Applied Energy 387 (2025) 125563

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Analyzing the impact of heating electrification and prosumaging on the future distribution grid costs

Philipp Mascherbauer [a],*, Miguel Martínez [b], Carlos Mateo [b], Songmin Yu [c], Lukas Kranzl [a]

[a] Technische Universität Wien, Energy Economics Group, Gusshausstrasse 25-29/370-3, 1040 Wien, Austria
[b] Institute for Research in Technology (IIT), Universidad Pontificia Comillas, Calle de Alberto Aguilera 23, 28015 Madrid, Spain
[c] Fraunhofer Institute for Systems and Innovation Research, Breslauer Str. 48, 76139, Karlsruhe, Germany

ARTICLE INFO

Keywords:
Distribution electricity grid
Grid reinforcements
Demand-side management
Residential buildings
Power distribution planning
Heat pumps
Electric vehicles

ABSTRACT

The electrification of households' heating systems will lead to an increase in the electricity demand, which will necessitate additional investments in the grid infrastructure. The interaction with other technologies, including PV, batteries, electric vehicles (EVs), and home energy management systems (HEMSs), further complicate the situation. In this study, we analyze the following question: How will prosumaging households, who consume, produce and manage their energy consumption with HEMS, impact the future reinforcement costs of the electricity distribution grid? We conducted case studies for two urban areas, Murcia in Spain and Leeuwarden in The Netherlands. First, by developing scenarios on the uptake of electrified heating systems, PV installations, battery storage, EVs and HEMSs, the energy demand of each building is modeled for the two areas under different scenarios. Then, the buildings' electricity load profiles were provided to a second model, to calculate the necessary distribution grid infrastructure to cover this demand on a granular spatial level. Results show that low voltage lines and transformers will need significant investments, especially in the regions where a high share of conventional heating systems are replaced by heat pumps but also in regions where the aggregate electricity peak demand is reduced.

1. Introduction

Decarbonization efforts and declining renewable electricity generation costs have been driving up the amount of renewable fluctuating electricity in the grid. To deal with the fluctuation increase, demand response (DR) can make an important contribution to the energy transition. At the same time, the rise in the adoption of electrified heating systems, mainly heat pumps (HPs), has been increasing the electricity demand of residential end users, which requires the reinforcement and expansion of the low-voltage distribution grids. This trend also interacts with the diffusion of several other technologies: decentralized PV systems, electric vehicles (EVs), and home energy management systems (HEMSs). Compared with the high voltage transmission lines, the monitoring and study of low-voltage distribution grids is less understood. It is hard to predict the impact of multiple technology trends of households on the distribution grid. The question arises how heavily the distribution grid will have to be reinforced in the future to handle the additional burden imposed by electrified heating systems, electric vehicle charging stations and so called Prosumagers, referring to households which consume, produce and manage their electricity demand, trying to minimize energy cost.

In this study, we investigate the grid reinforcement costs in two case studies under different scenarios concerning the uptake of electrified heating systems, storage systems, PV, building renovations and prosumagers until 2050. We are doing this by coupling two models. First the FLEX model calculates the hourly electricity demand of individual buildings in a given area. These electricity demand profiles are then fed into the reference network model (RNM), a granular spatial model, to calculate the needed investment and operation costs of distribution grids. With this approach, we achieve a very high level of granularity and detail which enables estimating possible future grid reinforcement needs in the distribution grid. We analyze two urban areas, in the north and south of Europe. By linking the two models for the two case studies, we try to answer two questions: First, how are future investments in distribution grids impacted by the decarbonization efforts of the residential building stock? Second, can prosumagers lower these investment costs?

The remainder of this paper is structured as follows. Section 2 overviews existing studies on buildings' flexibility potential and electricity distribution grid reinforcements in the residential sector, highlighting a literature gap between those two. Section 3 introduces our

* Corresponding author.
E-mail address: mascherbauer@eeg.tuwien.ac.at (P. Mascherbauer).

https://doi.org/10.1016/j.apenergy.2025.125563
Received 1 November 2024; Received in revised form 15 January 2025; Accepted 14 February 2025

Abbreviation	Full name
AC	Air Conditioner
COP	Coefficient of performance
DER	Distributed energy resources
DHW	Domestic Hot Water
DR	Demand Response
EV	Electric Vehicle
HEMS	Home Energy Management System
HP	Heat Pump
HV	High Voltage
LV	Low Voltage
MFH	Multi Family House
MV	Medium Voltage
O&M	Operation and Maintenance
OLTC	On-load tap-changing
PV	Photovoltaic
RNM	Reference Network Model
SFH	Single Family House

models in detail and Section 4 provides the input data and scenario definitions. Then, in Section 5, we present the results and discuss them. Finally, we conclude in Section 6, and point out the need for further research.

2. Literature review

In this section, the status quo of two strands of literature that will be combined in this paper are reviewed: (1) literature on the DR potential of residential buildings and (2) literature on future electricity distribution grid development due to electrified heating systems and DR by buildings. DR in residential buildings has a high potential to shift electric loads when heating systems are electrified. Wang et al. [1] show that electricity costs can be reduced by 14% and peak demand by 31% through DR. They did so by developing a predictive control model, optimizing the operation of the heating system without any thermal or electrical storages within the building except the building mass itself. A lot of publications consider the thermal mass to have big potential in DR programs [2–7], mainly because the investment costs are very low compared to any other storage technology [8].

However, the potential for DR in single buildings is higher and more lucrative if other storage devices are included [9]. Numerous studies investigate how a household can minimize their energy costs by utilizing different technologies, whereas only a small share of studies investigating thermal mass as a storage, focus on neighborhood or district level [3]. Examples for single building investigations are Kandler [10] and Salpakari et al. [11] who minimize the electricity cost of individual households considering flexibility based on battery storage, smart devices, EVs and the thermal mass of the building. Klinger [12] models the market potential of PV and stationary battery systems under the assumption that HP and EV are adopted. They find that PV and stationary batteries will become more lucrative for buildings with HP and EV. Often times dynamic electricity tariffs are used as incentive for homeowners to shift their demand. Due to the higher volatility in electricity prices since 2020, shifting the demand with a HEMS became a more economically viable option. Stute et al. [13] state that using dynamic electricity price tariffs as end consumer can reduce the energy costs significantly, especially when used in combination with a HP and an EV. They investigate 3 different price signals that vary in their hourly price spread. With a high price spread (10.7 €/MWh standard deviation) 62% of investigated buildings profit from investing into a HEMS. Sridhar et al. [14] investigate 5 different buildings and 3 different electricity tariffs using HEMS in Finland. They imply that a real time price is more effective than a time of use tariff as incentive to shift load. Also buildings with good insulation had the highest cost savings. A similar result was found by [15] who compared three different electricity tariffs for DR in a single building. They found that the building provided the highest flexibility under a real time price scheme.

While the above mentioned studies give insights into the optimal sizing of components such as PV and batteries, load shifting potential and the impact of electricity prices, the relation to the electricity grid is not investigated. Typically the electricity consumption rises when residential buildings shift load due to higher thermal losses. Miara et al. [16] show that HP consumption can rise by 20% due to higher required temperature levels in the thermal storage. In [17] the demand increases by 60% and additionally they state that the peak power during charging of the thermal storage was 50% higher than the original peak. This leaves the question, what happens to the distribution grid if many households in close proximity start to shift their electric loads?

Stute et al. [18] investigate how dynamic grid tariffs impact grid reinforcement requirements in Germany based on load flow analyses in low voltage grids by assigning simulated load curves from houses to grid connection points. They find that a tariff with a capacity subscription component is best to minimize grid reinforcement requirements. In [19] the distribution impacts on secondary transformers that will result from the energy transition are estimated based on spatially linked socio-economic data for Scotland. This approach allows to obtain cost estimates at a national level. Probabilistic power-flow assessments are a common approach to analyze the impacts on distribution systems of increasing adoption of different distributed energy resources (DERs), such as EVs [20] and HPs [21]. Moreover, some papers have studied the impacts of the co-deployment of EVs with solar photovoltaics (PV) [22] and HPs with PV [23] or even full residential electrification retrofits that combine EVs, HPs, PV and HEMSs [24]. Common result metrics of probabilistic power-flow assessments include the probability of exceeding grid limits as well as the number and severity of voltage and thermal limit violations [25]. Nevertheless, these assessments do not estimate the required grid reinforcements in future scenarios with higher electrification levels.

Few authors have estimated the cost of the network reinforcements required in future residential electrification scenarios. In [26], the required grid investments resulting from the uptake of EV, HPs, and PV in 2035 and 2050 were analyzed for a representative case study encompassing 170,000 Swiss households. The cost of distribution circuit and transformer upgrades for residential electric heating and EV charging in 2030, 2040, and 2050 for California have been estimated by [27]. Although the methodology employed in [27] considers forecasts hourly

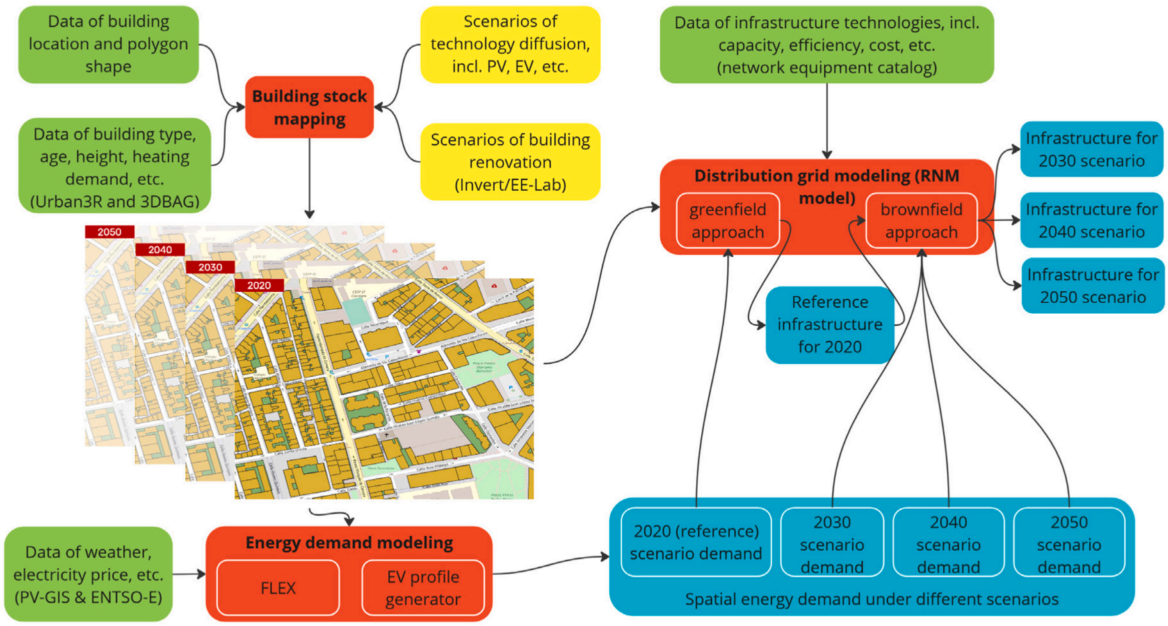


Fig. 1. Modeling framework of the study.

profiles for EVs and HPs, it does not consider the response of prosumagers to price signals that incentivize them to shift their demand to off-peak hours (e.g., time-of-use tariffs).

