s$$

where C_c is the cable cost in SEK/km and L_c is the cable length, and C_s is the cost of replacement of a substation in SEK/kVA for a substation with required capacity P_s. This cost is set by exceeding the capacity limit of the component once at a yearly basis.

Data requirements: Cost for transformer replacements, interest cost and normal amortization plans for such investments, pay back times in years.

3 Use case description

3.1 HIGH LEVEL DESCRIPTION OF HERRLJUNGA MUNICIPALITY

The distribution grids that are used for model validation and scenario simulations are collected from Herrljunga, Sweden. Herrljunga distribution grid is operated by Herrljunga Elektriska AB (13), and serves Herrljunga municipality with electricity and district heating. They also serve parts of Vårgårda and Vara municipalities with electricity as well. However, we only focus on Herrljunga municipality in this chapter.

Below, high level information about the municipality, its population, and the distribution grid are listed. This description is included to give an overall understanding of the case, and to be able to understand how this case s relates and can be transferable to other municipalities and distribution grids in Sweden. The case study contains the topics of geography, demography/socioeconomics, heating, electric demand, distribution grid, energy production, and ICT infrastructure.

Geography

Herrljunga municipality has a total land area of 500 km^2, and is located in the Västra Götaland region, around 80 km northeast of Gothenburg. The total population is 9,486 people, which gives a land area of 0.05 km^2 per person. 60% of the population lives in urban areas, and the rest in rural areas.

The average outdoor temperature and yearly rainfall for the municipality for the time period of 1960 to 1990 can be seen in the figure below. The weather data is compared to other cities scattered over Sweden, i.e., Luleå, Östersund, Stockholm, Kalmar and Malmö. As seen in the figure, the outdoor temperature is a little above average in Herrljunga in comparison to the average temperature. The rainfall is the highest in Herrljunga, and it can thus be argued that it is generally cloudier in this geographic area than in other areas. This will impact the PV electricity production.

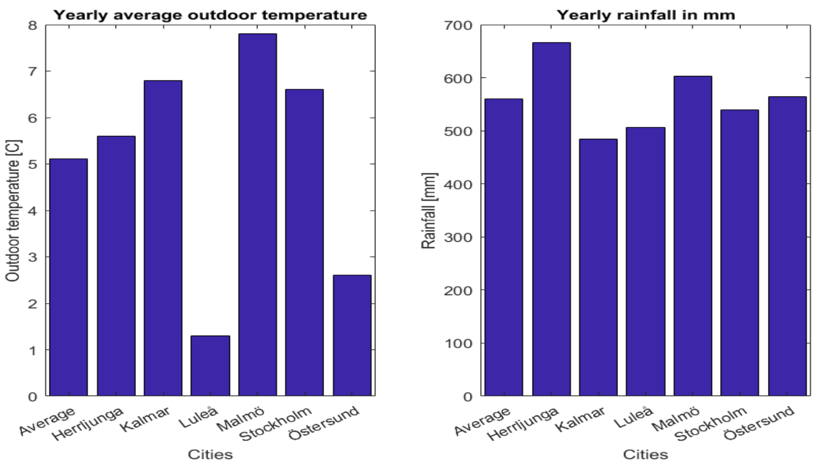

Figure 2: The left bar plot shows the average outdoor temperature for the different cities. The right bar plot shows the yearly rainfall for the cities. The average for all cities is also added as a reference.

Space heating

Herrljunga has a district heating network that supplies around 300 customers with heating. These customers are mainly living in multifamily buildings in the city area. But, it is more common that the houses are equipped with their own heating units. In Figure 3, the distribution of used heating solutions among 100 out of Herrljunga Elektriska's 5,000 customers is shown. Note, this sample is not necessarily representative for the actual heating solution distribution in Herrljunga. As seen in the figure, around 50 % of the customers have a heat pump installed, either in the form of an air-air heat pump (HP-air) or a ground source heat pump (HP-ground). Another predominant heating solution is bio fueled boilers, with around 30% market share. Only about three percent of the customers are using direct electric heating (El) for heating. Further, some customers are using a combination of bio fueled boilers and heat pumps (Bio-HP).

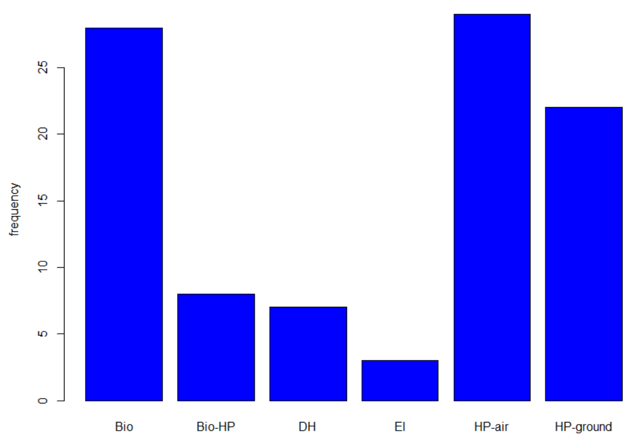

Figure 3: The heating solution distribution among the Herrljunga Elektriska AB:s customers.

Electric demand

There are 5,246 low voltage customers, which had an aggregated yearly electricity use of 78 GWh, i.e. in average 14,000 kWh per customer. In addition, there are five customers connected to the medium 10 kV voltage network with a total usage of 21 GWh. The total subscribed power among the customer is 22 MW (i.e., approximately 4 kW/customer).

Demography and socioeconomic factors

The demography distributions for Sweden and Herrljunga are shown in Figure 4. The distributions are divided between men and women. A quick ocular assessment says that Herrljunga has more people in the 60 to 70 age span and less people in the 20 to 30 age span as compared to the national average. This means that there are more retired people, which will imply less home/work behavior, e.g. higher electricity consumption during the day.

In the table below, some key socioeconomic figures are listed for Herrljunga municipality along with national Swedish averages, e.g., median income, percentage of highly educated people, etc. As seen, Herrljunga is a small municipality when looking at the national average. The income is slightly lower, so the purchase power should be less in Herrljunga. Also the ratio of highly educated people (defined as three years of education after high school) is lower than the average.

Table 1: The table shows socioeconomic data about Herrljunga and average Swedish municipality. All data is taken from ekonomifakta.se.

Socioeconomic factor	Herrljunga	Average Swedish municipality
Number of inhabitants	9,486 people	34,466 people
Average age	43.3 years	41.2 years
Median income	248,413 SEK/year	261,038 SEK/year
Ratio of highly educated people	14.6%	26.6%
Unemployment rate	4.4%	7.6%

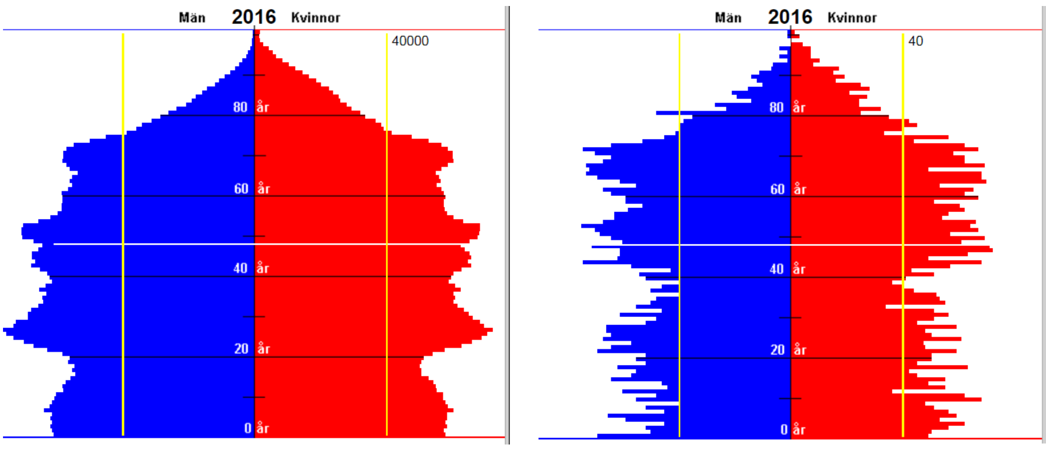

Figure 4: The age distribution divided between men (blue bars) and women (red bars). The left plot is the distribution for Sweden, and the right plot is for Herrljunga municipality.

Distribution network

There are 335 substations in the distribution network (0.064 substations per customer), with a total power capacity of 48 MW. The total length of cables and overhead lines is 876 km, where the cable to overhead line ratio is 6.82, i.e. nearly seven times more cable than overhead lines. The medium voltage level is 10 kV, and low voltage network is 400 V. The network is fed from the regional network at a voltage level of 10 kV. The average downtime of the grid (SAIDI) is 10 minutes in 2017.

Electricity production mix

There are 39 small-scale production units that are connected to the low voltage network, with individual energy metering. There are no high voltage production units. It is not specified what type of production units that are connected, but, it is most likely solar PVs. The total yearly production from these units is 1700 MWh.

ICT infrastructure

Since 2009 every customer in the distribution grid has smart meters with hourly metering. 60-65% of all households have fiber with a speed of 100 Mbit/s or more. No household in Herrljunga municipality is without a broadband connection. This implies that Herrljunga has well-established and developed communication infrastructure. In October of 2015, 67% of all Swedish households had access to a 100 Mbit/s broadband network (15).

3.2 TEST NETWORK 1: RURAL GRID

The first test network is a rural low-voltage grid. This grid supplies 18 customers, both agricultural customers and single-family buildings. It is fed from a 100 kVA secondary substation and contains a total of 3.4 km of cables.

3.3 TEST NETWORK 2: URBAN GRID

Figure 1 shows a map of the second test network, a suburban, a denser grid with 97 customers distributed over a smaller area than the first test network. It consists of 6.8 km of cable, connecting mainly single-family buildings with a 1000 kVA secondary substation.

Figure 5: A map of the urban grid that shows the customers, property borders and medium voltage substation

3.4 INPUT DATA DESCRIPTION

The required input that have been collected to run simulations for Herrljunga are summarized in the table below.

Table 2: The data sets that are used for the simulations

Dataset description	Time resolution	Geographic area	Data source
Household behavior in detached houses: Markov matrices based on TUD from a larger SCB study in 1996	1 min	Sweden	SCB (5)
Outdoor temperature for 2015[°C]	1 h	Hallum, Sweden	SMHI
Global solar radiation for 2015 [W/m²]	1 h	Gothenburg, Sweden	SMHI
Day-ahead electricity prices from Nord Pool for 2015	1 h	SE3, Sweden	Nord Pool
Hourly electricity consumption for every customer in the Herrljunga Elektriska AB network for 2015	1 h	Herrljunga, Sweden	Herrljunga Elektriska AB
Distribution grid data (network topology, cable, line, and substation capacities, etc.) for the two test grids	NA	Herrljunga, Sweden	Herrljunga Elektriska AB
Customer survey data for 100 customers which include information about their house, heating solution, and behavior	NA	Herrljunga, Sweden	Own survey

3.5 FUTURE SCENARIO DEVELOPMENTS FOR SWEDISH END-USERS

In this section, the scenario methodology will be introduced. Energy system related scenarios from the literature are described, which is followed by the scenarios that are proposed in this report.

Scenarios are visions of possible futures or aspects of possible futures. Scenarios are not predictions about the future but rather simulations of possible futures. They are used both as an exploratory method or a tool for decision-making, mainly to highlight the discontinuities from the present and to highlight the available options and their potential consequences. One of the purposes and uses of scenarios is to help decision-makers acquire knowledge and understanding to anticipate the context in which they have to act (5).

3.5.1 Proposed scenarios in the literature

Numerous reports have been made that sketch different potential futures and pathways for the Swedish energy systems. In the report (14) published by the Swedish Energy Agency, four scenarios for energy system developments beyond the year 2020 have been visualized:

1. **FORTE** (strong): In this scenario energy is the main driver for growth and progress in the economy. The focus is to have low and stable energy prices for the transport sector and industry. This scenario is close to the AS-IS situation, i.e. business as usual where large centralized production units at high voltage levels will serve the passive customer at the distribution grid level

2. **LEGATO** (interconnected): Energy is seen as a scarce resource on a global level. An important value is to have a sustainable and fair distribution of energy resource globally. In this scenario, energy efficiency and conversion is the key-words that drive the developments of the energy system
3. **ESSPRESSIVO** (expressive): Energy is a way to express your values and standpoints, etc. The energy consumer is more active in their choices of procured energy services, market participation and integration of small-scale energy production. In this scenario, the policy makers facilities a shift to a decentralized energy system, where the end-user can be engaged on the market with their flexibility and energy production.
4. **VIVACE** (vivacious): Energy is the tool for growth, but only on the terms of the climate. Sweden wants to be global forerunner of solutions and innovation in the domain of sustainable energy systems. This scenario is out of scope for this report as it only covers political orientations of the economy, and not end-user developments

Moreover, in the smart grid forum report (15) also four scenarios are presented for the Swedish energy systems to the year 2030. The scenarios are divided in two main categories and are related to the EU 2030 goals; (i) slow integration of intermittent energy production (A and C scenario), and (ii) fast integration of intermittent energy production (B and D scenario). More information about the respective scenarios is found below:

1. **Scenario A**: this is their base case scenario with increased electrification and assumptions that today's goals with renewable integration are unchanged. Investments in nuclear technologies are allowed in Europe. This scenario is similar to the FORTE scenario above.
2. **Scenario B**: this scenario is characterized by large investments in renewable energy in Europe, which is driven by the European Union. No new nuclear investments are allowed. Already established nuclear power plants are allowed to operate, although no new investments and retrofits are permitted for these. This scenario reflects a high share of renewable and intermittent energy production in Europe. Additionally, it is assumed that the share of small scale production increases, and demand response is integrated on the market.
3. **Scenario C**: this scenario is about expanding the renewable energy supply and increase the energy efficiency in the EU by, among other things, electrifying the industry, transport and heating sectors. In this scenario it is also assumed that the European markets are more integrated
4. **Scenario D**: this scenario combines developments in energy efficiency, renewable energy supply, and electrification, and can be seen as some kind of extreme scenario.

Note, the scenarios described above focuses on the high level developments and trends of electricity systems, and does not address scenarios that have specific effect on the distribution grids, i.e., a top down approach has been used.

