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Impact of Evolving EV Charging Profiles on Distribution Grid Reinforcement: A Case Study

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***Abstract*—The number of Electric Vehicles (EVs) is rapidly growing in several parts of the world and particular in Scandinavia. A large share of the EV chargers are expected to get connected to the distribution grid. This together with the ongoing electrification of other consumption, e.g. heating, will likely require grid reinforcement. Distribution System Operators need to consider the impact of EV charging in their grid planning. Contrary to conventional consumption, EV charging patterns are highly dependent on consumer behaviours and preferences. Hence, technical developments and behavioural changes may impact grid reinforcement needs. In a Danish case study, it is investigated how the evolution of EV charging impacts reinforcement needs. Furthermore, a generic and transparent framework to determine reinforcement needs of the distribution grid is presented. The case study is based on actual distribution grid data and EV charging data from the UK from 2017 and Denmark from 2023. The results show that the grid reinforcement needs are greatly impacted by the evolution of EV charging profiles.**

***Index Terms*—Distribution Grid, Electric Vehicles, Grid Planning, Grid Reinforcement**

I. Introduction

Recently, the government in Denmark has proposed moving the target of CO_2 neutrality to 2045, with a new goal of achieving a 110% reduction in CO_2 emissions by 2050 compared to the 1990 level [1]. As part of the goal of achieving the 110% reduction in CO_2 emissions, electrification plays a key role. Specifically, the share of Electric Vehicles (EVs) and Heat Pumps (HPs) are expected to increase substantially [2]. This increase will cause a higher demand for electricity being transported through the distribution grids, thus potentially generating reinforcement costs. The reinforcement needs are important to estimate for e.g. grid planning, tariff design or adjustment of the regulatory framework.

In [3], the authors present a methodology to assess the grid impact of different EV charging strategies for five different European countries. In the study, it was assumed that all EVs are using the same charging strategy and the charging profiles were artificially created and not based on real charging data. The approach uses Monte-Carlo simulations to determine the reinforcement costs. The authors of [4] propose an approach for determining needed grid reinforcements, where they use a probabilistic sampling process to randomly assign annual consumer profiles and use Monte-Carlo simulations to determine the needed grid reinforcement. The approach is used to investigate how different charging strategies impact the reinforcement needs. The charging strategies are applied to all EV chargers and do not consider that EV owners may have different priorities and behaviour. In [5], the current development status of EV flexibility services at the distribution grid level is discussed and recommendations are put forward. With respect to the regulatory framework, [5] recommends that the regulators set ambitious targets and support the development of the economic value-chain. This requires that regulators and other stakeholders understand the impact of different EV charging strategies on the distribution grid.

Consequently, there is a need for a simple, generic and transparent method to assess grid reinforcement needs. The paper's contributions are: 1) the introduction of such a framework 2) the investigation of the impact of evolving EV charging behaviour on the reinforcement needs in the distribution grid.

II. Method for the Quantification of Reinforcement Needs

The framework for determining and quantifying the grid reinforcement needs is shown in Fig. 1. The inputs to the

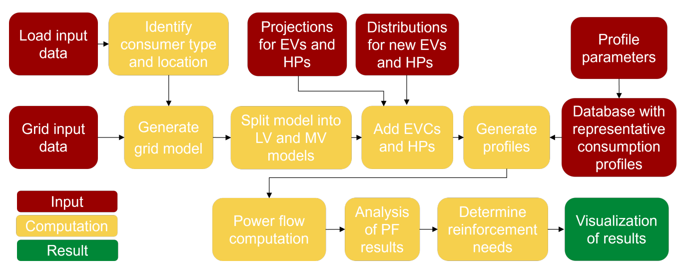


Fig. 1: Flow diagram showing the proposed framework for quantifying reinforcement needs.

proposed approach are shown as red blocks, the computation steps as yellow blocks and the result as green block.

A. Input data

1) Load input data: These data contain information about the loads present in the grid area under investigation. This could comprise information about the housing type (e.g. detached house, apartment, holiday cottage) and heating type (e.g. non-electric heating, electric heating, HP), but also more detailed information such as annual electricity consumption or dwelling area. Moreover, the load data have to contain information, which allow identification of their location and connection point in the distribution grid. This could be GPS coordinates, the address or name of the street cabinet, etc.

2) Grid input data: These data contain information about the components in the distribution grid, e.g. cabinets, cables, substation transformers, breakers, etc., as well as their connection in the area of interest. These could be provided in the Common Grid Model Exchange Standard (CGMES) [6]

3) Projections for EVs and HPs: These data contain information about the expected development of the number of EVs and HPs in the area and for the period of interest.

