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MODELING COUNTRY-SCALE ELECTRICITY DEMAND PROFILES

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ABSTRACT

All over the world, and in particular in Germany, a trend toward a more sustainable electric energy supply including energy efficiency and climate protection can be observed. Simulation models can support these energy transitions by providing beneficial insights for the development of different electricity generation mix strategies in future electric energy systems. One important input parameter for these large-scale simulations is the electricity demand, commonly obtained using empirical datasets. However, it is desirable to deploy dynamic electricity demand models to be able to investigate the behavior of the energy system under changing or specific conditions. In this paper we present such a model. We identify the most important parameters, such as the seasonality, the type of day, and the daily mean temperature to accurately model the large-scale electricity demand for Germany. We validate and implement our model in the context of a hybrid simulation framework and show its correctness and applicability.

1 INTRODUCTION

According to the Energy Policy Highlights (International Energy Agency 2013), the German government targets Germany to become one of the most energy efficient and environmentally sound economies worldwide. This energy transition not only includes the phase-out of nuclear power, a drastic reduction in greenhouse gas emissions, and a significant increase of electricity generated by Renewable Energy Sources (RES) but also a 20 % decrease of energy consumption in general by the year 2020.

These goals require a large effort in terms of planning and preparation, often relying on the accuracy of predictions. For example, to plan the construction of new gas power plants or the extension of photovoltaic installations, it is necessary to understand the exact consequences of the nuclear power phase-out on, e.g., the daily electricity feed-in profiles. In order to obtain such projections and investigate different options for future electricity mix strategies for the German federal state Bavaria, a research project has been started, in which we developed a hybrid (System Dynamics and Discrete-Event Simulation) simulation framework for large-scaled electricity generation systems (Pruckner and German 2013), (Pruckner and German 2014). The framework is subject to continual development.

An important input parameter of such a simulation is the demand profile, that is, a dataset that represents the aggregated electricity demand in the system. In our case, we used demand profiles provided by the European Network of Transmission System Operators for Electricity (ENTSO-E 2013), including the exact German electricity demand in an hourly resolution for the last three years. In order to simulate different scenarios (e.g., increased demand, mild winters, etc.) it is, however, desirable to not always use the exact same demand profile in a simulation. Therefore, based on empirical data such as recorded demand profiles and daily mean temperatures, we develop an electricity demand model that is able to generate realistic demand profiles to be used in a simulative environment. The contribution of this paper can be summarized as follows:

- We identify the characteristics and requirements to accurately model country-scale demand profiles
- We present an empirical energy demand model to be used in simulation
- We show the functionality of our approach using the commercial tool AnyLogic.

The remainder of the paper is organized as follows. In Section 2 we discuss related work. Section 3 presents our conceptual approach. Section 4 describes the implementation of our model in AnyLogic. In Section 5 we present the validation of the model and simulation results. Section 6 concludes the paper.

2 RELATED WORK

There are several publications on the field of modeling and simulation of electricity load profiles at the household level. Paatero and Lund (2006) presented a simplified bottom-up model to generate realistic domestic electricity consumption data on an hourly basis from a few up to thousands of households. The load is constructed from elementary load components (e.g., dishwasher, washing machine, television).

The modeling of household electricity consumption was also considered by Sorasalmi (2012). The aim of his work is to implement a tool capable of producing future scenarios of the electricity consumption and load profile changes. For the long-term model a System Dynamics approach is used, whereas the short-term model is implemented using a bottom-up approach.

Zeyringer et al. (2012) proposed a methodology which combines statistical data on the distribution of electricity consumers with standardized load profiles. This approach allows for the investigation of the integration of renewable energy technology in micro grids.

All three publications aim to model electricity demand profiles on the level of households. It is possible to obtain electricity load profiles for a small region by aggregating these demand profiles, however, the industry sector is not sufficiently taken into consideration, limiting their applicability for large-scale simulation. We show a method to model country-scale electricity demand profiles, using Germany as a proof of concept example.

Wagner (2012) investigated the residual load modeling and its application to electricity pricing. In order to model the residual load - defined as the difference between electricity demand and the amount supplied by RES - electricity demand plays an important role. Using stochastic models he was able to model residual load profiles.