3.5.2 Our scenarios

Our scenarios are based on the abovementioned references but have been tailored for the need and scope of this report. Four main scenario developments have been outlined from the reviewed reports: (1) energy efficiency, (2) electrification, (3) small scale PV production, and (4) digitalization and flexibility. Each of these scenarios is further described in their own subsection below.

Two types of calculations will be performed for each scenario; a realistic scenario and an extreme scenario. The realistic scenario will take in parameter value changes that are more conservative, and perhaps more likely in the short to mid future (up to five years). The extreme scenarios will encompass more extreme parameter changes, which may not be as probable but is still interesting as it reflects an extreme scenario, and, thus, the theoretical upper margin for the DSO to cope with. For example, a short term scenario could be that 50 % of the customers in a test grid buy an EV, and setup a slow charger at home (< 3 kW). An extreme scenario on longer term (e.g., ten years) could be that all customers have an EV, where the house is equipped with a fast charge (11 kW). Each scenario is defined with a realistic and an extreme parameter setup, respectively.

3.5.3 Energy efficiency

This scenario looks upon energy efficiencies pathways for the building isolation and the appliances used in the houses. The building could be built according to passive house requirements (i.e. very proper isolation), and the COP factor of the heat pumps could have been improved further.

Model parameters affected by scenario:

- Lambda, i.e. building isolation per building
- Coefficient of Performance (COP) factor of heat pump unit in the building with HPs.
- Scale factors on appliance use and DHW usage [%]

Realistic scenario

Lambda is set to 80 % of the original value reflecting that some simple isolation actions have been performed, such as installation of three-pane windows.

The HP technology is more efficient with a COP of 3 (Base case value is 2).

Extreme scenario

Lambda is set to 50 % of the original value. More advance isolation actions have been performed, and the house is very energy efficient. The HP technology is very efficient with a COP of 4.5.

3.5.4 Electrification

In this scenario, the customers have district heating or bio fueled boilers change to electric heating, mainly in the form of heat pumps. This scenario also constitutes the possibility for house owners to buy electric vehicles. This scenario looks upon a scenario where electricity is an energy carrier that is promoted by policy makers as cheap and abundant renewable electricity is available at a national scale due to, among other things, wind power expansion.

Model parameters affected by scenario:

- Number of heat pumps in the use case grid
- Number of electric vehicles in the use case grid, vehicle usage, the battery capacity, and the charging capacity (slow charging, or fast charging)

Realistic scenario

All buildings have a HP.

All buildings have an EV with a home charger of 3 kW, and a battery of 10 kWh of storage capacity

Extreme scenario

All buildings have a HP

All buildings have an EV with a home charger of 11 kW, and a battery of 20 kWh of storage capacity.

3.5.5 Small scale PV production

Here, the integration of solar PV production on building rooftops is promoted by policy makers through, among other thing, cost subvention of the PV panel and favorable taxation of self-consumption PV electricity or selling back PV production and get remuneration from DSO. This scenario opens up the development of more end-users setting up PV panels on their rooftops. Model parameters affected by scenario: Number and size of PV installations in the use case grid

Realistic scenario

All customers get PV panels with a capacity of 5 kW. These are normal-sized PV installation today on rooftops of detached houses in Sweden.

Extreme scenario

All customers get PV panels with a capacity of 10 kW. This scenario reflects a scenario where PV technology has decreased further in price, and it is rational to invest in larger PV installations.

3.5.6 Digitalization and flexibility

Due to a large scale integration of renewable energy production, the need for demand response is increasing on the electricity market. Additionally, the advancement of the ICT equipment, including high performant computing devices and communication, the technical platforms for realizing the demand response actions at appliance level is evolving. This combination makes is possible to use the demand flexibility from different appliances at the houses, which to some consumes electricity based on hourly electricity prices from the market.

- Number of flexible customers. Price sensitivity values of thermally controlled loads and electric vehicles.

Realistic scenario

All buildings with heat pumps have a load flexibility with the comfort range of +- 2 C for space heating, and +- 5 C for DHW.

Extreme scenario

All buildings with heat pumps have a load flexibility with the comfort range of +- 5 °C for space heating, and +- 15 °C for DHW.

3.5.7 Scenario combinations

The following scenario combinations will be simulated both for the realistic and extreme scenario types:

a) Small scale PV production + electrification

b) Small scale PV production + electrification + digitalization and flexibility

c) Small scale PV production + energy efficiency

These scenario combinations have been chosen in order to analyze a situation where the customers have a net energy surplus in the summer (high production and low load) and a high net energy deficit in the winter (low production and high load).

3.6 SCENARIO SUMMARY

The scenarios that will be simulated and analyzed for the rural and urban low voltage grids are summarized in the table below.

	Rural grid		**Urban grid**	
Base case (BC)	18 customers , 8 heat pumps (COP is 2), 0 PVs and EVs,		97 customers , 59 heat pumps (COP is 2), 0 PVs and EVs	
Scenario	**Realistic**	**Extreme**	**Realistic**	**Extreme**
Energy efficiency	8 heat pumps, COP is 3, isolation is 20% better than BC	8 heat pumps, COP is 4,5, isolation is 50% better than BC	59 heat pumps, COP is 3, isolation is 20% better than BC	59 heat pumps, COP is 4,5, isolation is 50% better than BC
Electrification	18 heat pumps, 18 EV with 3 kW chargers	18 heat pumps, 18 EV with 11 kW chargers	97 heat pumps, 97 EV with 3 kW chargers	97 heat pumps, 97 EV with 3 kW chargers

Small scale production	8 heat pumps, 18 PV panels of 5 kW	8 heat pumps, 18 PV panels of 10 kW	59 heat pumps and 97 PV panels of 5 kW	59 heat pumps and 97 PV panels of 10 kW
Flexibility	8 heat pumps, space heating and DHW flexibility of 1 and 5 C	8 heat pumps, space heating and DHW flexibility of 5 and 15 C	59 heat pumps, space heating and DHW flexibility of 1 and 5 C	59 heat pumps, space heating and DHW flexibility of 5 and 15 C
Small scale PV production + electrification	18 heat pumps, 18 EVs with 3 kW chargers and 18 PV with 5 kW	18 heat pumps, 18 EVs with11 kW chargers and 18 PV with 10 kW	59 heat pumps, 59 EVs with 3 kW chargers and 59 PV with 5 kW	18 heat pumps, 18 EV with 11 kW chargers and 59 PV with 10 kW
Small scale PV production + electrification + digitalization and flexibility	Same as above, but with space heating and DHW flexibility of 1 and 5 C, respectively and EV charging flexibility minSOC of 85%	Same as above, but with space heating and DHW flexibility of 5 and 15 C, respectively and EV charging flexibility minSOC of 70%	Same as above, but with space heating and DHW flexibility of 1 and 5 C, respectively and EV charging flexibility minSOC of 85%	Same as above, but with space heating and DHW flexibility of 5 and 15 C, respectively and EV charging flexibility minSOC of 70%
Small scale PV production + energy efficiency	8 heat pumps, COP is 3, isolation is 20% better than BC and 18 PV with 5 kW	8 heat pumps, COP is 4.5, isolation is 50% better than BC and 18 PV with 10 kW	59 heat pumps, COP is 3, isolation is 20% better than BC and 59 PV with 5 kW	59 heat pumps, COP is 4.5, isolation is 50% better than BC and 97 PV with 10 kW

4 Results and analysis

The results and analysis section is split in three section, viz. base case simulation, scenario simulations and KPI analysis. The results are presented with respect to test grid case, i.e. rural grid and urban grid, respectively. Note, the rural grid results will be described in more detail, and the urban grid more briefly. This is because the first case will include explanations of the content and meaning of the results that can be used to understand the simulation results of the urban test grid.

4.1 MODEL VALIDATION AND ASSESSMENT

In this section, results and analysis for the rural test grid simulations are presented. The simulation results are compared against measured data for validity. The results are split between cluster and bottom-up load model validation.

4.1.1 Cluster algorithm

Preliminary data analysis has been performed on the hourly load data collected for each customer in the rural test network. As stated in the method section, the data needs to be processed and cleaned before it is input to the cluster algorithm by, e.g. handle missing data observations. Some of the customers have single missing values which easily could be recovered through linear interpolation. However, for two of the customers interpolation was not possible and they were excluded from further analysis.

In the figure below, the hourly consumption for the whole year is displayed for each customer, respectively. As seen, most of the customers show a typical seasonal variation in their consumption, which is most likely linked to some electric heating source. However, customers 2 and 6 have very sporadic usages which indicate that these buildings are not used as permanent residences.

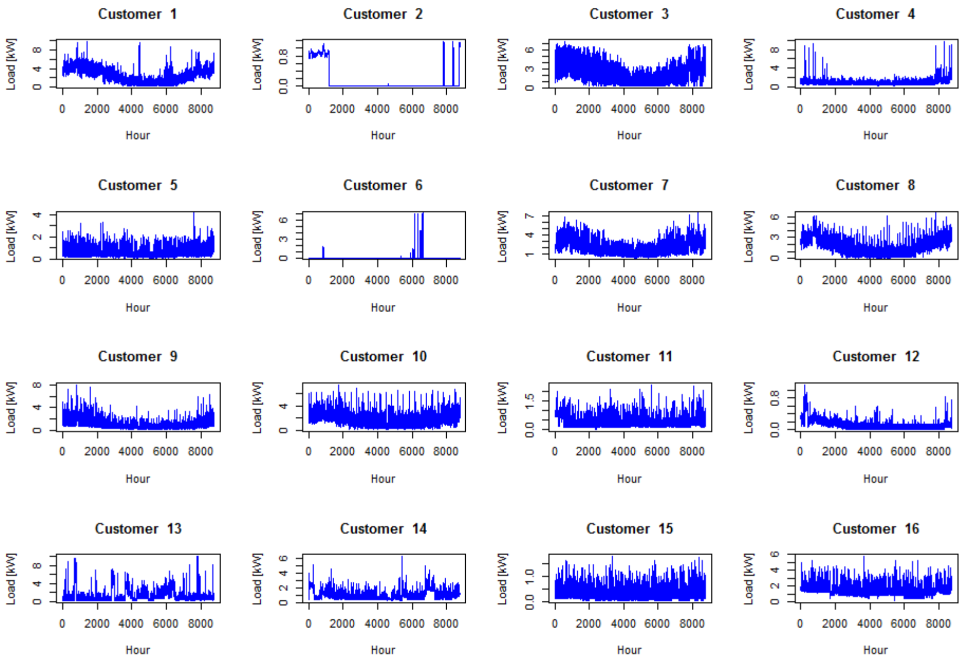

Figure 6: The hourly consumption for the whole year per customer

In the next figure, the aggregated load profile for all customers is shown for three different temporal resolutions (seasonal, day type, hours) in boxplots and temperature dependence of the load in a scatter plot. This figure is shown to make an understanding of the characteristics of the aggregated load behavior. As seen in the top left subplot, a strong seasonal trend can be distinguished in the load data, i.e. higher load during the winter months, and lower loads in the summer months. The load shows a non-linear relationship with outdoor temperature in the scatter plot in the lower right subplot. Furthermore, the median load is higher during holidays as compared to weekdays and weekends (see the subplot to the top right). This indicates that these are residential customers and not industrial/commercial customers. The hourly load profile shows a typical residential profile with a morning and evening peak loads.

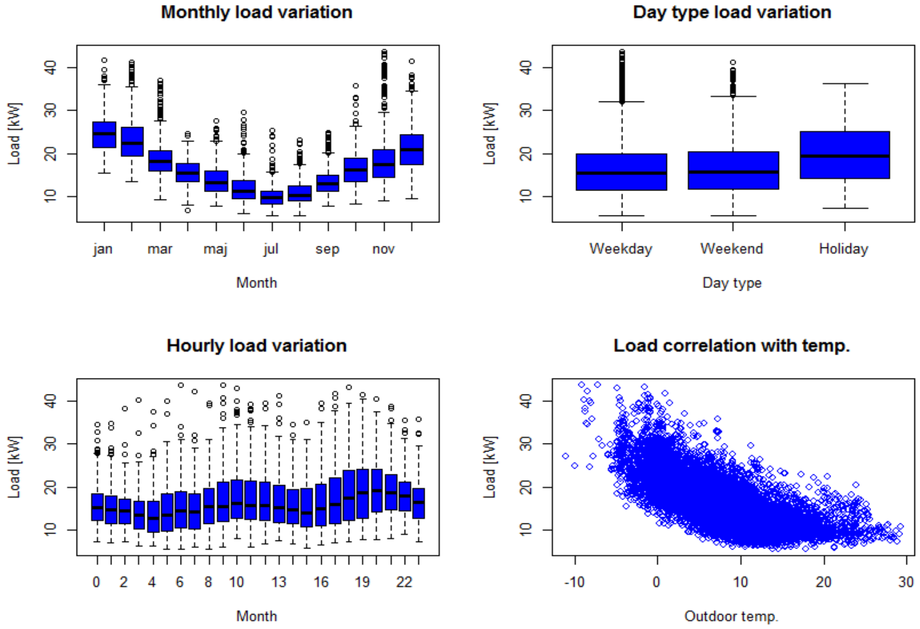

Figure 7: Top left subplot: monthly load levels in a boxplot. Top right subplot: day type load levels in a boxplot. Lower left subplot: hourly load levels in a boxplot. Lower right subplot: hourly load levels as a function to outdoor temperatures.

The clustering results are validated against survey data which has been collected from a subset of the customers in the Herrljunga Elektriska's grid. The energy use survey has been performed with 95 randomly chosen residential grid customers via telephone. NB: the load data of these customers have fulfilled the data cleaning requirements declared in Section II. The following questions have been asked to the respondents: (i) What kind of building do you live in (e.g., detached house, townhouse, multi-family building)? (ii) How large is the heated living space? (iii) How many persons in the household? (iv) What are the ages of these people? (iv) What kind of heating system is primarily used (heat pumps, radiators, district heating, boiler, etc.)? The data material from this survey works as a basis for the model validation.

The validation shows that the algorithm can separate customers based on key-attributes, e.g. electric vs. non-electric heating systems, families vs single households etc. In the figure below, the characteristics regarding family sizes and heating system for the surveyed customers per cluster are displayed in boxplots and bar plots. Here it can be seen that cluster 3 is a heat pump cluster with household consisting mostly couples without children. This cluster consists of almost half of the surveyed customers. Cluster 1 also tends to consist of customers with heat pumps, but, here, the family size tends to be bigger. The other clusters are mainly customers with non-electric heating systems.