4) Distributions for new EVs and HPs: In order to distribute the projected number of EVs (or rather EV Chargers, EVCs) and HPs in the grid area of interest, rules for the distribution are needed. The distributions need to take into consideration that there may be differences in the probability for installing an EVC depending on the housing type or parking possibilities. Similarly for HPs, the current heating system will influence the house owners decision.

5) Consumption profiles and profile parameters: The input should contain consumption profiles for different consumer types, e.g. detached houses with or without electric heating, grocery stores, offices. The profiles describe how the consumption varies over time and a combination of these profiles allows to determine the loading of the network elements, which connect the customers. The profiles should be representative of the respective customer group. The user model will typically define parameters of the profiles, such as a season and day.

B. Computation

The proposed approach uses simple power flow computations to determine the loading of the components in the grid and identify which components need to be replaced.

1) Generate grid model: In this block, the grid input data are converted into a power flow grid model.

2) Identifying consumer type and location: Based on the load input data, the electrical consumer type is determined. In combination with the grid input data and the grid model, the consumers' locations are identified. These household, commercial and industrial loads represent the base load.

3) Split the grid model into LV and MV level: In the approach, it is assumed that the used profiles are not individual consumption profiles but representative aggregated profiles, which represent a certain aggregation of consumers e.g. 100 detached houses without electric heating. The peak consumption that a component is loaded with depends on the simultaneity of the consumption. With respect to household consumption, since people are not all arriving at home at the same time and start preparing food at the same time, the maximum loading of a component is not equal to the sum of the customers' individual peak consumption. Consequently, the representative profiles are prepared for different aggregation sizes, which take into account simultaneity. Using these profiles requires that the grid is split, e.g. into MV and LV grids, which are then assessed individually.

4) Add EVCs and HPs to the grid model: The grid model is extended with additional loads representing EVCs and HPs. The input to this function is the projection of EVs and HPs in the area as well as the distributions.

5) Generate profiles: This function retrieves the correct profiles based on the type and number of consumers in the grid as well as the profile parameters set by the user.

6) Power flow computation: Time-series power flow calculations are carried out, e.g. using panda power [7]. The step size depends on the time-resolution of the provided profiles.

7) Analysis of power flow results: The results are analysed. The proposed approach allows for example to assess the impact on component loading or voltages in the grid.

8) Determine reinforcement needs: Based on the results of the analysis, the needed reinforcement of specific grid component types can be determined.

III. Results from the Danish case study

It is investigated how the reinforcements needs are impacted by evolving EV charging behaviour. This is investigated by running the model with two different standard profiles for EV charging. In one case, the charging profiles are from the UK and from 2017 [8]. In the second case, they are from Denmark (DK) in 2023 [9]. The EV penetration corresponds to the expected level in 2040 based on the projections in [2].

A. Data and model

The Danish Utility Regulator (DUR) received Danish DSO grid data to develop the DUR's grid model (called GRID [10])[1]. The GRID model is used in this study and DUR executed the computations, while DTU provided the EV models and the electrical engineer know-how to design and implement the framework. DUR is responsible for all chosen inputs, the made assumptions and the results of GRID.

B. Input data

1) Grid input data: Data about the grid is received in the CIM (Common Information Model) format, specifically in the CGMES standard [6]. The CIM data includes information about all the components, including their geographical location. In order to do a load flow analysis in PandaPower the CIM data is converted to PandaPower format. This is done using PandaPower's built in converter [7].

The data are split into different files by different primary substations. In this case study, 11 primary substations from one Danish DSO are considered. The substations are geographically dispersed in the western part of Denmark and chosen such that the geographical zones[2], that are used by the regulator, are all represented in a share, that is similar to the total share for all of Denmark.

In Fig. 2, a map showing the western part of Denmark specifies which areas are covered by those primary substations.

2) Load input data: For determining the base load, actual building data from the Danish building registry (BBR [11]) are matched with the energy consumers in the CIM data. Specifically, the addresses geographically closest to the loads are identified by reverse geocoding. All addresses are looked up in BBR, where data about each building is available. For

[1]The authors would like to thank Emil Niels Heinrichsen and Rasmus Ploug Jenle for their model contributions and willingness to discuss model specifics.