Authorities nowadays are struggling with grid congestion and the problem will increase when electric HPs and EVs are promoted more. Only a few studies study the consequence for local electricity grids, although it might be an important barrier for a further transition to a decarbonized building stock. This paper contributes to existing literature by carrying out a combined analysis of building thermodynamics and distribution grid in two exemplary case studies for future decarbonization scenarios. In this way, we provide new insights for potential grid related cost that occur when heating systems are switched, EVs, PVs are adopted and when households start to actively shift their electricity demand.

3. Methodology

The workflow of our modeling framework includes three parts as shown in Fig. 1. First, by combining Open Street Maps (OSM) [28] with other building databases, as well as the scenarios of building renovation and technology diffusion, we create the building stock map of the two case study regions for the four modeling years (2020, 2030, 2040, 2050). Second, the energy demand of each individual building, as well as the electricity demand of EVs, are calculated in hourly resolution. Third, taking the building stock map and the energy demand profiles as input, the RNM is used to calculate the distribution grid needs. For the year 2020, the RNM follows a greenfield approach and generates a reference distribution grid for each case study. Then, for the years 2030–2050, the RNM calculates the enhancement needs of the distribution grid, taking the 2020 grid as a baseline.

3.1. Building stock mapping

In this study, two regions which span over a 10 km^2 area in Murcia (Spain) and Leeuwarden (Netherlands) are selected to represent a south and north European climate.[1] We selected these two regions because of the available data resources, their climatic conditions and the shares of the installed heating systems. This way we tried to make the results transferable to similar regions in the south of Europe where buildings are not necessarily heated by gas boilers and central and north-eastern Europe where gas boilers dominate the residential heating sector. The building data of each individual buildings in the two areas are collected and processed as follows:

1. Building footprints were taken from SM.
2. The construction period and other relevant building related data like the building age and height is gathered from local databases (URBAN3R [29] for Murcia and 3DBAG [30] for Leeuwarden).
3. The polygon shapes from OSM are merged with the data from Urban3R and 3DBag. Non-residential buildings were filtered out if they were labeled as non-residential in one of the databases.
4. A manual inspection was done, to exclude very large buildings that were identified as non-residential via Google Maps. Buildings with a polygon area lower than 45 m^2 were also excluded.

As a result, 15 654 buildings in Leeuwarden and 4447 buildings in Murcia were parameterized. The data was collected for 2019 and 2020 for the two regions since for these years all needed data was available. The building type structure marks a significant difference in the two case studies, where in the selected area of Murcia, we have mainly multi-family buildings (MFH) and in Leeuwarden we see the majority of buildings being single family houses (SFH) and row houses or very small multi-family buildings (not more than two-three families). The attached wall area of each building to its neighbors was calculated using the polygon shapes. In further calculations the heat transfer to neighboring buildings was neglected.

To develop the building stocks in future modeling years, we combined the data from Invert/EE-Lab [31], open-sources, as well as assumptions when data is unavailable. The penetration paths of different

[1] Using EPSG 4326 the coordinates for selecting the areas are:
Leeuwarden: north: 53.2178674080337, south: 53.1932515262881, east: 5.82625369878255, west: 5.76735091362368
Murcia: north: 37.9988137604873, south: 37.9656536677982, east: −1.10710096876283, west: −1.13912542769010.

technologies for the two regions were developed based on open data and scenario assumptions. The number of persons per building was taken from URBAN3R and 3DBag respectively. If not available for specific buildings, it was chosen based on HotMaps data [32].

3.2. Energy demand modeling

3.2.1. FLEX model

FLEX is an energy model for individual households/buildings, which calculates the operation of technologies throughout a whole year (8760 h) in two modes: (1) simulation mode, in which the system operation is calculated following a rule-base approach, and (2) optimization mode, in which a EMS minimizes the operation cost of the household. As incentive to minimize energy cost, a variable electricity tariff is provided to the household. The model is introduced in [33] and has been used in [7,9].

The following inputs were used in the FLEX model to calculate the household energy demand:

- Indoor set temperature: average indoor set temperature is set to not fall below 20 °C in heated buildings. Direct electric heated buildings are an exemption, here the average indoor set temperature is set to 18 °C when heating is activated (plugged in), otherwise, the indoor temperature has no lower bound.
- Electricity demand per person: The average electricity demand is taken from the Eurostat [34].
- DHW demand per person: The average DHW demand is taken from Eurostat [34].
- Weather data: Air temperature and solar radiation was downloaded from JRC [35] for the respective cities on hourly granularity. 2019 was chosen for the weather data as more recent data was not available.
- Electricity price: Day ahead price for Leeuwarden was taken from the ENTSO-E [36] platform as end consumer electricity prices for 2019 with additional hypothetical grid fees so that the minimum price was at 5cent/kWh. For Murcia we used the actual tariffs for residential consumers from 2019 [37] for the "efficiency 2 periods tariff" of the active energy invoicing price, to match the price data with the weather data.

For every building a heating system is defined in the FLEX model. Heating systems included in this work were: air source HP, ground source HP, direct electric heating, conventional boiler (including gas, fuel, coal, biomass etc.) and no heating system at all. The necessary heating and cooling demand was calculated with a simplified five resistance one capacity (5R1C) approach, considering the thermal mass of the building as storage. Thermal storages for domestic hot water (DHW), heating and electricity (battery) are added if installed in the building. In the simulation mode the indoor temperature is kept above a certain threshold (20 °C). If a PV is installed and a battery or thermal storage is available these storages are charged with the surplus of the PV generation prioritizing the battery storage over thermal storages. The energy price has no influence on the behavior of the consumer. When a building used a HEMS (prosumager) meaning the energy costs were minimized, the following objective function was applied:

$$\min \sum P_t \cdot p_t \tag{1}$$

$$\text{s.t:} \quad P_t = P_{\text{appliances},t} + P_{\text{electric heating system},t} + P_{\text{battery},t} - P_{\text{PV},t} \tag{2}$$

$$P_{\text{electric heating system},t} = \frac{Q_{\text{heat demand},t}}{COP_{\text{heat demand,t}}} + \frac{Q_{\text{DHW demand},t}}{COP_{\text{DHW,t}}} + \frac{Q_{\text{DHW tank},t}}{COP_{\text{DHW tank,t}}} + \frac{Q_{\text{buffer tank},t}}{COP_{\text{buffer tank,t}}} \tag{3}$$

With P representing the electrical power and p the electricity price. The electrical power is the sum of the electricity powers of all appliances in the house ($P_{\text{appliances},t}$) including the charging and discharging power of the battery ($P_{\text{battery},t}$), any electric heating system ($P_{\text{electric heating system},t}$) minus the produced PV generation ($P_{\text{PV},t}$). The needed power for the electrical heating system is determined by the needed heating demand for space heating ($Q_{\text{heat demand},t}$) and domestic hot water ($Q_{\text{DHW demand},t}$) together with the charging and discharging of the respective thermal storages ($Q_{\text{DHW tank},t}$, $Q_{\text{buffer tank},t}$). By dividing the energy demands with their respective coefficient of performance (COP) factors, we obtain the electricity demand. The COP is dependent on the source and sink temperature and the overall efficiency of the system. The load-shifting behavior of buildings depends on the volatility, absolute levels, and frequency of electricity price fluctuations. Greater frequency and volatility encourage prosumagers to shift more electricity throughout the year. However, higher absolute prices reduce the incentive to shift demand due to losses incurred during preheating of thermal tanks or raising indoor temperatures. In any case the prosumager will increase its electricity consumption when prices are low and decrease its consumption at high prices compared to the normal consumer.

In general, the indoor set temperature for the buildings was set to a minimum of 20 °C with the possibility to be increased by 3 °C for Prosumagers. However, modeling the direct electric heating system requires a different approach. Direct electric heating systems in this study are considered to be plug in heat ventilators with an efficiency of 1. People use them only at specific times and mostly only over a certain time period instead of keeping a certain minimum room temperature. We tried to mimic this behavior by not setting a minimum indoor set temperature when heating is turned off. If heating is turned on, the average set temperature would be set to 18 °C. The probability distribution of people using the direct electric heating systems was chosen so that the resulting summed load profiles resemble the shape from real measured profiles [37].

With this information the FLEX model was used to calculate the heating, cooling and electricity demand of each building under different scenario assumptions. The resulting load profiles were used as input for the RNM. The source code is openly available on GitHub [38] and the complete formulation is provided as supplementary material.

3.2.2. EV profiles generator

Currently, EVs represent the most viable option for decarbonizing light-duty vehicles. The main challenge for characterizing hourly EV residential charging profiles in future scenarios is that the availability of data on residential EV charging is scarce [39]. Although there are few datasets and studies for early-adopter regions, such as Norway [40,41], we have developed a stochastic profile generator for residential EV charging based on the available building and mobility data in the regions of interest. This methodology also estimates future EV penetration levels and the locations of EVs within residential areas. Fig. 2 presents the flowchart of the proposed methodology, which follows similar steps to [42–44].