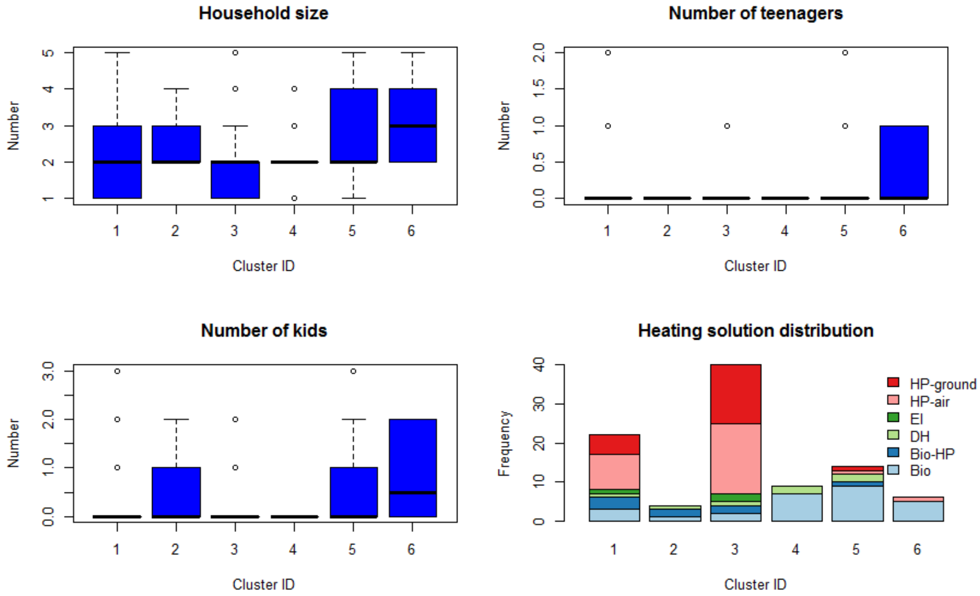

Figure 8: Top left subplot: household size in persons per cluster in a boxplot. Top right subplot: the number of teenagers in each household in a boxplot. Lower left subplot: the number of kids in the household. Lower right subplot: the frequency of used heating solution per cluster in a bar plot.

Moreover, the average cluster loads for different day types and temperature ranges are shown in Figure 9. As seen in the figure, the load level of cluster 3 decreases significantly when the outdoor temperature increases. This signals that the heat pumps cannot serve the whole heating demand of the house when it is very cold outside, and needs support of a secondary heating system, e.g. direct electric heating. Cluster 1 shows the same tendency, but not at the same magnitude. Further, cluster 2 has a higher load during intermediate temperatures (i.e. 8 to 16 °C) than during colder temperatures.

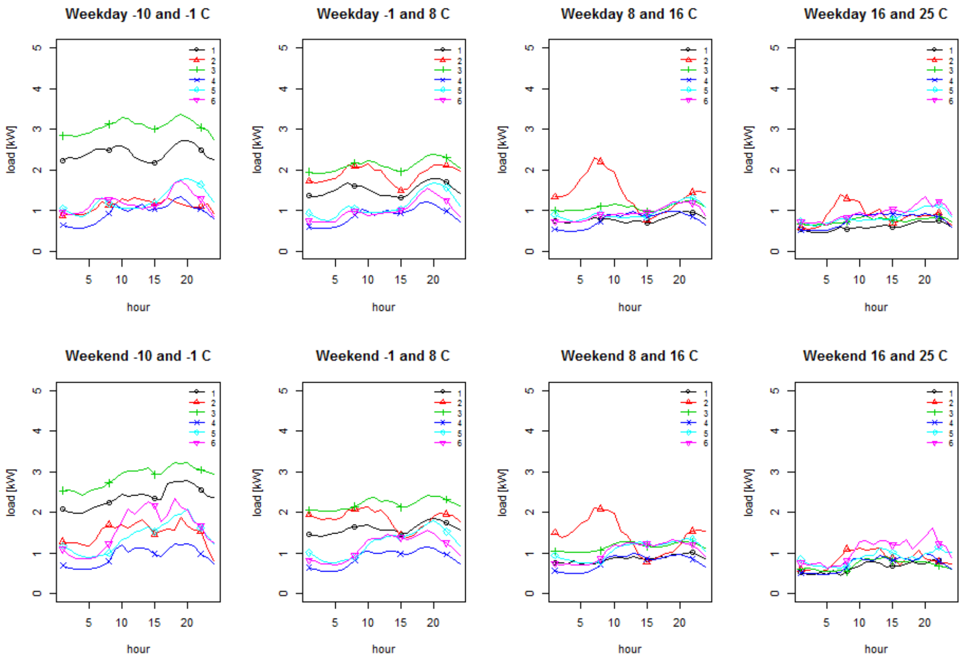

Figure 9: A diagram that shows average load profiles over the day for the respective clusters for the different stratifications, i.e., day types and outdoor temperature intervals

The results of the clustering of the customer in the test network are shown in the table below. Note, some of the customers are excluded as they did not pass the data cleaning steps. In total, three customers are excluded because of either too many missing values or too high or low annual consumption. As seen in the table, five of the customers got assigned to cluster 3, and three customers are assigned to cluster 1. This means that eight customer are households with heat pumps. Furthermore, three customers are assigned to cluster 4 which is a cluster with non-electric heating solutions and households consisting of couples. One customer is assigned to cluster 5 and 6, respectively.

Table 3: The assigned cluster for each customer in the rural grid

Customer	**V4**	**V8**	**V10**	**V1**	**V3**	**V9**	**V11**	**V18**	**V5**	**V12**	**V17**	**V15**	**V14**
Cluster	1	1	1	3	3	3	3	3	4	4	4	5	6

Based on the findings of customers with heat pumps and family composition, the following parameter value input will be provided to the bottom-up simulation models in the next step:

Cluster 1: households consisting of couples that live in detached houses with heat pumps. The median living space is 130 m^2.Three customers belong to this cluster.

Cluster 5: households consisting of couples with kids that live in detached houses with heat pumps. The median living space is 130 m^2. Five customers belong to this cluster.

Other clusters: households with non-electric heating systems for space heating and DHW purposes, i.e. appliance use only.

4.1.2 Bottom-up simulation load model

In order to quantify the validity of the developed bottom-up load model, simulated load is compared to the measured load in the grid, and a number of statistical measures are estimated to assist the validity check. This validation step is important as it provides evidence that the load model can reproduce the systematic load variation and characteristics of the real customers. If these results can be reproduced with reasonable accuracy, it is plausible to add changes in the model with confidence and thus incorporate parameter changes that reflect the various scenarios discussed in the previous chapter.

The input parameter values settings in the base case simulations are listed in the table below. These will be used to simulate the hourly load values that will compared against the measured consumption.

Table 1: The simulation parameters that constitutes the Base case

Parameter	BC value	Description
$N_{buildings}$	8 buildings	The number of simulated buildings. Taken from the cluster analysis
λ	170 W/m² °C	The insulation of the building
τ	100 hours	The time constant of the building
A_{solar}	10 m²	The amount of solar irradiance that can be absorbed through the windows
$N_{persons}$	2 persons	We assume two persons per household, taken from the cluster analysis
$N_{boilers}$	8 boilers	We assume that every household have a boiler
P_{boiler}	3 kW	The average capacity of the boiler
P_{hp}	6 kW	The installed heat pump capacity
COP	2	We assume an average COP value over the whole temperature range. However, if it's too cold, an electric heater kicks in with a COP value of 1
T_{DUT}	-12.2 °C	The dimensioning outdoor temperature. It is based on a time constant of 5-6 days in Herrljunga
Control approach	Outdoor temperature conrol	The control approach of the heating system is based on the outdoor temperature. i.e. the output heat pump depends on the current ambient temperature

Input data to the simulations include:

- Hourly outdoor temperature and irradiance readings from the SMHI weather station located in Hallum, Sweden – located about 30 km north from the Herrljunga city center.
- Behavioral data for people living in detached houses from Time of Use Data (TUD) studies conducted by SCB in 1996.
- Hourly load data for the eight heat pump customers in the test network.

In Figure 8, we can see four subplots which compare the simulated load data (generated by using the simulation model framework, parameter settings and input data) with the measured data for the base case. Note, the red curves are the measured load, and the blue curves are the simulated load. In the top left subplot, the hourly consumption values for a whole year are shown, and in the top right subplot the daily average consumption values for the quantities are shown. As can be seen, the model captures with quite a high precision the variation in the measured load, e.g. the peak loads and seasonal variations, except that some simulated peak loads are overestimated (see January, etc.). In the bottom right plot, the daily consumption values for the simulated and measured loads are plotted against outdoor temperature. The simulated load is close to the measured load in the temperature interval 0 to 15 degrees C. Outside this interval, the mismatch increases, especially for cold temperatures. These results may depends on the fact the heating model is simplified, and cannot capture complex interactions between the heat pump unit and the secondary heating units – which will affect the COP level of the heating process. The model assumes that the COP becomes 1 when the outdoor temperature is low. But in reality, the COP can be higher, and have a more non-linear function in relation to the temperature. This result will impact the model accuracy but is believed to be justified by that model becomes more simple model and that fewer assumptions will be required.

The model underestimates the real load during the summer months which indicate that the model cannot capture all heating/cooling processes occurring in the building, or other types of appliances that can exist at the premises.

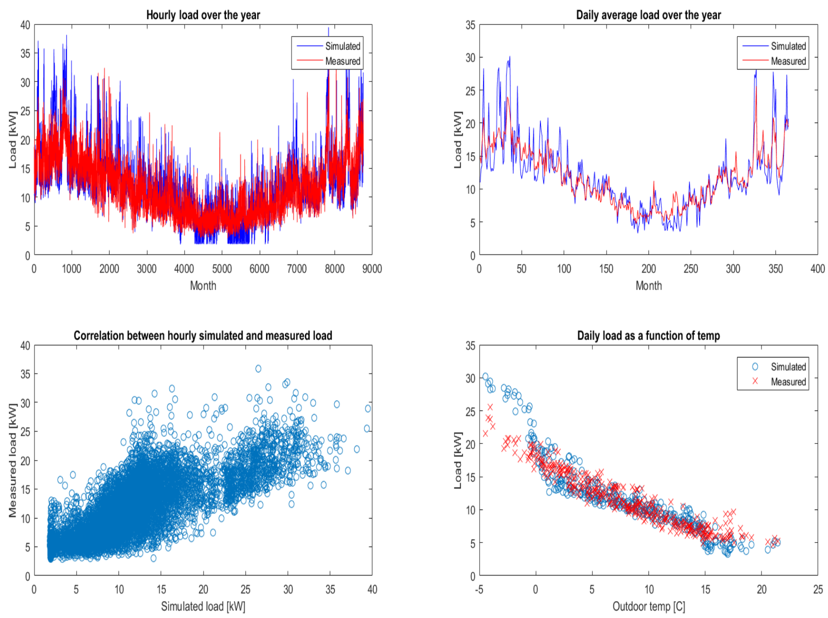

Figure 10: Top-left plot: the hourly simulated and measured aggregated load for the whole year. Top-right plot: the daily simulated and measured average load for the whole year. Bottom-left plot: correlation plot between the hourly simulated and measured load. Top-right plot: the simulated and measured daily load as a function of the outdoor temperature.

When making statistical comparison between the hourly simulated and measured load, a R^2 (coefficient of determination) value of 59 % and a Root Mean Squared Error (RMSE) of 3.19 kW is obtained. For the daily average load, the R^2 is 0.82. These results are acceptable for the purposes of the report, as there are many potential sources of error and uncertainties that the model cannot anticipate.

However, the systematic variation of the load is captured, and, thus, makes it accurate enough for this application.

A sensitivity analysis was also conducted by changing each parameter value individually and assessing the impact on the simulated load shape and as compared to the measured load. The parameter changes included control approach (indoor temperature controlled), reference indoor temperature set point, increased household size, insulation and time constant.

4.2 RURAL GRID RESULT AND ANALYSIS

4.2.1 Base case

For the rural test grid, the consumption and resulting load flow are simulated for an hourly basis for a full year for the base case. The results from these simulations are seen in Figure 11. In this figure, four plots can be seen. In the top left plot, the hourly voltage profile for the weakest bus[1] in the low voltage network is shown, together with the outdoor temperature profile. As seen, the voltage profile follows the temperature closely, where the lowest voltage occurs during low temperature (higher consumption from heat pumps) and higher voltage during the summer when the consumption is generally lower. The voltage distribution is shown in the top right plot, together with the defined voltage thresholds, i.e. +- 5% from the nominal value (in per unit). The voltage distribution is quite narrow, with a tail moving to the left. This means that the voltage levels tend to be under their nominal values. However, there is a significant margin between the end of the tail of the distribution and the limit line at a voltage of 0.95 per unit. Further, in the bottom left plot, the hourly load as a function of outdoor temperatures can be seen. A clear linear correlation between the two quantities can be distinguished. In the last plot, the load duration curve shows a significant load peaks for a few number of hours.

[1] This is defined as the bus with the lowest average voltage level on a yearly basis.