Connolly et al. (2010) studied 37 tools that can be used to analyze the integration of electricity generated by RES. Many of these tools also use the published data from the ENTSO-E, however, many tools do not use stochastic superimposition, that means, the electricity demand is the same for every year. For instance, a lower electricity consumption in winter months due to mild weather conditions and their impact on the electric energy system cannot be considered in detail.

In this paper we present a validated hybrid modeling approach for the simulation of electricity demand profiles, which are based on the published data from ENTSO-E. Based on findings of Gladysz and Kuchta (2008), we identify different factors which influence the electricity demand. Our investigations show that the season, the type of day (weekday, Saturday, Sunday, holiday), and the daily mean temperature have a significant influence on the daily electric energy consumption. Using the correlation between the daily mean temperature and the daily electric energy consumption, we are able to generate continuous electricity demand profiles for any given time period. Furthermore, we model the daily mean temperature as a stochastic process allowing us to generate realistic and varying demand profiles.

3 METHODOLOGY

In this section we describe our conceptional approach in three steps. In the first subsection we describe the statistical analysis performed on ENTSO-E load profiles of Germany to determine which input parameters need to be considered for our electricity demand model. In a second step we analyzed the correlation between daily mean temperatures and electricity consumption levels; lastly, we explain the development of a stochastic process for the simulation of daily mean air temperatures.

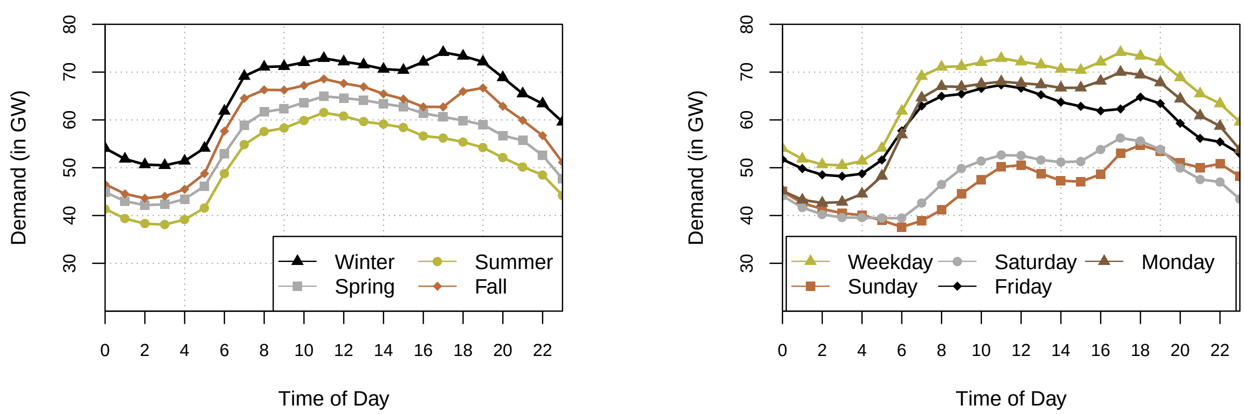
3.1 Data Analysis of ENTSO-E Load Profiles

According to Gladysz and Kuchta (2008), electricity consumptions levels are mainly influenced by two factors, namely atmospheric conditions such as the air temperature and by the day of the week. It can be observed that the electricity consumption levels on winter days are higher than on summer days (see also Figure 1(a)), because of lower air temperatures and, among others, larger heat demands.

Moreover, the electricity consumption level is influenced by weekly work-cycles, which means that on Saturdays or Sundays the electricity consumption levels are much lower than on workdays (see also Figure 1(b)). In order to find a representative classification for different weekdays and seasons, we analyzed the ENTSO-E load profiles for Germany. In total, electricity demand data in an hourly resolution is available for almost three years from 01/01/2011 to 31/10/2013.

For the statistical analysis we added every single observation information about the season (winter, spring, summer, fall), weekday, holiday (scholar-holidays, day after holidays, day before holidays), and the daily mean temperature. To find the parameters with the biggest impact on electricity consumption levels, we conducted a p-value analysis for each of them (the null hypothesis being that the given parameter has no influence). We found that the nature of the electricity demand profiles is mainly characterized by the yearly, weekly, and day-night cycles. Climate conditions, holidays and daily work times were also found to have a significant impact on electricity demand profiles. For validation purposes we fit a linear model taking all significant attributes into account and received an adjusted R-squared value of 0.89.