The model is structured into three stages:

1. *Modeling of EV adoption scenarios:*
   The first stage of the model determines the number of EVs and their location. The number of cars per household is estimated based on national surveys of car ownership per household. These surveys are used to characterize a probability distribution of the number of cars per household. Then, a random selection of car owners opting to transition from internal combustion engine vehicles to EVs is performed based on the projected EV penetration level for a specific year and scenario. EV adoption rates are estimated in accordance with objectives set by national authorities within the designated regions.
2. *Characterization of EV charging requirements:*
   The second step is to characterize the charging needs of each EV. In each scenario, the arrival time and daily distance traveled by each vehicle are assigned based on probability distributions. Then, the type of charger and the weekly charging frequency are assigned following the methodology in [45], which employs the

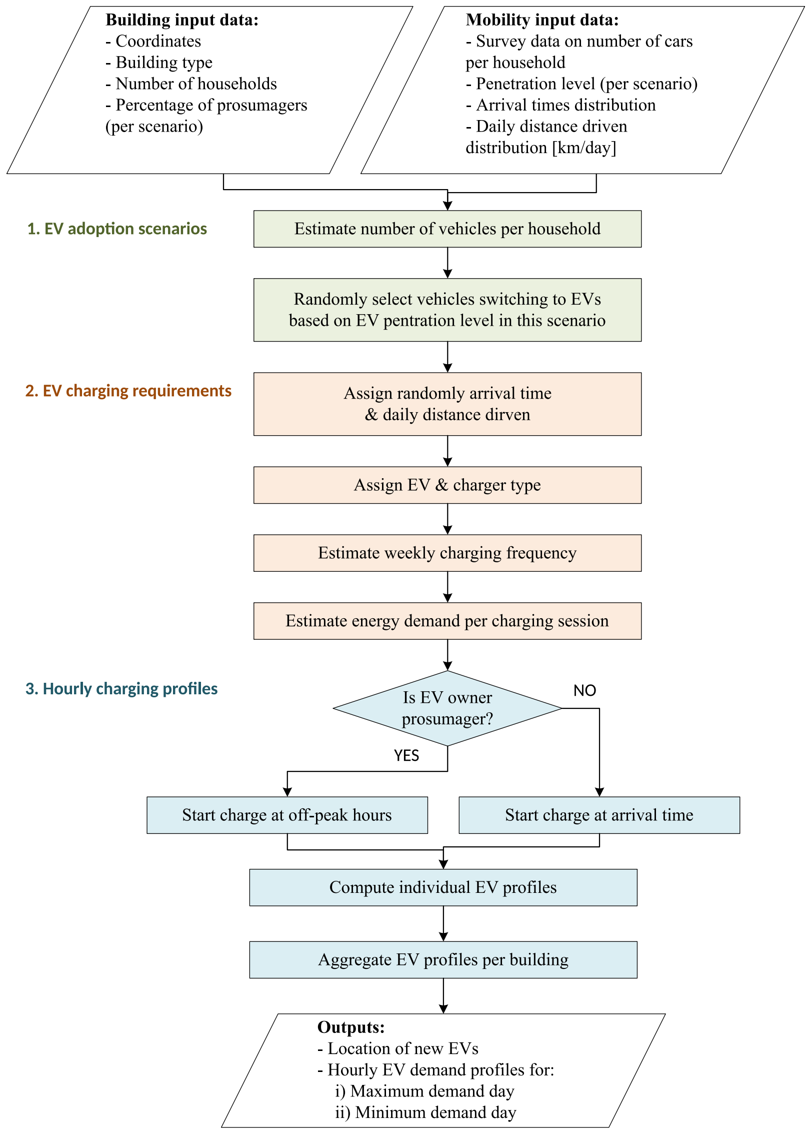


Fig. 2. Flowchart of residential EV load profile generator model.

daily energy demand of each EV as the primary input. Three AC charging power levels are considered: 3.6 kW, 7.2 kW & 11 kW. The weekly charging frequency allows for the calculation of the energy that is charged per session. While the majority of their charging needs are met at home chargers, EVs may occasionally charge at public charging points. A factor representing the charging demand met at public charging stations is incorporated into the model. This factor is set to 20% in 2030 but is increased to 30% in 2050, reflecting that early adopters have more consistent access to residential chargers.

3. *Modeling of hourly charging profiles:*
A question that has not been sufficiently addressed in other models [42–44] is how to establish the scenarios with the highest and lowest electricity demand from residential EVs for planning the distribution grid. For instance, synchronization of EV charging could happen due to low electricity prices or the night before a national holiday [46]. It is, therefore, assumed that, in the worst-case scenario, all EV owners will decide to charge on the same day. This does not imply that all EVs will charge simultaneously, as the diversity in the arrival times is still considered. On the other hand, for the scenario with the lowest EV demand, it is assumed that only EVs charging six or seven days per week will be charging that day, as they may be unable to postpone their charge to the next day.
The last step is to compute the hourly demand profiles for the EVs. If the EV owner is a prosumager, then it is assumed that its charger is capable of smart charging and can delay the charging session to off-peak hours with lower electricity tariffs. Otherwise, the EV will commence charging as soon as it is connected to the charger. Finally, the hourly demand profiles for EVs located in the same building are aggregated.

3.3. Distribution grid modeling

The resulting load and feed-in profiles for every single building computed with FLEX and EV profiles generator models are provided as input to the RNM to estimate the necessary electricity distribution grid investments in future decarbonization scenarios. Two representative days are considered to plan the distribution networks:

- Day with the highest electricity peak load (a winter day)
- Day with the highest peak feed to the grid (a spring day)

The RNM, introduced by [47], plans the layout of low voltage (LV), medium voltage (MV), and high voltage (HV) lines together with the positions and capacity of distribution transformers and substations. The objective is to minimize the distribution system costs while satisfying topological and quality of supply constraints. First, the RNM in greenfield mode obtains a synthetic model of the initial distribution grid for the base case (2020). Then, the RNM in brownfield mode reinforces this initial grid to accommodate the new loads (e.g., HPs, EVs, etc.) and PV installations in each future scenario.

3.3.1. Greenfield planning of "existing" distribution networks

In the base 2020 scenario, the RNM is employed to generate a synthetic model of the existing electricity distribution networks in the areas of interest. The greenfield planning functionality of the RNM allows for the design of a cost-effective distribution network to supply all consumers and distributed generators in a particular area while complying with voltage and thermal limits and geographical and reliability constraints. This model has been utilized to develop European large-scale synthetic grids from scratch in [48] and to plan the distribution network of new urban districts [49]. Even though the complete distribution grid at the country level is not modeled, the analysis remains reliable and replicable, as we do not solely consider the conditions of individual feeders, which is a common approach taken in this field.

The inputs to the RNM are the buildings' location and their load and generation profiles, the location and charging profile of EVs, the layout of street maps, a catalog of standard electrical equipment (e.g., power lines, distribution transformers, etc.), and general configuration parameters. The catalog of standard equipment considers reference unitary investment and operation and maintenance (O&M) costs for electricity distribution equipment in Spain [50].

The objective of the greenfield RNM is to minimize investment, energy losses, and O&M costs throughout the network's lifespan. It employs a bottom-up methodology whereby LV, MV, and HV grids are planned in a sequential manner. The initial step is to identify and size the supply points (e.g., MV/LV distribution transformers, HV/MV substations, etc.) for each voltage level. Subsequently, the routing and capacity of power lines is planned. The initial configuration of the power lines, a minimum spanning tree connecting all buildings to the supply points, is not always feasible. In such cases, the configuration is modified to comply with geographical and technical constraints. These constraints are primarily street layouts, voltage and thermal limits, and reliability indices. For the grid in Murcia, the load-based reliability indices used are the equivalent interruption time of installed power (known by its Spanish acronym: TIEPI) and the equivalent number of interruptions of installed power (known by its Spanish acronym: NIEPI) [51], which are the Spanish equivalent to Average System Interruption Duration Index (ASIDI) and the Average System Interruption Frequency Index (ASIFI) defined in [52].

The output of the greenfield RNM is the techno-economic parameters for each designated distribution network component and a detailed report of their cost by component type and voltage level. In addition, it provides geographic information system data for all network components, which can be used to represent these grids on a map (see Fig. 3).

3.3.2. Brownfield planning of distribution networks under future policy scenarios

The initial grids for each area of interest obtained with the greenfield RNM serve as a reference for the brownfield RNM to plan cost-efficient distribution network reinforcements needed to accommodate the new demand and distributed generation expected in future scenarios. This methodology has been employed to assess the impacts of high penetrations of DERs on the distribution grids, including batteries [53], solar PV self-consumption [54], and EVs [55]. However, this methodology has not previously been applied to assess the long-term impact of electrification policies (e.g., energy-efficient buildings, HPs, EVs, PV installations, etc.), nor to quantify the effect of an increasing share of prosumagers on the electricity grid infrastructure.

The brownfield functionality of the RNM proceeds similarly to the greenfield approach. The main difference is that an initial network is already provided to the brownfield RNM. Then, it connects new consumers and distributed generators to the initial network. The initial network configuration is improved using branch-exchange to make it technically feasible at the minimum cost.

A limitation of the brownfield RNM is that, while it optimally plans new locations of supply points (e.g., MV/LV distribution transformers) for new consumers, it can only increase the capacity of current elements to meet the additional demand of existing customers. This may lead to unrealistic numbers of parallel elements in long-term scenarios with very high demand and generation growth. This effect is seen in the 2040 and 2050 scenarios in Leeuwarden. Additional MV/LV distribution transformers were provided as input to the brownfield RNM to improve the results in these scenarios.

4. Scenarios

For each case study, we developed 12 scenarios which can be split into three scenario branches (see Fig. 4):

1. We distinguished between a *Strong policy* and a *Weak policy* scenario which describe the building stock. In the strong policy scenario, climate neutrality within the building stock is achieved in the year 2050 whereas in the weak policy scenario, policy implementations are left as they are right now, not leading to a climate neutral building stock in 2050. The strong and weak policy scenarios influence the future state of the buildings, meaning they determine the rate of renovation and needed heat demand, as well as the rate of installed HPs and PV and battery adoption.
2. For each policy scenario, we assume *low*, *medium* and *high* share of prosumagers. In this way, we gain insights into how future Prosumagers might impact the need for re-enforcements in the distribution grid.
3. We added the adoption of EVs to each scenario, meaning we are looking at one scenario *without EVs* and one *with EVs* (see Section 3.2.2). This way we can isolate the strong impact of EVs on the electricity grid.