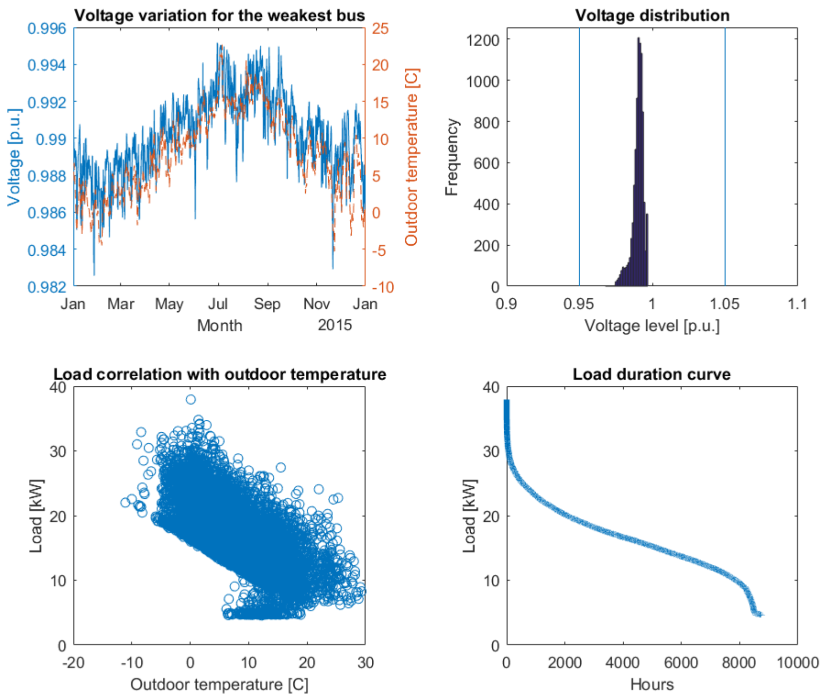

Figure 11: The simulation results from the base case simulations; Top left: the hourly voltage variation throughout the year in per unit on the weakest bus, outdoor temperature time series is also added to the plot. Top right: the voltage distribution of the weakest node, including the +-5 % voltage variation constraints. Bottom-left: hourly aggregated load as a function of outdoor temperature. Bottom-right: duration curve of aggregated load.

Table 4: The KPI results for the rural grid base case

The BC simulations generate the following KPI results:

KP1$_a$	**KPI1$_b$**	**KPI2$_a$**	**KPI2$_b$**	**KPI3**	**KPI4$_a$**	**KPI4$_b$**	**KPI5**	**KPI6**
69.0 %	43.0 %	0 %	0 %	0 %	333 SEK/month	240 SEK/month	39 SEK/month	13 SEK/month

As seen in the table, no voltage or overloading issues occur in the base case. The daily average load factor is 69%, and the yearly load factor is 43%. The monthly income for a flat tariff is in average 333 SEK per customer. The power tariff income is lower, 240 SEK/customer. So for this setup of customers it would be wiser to have a flat tariff. However, the power tariff cost will correlate with outdoor temperature due to the heat pump loads. If it is cold winter, e.g. a ten year winter, it is expected that this cost will increase. Thus, the customer takes a risk with such tariff designs. The regional tariff cost per customer and month is 39 SEK, i.e. around 10% of the local tariff income per customer. The capital cost for the network per customer is 13 SEK/month.

4.2.2 Scenario results

In the figure below, the KPI results for each realistic scenario together with the base case can be seen. In the bar plot, it should be easy to see how much the various scenarios affect the KPI as compared to the base case

Key-findings from this graph are the following:

- Technical problems are only occurring in the electrification scenarios. For all these cases the problems are related to under-voltage. The under-voltage problem is most troublesome in the Electrification/PV/Flexibility-scenario. No problems with overvoltage or overloading are occurring in the scenarios.
- For all scenarios the daily and yearly load factors are decreased when compared to the Base Case, except for the Electrification scenario, where it is slightly increased. The reason behind this could be that EV charging increase the consumption during the night, and, thus, decreases the load valley at these times. The load factor is the lowest in the PV related scenarios, where in PV/efficiency scenario it is almost 1/3 of the Base Case value
- The income and costs are increased in the electrification scenarios, and are reduced in the PV scenarios. The highest incomes are made for the DSO in the electrification scenario, where the flat tariff income is increase from 333 SEK/month, customer in the Base Case, to 443 SEK/month, customer in the electrification scenario, i.e. an income increase with almost 33%. However, this increase come at the expense of higher regional tariff cost and network expansion costs.

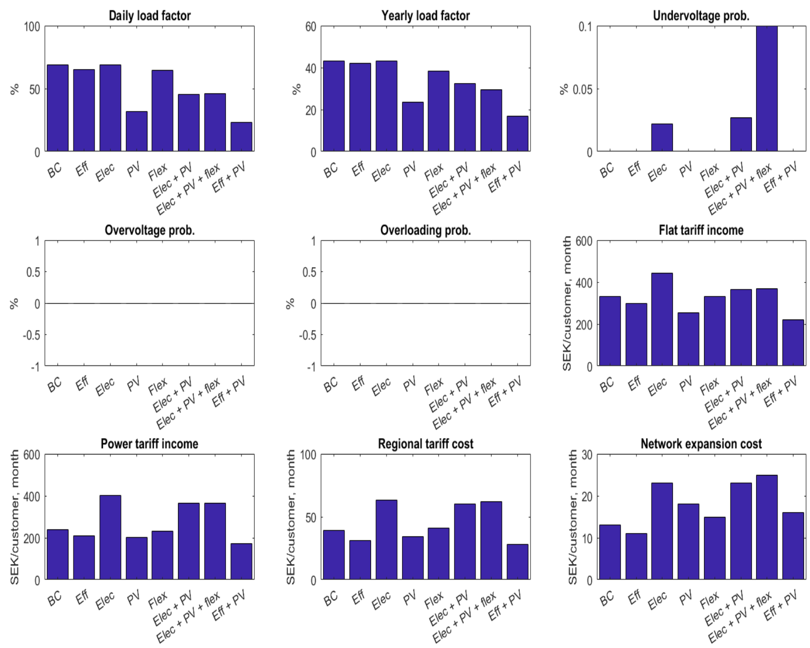

Figure 12: The KPI results for all the realistic scenarios in the rural grid. Base case is included as a reference

In Figure 13, the same type of KPI bar plots is presented for the extreme scenarios. The key-findings from these plots are:

- In all scenarios the load factor is decreased compared to the base case.
- The load factor becomes negative for the PV scenario, and is even more severe when it is combined with the energy efficiency scenario
- The load flexibility scenarios have a small impact on the KPI:s
- The power tariff income increases significantly in the electrification scenarios. However, this result comes at the expense of a higher risk of overvoltage and overloading of components. This will increase the capital cost of the network together with a higher regional tariff cost.
- A combined scenario of large scale introduction of PV and expanded electrification has the most severe effect on the technical KPI:s. Here the load duration curve will be unfavorable for the DSO, with very high peak loads during winter, and negative peaks during summer. Thus, both problems will be induced during both summer and winter, i.e. a more complex set of problems need to be addressed
- When PV and expanded electrification is combined with flexibility, the KPI:s are actually improved. This can be due to the fact that the used price profile (spot prices for SE3 during 2015) are favorable for the typical loading patterns of the network, and, thus, improves the loading factor, i.e. high prices when there is a high load, and thus decreases the average load levels at these times.

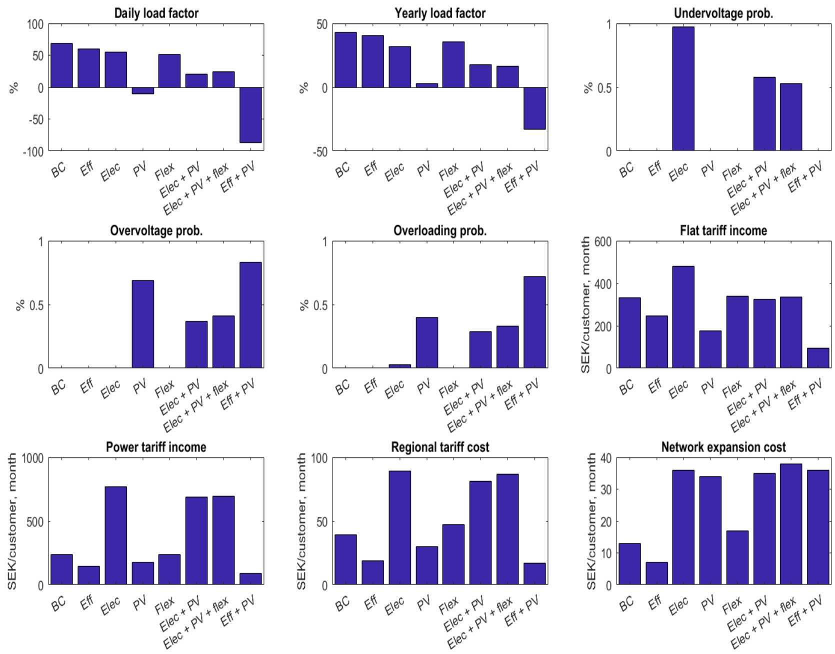

Figure 13: The KPI:s results for the extreme scenarios in the rural grid. The base case is included as a reference.

4.3 URBAN GRID RESULT AND ANALYSIS

4.3.1 Cluster results

The cluster algorithm is used in the same way as for the customers in the rural grid which is presented in section 4.1.1. The cluster properties are shown in Figure 14, where we can see that cluster 5 and 6 are heat pump clusters, and are dominated in this grid. Note, three customers are filtered out in the data processing step. This is also shown in Table 5 which states that 59 out of the 97 customers[2] in this grid are heat pump customers. These customers tend to have smaller household sizes than the other biofuel customer, i.e. clusters 1 to 4. Conclusions: 59 customers have heat pumps loads, and the rest does not.

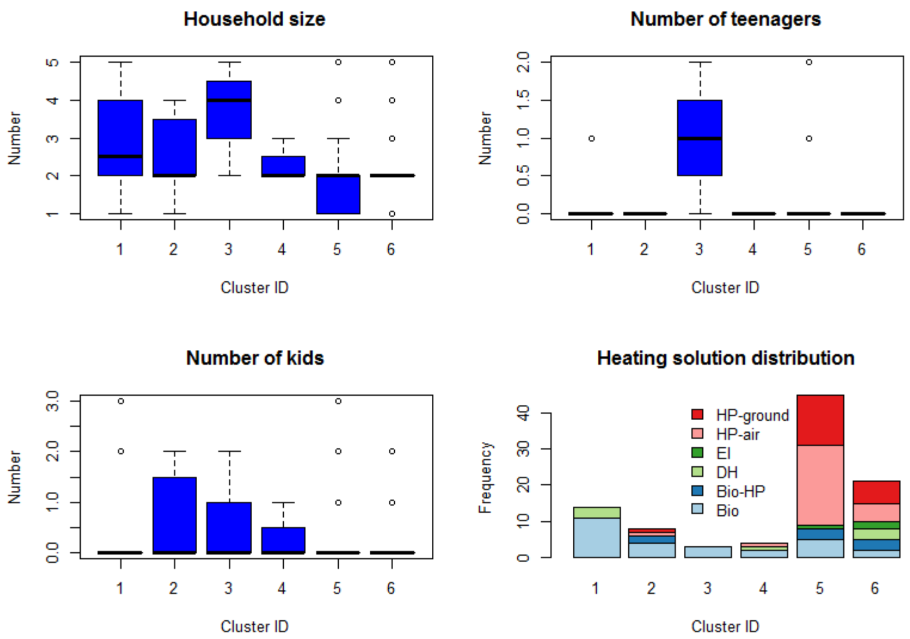

Figure 14: Top left subplot: the household size in persons per cluster in a boxplot. Top right subplot: the number of people under 20 years in the household per cluster in a boxplot. Lower left subplot: the number of kids in the household. Lower right subplot: the frequency of used heating solution per cluster in a bar plot.

Table 5: The assigned cluster for the customers in the urban grid

Cluster ID	**1**	**2**	**3**	**4**	**5**	**6**
Number of customers	12	7	5	11	34	25

4.3.2 Base case results

In Figure 15, the base case simulation results are shown for the urban test grid. This is the same type of plot as presented for the rural test grid. As seen, the

[2] This implies a 63% share of heat pump customers in the urban grid. This can be compared to the rural grid which has a 44% share of heat pump customers.

voltage profile follows the outdoor temperature closely. This grid actually has higher temperature load dependency than the rural grid, as seen in the bottom-left plot where a high linear dependency can be distinguished. This is because the urban grid has a higher percentage of heat pump ownership than the rural grid. The voltage distribution seems to be more spread than the distribution for the rural grid. However, the tail of the distribution still has some margin left to the 0.95 nominal values threshold. In the last plot, the load duration curve shows a significant load peaks for a few number of hours, which is the electric heating load during very cold temperatures.

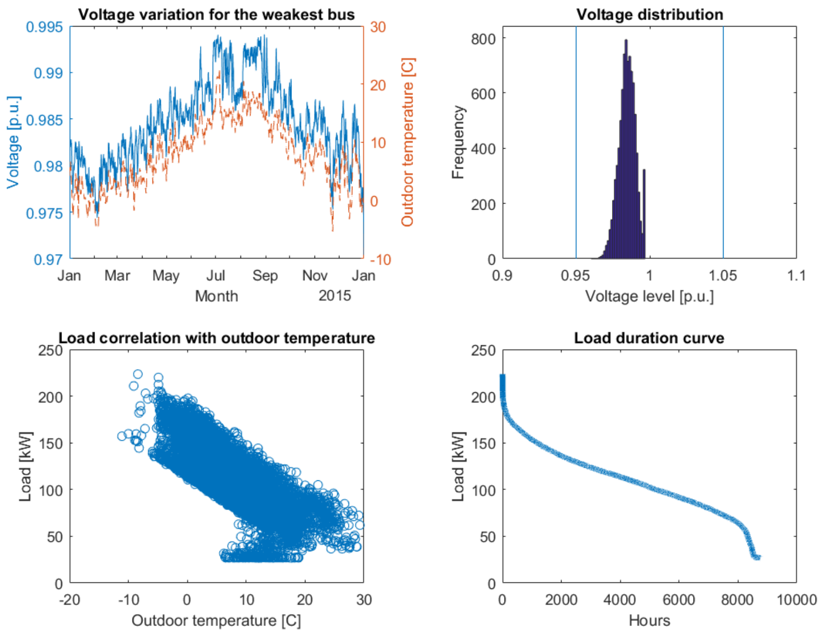

Figure 15: The simulation results from the urban grid base case simulations; Top left: the hourly voltage variation throughout the year in per unit on the weakest bus, outdoor temperature time series is also added to the plot. Top right: the voltage distribution of the weakest node, including the +-5 % voltage variation constraints. Bottom-left: hourly aggregated load as a function of outdoor temperature. Bottom-right: duration curve of aggregated load.