In a first step we observed that the season and weekday affects the typical daily trend in electricity demand profiles. Figure 1(a) depicts the typical electricity load curve for a representative Wednesday of each season. Not only were the amplitudes different for different seasons, but also have the curves different characteristics: In fall and winter two load peaks can be observed at hours 12 and 18 (6 p.m.), whereas there is only one load peak at 12 in spring and summer. Although the electricity demand profiles for summer and spring look similar, they are different in the daily electricity consumption level. The hourly demand values for workdays in spring are 5 GW higher on average than on a summer day.



(a) Workday for different seasons

(b) Different days of the week for winter

Figure 1: Characterization of electricity demand profiles based on published data from ENTSO-E

The second important factor is the difference between different days within a certain season. Figure 1(b) depicts electricity demand curves for different days of the week in winter. The daily electricity consumption on Saturdays and Sundays is much lower than on workdays. But even on workdays differences are observable:

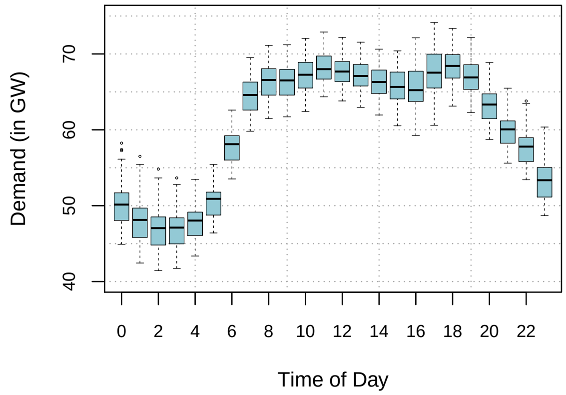


Figure 2: Boxplot of daily electricity demand for workdays in winter

Mondays are influenced by the very low electricity demand at Sunday evenings, causing the electricity demand to be lower in the early morning. Caused by the upcoming weekend on Fridays, the electricity demand decreases in evening hours earlier than on Mondays, Tuesdays, Wednesdays, or Thursdays.

Both seasonal and weekday aspects have to be considered for the classification, therefore electricity demand profiles are grouped accordingly. Since there are almost no differences and the day-night cycles are quite similar for Tuesdays, Wednesdays, and Thursdays we group them together, resulting in a total of twenty groups. We found that public holidays can be grouped with Sundays, days before public holidays can be grouped with Fridays. This is consistent with the findings of Gladysz and Kuchta (2008).

Each group was assigned the corresponding daily electricity demand data from the years 2011, 2012, and 2013. We normalized these values to account for different climate conditions and economic growth. Subsequently, every group was analyzed in detail. For instance, Figure 2 shows the boxplot for one of the twenty groups, namely a winter weekday. We see a variation in the electricity demand of each hour of the day, outliers are hardly observable. As the range of each box is very similar, we store the median of each hour within each group (resulting in $24 \cdot 20$ values).

3.2 Correlation between Electricity Consumption and Temperature

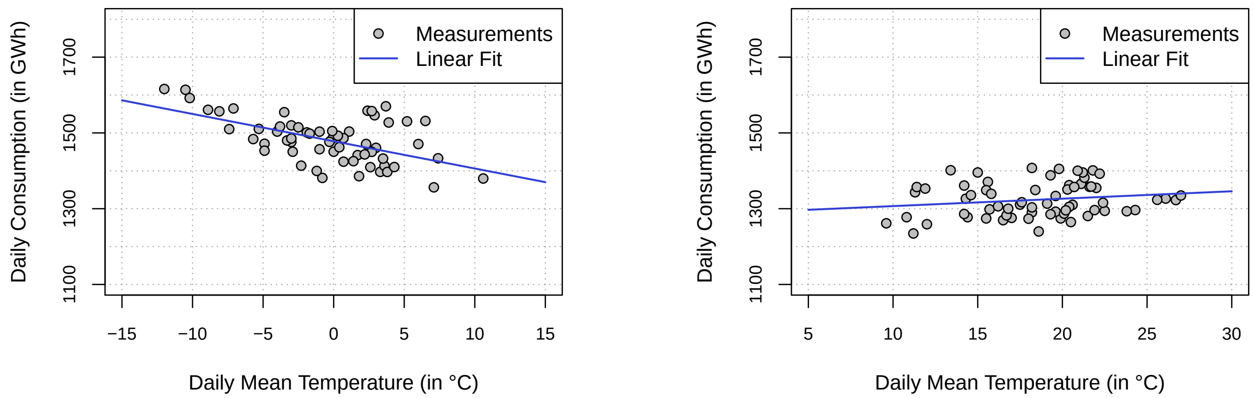
After we had found a classification of days for the electricity demand, we examined the correlation between the daily mean temperature and the electricity consumption. According to Valor, Meneu, and Caselles (2001) and Nischkauer (2005), electricity demand is linked to the air temperature. Our p-value analysis confirmed this, also showing a correlation between the daily mean temperature and the electricity consumption published by ENTSO-E.

