Regional, sectoral, and socioeconomic dimensions of energy consumption: The case of Germany

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Abstract:

To successfully mitigate greenhouse gas emissions, energy procurement, consumption, and distribution must be transformed. While procurement (comprising generation, imports, and storage) and distribution of energy - in particular from renewable energy sources (RES) - are the focus of debate and scientific analysis, the consumption side is often neglected. We developed new methods for generating disaggregated energy consumption data for the industrial and residential sectors. Using a combination of various methods from the fields of optimization, multivariate linear regression, and machine learning we are able to learn and reproduce the inherent patterns of energy consumption in micro data and further statistical reports. We then use the generated database on regionally, sectorally, and socioeconomically disaggregated energy consumption to analyze the diversity of energy consumers across Germany. Especially with regard to the residential sector, the vast discrepancy in energy poverty across Germany is striking. North-eastern Germany and the Ruhr area show high shares of energy poverty according to the HCLI indicator of up to ~50% while in southern Germany regions with only 7% of energy-poor households can be found.

Keywords: Energy transition, Energy consumption, Energy poverty, Optimization, Machine learning

1 Introduction

To successfully mitigate greenhouse gas emissions, energy procurement, consumption, and distribution must be transformed. While procurement (comprising generation, imports, and storage) and distribution of energy - in particular from renewable energy sources (RES) - are the focus of debate and scientific analysis, the consumption side is often neglected. The reasons for this lie in the large number of heterogeneous consumers who exhibit different decision-making behavior with regard to their energy consumption. Understanding the consumption side of the energy system better could help to (1) design more efficient policies that encourage energy consumers to take greater action within the scope of their capabilities, (2) increase the acceptance of energy policy measures, and (3) assess the transformation of energy procurement and distribution with lower uncertainties.

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For this, the open-source JERICHO-E-usage dataset has been developed at FCN-ESE that provides comprehensive data on energy consumption patterns in high spatial and temporal resolution for the four energy sectors (Priesmann et al., 2021a). Building on this dataset, the intrasectoral resolution is further increased by dividing the industrial sector into subsectors and disaggregating the household sector based on socioeconomic criteria. Intrasectoral heterogeneity arrives from socioeconomic structures, economic structures, regional climate conditions, and availability of energy carriers, among others. The Corona pandemic shows how important specific regional, sectoral, and socioeconomic data is for designing appropriate incentives widely accepted and encouraging participation. Therefore, the goals are to (1) generate highly resolved regional and intrasectoral data on energy consumption, (2) identify drivers for regional, sectoral, and socioeconomic differences, and (3) evaluate the data in terms of:

- Energy consumption,
- energy expenses, and
- energy poverty.

For this, data is combined from sources such as the Federal Statistical Office of Germany, the Socio-Economic Panel, the German Working Group on Energy Balances, and the Federal Employment Agency. The data sources are consolidated to ensure a high degree of validity in the resulting consumption data. For the industry sector, optimization methods are applied to minimize the deviation at a validation interface when generating regionalized data. Machine learning-based models are trained on micro census household data to understand the energy consumption behavior for the residential sector.

The resulting data is then analyzed for regional, sectoral, and socioeconomic differences in energy efficiency, energy poverty, energy prices, and energy expenses. In addition, the factors influencing these indicators can be derived and used to develop recommendations for incentive systems.

2 Theoretical Background

Andor et al. (2018) have demonstrated how discrepancies in the burden-sharing between the residential and the non-residential sectors for financing renewable energy influences the social acceptance of German households. In terms of socioeconomic factors, Priesmann et al. (2021b) have shown that lower-income households are most affected by electricity price increases including those caused by the introduction of RES support levies. They observe that higher-income households are less affected by price increases and that energy poverty is highly dependent on the electricity price and the underlying regulatory framework. The regional dimension of energy poverty has been analyzed by Besagni and Borgarello (2019) for the case of Italy or Sokołowski et al. (2020) for the case of Polen. For the case of Germany, regional analyses are scarce though can offer additional insights as shown by Drescher and Janzen (2021) who use a fixed-effects model accounting for differences across the federal states and additionally distinguish between rural and urban areas.

In the following, the differences between residential and industrial energy consumers are discussed. Then, we refer to socioeconomic differences within the residential sector and further elaborate on energy poverty.