[2]Namely, Inner City, Tall buildings, Housing, Summer houses, Infrastructure, Industry, Forest and wetlands, Other rural areas and Lake and ocean

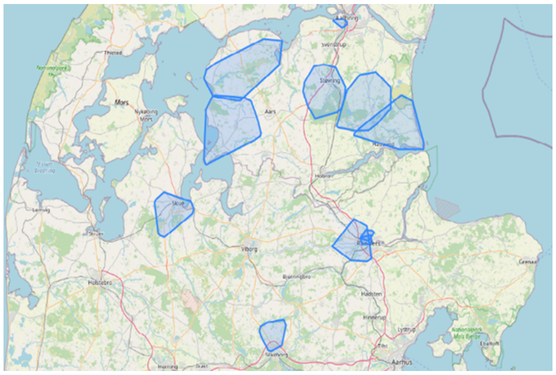


Fig. 2: Polygons estimating the area covered by the 11 primary substations included in the case study.

each building, there exists a 'use-code' and a 'heating-code'. The use-code identifies what the building is used for, e.g. residence, industry, etc. The heating-code identifies the type of heating that is used for the building (if any). Based on the use-code and the heating-code each specific building is given a standard consumption profile. Thus, each load in the CIM data can be associated with multiple profiles. From BBR, it is also identified if there are multiple apartments in a building, in which case each apartment will be given the relevant profile.

3) Projections and distributions for EVs and HPs: The projections for EVs and HPs are based on the national projections developed by the Danish Energy Agency (DEA) [2]. The consumption from and number of EVs and HPs can be seen in Table I. An approach similar to the one described in [12] was used for deriving distributions for EVCs and HPs.

TABLE I: Consumption and number of EVs and HPs according to the projections in [2]

	Consumption GWh	Number
EVs	$7,997$	$2,434,400$
Residential HPs	$3,720$	$480,031$
Commercial HPs	$2,295$	$19,969$

EV charger distribution: For the distribution of EVCs, the DEA provided indicators for distributing the consumption of EV level-2 chargers (AC chargers up to 22 kW) to municipalities and housing types. DEA assumed that in average 85% of an EV's consumption will be covered by this type of charger. Based on this distribution and assumptions on the average consumption of an EV in DK (assumed average daily driving distance of 45 km and average EV efficiency of 5 km/kWh), the number of level-2 chargers (EVCs) can be computed for each municipality and housing type. In combination with data on the buildings and housing in each municipality [3], ratios of chargers per housing type are derived. An example for Aalborg municipality is shown in Table II. With these distributions, the number of EVCs can be determined in a given grid based on the number and type of consumers.

HP distribution: A similar approach was used for deriving the distributions for HPs. As in [12], the assumption was that buildings with fossil fuel heating systems (based on e.g. oil, natural gas and wood) are likely to switch to HPs. Based on the share of these heating systems, the HPs are distributed to municipalities and housing/building types. The data used were obtained from Statistics Denmark[4]. Based on this simple distribution, it is expected that in 2040 32.8% of the fossil fuel heating system are replaced by HPs in residential buildings and 8.0 % in commercial buildings.

TABLE II: Distributions for EVCs per building/home for Aalborg municipality in 2040

Aalborg	Com. building	Apart-ments	Detached house	Town house	Farm house	Holiday cottage
2040	1.54	0.01	1.12	0.27	0.82	1.37

4) Base load profiles and HPs: Consumption profiles published by Green Power Denmark were used [13]. These profiles were created based on smart meter data from 300.000 Danish customers and are publicly available[5] The profiles are representative for the different consumer types, can be used for grid planning studies and take simultaneity into account for aggregations. The profiles have an hourly resolution and cover 24 hours. The profiles are provided for different aggregation sizes, percentiles, seasons and days. For example, the $95th$-percentile summer workday profile for an aggregation of 100 detached houses represents hourly consumption data, where there is only a 5% probability that the consumption of a random aggregation of 100 detached houses exceeds those values. The profiles are available for different housing types, e.g. detached houses, town houses, and apartments, and different commercial consumers, e.g. supermarkets. Moreover, consumption profiles for residential HPs are provided.

C. Electric vehicle profiles

Two sets of EVC profiles were analysed. For the first set (referred to as UK2017), publicly available data from the UK were used [8]. The second set of profiles (referred to as DK2023) was created based on residential EVC data provided by one of the largest charging point operators in Denmark.