Figure 3(a) shows this for workdays in winter. The measurements indicate a linear trend: the higher the temperature, the lower the electricity consumption. The correlation coefficient lies at -0.55.

The situation for workdays in summer 2013 is depicted in Figure 3(b), where the opposite can be observed, meaning the measurements indicate a positive linear trend: higher temperatures lead to higher electricity consumption levels. The correlation coefficient lies at 0.44.

Moreover, we investigated the correlation between daily mean temperatures and electricity consumption levels also for other seasons and weekdays, giving quite similar results. Please note, that this linear fit is not used to determine the daily electricity consumption level depending on temperatures, but to confirm a general correlation between both.

Figure 3(a) and Figure 3(b) also show that for a fixed daily mean temperature different daily consumption levels are possible. For a small range of daily mean temperatures (≈ 8 K) the electricity consumption is nearly Gaussian-distributed (cf. Figure 4) and can therefore be modeled accordingly as a function of the temperature range.



(a) Winter (b) Summer

Figure 3: Correlation between daily mean temperature and electricity consumption for workdays

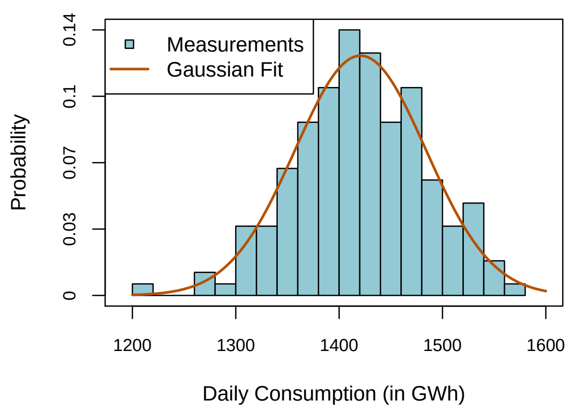


Figure 4: Histogram of daily electricity consumption levels for all workdays in the temperature range between 2 °C and 10 °C

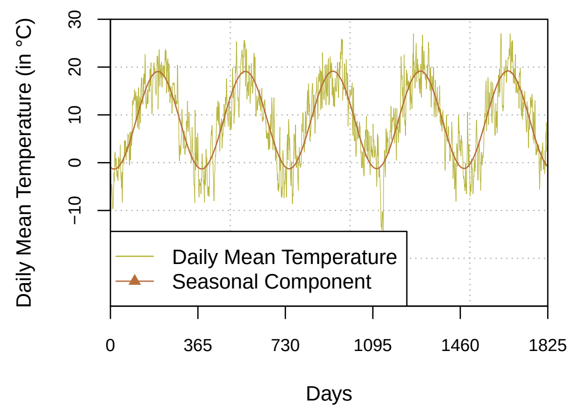


Figure 5: Daily mean air temperatures and the seasonal component for five years, recorded from a weather station in Bavaria, Germany

This correlation allows us to model the daily electricity demand as a function of only the daily mean temperature and the corresponding type of day (e.g., weekday, holiday, etc.). The resulting computational inexpensive model is able to generate electricity demand profiles for any time interval relying only on very few parameters.

3.3 Stochastic Process for the Simulation of Daily Mean Temperatures

In order to simulate daily mean temperatures we implemented a stochastic process. In the literature for time series analysis many different approaches for the modeling of daily mean temperatures can be found. Different stochastic processes were investigated by Ritter (2009). For the time series analysis of our observed daily mean temperatures we follow the works of Alaton, Djehiche, and Stillberger (2001) and Roustant, Laurent, Bay, and Carraro (2003).