Table 6: KPI results for the urban grid base case

For the base case, the following values on the KPI:s are obtained:

KP1$_a$ (daily load factor)	KPI1$_b$ (yearly load factor)	KPI2$_a$ (under-voltage)	KPI2$_b$ (over-voltage)	KPI3 (over-loading)	KPI4$_a$ (flat tariff income)	KPI4$_b$ (power tariff income)	KPI5 (regional tariff cost)	KPI6 (grid expansion cost)
73.7 %	49.0 %	0 %	0 %	0 %	362 SEK/month	274 SEK/month	41 SEK/month	14 SEK/month

From these results we can conclude that the urban grid in average terms has better values for both the technical and economic KPI:s than the rural grid. For example, the load factor and tariff income is improved as compared to the rural grid. Meanwhile, the regional tariff is just 2 SEK higher per customer. Hence, the urban grid customers are a better affair for Herrljunga Elektriska then the rural grid customers. No technical issues are occurring in the base case.

4.3.3 Scenario results

In Figure 16, the difference in KPI results between the urban and rural test grids are shown for the realistic scenarios. As seen, the daily load factor is better in the urban grid than the rural grid in each of the scenarios except for electrification-PV-flexibility scenario. For the yearly load factor, the flexibility scenario also yields a negative result as compared to the rural grid. This implies that the urban grid is more sensitive to flexible customers as there are a higher percentage of heat pump owners in this grid – thus more flexibility potential at the customer. Further, the rural grid is more prone for under-voltage problems in the electrification scenarios, which indicates that the rural grid is weaker than the urban grid. No problems related to overvoltage or overloading occurs in any of the grid in the realistic scenarios. The tariff (both flat and power) income is higher in every scenario in the urban grid, except in the electrification-PV scenarios for the flat tariff. In addition, the costs are generally higher in the rural grids, besides the flexibility scenario, where actually the costs are higher in the urban grid. The urban grid customers are more favorable in economic terms for the DSO, e.g. more robust against scenario changes than the rural grid.

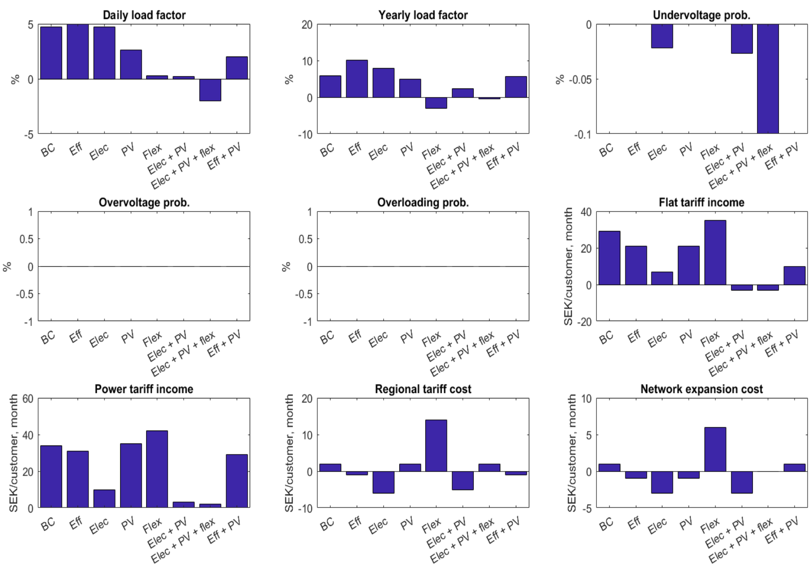

Figure 16: The difference in KPI ($KPIx_{urban}$-$KPIx_{rural}$) results between the urban and rural grids for the realistic scenarios.

Moreover, in Figure 17 the KPI difference results are shown for the extreme scenarios. The key findings from this figure are:

- The rural grid is more sensitive to voltage problems, and the urban grid is more sensitive to overloading problems. Note, in the efficiency/PV scenario there is a 2% risk of component overload, i.e. over 170 hours of overloading problems in the urban grid over one year. The rural grid is much more vulnerable to PV integration than the urban grid
- The daily load factor is better in the PV/efficiency scenarios in the urban grid, but poorer in the electrification/flexibility scenarios. Thus, a PV integration scenario is more favorable in a grid with a higher percentage of electric heating customers. However, the same result is not obtained for the yearly load factor, where in the efficiency/PV scenario the factor is less good than in the rural grid case. This could be due to the fact that PV electricity generation and HP load is not matched on a seasonal basis; where the max consumption of the heat pump is during the winter, when the PV generation is low
- The flat and power tariff income difference between the grids is reduced in almost every scenario when compared to the base case (except in the flexibility scenario). This mean that the urban grid is less robust against the scenarios when it comes to the tariff income for the DSO, as compared to the rural grid
- However, the cost KPI:s are generally better in the urban grids than the rural grids. This could be due to the fact that urban grid is stronger, and, thus, less exposed to network expansion actions

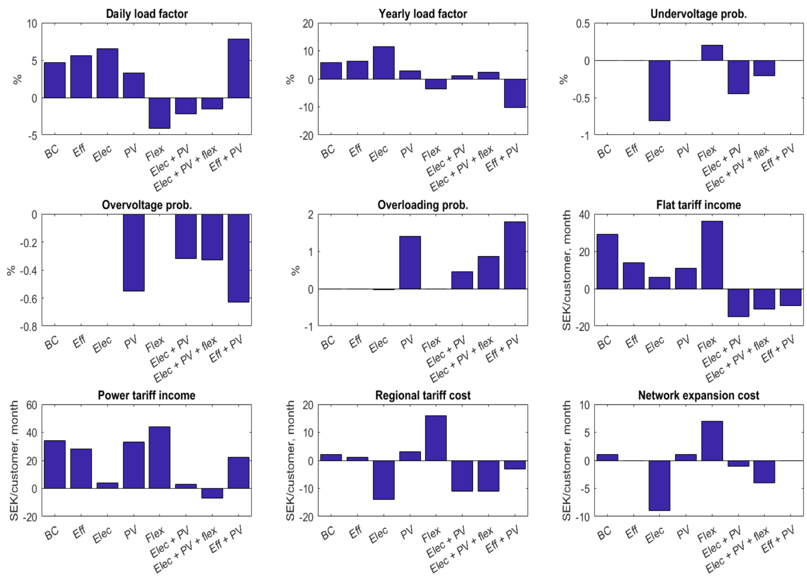

Figure 17: The difference in KPI results ($KPIx_{urban}$-$KPIx_{rural}$) between the urban and rural grids for the extreme scenarios.

5 Discussion

In this chapter, some discussion of the results will be made. The discussion is divided into the four following topics: (i) beneficial scenarios for rural and urban DSOs (ii) advantages, limitations and representativeness of the proposed models, (iii) possible solutions to handle challenges that arise in the scenarios, and (iv) the interactions between network regulation, scenarios and investment options.

5.1 BENEFICIAL SCENARIO DEVELOPMENTS FOR RURAL AND URBAN GRID OWNERS RESPECTIVELY

Best scenario for rural grid DSO

In the rural grids, the most beneficial scenarios are those connected to energy-efficiency developments. This is because these grids are generally weaker, and a lower electricity use decreases the stress on the grid, which is an advantage. The energy efficiency measures will provide grid capacity for a potential EV integration. It is shown that the electrification scenario introduces under voltage problems, and will thus drive investment need in the grid. The investment need may not be compensated by the additional kWhs that are transferred to the end-user.

Further, the PV realistic scenario does not result in any technical problems. However, the revenue is significantly cut, and will make the rural customers less profitable for the DSO. In addition, PV panels do not solve the peak load issues that occur during the winter time, which energy efficiency actually does by reducing the electricity demand during cold temperatures in the winter time.

Recommendation: promote energy efficiency measures to cope with EV introduction in a more cost-effective way. In addition, new revenue streams can be generated from e.g. EV systems support/sales/service

Best scenario for urban grid DSO

Electrification is a beneficial scenario for a DSO with urban grids. This is because the urban grids are robust, and can handle a large scale integration of EV:s without implying a severe risk of overload the network. Meanwhile, the electrification scenario implies that the DSO transfers additional kWhs’ to the customers, i.e. their income increases. However, if the electrification scenario is combined with a PV scenario, it does not necessarily lead to a better business case for the DSO, as the customer now potentially can use the EV battery for optimizing self-consumption of the PV electricity production, e.g. by storing electricity during the day and then use in the evening and morning. This may lead to decreased revenues. Hence, it is complicated to derive exact impacts on DSO business, as it will depend how other things change at the customer site, e.g. small scale production and control strategies. More research must be made on this topic to draw more precise conclusions.

Recommendation: promote electrification at customer premises to improve the revenue stream. However, fast charging of EV:s can cause technical problems, and may drive investment costs in the urban grid which is not beneficial for the DSO:

5.2 MODEL REPRESENTATIVENESS, ADVANTAGES AND LIMITATIONS

Model advantages

The main advantage with the model framework is that it is simple enough to model the low voltage grid and its individual customers, while complicated enough to capture unique household behavior and characteristics. Thus, it is designed to make an appropriate tradeoff between aggregated top-down and disaggregated bottom-up modelling techniques. It is possible to scale the models to entire medium voltage grids, containing hundreds to thousands of customers. In addition, the model approach makes it possible to control all parameter and-data inputs to the model, and, thus it is possible to test and simulate a wide range of scenarios of end-user scenarios in distribution grids. For example, very cold winter periods can be simulated in combination with previous outages to see how heat pump peak loads will impact the grid operation

Generalized models open up for a wide range of customer types, e.g. detached houses with different heating systems, family sizes, building categories, small scale production and EV:s. A complex composition of the building stock can be simulated, and, therefore, better reflect the real customer setup in a distribution grid. The EV, PV and flexibility modules create the opportunity to study the load profiles of future the customers. This can be valuable when the DSO is planning the grid for future demand.

Model limitations

The model consists of numerous assumptions and simplifications that will impact the accuracy of results, e.g. the load levels of individual buildings, and load flows in the grid that are not perfectly predicted. For example, the thermodynamics in the buildings are based on simplified lumped capacitance models, and will not capture the non-linear dynamics of the real indoor climate. In other words, the model will capture the trends of the studied system, and not the real outcomes and dynamics of it. So, the model cannot be used to make actual prediction of the system dynamics in the distribution grid. Rather it can be used for analysis and evaluation of various scenario developments for the DSO.

Moreover, the behavior of the end-users is only split between weekdays and weekends, which mean that potential seasonal effects of the behavior are not included, e.g. summer time vacation etc. This will decrease the accuracy of the model, while make it more simple as less data and assumption are required

The model simulates the load at an hourly time resolution. Thus, possible intra-hourly load peaks which can affect the voltage and power flow will not be highlighted by the model, and can underestimate the scenarios' technical impact on the distribution grid operation.

The model only includes rule-based controllers, which is the standard type of controller in heating systems today. However, other type controllers might be introduced on the market in the future, e.g. as model predictive control (MPC) which uses forecast data of e.g. weather, prices to optimize the control and consumption of these systems. The controller will to a large extent affect the load curve, and, thus, relevant to include in future works

There are other KPI:s that can provide additional insights about the likelihood and impact of the scenarios. These KPI:s are mainly customer oriented, e.g. total electricity cost per month (retail + network), self-sufficiency of energy on a yearly basis and comfort (indoor temperature, and SOC), and can be interesting to discern feasible future scenarios. Societal KPI:s can also be considered, such as reduction of primary energy usage and CO_2 emissions due to energy efficiency, electrification of transportation and renewable energy production measures at the customer sites. Such changes may have a positive impact on society, and will thus be interesting for policy makers to analyze further.

Generalization considerations regarding method and results

The methodology presented in this report is considered to be general and thus applicable for other Swedish DSO that wants to make scenario analysis in their low from the case study results, as the customer composition and low voltage grid design might be different in other grids, as compared to the Herrljunga Elektriska examples.

The data that is required for conducting simulations for other distribution grids in Sweden is listed below (and thus assess the KPI impact for other grids):

1. Hourly **weather data**, i.e. outdoor temperature and solar irradiance data. This data can easily be freely obtained from weather service providers such as SMHI. The risk is that not all weather parameters will be available for the geographic area of interest. To overcome this problem, data from the closest weather station can be used, or the average values from the two to three closest stations.

2. **Behavioral data** for people living in detached houses. The same TUD that is used in this study can be used in a replication study. The TUD is divided between weekdays and weekends.

3. Hourly **load data** from the customers in the distribution grid. This data will be required for the clustering algorithm and an optional validation of the bottom-up load simulation model. Here, it is important that the data is quality checked with respect to time synchronization and missing values so that the data can be used for the intended applications.

4. **Prior knowledge** about interesting low voltage distribution grids that can be used for simulations. This refers to urban or rural grids with primarily residential customers, i.e. avoiding grids with industrial and commercial customers as models for these customer segments are not included.

5. **Grid data**, e.g. network topology, substation, line and cable data is required. In essence, a conductivity matrix will be generated for load flow

calculations. This data can be retrieved from the Network Information System (NIS).

6. **Price data** from Nord pool spot for the applicable price area.
7. Available **tariff structures** for the DSO is required for the economic KPI:s

With this data appropriately formatted, grid simulations can be performed for any given distribution grid, and KPI:s can be estimated for any scenario that is found interesting and relevant. Note, a MATLAB license is required to use the model.

5.3 POSSIBLE TECHNICAL AND ECONOMIC SOLUTIONS FOR DSO CHALLENGES

The potential issues and challenges can be addressed by applying different technologies. Seven main solution categories have been identified and will be discussed based on their advantages and drawbacks to solve the technical challenges that arise in the scenarios. For example, the solutions can be focused on solving grid related issues e.g. voltage and overloading, or customer-related challenges such as customer tariff incomes or daily load factor. Or solutions that can improve the load factor in some of the scenarios will be highlighted. These solutions are described in Table 7. Note, in future work, the authors aim to simulate the feasibility of the solution in the various scenarios.