2.1 Distinction of residential and industrial energy consumers

End-users of electricity in Germany are categorized into two groups according to their type of consumption metering (BNetzA and BKartA, 2014a). The first group comprises mainly industrial and commercial enterprises whose electricity consumption is measured in 15-minute intervals. In 2018, industrial and commercial end-users in Germany consumed 328 TWh of electricity, a share of 73% of total final electricity consumption (AGEB, 2020). The second group's electricity consumption is up to today estimated based on standard load profiles and consists primarily of private households and small businesses (though the compulsory installation of smart metering in Germany since 2020 will enable individual load profiles in the future). In 2018, private households accounted for 127 TWh or 25% of the total electricity consumption (AGEB, 2020). Generally, a consumption below 10 MWh/a applies to private households and small industrial businesses, the range between 10 MWh/a and 2 GWh/a to commercial and small industrial businesses, and values of over 2 GWh/a to industrial electricity use (BNetzA and BKartA, 2014b).

Energy-intensive industries, as opposed to private households, do not always have to pay the full price of electricity. In Germany, these industries include steel, aluminum, copper, paper, chemical, and textile industries (Fraunhofer ISI and Ecofys, 2015a). The manufacturing industry in particular benefits from reductions and exemptions of certain price components. These benefits include general electricity tax reliefs, electricity tax capping, and exemptions of certain manufacturing processes as well as the special equalization² scheme of the EEG. Most reductions and exemptions are justified with the reference to maintaining international competitiveness (UBA, 2019). These privileges are linked to different criteria – such as absolute electricity costs in revenue or gross value added, among others (Fraunhofer ISI and Ecofys, 2015b). This causes a discrepancy between the share of total electricity consumed and the share of total RES support levy revenues stemming from the residential and industry sectors as shown in Figure 1.

² The special equilization scheme allows companies that are considered as energy-intensive and that are participating in international competition to pay a reduced EEG levy.



Figure 1: Total electricity consumed and the share of total RES support levy revenues per sector for the year 2019 (BDEW, 2020).

The prevalence of privileged industrial companies is small: e.g., in 2015, only 4% of all industrial companies benefitted from a reduced or waived RES support levy (BDEW, 2015). Looking at the regional distribution, differences can be observed due to the regional variation of energy-intensive industry subsectors. Nonetheless, the companies that do benefit from a reduction in or exemption of the RES support levy consumed roughly half of the total industrial electricity. The current relief volume of all taxes, levies, and surcharges is €16 bn per year, to which the privileges concerning the RES support levy contribute the most with €7.1 bn (UBA, 2019). This leads to private households and commerce currently bearing some 56% of the costs for the RES support and industry only 25% (BDEW, 2020). The rest is allocated to the public, agriculture, and transport sectors.

2.2 The electricity price development for industrial and residential end-users

Industrial electricity customers in Germany were confronted with an immense increase in electricity prices (see Figure 2). The absolute changes are illustrated by reference to companies with yearly electricity consumption of 160 to 2,000 MWh. The cost development between 2003 and 2018 is compared by adjusting the cost terms for inflation using the consumer price index (CPI) with the base year 2003³. The average cost of electricity per kWh for the shown consumption band increased by 9.98 €-ct/kWh from 2003 to 2018 or ~125% in normal prices. When accounting for inflation, the average costs increased by 6..48 €-ct/kWh or ~81%. The increase in RES support levy accounts for the majority of the increase in industrial electricity prices – though companies can benefit from a reduction or exemptions of the RES support levy.

³ See Destatis (2020) for CPI values.



Figure 2: Development of the industrial average cost of electricity per kWh, by component, for the annual consumption of 160 to 2,000 MWh (BDEW, 2019; Destatis, 2020).

Residential electricity customers also witnessed a rapid increase in electricity prices in Germany in the period from 2003 to 2018. The absolute changes in residential electricity prices are illustrated by reference to the medium consumption band DC. Figure 3 shows that the average cost of electricity per kWh for the residential sector increased by 12.28 \in -ct/kWh from 2003 to 2018, which results in a relative change of ~71%. The grey columns in Figure 3 depict the average cost of electricity per kWh in constant 2003 Euros. When accounting for inflation, average cost increased by 6.53 \in -ct/kWh (in 2003 Euros). Thus, the relative cost increase from 2003 to 2018 merely amounted to ~38%.



Figure 3: Development of the private household average cost of electricity per kWh, by component, for the annual consumption of 3500 kWh (BDEW, 2019; Destatis, 2020).

Market-based cost components, including procurement and supply, accounted for merely ~21% of the average cost of electricity for residential consumers in 2018. The main drivers for the cost increases are taxes, levies, and surcharges. This cost component rose from 6.81 \in -ct/kWh in 2003 to 15.98 \in -ct/kWh in 2018, which results in a relative increase of ~135%. The main reason for the surge in taxes, levies, and surcharges is the RES support through the EEG levy, which during this time period rose by ~1617%. The second-largest government-imposed cost component is the value-added tax (VAT), followed by the electricity consumption tax, the latter of which was introduced in 1999 to incentivize more energy-efficient electricity consumption and, therefore, indirectly reduce CO₂ emissions (Bundestag, 1999). Another considerable share relates to the concession levy, which refers to payments flowing from distribution network operators to municipalities for the right of way to install new power lines (Agora Energiewende, 2017).