We use a five year daily mean air temperatures dataset recorded by a weather station in Bavaria, Germany. The time series data and the seasonal component are shown in Figure 5. According to Roustant et al. (2003) a ARMA (Auto-Regressive Moving Average) model can be utilized to capture most of the features of daily mean temperatures (e.g., seasonality, quick reversion to the mean, correlations from the days before).

The daily mean temperature T_t for day t can therefore be modeled by

$$T_t = Y_t + \sigma_t Z_t.$$

For the seasonality Y_t, standard deviation σ_t, and the auto-regressive process Z_t the following models are used:

- Based on the findings of Alaton et al. (2001) we use a linear model and estimate parameters A, B, C and φ for the function
$$Y_t = A + Bt + C\sin(\omega t + \varphi)$$
for the linear trend and seasonality Y_t.
- The deterministic, periodic process for the standard deviation of T_t is described by σ_t. We estimate parameters a, b, and c for the function
$$\sigma_t = a + b\cos\left(\frac{2\pi t}{365}\right) + c\sin\left(\frac{2\pi t}{365}\right).$$
- The stochastic process Z_t is an AR(3) process. We estimate parameters β_0, β_1, and β_2 such as
$$Z_t = \beta_0 + \beta_1 Z_{t-1} + \beta_2 Z_{t-2} + \varepsilon_t,$$
where ε_t is a White-Noise-Process with $\varepsilon_t \sim \mathcal{N}(0,1)$.

Our parametric form allows an easy computation of maximum likelihood estimators based on the five years dataset. The values of different model parameters are shown in Table 1.

Table 1: Overview of estimated model parameters for the daily mean temperature process T_t

A	B	C	φ	a	b	c	β_0	β_1	β_2
8.861	$0.868 \cdot 10^{-5}$	10.192	-1.843	3.73	0.49	0.3289	0.9533	-0.2399	0.051

4 IMPLEMENTATION

In this section we describe the implementation of our electricity demand model in Anylogic 6 and further challenges in order to avoid discontinuity between days. A full step by step description of the algorithm can be found in Algorithm 1.

4.1 Implementation in AnyLogic 6

Our simulation framework uses a hybrid simulation approach which combines Discrete-Event Simulation and System Dynamics in one framework (Pruckner and German 2013). For instance, control decisions can be modeled by discrete events, whereas power flows can be modeled by the System Dynamics paradigm. The situation for the implemented electricity demand model is quite similar: Daily mean temperatures can be modeled by a discrete event, whereas the electricity demand can be modeled as a power flow and is therefore a continuous process with respect to time.

The classification of days (using the median of each hour) are implemented as table functions. Table functions (shown in Figure 6) are elements from the System Dynamics toolbox and provide the possibility to bring hourly electricity demand profiles to a continuous mode by means of interpolation. This is a very useful feature for large-scaled energy system simulations.

AnyLogic provides the possibility to obtain the current month and weekday in every simulation step. Based on the current month, we can choose the season: we assume that winter corresponds to December, January, and February; spring to March, April, and May; summer to June, July, and August; and fall to

SELECT hourly demand medians $h_{t,1},\ldots,h_{t,24}$ for day t based on season, weekday, holiday;
COMPUTE daily mean temperature T_t;
SELECT Gaussian parameters μ_t,σ_t based on T_t;
CHOOSE scaling parameter p_t from Gaussian distribution;
MULTIPLY $h_{t,1},\ldots,h_{t,24}$ with p_t to receive $h'_{t,1},\ldots,h'_{t,24}$;
MODIFY $h'_{t,1},\ldots,h'_{t,3}$ to connect more smoothly to demand level of $h'_{t-1,23}$ and $h'_{t-1,24}$;

Algorithm 1: Computation of electricity demand profile for day t

September, October, and November. Based on the current weekday, we then choose the corresponding table function, i.e., the type of day.

The computation of daily mean temperatures can be modeled as a discrete event, that means every 24 hours a cyclic event triggers and computes the daily mean temperature for the following day. Based on this temperature, we can select the parameters - mean and standard deviation - for a Gaussian-distributed parameter based on the remarks in Section 3.2. This parameter is then used as a scaling parameter (via multiplication) for the hourly median of the corresponding table function. The electricity demand in between hours is interpolated and thereby brought to a continuous flow using a dynamic variable.