4.1. Policy scenarios

As introduced in Section 3.1, two scenario results from Invert/EE-Lab were selected to parameterize the building stocks in the two regions from 2030 to 2050. In the strong policy scenario, we assume more efficiency measures are implemented and the heating and cooling demand of buildings are lower. Fig. 5 shows the percentage of installed heating systems for the strong and weak policy scenarios. In both scenarios, the share of conventional heating systems is strongly reduced and electrified heating systems are increased. In Murcia already 20% of buildings use air sourced HPs in 2020. This is because in Murcia summers are very hot and winters are mild, and many buildings have air-source HPs installed for cooling in the summer and for heating in the winter. Additionally, we have a lot of direct electric heating systems (39%) in the base year, which almost do not exist in the Leeuwarden region. In Leeuwarden, conventional heating systems dominate strongly in 2020 and are mainly replaced by HPs in the following years. In the strong policy scenario the renovation rates (expressed as percentage of renovated ground floor area per year) are much higher than in the weak policy scenario. 2.3% of all SFHs and 4.7% of all MFHs in Murcia are yearly renovated between 2019 to 2050. In Leeuwarden the rates are 3.8% for SFH and 3% for MFH. On the contrary, in the weak policy scenario these rates are 1.4% for SFH and MFH in Murcia and 1% and 0.8% in Leeuwarden. The renovation rates in Murcia are higher because here fewer deep renovations and more light-investment renovations are undertaken (e.g. changing windows) because of the

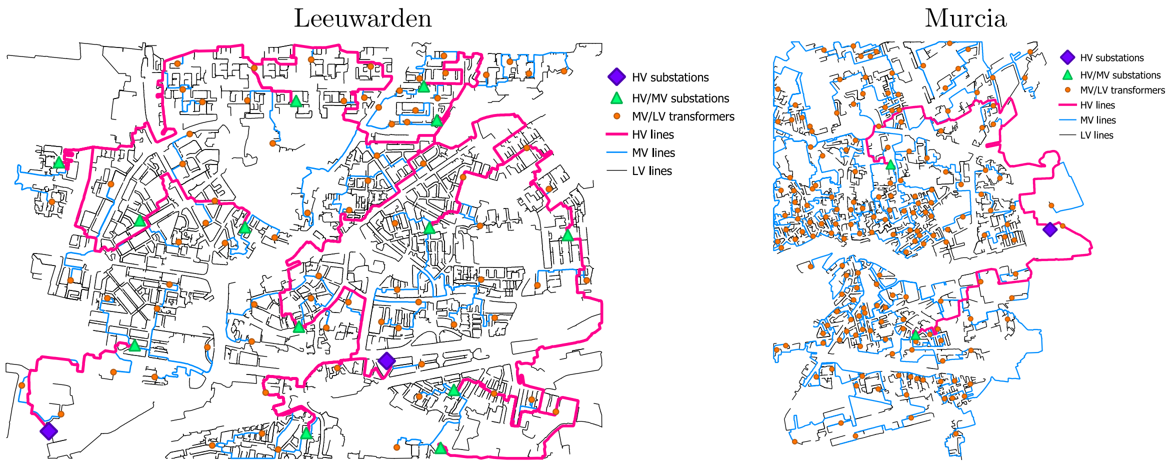


Fig. 3. Greenfield grid in 2020 for Leeuwarden (left) and Murcia (right).

Table 1
Possible additional installations for each building.

Building type	PV	Battery	DHW-Tank	Heating buffer tank	AC
SFH	0, 5 (kWp) + orientation: maximum yield, east, west	0, 7 (kWh)	0, 300 (l)	0, 700 (l)	Yes, No
MFH	0, 15 (kWp) + orientation: maximum yield, east, west	0, 15 (kWh)	0, 700 (l)	0, 1500 (l)	Yes, No

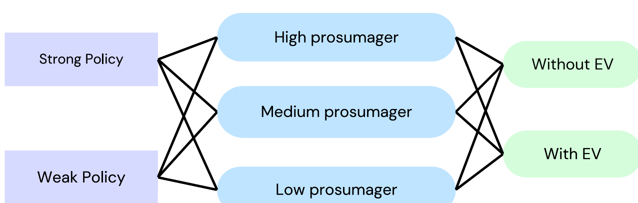


Fig. 4. Integration of various policy, prosumager, and electric vehicle scenarios to form the final 12 scenarios analyzed in our models.

Table 2
Building technology adoption in the scenarios.

Building technologies	Leeuwarden/Murcia			
	2020	2030	2040	2050
AC (strong policy)	20%/50%	30%/60%	50%/80%	70%/90%
AC (weak policy)	20%/50%	35%/65%	60%/80%	80%/95%
PV (strong policy)	2%/1.5%	15%	40%	60%
PV (weak policy)	2%/1.5%	10%	30%	50%
DHW tank	50%	55%	60%	65%
Buffer tank	0%	5%	15%	25%
Battery (weak policy)	10%	12%	16%	25%
Battery (strong policy)	10%	12%	20%	30%

Table 3
Share of prosumagers in the prosumager scenarios.

Scenarios	Leeuwarden/Murcia			
	2020	2030	2040	2050
Low	0%	5%	10%	20%
Medium	0%	10%	30%	50%
High	0%	15%	40%	80%

mild climate. In both policy scenarios the average final energy demand for heating (kWh/m^2) is reduced significantly from 2019 to 2050. In the strong policy scenario the final energy demand is reduced by 71% in Murcia and by 59% in Leeuwarden. In the weak policy scenario the heating demand is reduced by 68% in Murcia and 56% in Leeuwarden. Because of the high electrification of the building stock, even with existing policy measures, poorly insulated buildings are refurbished in the future because it is more economical. This explains the rather small difference between savings in heating demand between the strong and weak policy scenario.

Regarding additional installations in the buildings, their possible options are shown in Table 1. We consider the orientations of PV with 50% oriented for maximum generation, 25% oriented east, and 25% oriented west. Battery systems are only installed in buildings that have a PV and heating buffer tanks are only installed in buildings that utilize a HP. There is no correlation between the installations of HPs and PVs. We did not restrict the maximum power of the air conditioning (AC), assuming that it is sufficiently strong to keep the indoor temperature below a certain set temperature (27 °C).

Table 2 shows the assumed distribution of all additional installations. Percentages in the table indicate how many buildings are equipped with the respective technology. Batteries are only installed in buildings with PV, thus the percentage of buildings with a battery refers to all buildings with a PV. The same applies to the buffer tank, which is only installed in buildings that have a heat pump. The number of installed PVs rises more in the strong policy scenario. In the weak policy scenarios, we estimated a higher percentage of AC than in the strong policy scenarios due to lower investments in building refurbishments and passive shading systems, increasing the need for active cooling. The percentage of installed PV systems is the same in both regions, whereas the AC adoption differs due to the different climate zones. Thermal and battery storages share of all buildings are the same in both case studies. The percentage of installed battery systems is varied slightly in the strong and weak policy scenarios.

4.2. Prosumager scenarios

Regarding the shares of prosumagers, we made the same assumptions for the two regions as shown in Table 3.

Fig. 5. Comparison of heating systems for different policy scenarios in Leeuwarden and Murcia.

Table 4
Probability distribution of number of cars per household for Leeuwarden and Murcia.

Number of EVs per household	0	1	2	3+
Leeuwarden, NL	46%	33%	16%	5%
Murcia, ES	18%	46%	28%	8%

4.3. EV scenarios

Two types of input data are used to generate the EV load profiles in future scenarios with the methodology presented in Section 3.2.2:

- *Building data*: building coordinates, building type, and number of households per building from Section 3.1. In addition, we consider the prosumager shares in Table 3.
- *Mobility data*: survey data on the number of cars per household, EV adoption targets, probability distribution of arrival times, and cumulative density function of daily distance driven.

The number of cars per household in Table 4 is determined based on car ownership survey data for Leeuwarden [56] and Murcia [57]. The penetration of EVs in 2030 has been set in accordance with national objectives for EVs outlined in National Climate and Energy Plans [58]. In 2050, we assume that all light-duty vehicles will have zero emissions and battery-electric vehicles remain the dominant technology in this segment.

The arrival time and daily distance traveled by each vehicle are assigned based on probability distributions. Fig. 6(a) illustrates the probability distribution of the times at which EV owners arrive home, based on public mobility data from cell phone terminals in Spain [59] and a sample private EV charging sessions in the Netherlands [60]. Fig. 6(b) shows the cumulative density function of the distance traveled by Murcians on a daily basis. This distribution is derived from the number of trips per day and individual trip distances in Murcia [59]. In the absence of granular data for Leeuwarden, the same distribution is used as the average distance driven in a day is comparable for both regions.

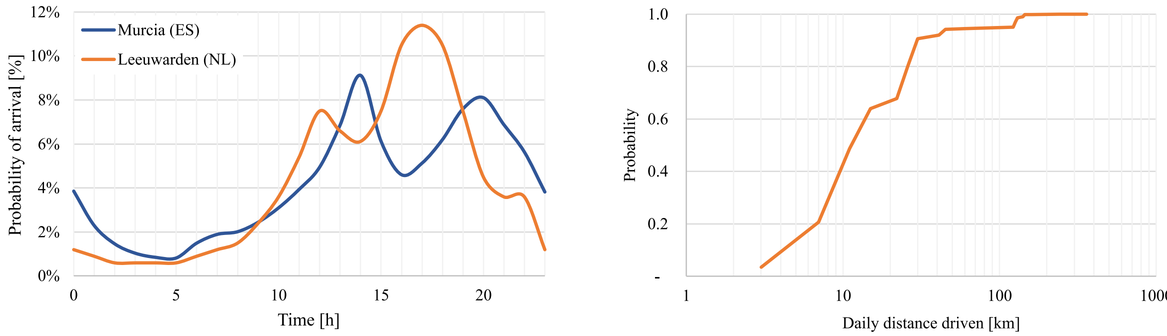
5. Results and discussion

In this section, we are going to first present the peak load results for both case studies regarding the maximum peak demand and the maximum amount of electricity fed to the grid, both on an aggregated level. These peak demands are decisive for the grid design and, subsequently, for the calculation of the costs of the distribution grid. Secondly, we present the results of the additional costs needed, followed by a discussion.

5.1. Peak demand

Fig. 7 shows the aggregated peak demand of all buildings together in each region for 2030, 2040 and 2050. We can clearly see that on an aggregated level the building related peak demand (without EV) decreases in Murcia due to the phasing out of direct electric heating systems. On the other hand, the building related peak load strongly increases throughout the years in Leeuwarden due to the replacement of gas boilers with HPs. The strong policy scenario leads to a higher power consumption in 2040 due to higher adoption of HPs, but in 2050 the effect of better insulation counteracts and we see lower peaks in the strong policy scenario in both case studies. Without EVs, the share of prosumagers only marginally impacts the total peak demand (from 0–0.5% change in peak value). Prosumagers decrease the original peak demand significantly, however by shifting demand they create new peaks, leading to a similar overall peak demand occurring at a different hour.

Looking at the scenarios with EV, the difference between the prosumager scenarios is most visible. The simultaneous charging of prosumagers leads to massive power peaks. In Leeuwarden the number of EVs is much higher than in Murcia, therefore also the impact on the peak load is substantially higher. This peak demand shows, that simultaneous charging of EVs will most likely not be possible in the future and should not be incentivize by hourly prices for EVs in regions with high EV adoption. But also in Murcia we can see that the uptake of EVs overshadows the impact of electrified heating systems. Therefore, it is crucial to apply smart EV charging (like in [61]), which will need a different approach for coordinated charging.



(a) Probability distribution of arrival times.

(b) Cumulative density function of daily distance driven.

Fig. 6. Probability distribution of arrival times.