1) UK2017 profiles: The UK data set (from [8]) contains charging session information from approx. $25,000$ residential EVCs in 2017. The provided data are charging session data, containing a session ID, charger ID, start time, end time, charged energy and plug-in duration. These data were converted into time-series for each EVC with a simple approach assuming uncontrolled charging. For that purpose, first the charging power was determined. This was done by computing the average charging power for each charging session and then the 99th-percentile value for each charger was calculated and stored as maximum charging power. Subsequently, each charging session was converted into a time series with hourly resolution assuming that the EV immediately starts charging when plugged in and charges with maximum charging power until the energy demand is fulfilled. Finally, the method de-

[3]Statistics Denmark: Table BYGB12: Buildings and BOL103: Dwellings.

[4]Statistics Denmark: Table BYGB40: Buildings and their heated area.

[5]Link to Green Power Denmark Profiles (last accessed 2024-07-29)

scribed in [9] was used to create representative EVC profiles, which take into consideration simultaneity of aggregations.

2) DK2023 profiles: The DK data set contains data from approx. 3,500 residential EVCs, which were provided as time series with hourly resolution. The EV owners have the possibility to control their charging through a delay function in the charging app. A large share of owners are using this functionality to delay charging to hours with lower electricity prices [14]. To create the representative profiles, the same methodology as for the UK data was used. Details about the profiles can be found in [9].

3) Comparison of the EV charger profiles: Only 3-phase chargers were considered, which typically charge with a maximum of 11 kW. Figure 3 shows a histogram of the annual consumption served by the EVCs. It can be observed that

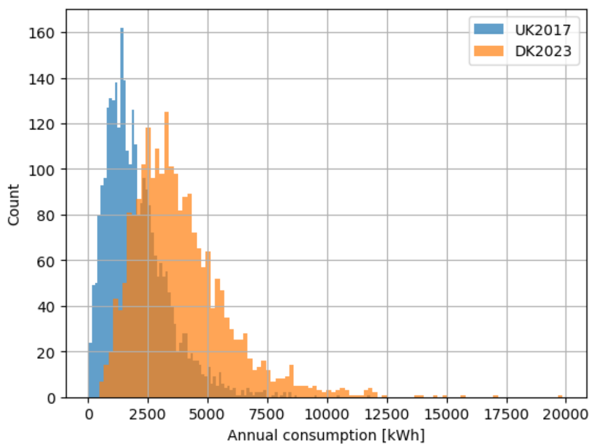


Fig. 3: Histograms of the annual consumption of the chargers.

the annual consumption in the UK2017 data are generally lower than in the DK2023 data. The mean in the UK data is approx. 2030 kWh and for the DK data approx. 3870 kWh. Figure 4 shows a comparison of the UK2017 and DK2023 EVC 95th-percentile profiles for a winter workday for five and 50 EVCs. The winter workday profile was chosen, since the peak power is the highest. The graph shows that the EVC profiles have quite different characteristics. While the UK2017 EVC profile has a peak in the evening around hour 19 of 4.2 kW per EVC for five EVCs, the DK2023 EVC profile has a peak of 6.6 kW per EVC around hour 1, where electricity prices are usually low. It can be observed that the peak power per EVC decreases when the aggregation size increases, for 50 EVCs it reduces to 1.7 kW (UK2017) and 3.8 kW (DK2023).

D. Simulation results

In Denmark, the highest loading from conventional consumption occurs during the winter on a workday, see [13]. This is also the case for EVCs (see [9]). Consequently, it is expected that the loading on a winter workday will determine the grid reinforcement needs. The impact of the two EVC profiles will be investigated. For all simulations 95th-percentile profiles for a winter workday were used.

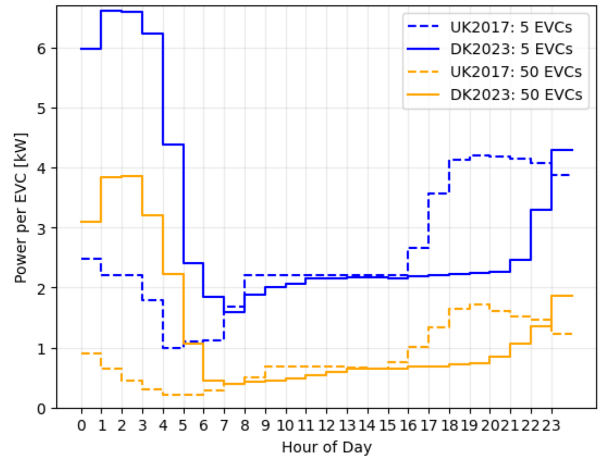


Fig. 4: Comparison of the EVC consumption profiles for UK2017 and DK2023. The curves show the 95th-percentile profiles for a winter workday for five and 50 EVCs.