2.3 Energy poverty with a focus on Europe and Germany

Whether a household is considered energy poor can be analyzed using energy poverty thresholds. This threshold, also referred to as energy poverty line, can be calculated using various approaches such as the 10% poverty line, the two times median share poverty line, or the high-cost/low-income poverty line (Heindl, 2014). Based on the distinction between energy-poor and non-poor households, indicators for the degree of energy poverty within a society can be derived, such as the FGT index (Foster et al., 1984).

3 Methodology

In the following, the developed and applied methodology for generating regionally, sectorally, and socioeconomically resolved data on electricity consumption, electricity expenditures, and electricity poverty are described.

3.1 Disaggregating industrial energy consumption

For the industrial sector, the goal is to generate data on energy consumption per energy carrier and industry subsector. The chosen resolution is the NUTS3-level which comprises 401 regions for the German case. The model structure is shown in Figure 4.



Figure 4: Structure of the consolidation model for generating data on industrial energy consumption.

We selected a consolidation approach that uses a multitude of different reported statistical datasets. By defining interfaces on different aggregation levels (regionally and sectorally), the information contained in every reported dataset can be used to improve the quality of the constructed dataset. The reported datasets for the year 2018 comprise the following:

- Destatis (2021a): Data on company sites and employees per NUTS0, NUTS1, and NUTS3 region
- Destatis (2021b): Data on company sites per industry subsector

- Bundesagentur für Arbeit (2019): Data on employees per NUTS3 region and industry subsector
- Destatis (2021c): Data on energy consumption per NUTS0, NUTS1, and NUTS3 region
- Destatis (2021d): Data on energy consumption per industry subsector
- Eurostat (2021): Data on heating days per NUTS3 region

After collecting and preprocessing the data, an optimization model is formulated. The objective is to minimize the deviations at the NUTS3 level per industry subsector and energy carrier:

$$\min_{\Delta_{nuts3, i, e}^{+}, \Delta_{nuts3, i, e}^{-}} \sum_{nuts3} \sum_{i} \sum_{e} \Delta_{nuts3, i, e}^{+} + \Delta_{nuts3, i, e}^{-}$$
(1)

This deviation stems from a regression-like constraint as shown in Eq. (4). Further, Eq. (2) shows an exemplary constraint for an interface that is based on secured data while Eq. (3) shows an exemplary constraint for an interface where the reported consumption data is expected to underestimate real energy consumption. This validation is performed by aggregating reported data (per region or per sector) in a validation step and checking whether the aggregated sums meet the reported total consumption.

$$\sum_{nuts3} \sum_{i} x_{nuts3, i, e} = (1 + \gamma_{nuts0, e}^{+} - \gamma_{nuts0, e}^{-}) * \overline{CONS}_{nuts0, e} \quad \forall i \in I$$
(2)

$$\sum_{i} x_{nuts3, i, e} \ge (1 - \alpha) * \overline{CONS}_{nuts3, e} \quad \forall nuts3 \in NUTS3; \forall e \in E$$
(3)

$$x_{nuts3, i, e} = \beta_{i,e}^{empl} * \overline{EMPL}_{nuts3, i} + \beta_{i,e}^{sites} * \overline{SITES}_{nuts3, i} + \beta_{i,e}^{empl, sites} * \overline{EMPL}_{nuts3, i} / \overline{SITES}_{nuts3, i} + \beta_{e}^{heat} * \overline{HD}_{nuts3} + \Delta_{nuts3, i, e}^{+}$$

$$-\Delta_{nuts3, i, e}^{-} \forall nuts3 \in NUTS3; \forall i \in I; \forall e \in E$$

$$(4)$$

3.2 Disaggregating residential energy consumption and expenditures

For the residential sector, the goal is to data on electricity consumption and expenditures as well as socioeconomic indicators. The chosen regional resolution is again the NUTS3-level. The methodological approach is depicted in Figure 5.



Figure 5: Model structure for generating regionally and socioeconomically resolved energy consumption data for the residential sector.

In a first step and using the income and consumption sample (ICS) of Germany (RDC of the Federal Statistical Office and the statistical offices of the Länder, 2018), a multivariate linear regression model is set up to map household incomes to various descriptive variables. In a second step, this regression model is used to disaggregate census data (Statistische Ämter des Bundes und der Länder, 2011) into individual households (resulting in ~37 mil. table rows). For this, again an optimization approach is applied. The objective of this optimization model is to minimize the deviation from the relations depicted by the regression model while meeting (1) the distribution of socioeconomic, (2) dwelling information provided by the census, and (3) reported household income information per NUTS3 region (Destatis, 2021e).