By cyclic execution of the daily mean temperature event, we are able to obtain electricity demand profiles for several years. Milder winters or summers are then a possible outcome of the auto-regressive temperature generation process. Furthermore, changing the parameters in Table 1 allows for the simulation of untypical mean temperatures along with the corresponding electricity demand.

4.2 Discontinuity

Due to the Gaussian scaling parameter, which is generally different for consecutive days, it is not guaranteed that the last hour of one day can be smoothly connected to the first hour of the consecutive day, potentially leading to big leaps between two consecutive values. In order to avoid this, we slightly modify the electricity demand of the first few hours of the day to better match the demand level of the last hours of the preceding day. Using linear interpolation, we could reduce the described problem considerably.

5 MODEL VALIDATION AND RESULTS

In this section we validate our simulation model by first analyzing the time series process for the daily temperatures and consecutively the resulting electricity demand profiles by comparing them to real data.

A quantitative evaluation of our electricity demand model is a difficult task: first, one important input parameter for the consumption level is the temperature which is modeled using a stochastic process. This makes it impossible to compare a simulated year with a real one. We therefore validate the temperature model individually and use recorded temperature series to compare simulated and real electricity demand profiles. Second, real electricity demand profiles are object to fluctuations caused by, e.g., economic factors, social events, school vacations, and extreme weather conditions such as floods or storms. Furthermore, temperature levels within Germany vary, making it impossible to perfectly correlate one distinct temperature to an electricity consumption level, as our recorded data lacks most of this information. To eliminate these

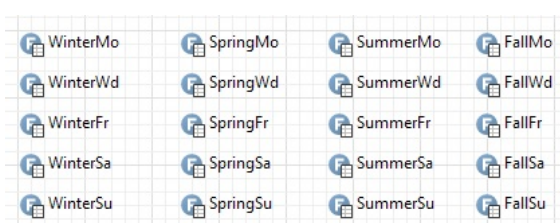


Figure 6: Overview of different type of days sorted by season and weekday

effects we would require several decades of real electricity load profiles, however, these are not available and even if they were it would be difficult to merge them due to long-term effects like economic growth or global warming. Lastly, we do not aim to exactly reproduce electricity demand profiles but to generate realistic ones. Therefore, using goodness of fit tests would defeat the purpose of our model, that is, to create varying non-deterministic yet realistically looking electricity demand profiles.

This leaves the possibility of a qualitative evaluation such as the visual comparison of real and simulated data. In order to ensure that our model indeed produces realistic electricity demand profiles, we investigate specific characteristics such as the linear correlation of temperatures and consumption levels and also daily, weekly, and seasonal cycles.

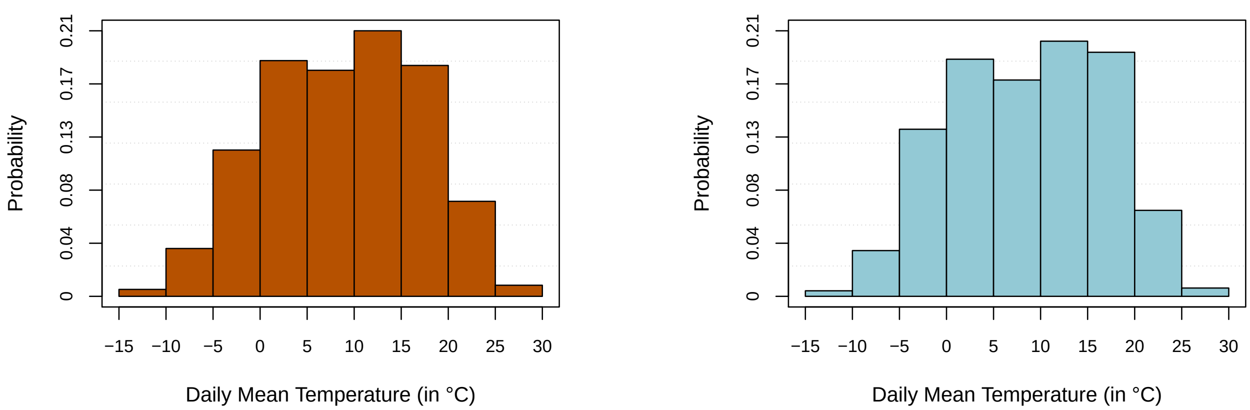
5.1 Validation of the Daily Mean Temperature Process

For the validation of our stochastic process for the simulation of daily mean temperatures, we performed different goodness of fit tests. Therefore, we generated a temperature time series for 20 years, that means we investigated more than 7000 observations. For our purposes, parameters such as the minimum value, maximum value, and mean value are very important. A comparison of simulated and real values is shown in Table 2. As can be seen, our simulated stochastic process for daily mean temperatures fits very well.