Table 7: The possible solutions to handle the various problems in the scenarios are shown in the table. Advantages and benefits with the solutions are also listed

Solution category	Description	Added value (advantages)	Drawbacks	Suitable for scenario
Fit and forget traditional technology	Building new lines and cables, replacing or upgrading substations. These are physical investments and it is the traditional method for DSOs to solve problems and handle challenges in their grid	More distribution capacity in the grid Predictable investment, you know what functionality you get for the money The grid reliability can more easily be assessed	Costly/ inefficient to solve problems that occur infrequently, e.g. severe yearly peak load Could be costly for extreme PV scenarios	Electrification, flexibility, PV
Load tap changer control	Add control capability in the secondary substation to control voltage level by regulating nominal voltage level based on actual load and production	More robust and resilient distribution grid with respect to varying loading conditions. The voltage level can be too high or low as the tap changer settings are not properly set	Frequent tap changing operation wears out the equipment in the substation. This may drive the costs for the DSO	PV, electrification

Solution category	Description	Added value (advantages)	Drawbacks	Suitable for scenario
	conditions in the grid	This is extra valuable in a PV/electrification scenario as the loading difference will be higher between summer and winter		
Energy Storage	Add a battery device in the grid that can charge or discharge electricity based on loading conditions The battery is properly dimensioned between energy and power w.r.t the application	Can both shave peak loads and absorb energy during high PV production. It is also faster than a tap changer function control and has the potential for ongoing regulation capability (more flexible), whereas a tap changer will be used more infrequent. Can be used for both voltage regulation and balancing	Costs associated with charge/ discharge cycles (battery degradation). Operational state of battery will introduce limitations of usage of battery, e.g. if it is full or empty on energy Regulatory constraints for DSOs to use batteries as a generation resource	PV, electrification, flexibility
Microgrids	Formed by a group of loads a distributed energy resources to act as single controllable unit. The microgrid has the capability of going off-grid from the overlaying network, i.e. manage its own energy supply (18)	Manage operation complexity with new load and production at a more local scale. This is a way to manage technical challenges for DSOs. Can provide ancillary services to the overlaying distribution grid	Microgrids introduce financial risks for DSO:s as the customers will be more self-sufficient on energy, i.e. sell less energy and grid services	Electrification, PV
PV inverter control	Reduce the active power injection to the grid by the PV inverters to handle power quality and overloading problems. Active	Flexible solution that utilizes an existing technical infrastructure. Voltage control could be managed locally without a	Will curtail renewable energy production, i.e. unfavorable for the environment	PV

Solution category	Description	Added value (advantages)	Drawbacks	Suitable for scenario
	power control is more suitable in low voltage grids than reactive power as these are more resistive.	centralized control architecture	Economically unfavorable for the customers The DSO are not allowed to control the customers installation today	
Tariff design	The customers get different tariff contracts, e.g. time dependent tariff to decrease peak loads, increase the self-consumption, etc.	Could be a cost effective way to handle problems that happened seldom or increase the overall efficiency of the grid	Uncertain response from customers. This is a disadvantage if the grid reliability is dependent on customer response Introduces economic risks for the DSO as the income will be more weather dependent	PV, electrification, flexibility

5.4 THE INTERACTION BETWEEN NETWORK REGULATION, SCENARIOS AND INVESTMENT OPTIONS

In the figure below, the interaction between network regulation, investment options and scenarios is sketched out. The DSO business is regulated, which implies that the revenue and profit that they can take out from their customers are set by the energy market inspectorate[3]. These profits/income are regulated by the income framework which determines how the DSO can charge their customer, and how they can invest in the grid to maintain an appropriate availability, reliability and quality of the grid service. The regulation is done in advance for the upcoming four year period to increase the foresight on the income stream of the DSO. Hence, the actor knows how much room there are for future grid investments. DSO:s are reviewed each period, if their fees are not justified by the regulator, where the DOS income framework is evaluated based on its capital costs and operating costs, and is also dependent on the quality of DSO service.

[3] Energimarknadsinspektionen in Sweden, https://www.ei.se/

Energiforsk

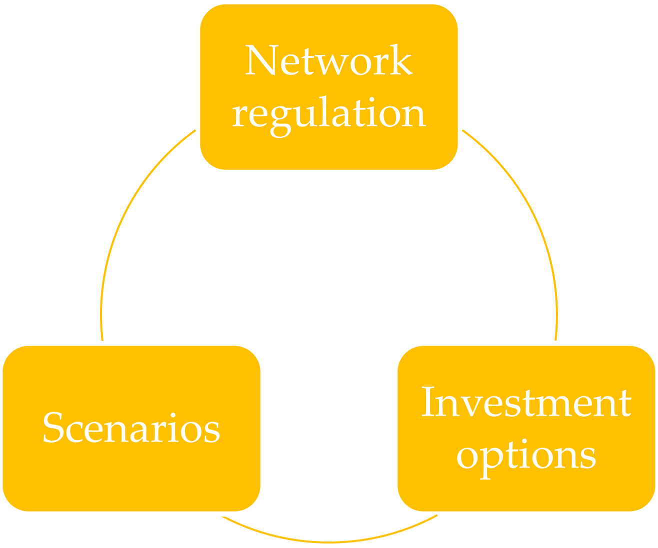

Figure 18: The interaction between network regulation, scenarios and investment options

The income framework will guarantee that the DSO is not overcharging their customers, and that the fee is fairly set w.r.t. the cost structure and service quality of the DSO. Today, the incentives to make energy efficiency measures, and get rewarded for this in the regulation, are very limited. The income comes from the network tariff – which is composed by three cost components; fixed, energy and power components: The fee should cover the grid costs plus a reasonable rate of return on their investments. The cost structure of a DSO is visualized in Figure 19. As seen, three types of cost categories exist; operations, planning and administration. The income structure through customer tariffs is included in the diagram. These factors will drive the cost for the DSO and depending on the scenario and investment strategy of the DSO; the cost for the components will be different.

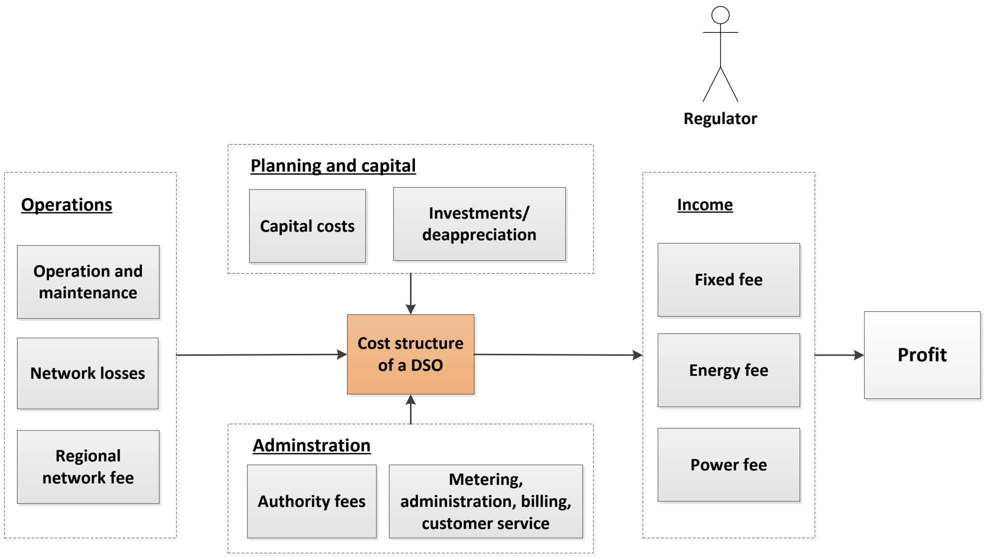

Figure 19: The cost and income structure of a DSO.

If the tariff costs are increased too much, there is a risk that customers might go off-grid to avoid these costs. This will imply that the DSO:s customer base will decrease, and to cope with this, the DSO will have to increase the tariff for the remaining customers, which may accelerate the number of customers that go off-grid, and drive the depletion of the customer base. This is a negative spiral for the DSO and will set a roof value for how much the tariffs can be increased. This problem can be more severe for rural grids where customers actually can setup solar PV and optionally wind turbines. Multifamily buildings in urban grid will have less good prerequisites for such developments, as energy self-sufficiency on a yearly basis is not likely as it is dependent on district heating and it will not be probable that they can setup wind turbines. Thus, it will be important for the DSO to make wise and cost-efficient investments to minimize the risk for such a negative spiral scenario.

So, for the DSO it will be important to make wise investments that minimize their operational and planning expenditures, while maximizes the benefit of the customers, e.g. reasonable tariff cost, and a good reliability and quality of service. For example, the traditional fit and forget investment strategy will not address the issues with capital costs and daily load factor. It will however solve voltage and overloading problems. The question is whether this investment strategy will be feasible for the future conditions, especially to handle problems that occur seldom, e.g. yearly peak loads. These questions will be addressed in future projects.

6 Conclusions

The aim of the report is to analyze how various scenarios uncertainly changed load patterns in detached houses in Sweden affects the operation and business of a DSO. The methodology was (i) clustering customers based on hourly load data to get their parameter settings, (ii) emulate load profiles from detached houses with a simplified bottom up simulation approach, (iii) simulate low voltage grids with load flow models, (iv) propose plausible customer scenarios, and (v) define KPI:s that makes it possible to evaluate the techno-economic impact. The method is considered to be useable for all DSOs.

Customer and distribution grid data from two low voltage test grids (rural and urban) were used as input to the simulations, and used as a basis of the analysis in the case study. The rural grid had 18 customers, and the urban grid 97 customers living in detached houses, respectively. The cluster algorithm showed that both grids had a significant share of heat pump loads.

The results from the simulations showed that the rural grid was sensitive to under-voltage problems in the electrification scenarios (i.e., more heat pumps and EV:s), and the urban grid was more prone to overloading issues. In all scenarios, the load factor tended to decrease as compared to the base case. This is a negative for DSO:s as the revenue is partly dependent on the load factor. Lastly, the income from customer tariffs increased in the electrification scenarios, and decreased in the PV scenarios, which is logical as the former increases the average consumption, and the latter decreases the consumption.

It was discussed that DSO:s with rural grids should promote their customers to take energy efficiency actions so that the existing grid could better cope with an anticipated EV integration. Urban DSO:s should stimulate an increased electrification of their customers as their revenue goes up, while the grid can handle it technically due to redundant grid capacity.

6.1 FUTURE WORK

In this section, some potential future work topics are proposed. The first possible future work could be to model and simulate scenarios with different customer tariff schemes, e.g. Time Use Tariff, critical pricing, power tariffs, etc., to assess the potential of using such contracts to handle the problems that are created in the scenarios. Note, an interesting effect of introducing power tariffs is that the revenue will be more weather dependent, e.g. if it is a warm winter the income will tend to decrease as the space heating demand will decrease, and, thus, as the peak consumption will decrease. Such risks are thus interesting to assess as well by simulating years with different weather situation (cold vs warm winters). The other solutions that are presented in the previous section would also be interesting to analyze, for further validity check

A second suggestion is to conduct validation studies of the load flow model by collecting voltage and power measurements from real distribution grids. In this report, no validation has been made as such data is lacking. The validation will provide confidence that the model can be used for the intended applications. As for now, the voltage in the secondary substation is assumed to be constantly 400 V, which evidently is not the case in reality, as this voltage level depends on power flow processes higher up in the distribution grid (e.g., the medium voltage level). The model may underestimate the scenario's impact on the voltage quality as it is calculated now.

A third suggestion is to simulate the customer load profiles at a higher time resolution, e.g. 5 min or 1 min, to capture faster load spikes which may have a negative impact on the technical KPI:s. As the simulations are done on hourly averages, the technical impact of the scenarios may be underrated. However, if the time resolution is increased some data processing techniques must be applied on the weather data as this is only measured on at an hourly basis. Solar radiation data will be more sensitive to interpolation methods as this data can vary significantly even between minutes due to cloud movements etc. Outdoor temperature variation is much slower, and therefore less sensitive to interpolation.

Lastly, a more complex blend of scenarios can be considered and see how those developments affect the KPI:s. These scenarios include new technologies (e.g. MPC), advanced market models where customers have combined systems of PV and batteries, and, thus, have the capability to charge/discharge the battery optimized based on various market control strategies, e.g. maximize self-consumption

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8 Appendix

In the appendix, more elaborate description of the components in the simulation model framework can be found. The section is structured by: (i) clustering algorithm, (ii) bottom up load model, (iii) flexibility models, and (iv) low voltage grid model.

8.1 CUSTOMER CLUSTERING ALGORITHM

The main purpose of the clustering algorithm is to be able to input hourly load data from all customers in a distribution network, and get the category for each customer. These insights are then used for setting the parameter values in the bottom up simulation model in the upcoming step.

The structure and method of the clustering algorithm are described in this section. The method is composed by a number of steps, namely: (i) data processing and cleaning, (ii) data transformation, and (iii) data clustering. Each step is described in more detail below.

8.1.1 Data processing and cleaning

The first step is to read raw load measurements from the smart meters along with air temperature data from open Application Programming Interfaces (API:s) supplied by weather forecast service institutes, e.g. SMHI (1). This step reads the data in text or JSON format and processes it. When the data is read, it must be pre-processed as follows: filter irrelevant customers and dealing with missing observations. Customers are filtered on their annual energy consumption (customers with too low or too high annual consumption is excluded) and a reasonably balanced ratio between the average and median hourly load. The first filter criterion is introduced to exclude larger industrial/commercial customers and smaller loads, e.g. street lighting. These kinds of loads and customers are excluded in this report. The second criterion will remove customers that have skewed load distributions due to high vacancies. A skewed distribution may distort the performance of the clustering algorithm, and will be explained later. Possible smaller gaps of missing data are recovered through linear interpolation. If the gap is too large, the customer is removed from the data set. Altogether a number of customers are filtered based on these conditions.

8.1.2 Data transformation

The hourly load data is typically given for a longer time period, e.g. a whole year. This results in 8760 data points per customer and year. A clustering algorithm cannot handle that many variables. Thus, the data is reduced with a stratification method (2) before it is input to the clustering algorithm. This method computes the average load level within chosen time and outdoor temperature ranges. Time is composed by hour of the day and day type (weekday, weekend, or holiday), and mainly captures behavioral attributes of the end-users. Temperature is the number of intervals ranging from the coldest to the warmest registered temperature readings. This parameter will explain load variations that are linked to physical processes, e.g. the use of heating systems. Note, the reduced data is normalized with a max-min method for each customer (3). This normalization will make the clustering depend on load shape rather than absolute load levels.