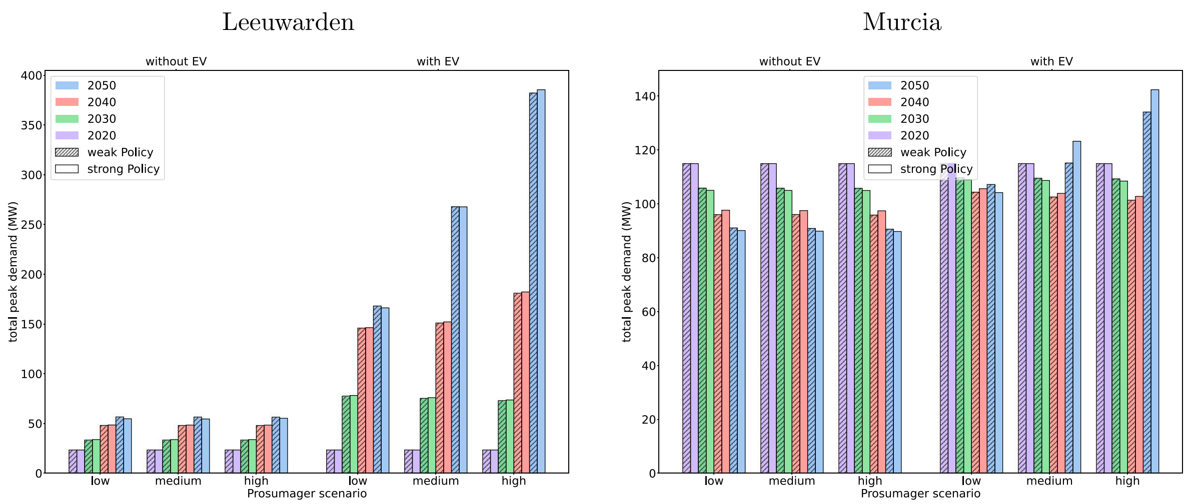


Fig. 7. Peak grid load on aggregated level on the peak demand day for different scenarios in Leeuwarden and Murcia.

5.2. Peak feed in

Fig. 8 shows the peak load that is fed to the grid on the day with the highest feed in (sunny day in Spring where neither heating nor cooling is needed). Here we see a difference between the prosumager scenarios as the prosumagers maximize their self consumption. Also there is a clear difference in the two policy scenarios as more PV is adopted in the strong policy scenario. Since both areas are urban and the PV areas are not larger than 15 kWp per building, big parts of the generation can be self consumed or stored in thermal and electrical storages. Because the area in Murcia has more large MFHs, the maximum amount of electricity fed to the grid is smaller than in Leeuwarden with rising PV share. In the scenarios with EV the total peak feed in is reduced because some of the vehicles can be charged by the surplus of PV. However, the effect on EVs charging using excess PV generation at the hour of maximum feed in is not very pronounced because many cars have not arrived at home yet.

5.3. Electricity grid reinforcements

This section analyzes and compares the techno-economic results of the distribution networks planned with the RNM model under the different policy and prosumaging scenarios. The results include the additional investment and O&M grid costs for each scenario and the increase in power losses for the peak demand day in each future scenario relative to the base case. The results for the base case grids in Murcia and Leeuwarden are presented in Appendix A. Investments in network reinforcements are classified into three types of elements: low voltage (LV) lines, medium to low voltage (MV/LV) distribution transformers, and medium voltage (MV) power lines. Fig. 9 shows the total cost increase, including O&M and investment costs for the distribution grid under different scenarios.

In Fig. 9, the results for Leeuwarden indicate a significantly higher requirement for grid reinforcements than in Murcia. This difference can be attributed to the high initial dependence on conventional heating systems in Leeuwarden (Fig. 5), whereas in Murcia, many households have already adopted electric heating in 2020. Additionally, Leeuwarden exhibits a lower urban density, comprising a greater proportion of single-family residences. This leads to a higher PV excess generation fed to the grid (Fig. 8), as there is a higher installed PV capacity per household and a lower demand in periods with high PV generation.

Generally, strong policy scenarios necessitate more grid reinforcements than weak ones, as the electrification level of buildings is higher and also the adoption rate of rooftop PV. However, the differences in the grid reinforcements results in Fig. 9 between the two policy scenarios are not particularly pronounced, as the heat demand in the strong policy scenario is reduced due to higher refurbishment rates. The most notable distinction in Fig. 9 is that in Murcia, grid reinforcement in strong policy scenarios is more pronounced in 2040, reflecting a faster adoption rate of EVs and HPs. Nevertheless, the incremental costs for 2050 remain similar across both strong and weak policy scenarios.

Including EV loads generally increases the peak demand, leading to a substantial increase in grid reinforcements. However, a comparison of the 2050 low prosumager scenarios for Leeuwarden with and without EVs in Fig. 7 does not show this effect. This can be explained by the high PV penetration in Leeuwarden in 2050, which leads to reversed

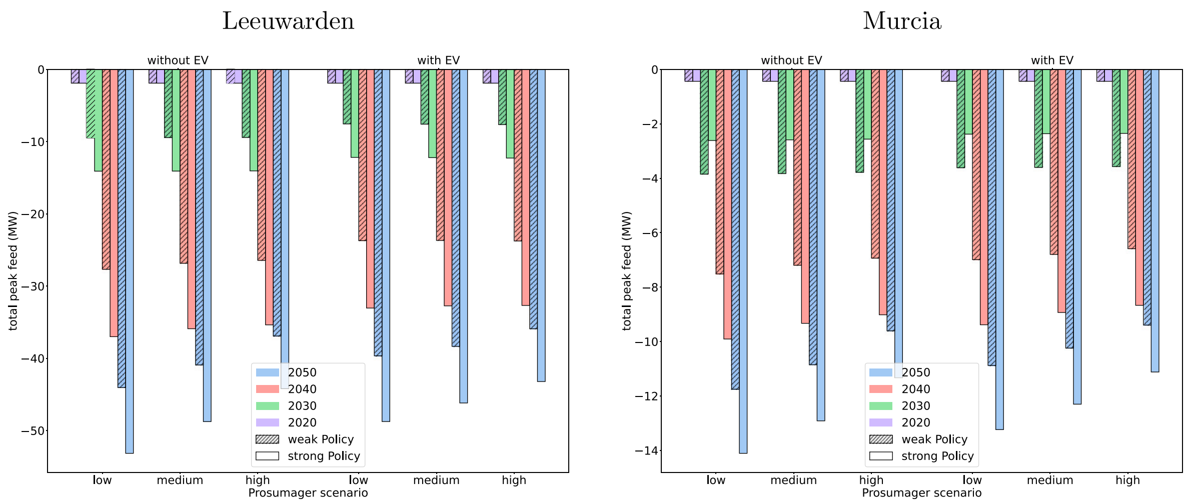


Fig. 8. Peak feed in to the grid on the peak feed-in day for different scenarios in Leeuwarden and Murcia.

power flows and overvoltages at midday. The presence of new EVs charging during these hours reduces the peak PV feed-in (Fig. 8), lowering reinforcement needs in low voltage lines, as illustrated in Fig. B.10. Moreover, the decreasing investments in 2050 in Leeuwarden scenarios with no EVs when moving from low to high prosumager scenarios is attributed mainly to the higher PV self-consumption of prosumagers.

Higher shares of prosumagers positively affect grid investment needs unless their controllable loads, particularly EVs, are synchronized at off-peak tariff periods. In 2050, the incremental cost increase is significantly lowered by prosumagers in Leeuwarden without EVs despite a very high share of prosumagers. However, the simultaneous charging of EVs leads to much higher peak demand at off-peak tariff periods (Fig. 7) and higher grid investments, especially in scenarios where prosumagers account for more than 40% of total customers. Thus, new economic incentives or demand response participation schemes should be implemented in the future to avoid synchronization of controllable loads at the hours with low tariffs, especially when it comes to EV charging.

The primary driver for the cost increase in Leeuwarden is the cost of new MV/LV distribution transformers and the rollout of on-load tap-changing (OLTC) transformers (see Fig. B.12 in Appendix B). These investments are necessary due to the significant voltage differences between high PV feed-in and peak demand hours throughout the year. Also, the LV power lines will need significant investments (Fig. B.10).

On the other hand, the investment needed in distribution transformers is significantly smaller in Murcia (Fig. B.12). In Murcia, there is already a significant percentage of households with electric heating and more multi-family houses, so the initial MV grid in 2020 is stronger and denser. The main driver for additional costs in Murcia is the reinforcements in LV lines (Fig. B.10). Switching the remaining buildings to electrified heating systems requires higher capacity LV power lines connecting these houses. The reinforcement in LV lines could be significantly reduced by prosumagers if EVs are charged in a grid-friendly way. Moreover, we can see that with an increase in building renovation (strong policy scenario without EVs), the grid will not need additional investments in 2050 compared to 2040.

PV adoption does not have a strong impact in Murcia because the available rooftop area is lower, and most of the PV generation is self-consumed. On the other hand, in Leeuwarden, the uptake of PV does lead to an increase in costs. This could be reduced through prosumagers who try to maximize self-consumption and through additional local storage technologies (batteries, tanks), which can also be observed in the power losses (Fig. B.13). With a higher share of prosumagers the power losses decrease. However, power losses can also be reduced due to higher grid reinforcements, which have a higher capacity and lower resistance.

5.4. Discussion

For this study, we have selected two residential areas as examples of European distribution grids that will need enhancement under long-term decarbonization policies to achieve climate neutrality by 2050. Electricity is expected to play a fundamental role in decarbonizing residential areas due to the increasing electricity consumption of HPs and EVs. Nevertheless, a comprehensive simulation of the impacts across the entire distribution grid at a continental level would be impractical in terms of the computational resources required. Although this is a limitation of our study, we provide insight into potential reinforcement needs for a location with a very high penetration of gas boilers in a colder climate as well as a location with a warm climate and an already high share of electric heating systems. With this in mind, the methodology and the insights of the results are transferable to other regions with similar building and heating system characteristics. It is anticipated that grid reinforcements will be required in both locations, although the extent of these investments and the underlying drivers are different.

The aggregated peak load in both regions is expected to grow, with EV adoption being the largest factor for its growth. However, if new EV loads are not considered, the peak load on an aggregated level will rise in Leeuwarden but decline in Murcia. Investments in grid reinforcements are expected in all scenarios, even in those with lower aggregate peak loads. Note that the aggregated peak demand masks local peaks that can occur at individual feeders where the additional consumption of HPs is higher than the demand reduction achieved with increased energy efficiency and self-consumption. The long-term investment requirements for LV and MV grids in Leeuwarden are anticipated to be higher than in Murcia. This is due to a combination of factors, including the higher peak demand growth in Leeuwarden and the stronger initial distribution grid in Murcia, which already supplies a significant share of buildings with electric heating. Overall, it can be said that replacing heating systems will also be a driving factor for cost increases in European distribution grids.