Table 2: Parameters for the validation of the stochastic process for daily mean temperatures

	Minimum	1st Quartil	Median	Mean	3rd Quartil	Maximum
Real Values (in °C)	-14.20	2.40	9.40	8.94	15.30	27.0
Simulated Values (in °C)	-14.476	2.018	8.922	8.636	15.458	28.064

Furthermore the distributions of the simulated and real data are quite similar (shown in Figures 7(a) and 7(b)). In both histograms the highest probability is reached for daily mean temperatures between 10 and 15 °C and the distributions look almost identical.



(a) Real distribution

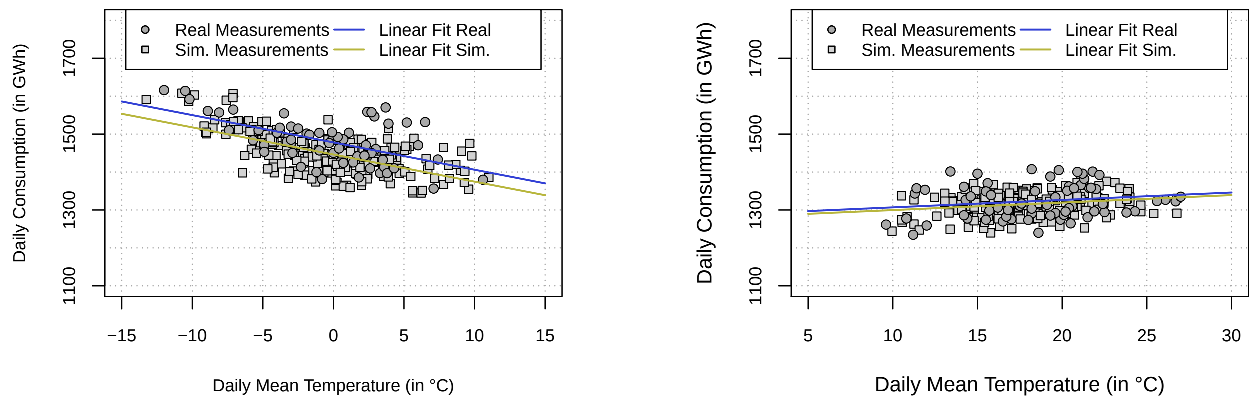
(b) Simulated distribution

Figure 7: Distribution of real and simulated daily mean temperatures

5.2 Validation of the Electricity Demand Profiles

For the validation of the electricity demand profiles, we simulated the electricity demand for 20 years in AnyLogic and consider the annual electricity consumption, that is, the integral of all simulated values for every year. The annual electricity consumption can be compared to real data from the ENTSO-E dataset. According to official ENTSO-E load profiles the electricity consumption in Germany lay at 484 TWh in 2011 and 468 TWh in 2012. The mean value of all simulation runs lay at 477 TWh, whereas the minimum value was 472 TWh and the maximum value was 481 TWh. This shows that our model is capable to generate realistic annual electricity consumption levels.

The correlation between the daily mean temperature and electricity consumption for winter workdays is shown in Figure 8(a). We observe by comparing the linear fits that on average, our simulation model slightly underestimates the ENTSO-E dataset. However, this underestimation is only marginal and also constant and could therefore be easily fixed using a scalar coefficient. Figure 8(b) depicts the same correlation for summer workdays. Here, our model fits the ENTSO-E data very well as the similarity of the linear fits shows.