8.1.3 Data clustering

Subsequently, these reduced normalized data sets are input to a K-means clustering algorithm, which groups customers with similar load shapes together. The number of clusters *K* must be specified before the calculations, which often is highlighted as the drawback with this method. In short, the K-means is an iterative algorithm which computes the location of *K* centroids that minimize the sum of the Euclidean distance between the data points and the centroids (3). This step outputs a cluster assignment to all customers.

8.2 BOTTOM-UP BUILDING LOAD MODEL

The bottom-up building load model consists of three separate modules: (i) end-user behavior, (ii) appliance and hot water usage which are mainly driven by behavior, and (iii) HVAC system load which is primarily driven by weather dynamics and building properties. The model is also extended with electric vehicle usage and charging, along with PV generation. These two models can be used to reflect futures where the transportation sector is electrified and small scale local production at home is more common.

Moreover, with these models it is possible to simulate load profiles at a load level for a single occupant, a group of individuals in a building (e.g., a household) and an aggregation of buildings. In Figure 3.1 a conceptual diagram showing the main principles of the modeling approach used to simulate the load in detached houses is shown. As seen in the top-right part of the figure, a building is instantiated and in turn populated by a random number of individuals. Each individual has a stochastic occupancy behavior which will in turn correlate with an energy-use of appliances and DHW, along with the need to heat, cool and ventilate the building. At the bottom of the diagram, the electric vehicle and PV modules can be seen. The EV module inputs activity data from the behavioral module along with EV load parameters, e.g. driving patterns and charging pole capacity. The PV module inputs solar irradiance data and building data e.g. the roof top area.

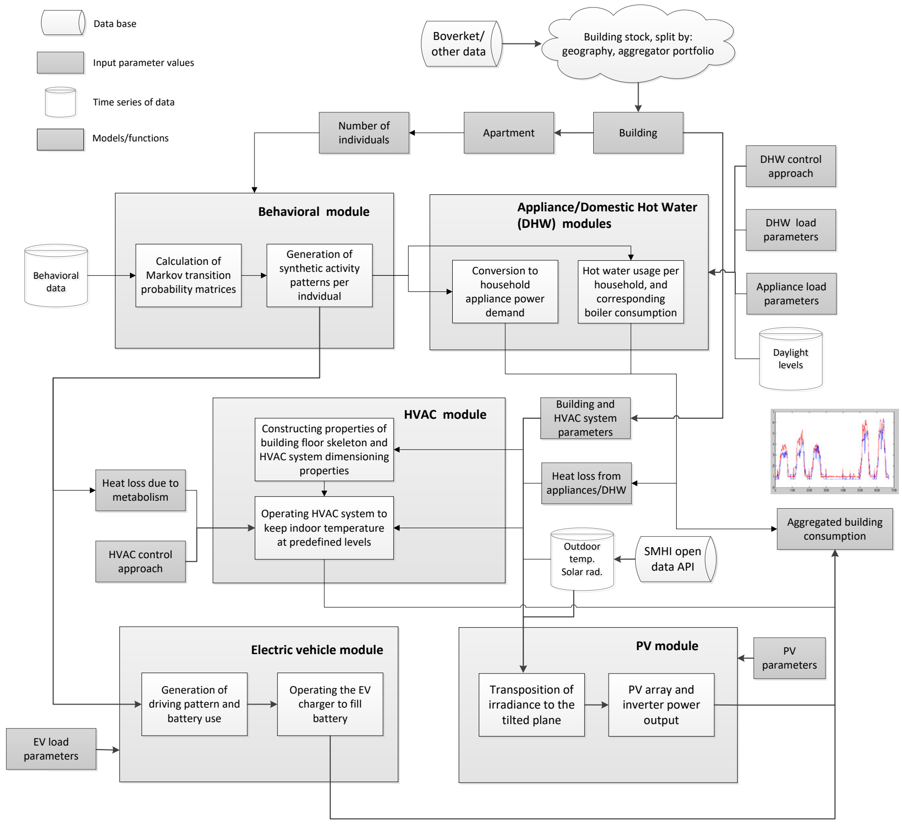

Figure 20: A diagram showing the interactions between modules, functions, parameters, and input data in the bottom-up simulation model.

8.2.1 End-user behavior

The behavior of the individuals is simulated through non-homogenous Markov chains. A Markov chain is a time-discrete stochastic process which describes how courses of action evolve over time by transiting between a set of states with certain probabilities. Between time steps t and $t + 1$, an individual can change its current state E_i to a new state E_j with probability p_{ij} . By estimating transition probabilities between all possible states and time steps, a transition matrix $M(t)$ can be defined. In short, $M(t)$ is a quadratic matrix where the size of each matrix is determined by the number of states. Then, N instances of $M(t)$ are defined, i.e. one matrix for each time step. The data used for estimating the transition matrices are taken from the Time of Use Data (TUD) that SCB conducted in the year 1996 with 463 participants. Here, each subject wrote a diary about their activities at a 5 min time resolution, for one weekday and one weekend day respectively. These data are more than 20 years old, but they are the most detailed ones available, and it has been shown that the crucial activities related to energy use still yielded valid load profiles 13 years later (5), and most likely today.

For each individual in the building, two separate Markov chain processes are simulated – one Markov chain for appliance usage (consisting of ten states), and one Markov chain for domestic hot water usage (consisting of two hot water consuming states – bathing and showering only). This implies that an individual can do two energy usage activities in at the same time, such as showering and

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cooking. However, the advantages this offers in simplicity believed to outweigh the increasing accuracy at the cost of a more complex model. More information about Markov models and their defined states can be found in (4).

The notable model parameters for this module are the following:

- Number of individuals per building which defines the number Markov chains that will be simulated
- Weekday vs weekend behaviors, which determines which days in the TUD to use for estimating the transition matrices

8.2.2 Appliance usage and domestic hot water (DHW)

The activity data is converted to electricity usage from usage of appliances and hot water. Widén et al (6) defines three classes of models which can transform an activity type into load profiles from various appliances: (a) electricity consumption that is constant during an activity, e.g. cooking devices, (b) a variable load cycle which is started directly after an activity is finished, e.g. dishwasher, and (c) a constant electricity consumption during the activity, e.g. TV watching and a stand-by consumption during non-use. In addition, these models take into account to energy-usage activities that are done collectively. For example, if two individuals in a household watch TV at the same time, there will only be energy-use from one TV set. For lighting-use, a separate model is proposed which is dependent on occupancy patterns of the individuals, along with the daylight levels. Hence, the seasonal and diurnal variation of lighting load is accounted for in the model (6). Subsequently, by assigning reasonable load parameter values and run times for the appliances, electricity consumption profiles can be generated with the aforementioned activity data for an arbitrary number of households and time frames. NB, the appliance usage will not be subject to any flexibility process, i.e. this data is considered to be non-controllable.

Moreover, a non-homogenous Markov chain with the following states is proposed for DHW processes: away, sleeping, bathing, showering and other. Only the states bathing and showering imply a usage of DHW. The DHW tank is modelled as energy storage where the energy Q_{drain} is discharged from the storage according to the following equation:

$$Q_{drain}(t) = V_{flow}^{a}(t) \times C_{p,water}$$

$C_{p,water}$ is the specific heat capacity of water. T_{outlet} and T_{inlet} are the temperatures of the inlet and outlet water, respectively. V_{flow}^{a} is the total hot water flow to serve the current DHW activity a of the household member (showers or baths). This flow is determined by hot water usage parameters of the activity, e.g. 10 liters of per minute of showering, and 150 liters of hot water use for a bath. Subsequently, the rule based controller charges the storage with P_{charge} at time t according to the following logic:

$$P_{charge}(t) = \begin{cases} 0, & if \quad T_{tank}(t) \geq T_{ref} + \delta/2 \\ P_{boil}, & if \quad T_{tank}(t) < T_{ref} - \delta/2 \\ P_{charge}(t-1), & otherwise \end{cases}$$

So, the electric boiler will supply energy to the tank at full capacity (P_{boil}) as soon as the tank temperature T_{tank} deviates from the reference temperature plus the dead band interval. If the tank temperature is above the reference temperature the controller does not charge the storage, and if the tank temperature is within the dead band, it executes the same control decision as in the previous time step.

Notable model parameters:

- P_{boil} – charging power of boiler [kW]
- V_{tank} – the size of the hot water tank [liters]
- $T_{ref,\ tank}$ – the reference tank temperature [°C]

Control decision: Decide whether to use the boiler at time *t* or not. This decision will depend on the current temperature level of the water tank, the electricity price, and the comfort constraints of the end-users In other words, decide when to turn on and off the heating capacity P_{boil} and thus charge the tank with energy (change the tank temperature)

8.2.3 Space Heating (SH)

The space heating module captures the thermodynamic processes in the building, and uses the building's Heating Ventilation and Air Condition (HVAC) system to maintain a desired indoor temperature. A simplified lumped capacitance methodology is applied to model these processes. The main objective of the HVAC module is to regulate the quantity of heating/cooling energy supplied by, e.g. heat pumps, to maintain a predefined indoor temperature (T_{ref}). The indoor temperature (T) will deviate from this set point value due to the following disturbances: (i) outdoor temperature (T_{out}), (ii) solar radiation (G_{sun}), and (iii) internal heat gains from occupants and appliances (G_{int}). Ambiance leakage, i.e. disturbance (i), is the only factor that can drain energy from the building, and the others disturbances can be seen as energy providers to the system. The leakage amount transferred between indoor and outdoor environment is determined by the conduction properties of the building skeleton (transmission losses), along with an amount of indoor air that is released from the building (leakage/ventilation losses). The transmission losses λ_{trans} are defined by:

$$\lambda_{trans} = \sum_j U_j A_j$$

U_j is the transmission coefficient of each building component j, and A_j is the total area of that component. Further, the leakage losses λ_{vent} are determined by:

$$\lambda_{vent} = V_b \times N_{vent} \times C_p \times (1 - \alpha_{rc})$$

V_b is the total volume of the building, N_{vent} is the air exchange rate. C_p is the specific heat capacity of air, and α_{rc}) is the heat recycle coefficient. Then, the heating losses Q_{loss} are quantified by:

$$Q_{loss} = (\lambda_{vent+}\lambda_{trans}) \times (T(t) - T_{out}(t))$$

Energy is supplied to the indoor environment through solar radiation and internal heat gains, denoted as Q_{sun} and Q_{int}. Simplified models have been implemented that accounts for these processes. Evidently, as all of these energy flows will not be in balance to provide a stable and desirable indoor temperature, a HVAC system exists that can compensate the energy imbalances. Such a system could be a heat pump, direct electrical heating system, bio fueled boiler, etc. The HVAC system's capacity to supply heating energy *Qreg* is dependent on the installed power capacity *Preg*, along with the COP indicator of the system. COP defines how much of the electrical energy input that is converted to heating/cooling energy. For example, for direct electric heaters the COP is 1, and typical air-air heat pumps have COP values between 2 and 3.5. These values vary with respect to model type, compressor power, outdoor temperature, etc. The installed capacity of the heating/cooling system (P_{reg}) is mainly dependent on the thermal capacitance of the building (C_{in}), and historical outdoor temperature data of the region (T_{DWT}). As a consequence of all the aforementioned processes, there will be a net flow of energy from/to the building that will affect the indoor temperature T between time step *t* and *t+1* according to:

$$T(t+1) = T(t) + \frac{1}{C_{in}}(Q_{reg}(t) + Q_{sun}(t) + Q_{int}(t) - Q_{loss}(t))$$

Hence, the indoor temperature for the next time step is dependent on the temperature value of the previous time step, the net flow of energy and the thermal properties of the building. Different rule based controllers strategies can be applied to regulate the indoor temperature. The first alternative is to control heating based on current temperature readings from the indoor thermostat. This controller will work in the same way as the DHW controller defined above. The second alternative is to control the heating output based on the outdoor temperature. Here, a linear response between the outdoor temperature and the heat pump is assumed. The response includes a compensation for expected internal gains from solar energy, occupants and appliances.

Notable model parameters:

- λ_{trans} and λ_{vent}: the isolation and ventilation loss factors of the building [kW/°C]
- τ: the thermal inertia of the building [hours]
- P_{reg}: the capacity of the heating system [kW]
- *COP:* the COP factor of the HP. Depends on HP type, air, ground, and the supply temperature of the system
- T_{DWT}*:* the dimensioning temperature of the heating system. This parameter is dependent on the thermal inertia of the building along with the coldest registered outdoor temperatures in the region [°C]
- *Controller:* the type of controller used, could be based on indoor temperature, outdoor temperature, etc.
- $T_{ref,\,SH}$: the reference indoor temperature [°C]

Control decision: P_{reg} at time t, i.e. the operational state of the heat pump, along with the indoor temperature set point

8.2.4 Electric Vehicles (EV)

A simplified model of electric vehicle usage and the charging of its battery have been developed. In this section the model will presented. In the figure below, a schematic overview of the model can be seen. As seen, the model is structured by a number of steps, where each step represents a distinct process which will impact the EV use and the charging demand at home. Each step is described in more detail below.

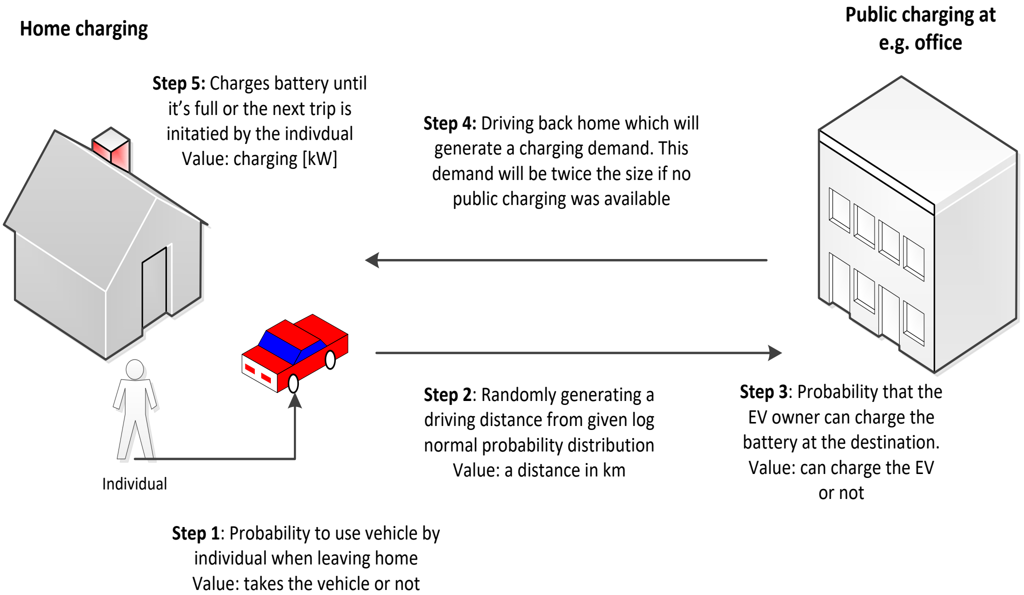

Figure 21: A schematic overview of the electric vehicle module

Step 1: the end-user behavior module outputs a time series of occupant or vacant states over the day. When the individual goes from an occupant state (home) to a vacant state (away), there is a pre-specified probability that the individual will use the EV. Here, a random number between 0 and 1 is generated, which then is compared to the assigned probability for using the car. If the generated value is lower than the probability, the individual will use the car.