The maximum loading limit, which triggers the need for reinforcement of a component, is an input to the model. The following limits were assumed, the maximum loading limit of a 20 − 60 kV/10 kV transformer was set to 70%, for a 10 − 20 kV/0.4 kV transformer 100% , for 10 − 20 kV cables 66% and 90% for 0.4 kV cables. That is, if a 0.4 kV cable is loaded with 90% of its capacity or above at any time of the simulation, it is categorized as in need of reinforcement.

In Table III, the number of transformers and cables (in km.) to replace, simulating the model with the two EVC profiles described in Section III-C, are presented. In addition, the percent share of components to replace out of all the components in the simulation are presented in parentheses for the two scenarios.

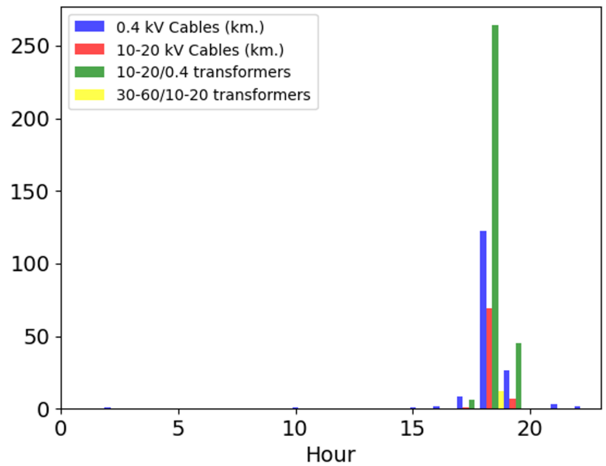
TABLE III: Transformers and cables (in km.) in the different scenarios.

	Total in simulation	To replace (share of total) UK2017	DK2023
0.4 kV cables (km.)	3183.7	166.4 (5.23%)	227.6 (7.15%)
10 − 20 kV cables (km.)	1473.1	77.0 (5.22%)	92.8 (6.30%)
10 − 20 kV/0.4 kV transformers	1496	315 (21.06%)	448 (29.95%)
30 − 60 kV/10 − 20 kV transf.	24	12 (50.00%)	13 (54.17%)

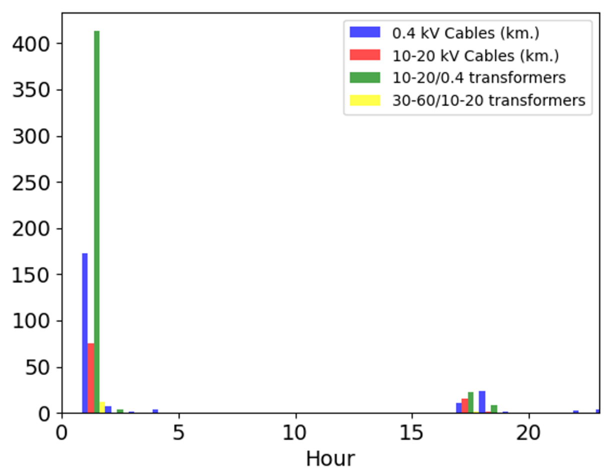
From Table III, it is clear that the increase of EVs and HPs will cause a need for reinforcement of the grid. Furthermore, the share of transformers that need replacement is larger than cables (in kilometers). This is driven by 10 − 20 kV/0.4 kV-transformers, as there are few transformers in a higher voltage level, in the examined grids as can be verified from Table III.

The share of cables that need to be replaced only rises marginally when updating the EVC profiles. The share of 10 − 20 kV/0.4 kV transformers that need to be reinforced changes more substantially, from 21.06% to 29.95% when the DK2023 EVC profiles are used.

In Section III-C, it is described how the EVC patterns have changed such that EVs charge during the night rather than the evening. The effect of this is presented in Fig. 5a and 5b, where the hour of the maximum load for overloaded components is visualized. From Fig. 5a it is clear that the peak



(a) Overload times with EVC profiles UK2017.



(b) Overload times with EVC profiles DK2023.

Fig. 5: Time of maximum load of overloaded components in simulation with EV profiles from 2017 and 2023.

of the overloaded components is between hour 17 and 20. That is, the peak is clustered around the "normal" evening peak. From Fig. 5b, it can be observed that the most overloaded components have their peak-load between hours $1-3$ in the morning when the DK2023 profiles are used. Hence, the EVCs created a new higher peak than the "normal" evening peak.