Moreover, feed-in from solar PV generation is also expected to increase, causing reversed power flows and overvoltage issues. This is especially significant in Leeuwarden, where the combination of a higher roof area available for PV and a higher share of conventional heating systems replaced by HPs, can lead to needed medium to low voltage

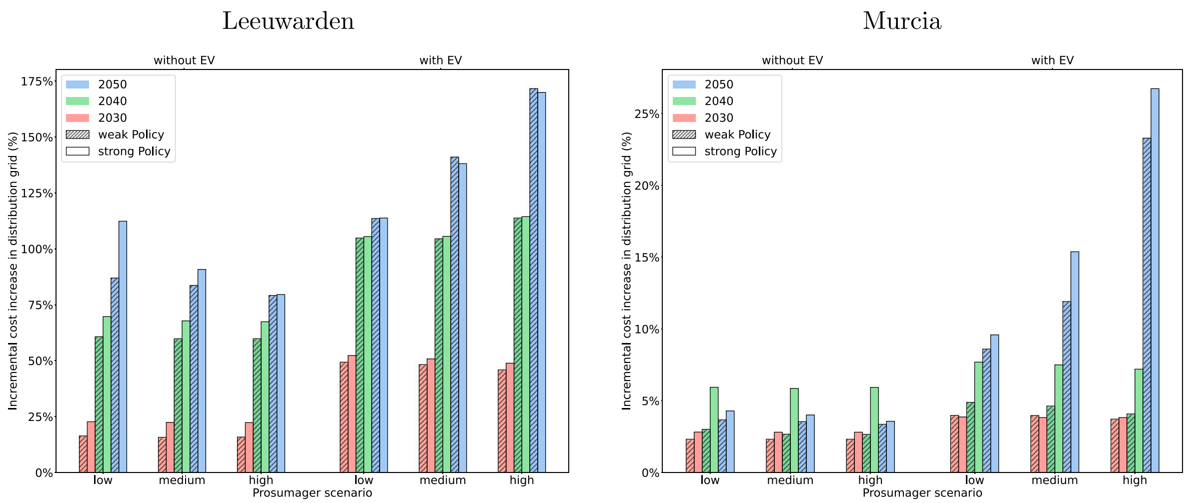


Fig. 9. Distribution grid percentage cost increase in Leeuwarden and Murcia in different scenarios.

transformer investments 2–4 times the cost of the initial transformer capacity. We acknowledge that this may be an overestimation since our model employs OLTC transformers to address the difference in voltages between peak load and peak generation periods. While there may be other options for voltage control that could be considered, this result highlights the value of long-term planning for electricity grids in enabling decarbonization policies.

A limitation of our study is that we did not have access to detailed data on the hosting capacity in Leeuwarden and Murcia to accommodate new demand and generation without reinforcement. Therefore, the need for grid extension in the first years might be lower than our study predicts. However, distribution grids in Leeuwarden currently have limited capacity for additional generation and queues for connecting new demand [62]. Besides, our long-term results would not be substantially different if the actual hosting capacity were considered to model the initial networks, as the hosting capacity is likely to be recuperated as distribution grids are reinforced and the increase in demand is many times higher than the initial hosting capacity.

Prosumagers can lower these additional grid costs only by shifting demand to off-peak hours and increasing self-consumption. Nevertheless, as illustrated Fig. 8., EV scenarios with medium and high shares of prosumagers in 2050, with a share of prosumagers beyond 40%, result in higher incremental grid costs due to the synchronization of controllable loads. The necessary investments in grid reinforcement would require significant expenditures, particularly in Leeuwarden, due to the inadequate management of controllable loads. In the coming years, alternative solutions that take into account the status of the distribution grid (e.g., smart charging strategies, local flexibility markets, alternative tariff incentives, etc.) are likely to be introduced. While our EV scenarios involving medium and high shares of prosumagers may possibly not materialize in 2050, our findings underscore the value of these alternatives. These alternatives should be explored in future research to unlock the full potential of prosumagers to improve distribution network planning.

Not considering a correlation between HP and PV installations might result in slightly higher needed investments than needed. The direct effects of climate change on weather profiles are not considered in our study. An increase in active cooling systems is considered in this study, but compared to heating, cooling does not drive the peak electricity demand. On the one hand, the temperature difference between the source and sink is lower for cooling purposes, making a typical compressor-driven HP more efficient for cooling than for heating. At the same time, cooling demand overlaps well with locally produced PV generation. Thus, it is expected that the peak demand will still occur on a winter day, especially considering that extreme weather events will increase.

6. Conclusion

The electrification of residential energy uses, such as heating and transport, will challenge future electricity grid development plans. Analyzing this requires looking at the problem at the lowest level because the location of new loads and PV installations plays a very strong role. By incentivizing consumers to shift load to off-peak hours with automated heating systems and EV chargers, the stress on the local distribution grid can be lowered. However, this does not apply to future scenarios characterized by a high percentage of prosumagers, particularly those scenarios involving EVs and where prosumagers account for more than 40% of the total share. Our findings indicate that very high prosumaging with current electricity tariffs, which do not reflect the distribution grid's status, will create new load peaks due to the synchronization of controllable loads. Therefore, very high prosumaging will significantly increase the stress on the distribution grid and will require substantially higher investments, unless demand response mechanisms that consider the local distribution grid's status are implemented.

Two urban areas have been selected for this case study: Murcia, Spain, and Leeuwarden, Netherlands. The amount of reinforcements in Murcia is less than in Leeuwarden because there is already a significant percentage of households with electric heating in Murcia. Murcia exhibits a higher prevalence of multi-family residential buildings with comparatively reduced rooftop area per household, which can be allocated to solar PV installations. The results for Leeuwarden indicate that the grid will require extensive reinforcement costs by 2040, due to both the high demand growth from HPs and EVs and the wide voltage fluctuations observed between the lowest and highest voltages achieved on the peak demand and feed-in day, respectively. It may be necessary to incorporate unconventional planning practices, such as OLTC transformers or voltage regulators, in order to address the technological challenges of future long-term scenarios. Furthermore, it may be beneficial to engage in long-term planning for electricity distribution networks, given the potential challenges associated with identifying suitable locations for additional distribution transformers, particularly in urban areas.

The findings of the two case studies demonstrate the importance of long-term planning for grid investments, as outlined in the EU Grid Action Plan, and the need for future work to explore how local grid services (e.g., proposed Network Code on Demand Response) can enhance the positive impacts of prosumagers on distribution network planning.

Table A.6
Power lines data for the initial 2020 grid in Murcia, Spain.

	Overhead [km]	Underground [km]	CAPEX [€]	O&M [€/yr.]
LV power lines	128.22	53.74	4 449 982.63	44 854.27
MV power lines	33.94	64.20	9 764 809.24	101 348.42
HV power lines	0.00	16.77	11 849 694.02	122 973.15

Table A.7
Distribution transformers and substations data for the initial 2020 grid in Murcia, Spain.

	Quantity	Installed power [MVA]	CAPEX [€]	O&M [€/yr.]
MV/LV Distribution Transformers	185	129.28	10 411 964.00	238 285.00
HV/MV Substations	2	160.00	4 150 464.00	223 223.42

Table A.8
Power lines data for the initial 2020 grid in Leeuwarden, Netherlands.

	Overhead [km]	Underground [km]	CAPEX [€]	O&M [€/yr.]
LV power lines	0.00	358.34	18 633 040.48	192 786.04
MV power lines	0.00	64.20	14 571 778.07	109 674.67
HV power lines	57.43	0.00	8 680 541.24	90 101.68

Table A.9
Distribution transformers and substations data for the initial 2020 grid in Leeuwarden, Netherlands.

	Quantity	Installed power [MVA]	CAPEX [€]	O&M [€/yr.]
MV/LV Distribution Transformers	90	30.6	4 829 724.00	110 537.00
HV/MV Substations	13	390	7 553 130.00	203 190.00

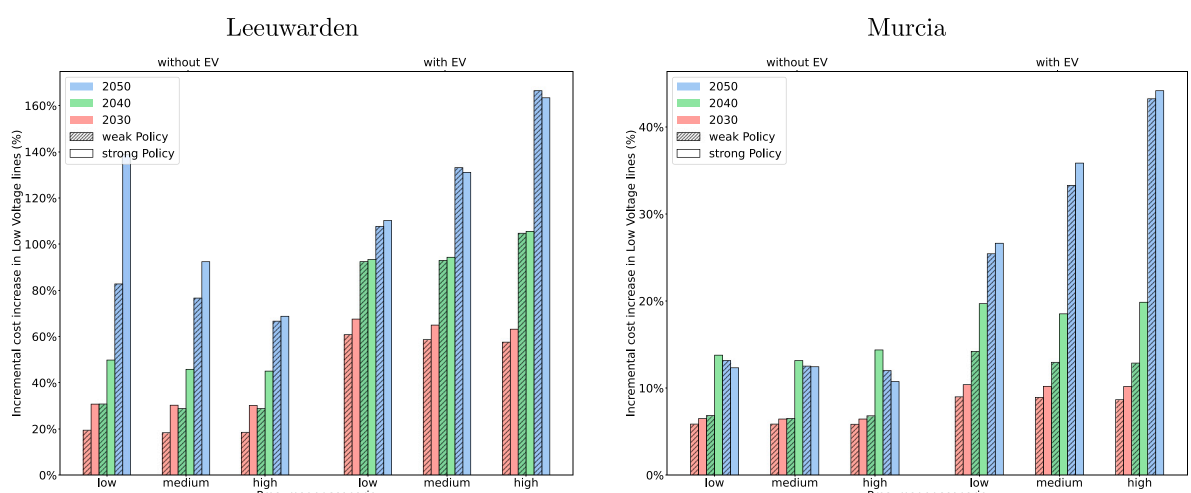


Fig. B.10. Low Voltage lines percentage cost increase in Leeuwarden and Murcia in different scenarios.

CRediT authorship contribution statement

Philipp Mascherbauer: Writing – review & editing, Writing – original draft, Visualization, Methodology, Data curation, Conceptualization. **Miguel Martínez:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Data curation, Conceptualization. **Carlos Mateo:** Writing – review & editing, Methodology, Formal analysis. **Songmin Yu:** Writing – review & editing. **Lukas Kranzl:** Writing – review & editing.

Software availability

The source code for the FLEX model can be found on GitHub[2] under MIT Licence.

[2] https://github.com/H2020-newTRENDs/FLEX.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 101022622.