Step 2: If the individual uses the car, the second step is to generate a driving distance D for the initiated trip. This distance value is drawn from a lognormal probability distribution with predefined means μ_D and standard deviation σ_D of driving distance. Such data is typically taken from national travel surveys, e.g. Trafikanalys. (7). Below, the equation for randomly generate distances can be seen.

$$D = Lognormal(\mu_D, \sigma_D^2)$$

Step 3: The subsequent step is to decide if public charging is available at the destination, e.g. the office building. This step works in the same fashion as step 2. In other words, a probability value for public charging availability is specified and then compared against a randomly generated value. If public charging is available, it is assumed that the whole energy demand of the trip to the destination is covered by that charging. Otherwise, the energy demand will be twice as large when the user drives home, i.e. the energy use for driving the destination, plus the energy use for driving home. The availability of public charging $\beta_{public,charge}$ is a Boolean variable, where $\beta_{public,charge}$ is 1 if its available, and 0 otherwise. The driving distance to home (D_{home}) can be formulated as follows:

$$D_{home} = \begin{cases} 0.5 \times D, & if\ \beta_{public,charge} = 1 \\ D, & otherwise \end{cases}$$

Step 4: Here, energy use for driving back to home is then estimated based on the outcome in step 3.

$$E_{trip} = v \times D_{home}, \qquad [kWh]$$

v is the average energy use per kilometer for the EV. Then, due to the energy use the State of Charge (SOC) of the battery will be decrease according the following equation due to the trip:

$$SOC = \frac{E_{state} - E_{trip}}{E_{bat}}, \qquad [\%]$$

E_{state} is the energy content in the battery prior to the trip and E_{bat} is the total energy storage capacity of the battery.

Step 5: when the individual is going from a vacant to occupant state in the Markov-model, the electric vehicle will be charged at home until it is fully charged or the individual initiates a new trip. Note, the charging capacity is limited by the socket P_{home}. Here, it is possible for the user to have slow or fast charging. Below the equation for the charging state at time t can be seen:

$$P_{charge}(t) = \begin{cases} P_{home}, & if\ \ SOC(t) < 1 \\ 0, & if\ SOC(t) = 1 \end{cases}$$

The SOC in the battery will change as follows between time slots t and $t+1$ because of the charging:

$$SOC(t+1) = \frac{P_{charge}(t) * \Delta t + SOC(t) * E_{bat}}{E_{bat}}.$$

Here, Δt is the time length. Step 1 to 5 is repeated in every simulation step.

Notable model parameters are:

- Battery size
- Charger capacity
- Probability to have a charger at work place
- Driving distance from home to work

Control decision: how to charge the battery when it is plugged in at the charging station at home, i.e. $P_{charge}(t)$.

8.2.5 Solar PV

The PV system model converts beam and diffuse radiation components on the horizontal plane to AC power output from the inverter in a number of steps. First, the irradiance that is absorbed in the solar cells is determined using the following model, which includes a transposition of the radiation components to the tilted plane of the PV modules and a calculation of absorbed irradiance:

$$G_T = k_b G_b R_b + G_d \left(k_d (1 - A_i) \left(\frac{1 + \cos\beta}{2} \right) + k_b A_i R_b \right) + k_g (G_b + G_d) \rho_g \left(\frac{1 - \cos\beta}{2} \right)$$

where G_b and G_d are beam and diffuse radiation on the horizontal plane, respectively, R_b is a scaling factor for beam radiation based on the incidence angles of the radiation on the tilted and horizontal planes, A_i is the anisotropy index, which is the fraction of extraterrestrial radiation preserved as beam radiation, β is the tilt angle of the tilted plane, ρ_g is the albedo of the ground, and the factors k_b, k_d and k_g are incidence angle modifiers (IAMs). For the latter, a fifth-degree polynomial function is used, given by King et al (8) as:

$$k_x = \sum_{i=0}^{5} b_i \theta_x^i$$

The coefficients b_i are fitted to measurement data, e.g. in (9). For k_b, the incidence angle θ of beam radiation is used. For the other two components, the effective angles of incidence for isotropic and ground-reflected radiation, θ_d and θ_g, respectively, are used. They are empirically related to the tilt angle β (10)

$$\theta_d = 59.7 - 0.1388\beta + 0.001497\beta^2$$

$$\theta_g = 90 - 0.5788\beta + 0.002693\beta^2$$

With *N* being the number of modules, the output of the photovoltaic system is:

$$P = N A_m G_T \eta_c (1 - q_{add}) \eta_e$$

where A_m is the module area, η_c is the module efficiency, q_{add} is additional array losses, and η_e is the efficiency of additional equipment, mainly the inverter(s). This PV system model is the same as the one in (11), where more details and validation of the model can be found.

8.3 FLEXIBILITY MODELS

The models presented in section 8.2 reflect non-flexible electricity consumption, where this usage is mainly controlled with respect to weather situations (outdoor temperatures) and end-user behavior (DHW demand). In this section, these base controllers will be extended with flexible controllers which can steer the usage of space heating, DHW and electric vehicle charging with respect to external dynamic price signals, e.g. an hourly day-ahead price. Two types of flexible controllers are implemented, one for thermostatically controlled loads (SH and DHW) and one for the EV charging.

8.3.1 Thermostatically controlled loads

For thermostatically controlled loads an indoor temperature comfort interval along with price sensitivity parameters constitutes the flexible controller. The controller relates an electricity price with an allowed comfort and the price parameters specified by the end-users, and then compute a new temperature set-point for the controller to work against a higher or lower price. The figure below shows the main-functioning of the controller.

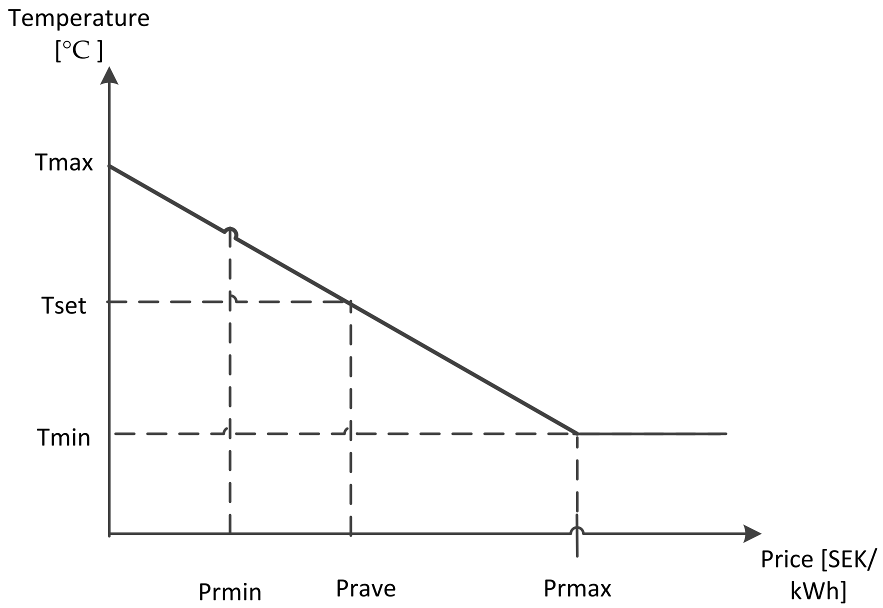

Figure 22: The functioning of the flexible thermostat controller.

As seen, the figure shows a linear function between a minimum price (P_{min}), average price (P_{ave}) and maximum price (P_{max}), to a minimum temperature (T_{min}), reference temperature (T_{ref}) and maximum temperature (T_{max}) set point for the thermostat. The linear function is estimated as follows:

The slope of the line (α): $\alpha = \frac{-\Delta T}{Pr_{max}-Pr_{ave}}$, where Pr_{max} is the maximum price of the end user, P_{ave} is the average price. ΔT is the maximum allowed temperature deviation from the reference, e.g. 2 °C.

The magnitude of the line (β): $\beta = \left(-\Delta T + T_{ref}\right) + Pr_{max} * \alpha$.

The flexible rule based controller will find a new temperature reference set-point (T_{ctrl}) at time t according to the following logic:

$$T_{ctrl}((t) = \begin{cases} T_{ref} - \Delta T, & if \qquad Pr(t) \geq Pr_{max} \\ T_{ref} + \Delta T, & if \quad if\ Pr(t) \leq \left(\frac{1}{\alpha}\right) \cdot (T_{ref} + \Delta T) \\ \alpha P(t) + \beta, & \qquad otherwise \end{cases}$$

The new thermostat controller set point is then inserted to the space heating model which will influence the consumption level of the space heating/DHW unit, and consequently the indoor or tank temperature.

8.3.2 Electric Vehicles

The flexible rule based controller for EV:s works in the same fashion as the thermostatically controller loads, except for some minor differences.

In essence, the flexibility of the charging of EV:s is determined by a minimum SOC level (SOC_{min}) which is specified by the end user. The SOC_{min} explains how much of the battery that is subject to flexible charging, i.e. charging that can be postponed to a later point in time. The figure below shows the functioning of the controller.

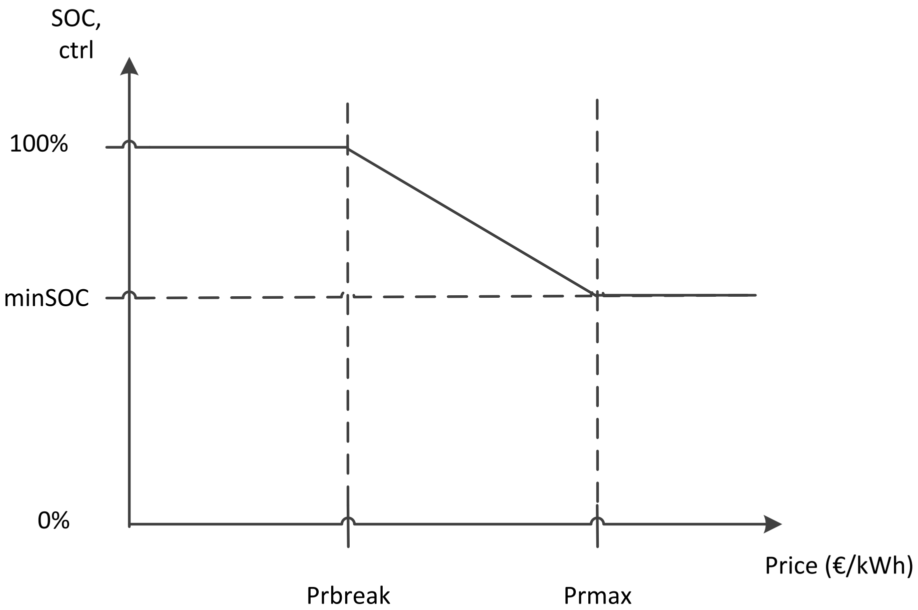

Figure 23: the functioning of the flexible EV charging controller

As seen, the set-point value of the SOC (SOC_{ctrl}) is determined by three parameters; (i) the SOC_{min}, (ii) Pr_{break} – the threshold price, and (iii) Pr_{max} - the maximum price. The SOC set-point is 100% until the price exceeds a specified limit Pr_{break}. Then, the set-point decreasing linear fashion with respect to increasing price until the minimum allowed SOC is reached. This occurs when the price is Pr_{max}. After this, the set-point will be SOC_{min} independently of the price increase.

In mathematical terms the controller can be expressed as follows:

The slope of the line (α): $\alpha = \frac{minSOC-100}{Pr_{max}-Pr_{break}}$, where Pr_{max} is the maximum price of the end user, P_{break} is the average price. $minSOC$ is the minimum allowed SOC, e.g. 80%.

The magnitude of the line (β): $\beta = 100$.

The flexible rule based controller will find a new SOC set-point (SOC_{ctrl}) at time t according to the following logic:

$$SOC_{ctrl}((t) = \begin{cases} minSOC, & if \quad Pr(t) \geq Pr_{max} \\ 100\%, & if \quad Pr(t) \leq Pr_{break} \\ \beta + \alpha \cdot (Pr(t) - Pr_{break}), & otherwise \end{cases}$$

This set-point is input to the EV model in section 8.2.4.

END-USER SCENARIOS AND THEIR IMPACT ON DISTRIBUTION SYSTEM OPERATORS

Elnäten håller på att omvandlas från traditionella centraliserade system med storskaliga produktionsanläggningar som producerar el på höga spänningsnivåer, till decentraliserade system där slutkunderna på lågspänningsnivå producerar sin egen el och är aktiva i sin förbrukning.

Här presenteras ett simuleringsramverk som gör det möjligt att analysera och utvärdera hur olika kundrelaterade scenarier påverkar den teknoekonomiska verksamheten för den som äger ett lokalt elnät.

Resultaten av simuleringarna visar att ett landsbygdsnät är känsligt för underspänningsproblem i ett elektrifieringsscenario, och att elnät i tätorter är mer sårbara för överbelastning i detta fall.

Lastfaktorn tenderar att försämras i alla scenarier jämfört med basfallet vilket är negativt eftersom intäkter delvis är kopplat till lastfaktorn. En slutsats är att man i landsbygdsnät bör stödja sina kunder att energieffektivisera så att det befintliga nätet kan hantera en framtida elbilsintegration. En nätägare med nät i en tätort bör stimulera sina kunder till en utökad elektrifiering så att intäktsströmmarna kan öka.

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