IV. Conclusion

A generic, simple framework for identifying future reinforcement needs of the distribution grid was presented. The framework is transparent regarding the implementation and gives a clear overview over inputs and assumptions. It is easy to analyse different geographical areas or scenarios with different assumptions or based on other input data (e.g. EVC profiles). In the regulatory context, such a tool is important for the dialog between different interest groups. For example, to make policies and regulations efficiently, policy makers and regulators need an understanding of how calculations about future reinforcement costs are made and how sensitive the results are with respect to the assumptions and chosen inputs.

To investigate the impact of different EVC profiles, actual Danish distribution grid data and actual consumption data were utilized to create the model. In the case study, it was run with two different sets of EVC profiles - one set based on British charging data from 2017 (UK2017) and one based on Danish data from 2023 (DK2023). The results showed that the charging behaviour is evolving, which in turn impacts the reinforcement needs. It could be observed that with the DK2023 EVC profiles the peak was moved from the evening to the night. Moreover, the share of components that needed to be reinforced increased particularly for 0.4 kV cables (from 5.23% to 7.15%) and $10-20\text{kV}/0.4\text{kV}$ transformers (from 21.06% to 29.95%). This change is likely due to higher simultaneity, shift of the peak and larger average annual consumption in the DK2023 profiles.

The next steps will be to determine the necessary replacements and expansions based on reinforcement rules. This will provide a list of new components, which can be used to compute the reinforcement costs. Another extension will be an approach to upscale the results to DSO or national level.

References

[1] Danish Goverment, "Ansvar for danmark - det politiske grundlag for danmarks regering," Regeringen, Tech. Rep., 12 2022.

[2] Energistyrelsen, "Analyseforudsætninger til energinet 2022 (af22)," Energistyrelsen (Danish Energy Agency), Tech. Rep., 05 2023.

[3] C. Matrose, T. Helmschrott, M. Gödde, E. Szczechowicz, and A. Schnettler, "Impact of different electric vehicle charging strategies onto required distribution grid reinforcement," in *2012 IEEE Transportation Electrification Conference and Expo (ITEC)*. IEEE, 2012, pp. 1–5.

[4] A. Schoen, J. Ulffers, H. Maschke, E. Junge, C. Bott, L. Thurner, and M. Braun, "Considering control approaches for electric vehicle charging in grid planning," in *ETG Congress 2021*, 2021, pp. 1–6.

[5] S. Striani, K. Sevdari, L. Calearo, P. B. Andersen, and M. Marinelli, "Barriers and solutions for evs integration in the distribution grid," in *2021 56th International Universities Power Engineering Conference (UPEC)*, 2021, pp. 1–6.

[6] C. Ivanov, "Common grid model exchange standard (cgmes)," entsoe, Tech. Rep., 2014.

[7] L. Thurner, A. Scheidler, F. Schäfer, J. Menke, J. Dollichon, F. Meier, S. Meinecke, and M. Braun, "pandapower — an open-source python tool for convenient modeling, analysis, and optimization of electric power systems," *IEEE Trans. on Power Syst.*, vol. 33, no. 6, Nov 2018.

[8] UK Department of Transport, "Electric chargepoint analysis 2017: Domestics," United Kingdom, DoT, Tech. Rep., 12 2018.

[9] T. Weckesser, J. Odgaard, G. Yousefi, M. Thingvad, and C. Ziras, "Danish electric vehicle charging profiles for distribution grid planning and design," in *CIRED 2024 Vienna Workshop*, 2024 (in press).

[10] Danish Utility Regulator, "Automatisk indikator som tillæg til elnetvirksomhedernes indtægtsrammer," Forsyningstilsynet, Tech. Rep., 01 2024.

[11] Danish Property Assessment Agency, "Danish home and building registry (bbr)," https://bbr.dk/forside, accessed: 2024-06-07.

[12] T. Weckesser and M. Vesterbæk, "A robust approach for determining future projections for the distribution grid based on national projections," in *CIRED 2021 26th International Conference and Exhibition on Electricity Distribution*, vol. 2021, 2021.

[13] K. R. Rosenørn, T. Weckesser, J. Mehmedalic, H. Hansen, P. J. Douglass, and J. Rasmussen, "Ra 623 - analyseforudsætninger for distributionsnettet del 2: Simuleringsprofiler," DEFU, Tech. Rep., 2021.

[14] C. Ziras, M. Thingvad, T. Fog, G. Yousefi, and T. Weckesser, "An empirical analysis of electric vehicle charging behavior based on real danish residential charging data," *Electric Power Systems Research*, accepted.