Appendix A

This appendix provides complementary results of the initial distribution grids in 2020 generated with the greenfield RNM for Murcia and Leeuwarden. Tables A.6 and A.7. summarize the results of the power lines in the distribution networks of Murcia and Leeuwarden, respectively. The results include the total length of overhead lines and

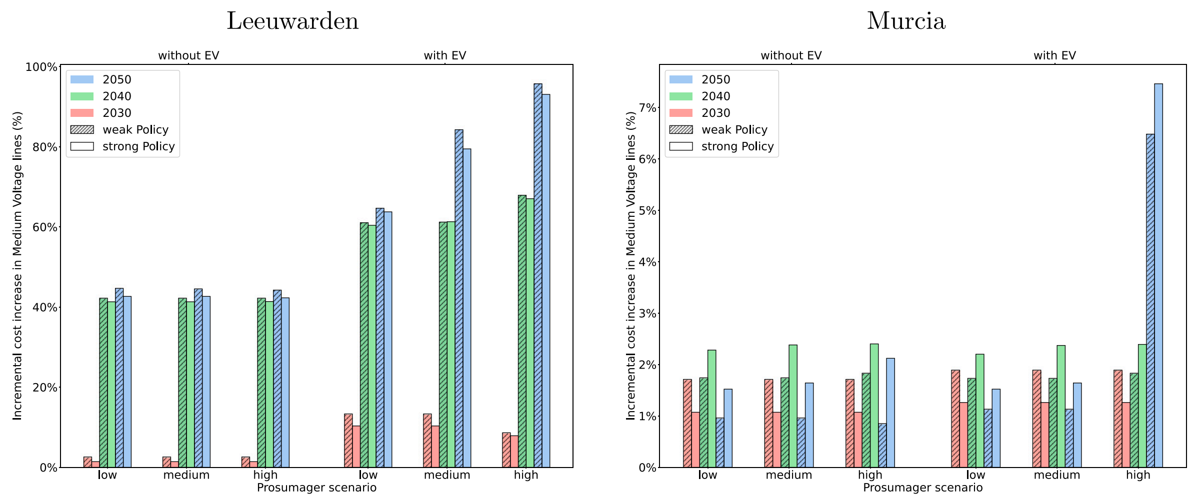


Fig. B.11. Medium Voltage lines percentage cost increase in Leeuwarden and Murcia in different scenarios.

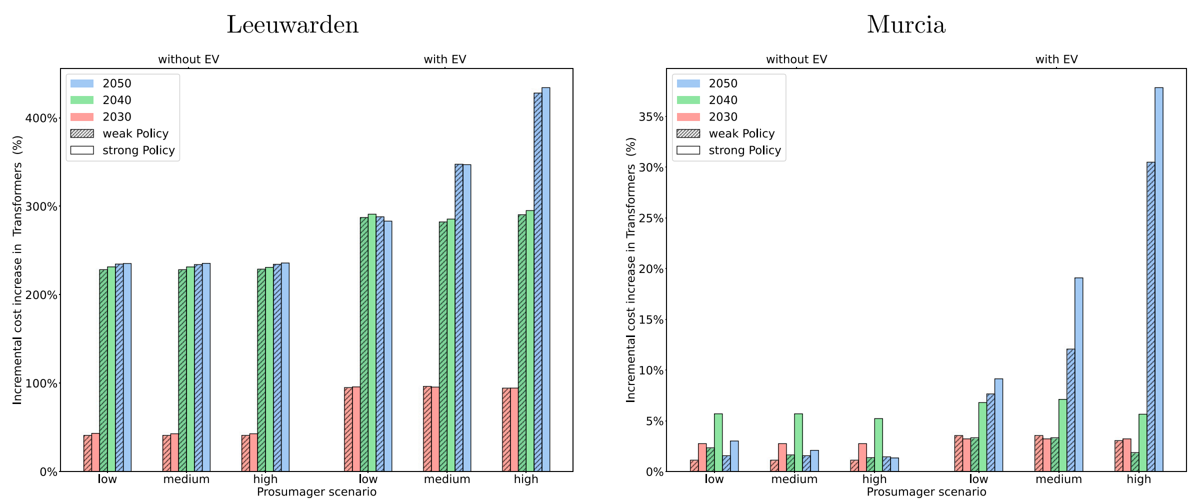


Fig. B.12. Transformer percentage cost increase in Leeuwarden and Murcia in different scenarios.

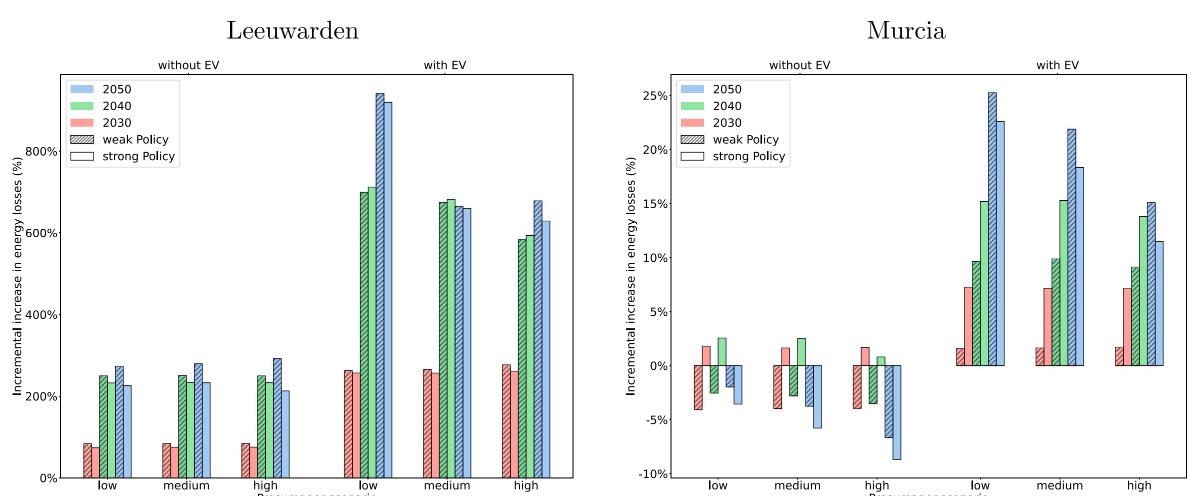


Fig. B.13. Percentage increase in power losses in Leeuwarden and Murcia for different scenarios.

underground cables for each voltage level. Note that in Leeuwarden all LV and MV lines are underground, while in Murcia there is a mix of underground and overhead lines. Similarly, Tables A.6 and A.8 compare the results for distribution transformers and substations in the initial grids. Murcia has a much higher initial installed capacity for distribution transformers. This can be attributed to Murcia's higher housing density and the prevalence of electric heating and cooling systems. The higher capacity and denser configuration of the MV grid in Murcia relative to Leeuwarden suggests that future reinforcement requirements will be lower.

Moreover, these tables show the total CAPEX and O&M costs of power lines, distribution transformers and substations for the initial 2020 grids. These values are the reference used to calculate the incremental costs for these distribution grids in future scenarios in Section 5.3 (see Table A.9).

Appendix B

In this section complementary results for the case studies are provided showing the incremental cost increase for LV and MV lines, transformers and the power losses (see Fig. B.11).

Appendix C. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.apenergy.2025.125563.

Data availability

Data will be made available on request.