Finally, a machine learning-based model is constructed based on the ICS dataset mapping various socioeconomic and dwelling information on electricity expenditure (see Figure 6).



Figure 6: Illustration of the feed-forward neural network model for mapping socioeconomic and dwelling information on electricity expenditure.

The feed-forward neural network model was compared against a multivariate linear regression model and showed higher accuracy in terms of R2 (~0.74 compared to ~0.41). The model is then used to estimate the electricity expenditure per household in Germany. Residential energy consumption is calculated using base and operating prices for the year 2018 that is provided by (Priesmann et al., 2021b).

3.3 Calculating energy poverty indicators

We further investigate the impact of the current allocation mechanism and of our reform proposal on a modified form of energy poverty, which we call electricity poverty, using the two times median share poverty line and the high cost / low income (HCLI) poverty line, as suggested by Heindl (2014). The two times median share poverty line considers those households as electricity-poor whose electricity expenditure shares on income accounts for more than twice the median value. In comparison, the HCLI poverty line considers those households as electricity poor whose electricity expenditure shares are higher than the median value while, at the same time, having an income below 60% of the median. We use equivalized incomes and expenditures according to the OECD equivalence scale for our analysis. We then derive measures for electricity poverty using the FGT index from Foster et al. (1984). $P_{\alpha} = \frac{1}{N} \sum_{i=1}^{q} \left(\frac{e_i - z}{z}\right)^{\alpha}$, where *N* is the number of households, *q* the number of households below the poverty line, e_i the expenditure or expenditure shares for energy services (in this case only electricity), and *z* the poverty line. We use values of $\alpha = 0$ (headcount ratio), $\alpha = 1$ (poverty gap index), and $\alpha = 2$ (squared poverty gap, measuring poverty intensity).

4 Results and Discussion

In the following, the resulting data on disaggregated consumption, expenditures, and energy poverty indicators are presented and discussed.

4.1 Energy consumption for the industrial and residential sectors

Figure 7 shows the results for the disaggregated energy consumption of the industry sector (here with electricity as one of seven available energy carriers). Large differences in the regional and sectoral distribution of electricity consumption can be observed.



Figure 7: Regional and sectoral distribution of final energy consumption (electricity) for the industrial sector in 2018.

Figure 8 shows the results for the disaggregated electricity consumption of the residential sector. As households are modeled individually, further insights on socioeconomic differences within regions can be generated. As shown, the share of electricity consumption per income



decile among total consumption differs across Germany⁴. Blank regions are due to numerical issues when disaggregating households based on the census dataset.

Figure 8: Regional and socioeconomic distribution of final energy consumption (electricity) for the residential sector in 2018.

4.2 Comparing electricity expenditures in the residential sector

Figure 9 shows the resulting electricity expenditure per household and the electricity expenditure share in net income. Electricity expenditure is highest in southern Germany. However, due to high household incomes, the electricity expenditure shares in net income are among the lowest. In contrast to this, households in north-eastern Germany have the lowest electricity expenditure but due to low household incomes, the share of this income spent on electricity is highest across Germany.

⁴ Income decile 1 comprises the 10% of households with the lowest yearly net income per household resident while the 10% of households with the highest incomes are allocated to income decile 10.



Figure 9: Average household incomes, electricity expenditure, and electricity expenditure share in net income.

4.3 Comparing energy poverty indicators

Figure 10 shows the share of energy (in this case electricity) poor households using the HCLI indicator. What is striking is that the north-eastern regions show by far the highest shares of electricity poor households with regions having up to ~50% of households defined as electricity poor (see Figure 9). Also worth mentioning are scattered regions in the Ruhr area, which also shows high shares of electricity poor households.





5 Conclusion

We have developed new methods for generating disaggregated energy consumption data for the industrial and residential sectors. Using a combination of various methods from the fields of optimization, multivariate linear regression, and machine learning proved to be capable of learning and reproducing the inherent patterns of energy consumption in micro data and further statistical reports. Using the generated new database on regionally, sectorally, and socioeconomically disaggregated energy consumption data, we can now better capture the diversity of energy consumers across Germany. Especially with regard to the residential sector, the vast discrepancy in energy poverty across Germany is striking. North-eastern Germany and the Ruhr area show high shares of energy poverty according to the HCLI indicator of up to ~50% while in southern Germany regions with only 7% of energy-poor households can be found.

The generated data basis and the conducted analyses can be used to derive recommendations on how to change the regulatory framework in order to reduce energy poverty and increase acceptance for a transition towards more sustainable energy systems.

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