References

[1] Wang C, Wang B, You F. Demand response for residential buildings using hierarchical nonlinear model predictive control for plug-and-play. Appl Energy 2024;369:123581. http://dx.doi.org/10.1016/j.apenergy.2024.123581.
[2] Reynders G, Nuytten T, Saelens D. Potential of structural thermal mass for demand-side management in dwellings. Build Environ 2013;64:187–99. http://dx.doi.org/10.1016/j.buildenv.2013.03.010.
[3] Lind J, Möllerström E, Averfalk H, Ottermo F. Energy flexibility using the thermal mass of residential buildings. Energy Build 2023;301:113698. http://dx.doi.org/10.1016/j.enbuild.2023.113698.
[4] Le Dréau J, Heiselberg P. Energy flexibility of residential buildings using short term heat storage in the thermal mass. Energy 2016;111:991–1002. http://dx.doi.org/10.1016/j.energy.2016.05.076.
[5] Golmohamadi H. Stochastic energy optimization of residential heat pumps in uncertain electricity markets. Appl Energy 2021;303:117629. http://dx.doi.org/10.1016/j.apenergy.2021.117629.
[6] Sperber E, Frey U, Bertsch V. Reduced-order models for assessing demand response with heat pumps – Insights from the German energy system. Energy Build 2020;223:110144. http://dx.doi.org/10.1016/j.enbuild.2020.110144.
[7] Mascherbauer P, Kranzl L, Yu S, Haupt T. Investigating the impact of smart energy management system on the residential electricity consumption in Austria. Energy 2022;249:123665. http://dx.doi.org/10.1016/j.energy.2022.123665.
[8] Zhang Y, Johansson P, Kalagasidis AS. Techno-economic assessment of thermal energy storage technologies for demand-side management in low-temperature individual heating systems. Energy 2021;236:121496. http://dx.doi.org/10.1016/j.energy.2021.121496.
[9] Mascherbauer P, Schöniger F, Kranzl L, Yu S. Impact of variable electricity price on heat pump operated buildings. Open Res Eur 2022;2:135. http://dx.doi.org/10.12688/openreseurope.15268.1.
[10] Kandler C. Modellierung von zeitnutzungs-, mobilitäts- und energieprofilen zur bestimmung der potentiale von energiemanagementsystemen (Dissertation), Technische Universität München; 2017, http://dx.doi.org/10.13140/RG.2.2.17638.73281.
[11] Salpakari J, Rasku T, Lindgren J, Lund PD. Flexibility of electric vehicles and space heating in net zero energy houses: an optimal control model with thermal dynamics and battery degradation. Appl Energy 2017;190:800–12. http://dx.doi.org/10.1016/j.apenergy.2017.01.005.
[12] Klingler A-L. The effect of electric vehicles and heat pumps on the market potential of PV + battery systems. Energy 2018;161:1064–73. http://dx.doi.org/10.1016/j.energy.2018.07.210.
[13] Stute J, Pelka S, Kühnbach M, Klobasa M. Assessing the conditions for economic viability of dynamic electricity retail tariffs for households. Adv Appl Energy 2024;14:100174. http://dx.doi.org/10.1016/j.adapen.2024.100174.
[14] Sridhar A, Thakur J, Baskar AG. A data-driven approach with dynamic load control for efficient demand-side management in residential household across multiple devices. Energy Rep 2024;11:5963–77. http://dx.doi.org/10.1016/j.egyr.2024.05.023.
[15] Fitzpatrick P, D'Ettorre F, De Rosa M, Yadack M, Eicker U, Finn DP. Influence of electricity prices on energy flexibility of integrated hybrid heat pump and thermal storage systems in a residential building. Energy Build 2020;223:110142. http://dx.doi.org/10.1016/j.enbuild.2020.110142.
[16] Miara M, Günther D, Leitner ZL, Wapler J. Simulation of an air-to-water heat pump system to evaluate the impact of demand-side-management measures on efficiency and load-shifting potential. Energy Technol 2014;2(1):90–9. http://dx.doi.org/10.1002/ente.201300087.
[17] Kelly NJ, Tuohy PG, Hawkes AD. Performance assessment of tariff-based air source heat pump load shifting in a UK detached dwelling featuring phase change-enhanced buffering. Appl Therm Eng 2014;71(2):809–20. http://dx.doi.org/10.1016/j.applthermaleng.2013.12.019.
[18] Stute J, Klobasa M. How do dynamic electricity tariffs and different grid charge designs interact? - Implications for residential consumers and grid reinforcement requirements. Energy Policy 2024;189:114062. http://dx.doi.org/10.1016/j.enpol.2024.114062.
[19] McGarry C, Dixon J, Elders I, Galloway S. A high-resolution geospatial and socio-technical methodology for assessing the impact of electrified heat and transport on distribution network infrastructure. Sustain Energy, Grids Netw 2023;35:101118. http://dx.doi.org/10.1016/j.segan.2023.101118.
[20] Hartvigsson E, Taljegard M, Odenberger M, Chen P. A large-scale high-resolution geographic analysis of impacts of electric vehicle charging on low-voltage grids. Energy 2022;261:125180. http://dx.doi.org/10.1016/j.energy.2022.125180.
[21] Navarro-Espinosa A, Mancarella P. Probabilistic modeling and assessment of the impact of electric heat pumps on low voltage distribution networks. Appl Energy 2014;127:249–66. http://dx.doi.org/10.1016/j.apenergy.2014.04.026.
[22] e Silva LES, Vieira JPA. Combined PV-PEV hosting capacity analysis in low-voltage distribution networks. Electr Power Syst Res 2022;206:107829. http://dx.doi.org/10.1016/j.epsr.2022.107829.
[23] Protopapadaki C, Saelens D. Heat pump and PV impact on residential low-voltage distribution grids as a function of building and district properties. Appl Energy 2017;192:268–81. http://dx.doi.org/10.1016/j.apenergy.2016.11.103.
[24] Earle L, Maguire J, Munankarmi P, Roberts D. The impact of energy-efficiency upgrades and other distributed energy resources on a residential neighborhood-scale electrification retrofit. Appl Energy 2023;329:120256. http://dx.doi.org/10.1016/j.apenergy.2022.120256.
[25] Navarro-Espinosa A, Ochoa LF. Probabilistic impact assessment of low carbon technologies in lv distribution systems. IEEE Trans Power Syst 2016;31(3):2192–203. http://dx.doi.org/10.1109/TPWRS.2015.2448663.
[26] Gupta R, Pena-Bello A, Streicher KN, Roduner C, Farhat Y, Thöni D, Patel MK, Parra D. Spatial analysis of distribution grid capacity and costs to enable massive deployment of PV, electric mobility and electric heating. Appl Energy 2021;287:116504. http://dx.doi.org/10.1016/j.apenergy.2021.116504.
[27] Elmallah S, Brockway AM, Callaway D. Can distribution grid infrastructure accommodate residential electrification and electric vehicle adoption in northern california? Environ Research: Infrastruct Sustain 2022;2(4):045005. http://dx.doi.org/10.1088/2634-4505/ac949c.
[28] OpenStreetMap contributors. Open street maps. 2017, https://www.openstreetmap.org [Accessed 27 October 2024].
[29] Urban3r contributors. URBAN3R . 2024, https://urban3r.es/ [Accessed 27 October 2024].
[30] Peters R, Dukai B, Vitalis S, van Liempt J, Stoter J. Automated 3D reconstruction of LoD2 and LoD1 models for all 10 million buildings of the netherlands. Photogramm Eng Remote Sens 2022;88(3):165–70. http://dx.doi.org/10.14358/PERS.21-00032R2.
[31] Müller A. Energy demand assessment for space conditioning and domestic hot water: A case study for the Austrian building stock. 2015, p. 285.
[32] The Hotmaps Team. Hotmaps . 2020, https://www.hotmaps.eu/map [Accessed 27 October 2024].
[33] Yu S, Mascherbauer P, Haupt T, Skorna K, Rickmann H, Kochanski M, Kranzl L. Modeling households' behavior, energy system operation, and interaction in the energy community. 2024, [Accessed 27 October 2024].
[34] Eurostat. Nrg-d-hhq. 2024, http://dx.doi.org/10.2908/NRG_D_HHQ, [Accessed 27 October 2024].
[35] Centre ECJR. Photovoltaic geographical information system. 2024, https://re.jrc.ec.europa.eu/pvg_tools/en/ [Accessed 27 October 2024].
[36] Platform T. ENTSO-e. 2024, https://transparency.entsoe.eu/ [Accessed 27 October 2024].
[37] Esios. 2024, https://www.esios.ree.es/es [Accessed 27 October 2024].
[38] Yu S, Mascherbaue rP, Haupt T, Skrona K, Rickmann H, Kochański M, L. K. FLEX model. 2024, https://github.com/H2020-newTRENDs/FLEX [Accessed 27 October 2024].
[39] Calearo L, Marinelli M, Ziras C. A review of data sources for electric vehicle integration studies. Renew Sustain Energy Rev 2021;151:111518. http://dx.doi.org/10.1016/j.rser.2021.111518.
[40] Sørensen ÅL, Lindberg KB, Sartori I, Andresen I. Residential electric vehicle charging datasets from apartment buildings. Data Brief 2021;36:107105. http://dx.doi.org/10.1016/j.dib.2021.107105.

[41] Sørensen Å, Sartori I, Lindberg K, Andresen I. A method for generating complete EV charging datasets and analysis of residential charging behaviour in a large norwegian case study. Sustain Energy, Grids Networks 2023;36:101195. http://dx.doi.org/10.1016/j.segan.2023.101195.

[42] Unterluggauer T, Hipolito F, Rich J, Marinelli M, Andersen PB. Impact of cost-based smart electric vehicle charging on urban low voltage power distribution networks. Sustain Energy, Grids Networks 2023;35:101085. http://dx.doi.org/10.1016/j.segan.2023.101085.

[43] Sørensen rL, Westad MC, Delgado BnM, Lindberg KB. Stochastic load profile generator for residential EV charging. In: E3S web of conferences. E3S web of conferences, vol. 362, 2022, p. 03005. http://dx.doi.org/10.1051/e3sconf/202236203005.

[44] Fischer D, Harbrecht A, Surmann A, McKenna R. Electric vehicles' impacts on residential electric local profiles – A stochastic modelling approach considering socio-economic, behavioural and spatial factors. Appl Energy 2019;233–234:644–58. http://dx.doi.org/10.1016/j.apenergy.2018.10.010.

[45] Gonzalez Venegas F, Petit M, Perez Y. Plug-in behavior of electric vehicles users: Insights from a large-scale trial and impacts for grid integration studies. ETransportation 2021;10:100131. http://dx.doi.org/10.1016/j.etran.2021.100131.

[46] Unterluggauer T, Hipolito F, Klyapovskiy S, Andersen PB. Impact of electric vehicle charging synchronization on the urban medium voltage power distribution network of frederiksberg. World Electr Veh J 2022;13(10). http://dx.doi.org/10.3390/wevj13100182.

[47] Mateo Domingo C, Gomez San Roman T, Sanchez-Miralles A, Peco Gonzalez JP, Candela Martinez A. A reference network model for large-scale distribution planning with automatic street map generation. IEEE Trans Power Syst 2011;26(1):190–7. http://dx.doi.org/10.1109/TPWRS.2010.2052077.

[48] Mateo C, Prettico G, Gómez T, Cossent R, Gangale F, Frías P, Fulli G. European representative electricity distribution networks. Int J Electr Power Energy Syst 2018;99:273–80. http://dx.doi.org/10.1016/j.ijepes.2018.01.027.

[49] De Rosa L, Martínez M, Linares JI, Mateo C, Gomez T, Cossent R, Postigo F, Sánchez-Miralles Á, Martín-Martínez F. Design and assessment of energy infrastructure in new decarbonized urban districts: A spanish case study. Energy Rep 2024;11:4631–41. http://dx.doi.org/10.1016/j.egyr.2024.04.037.

[50] Boletín Oficial del Estado. BOE-A-2015-13488 https://www.boe.es/eli/es/o/2015/12/11/iet2660 [Accessed 27 October 2024].

[51] Boletín Oficial del Estado. BOE-A-2000-24019 https://www.boe.es/eli/es/rd/2000/12/01/1955/con [Accessed 27 October 2024].

[52] IEEE guide for electric power distribution reliability indices. In: IEEE Std 1366-2022 (Revision of IEEE Std 1366-2012). 2022, p. 1–44. http://dx.doi.org/10.1109/IEEESTD.2022.9955492.

[53] Mateo C, Reneses J, Rodriguez-Calvo A, Frías P, Sánchez Á. Cost–benefit analysis of battery storage in medium-voltage distribution networks. IET Gener Transm Distrib 2016;10(3):815–21. http://dx.doi.org/10.1049/iet-gtd.2015.0389.

[54] Mateo C, Cossent R, Gómez T, Prettico G, Frías P, Fulli G, Meletiou A, Postigo F. Impact of solar PV self-consumption policies on distribution networks and regulatory implications. Sol Energy 2018;176:62–72. http://dx.doi.org/10.1016/j.solener.2018.10.015.

[55] Martínez M, Moreno A, Angulo I, Mateo C, Masegosa AD, Perallos A, Frías P. Assessment of the impact of a fully electrified postal fleet for urban freight transportation. Int J Electr Power Energy Syst 2021;129:106770. http://dx.doi.org/10.1016/j.ijepes.2021.106770.

[56] Centraal Bureau voor de Statistiek. Car ownership per household. 2023, https://www.cbs.nl/nl-nl/maatwerk/2024/08/autobezit-per-huishouden-1-januari-2023 [Accessed 04 July 2024].

[57] de Estadística IN. Survey on essential characteristics of population and housing. 2021, https://www.ine.es/dyngs/INEbase/en/operacion.htm?c=Estadistica_C&cid=1254736177092&menu=ultiDatos&idp=1254735572981 [Accessed 04 July 2024].

[58] European Commission. National energy and climate plans. 2024, https://energy.ec.europa.eu/topics/energy-strategy/national-energy-and-climate-plans-necps_en [Accessed 04 July 2024].

[59] Ministerio de Transportes y Movilidad Sostenible. Mobility open data. 2024, https://data.mitma.gob.es/public/mov-municipal [Accessed 04 July 2024].

[60] Elaad Platform. Elaadnl open datasets for electric mobility research | update april 2020. 2024, https://platform.elaad.io/analyses/ElaadNL_opendata.php [Accessed 04 July 2024].

[61] Lotfi M, Almeida T, Javadi MS, Osório GJ, Monteiro C, Catalão JP. Coordinating energy management systems in smart cities with electric vehicles. Appl Energy 2022;307:118241. http://dx.doi.org/10.1016/j.apenergy.2021.118241.

[62] Netbeheer Nederland. Capaciteitskaart. 2025, [Accessed 08 January 2025].