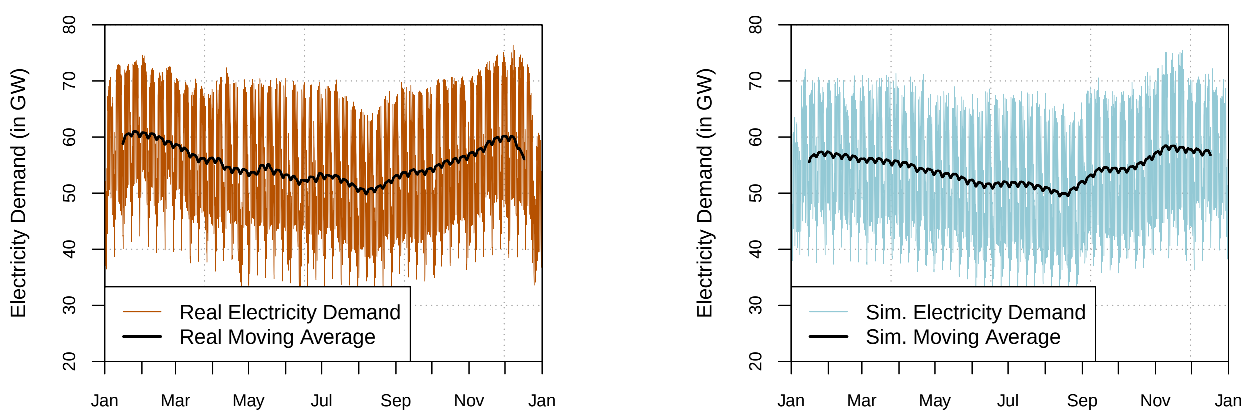


(a) Winter (b) Summer

Figure 8: Validation of the correlation between daily mean temperatures and daily electricity consumption

5.3 Results

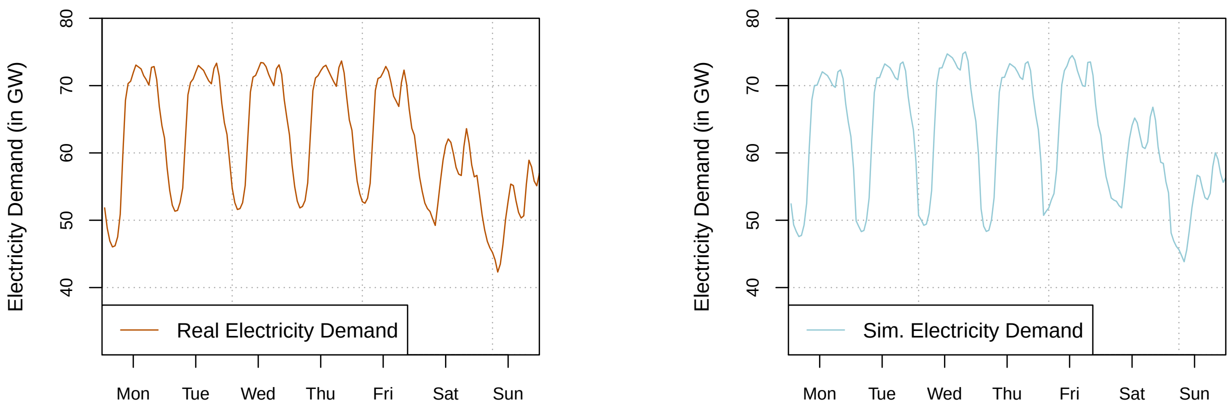
The main goal of this work is to provide realistic electricity demand profiles as an input for simulation. For validation purposes we compared one year of real data (cf. Figure 9(a)) with one outcome of our simulation model (cf. Figure 9(b)). As can be seen that our model accounts not only for the typical seasonal trends (higher demand in winter, lower demand in summer), but also for atypical electricity demand in both summer and winter holidays. We observe that the average electricity demand of the simulation model and the real data are very similar, indicating the correctness of our model at a larger scale.



(a) Real values (b) Simulated values

Figure 9: Real and simulated electricity demand for one year

For a more detailed comparison, we analyzed the real and simulated electricity demand for one week in winter as shown in Figure 10(a) and Figure 10(b), respectively. In this case, for validation purposes, we used the real recorded temperature as an input for our simulation model. Results show that our model is able to capture typical day-night and weekly cycles: We can observe the specific electricity demand peaks at noon and in the evening hours as well as lower demand at Monday mornings and Friday evenings. Furthermore the simulation model accounts for the electricity demand characteristics of Saturdays and Sundays. This shows that also on a smaller scale our model produces realistic demand profiles and can therefore be used as an input for the simulation of energy systems.



(a) Real values

(b) Simulated values

Figure 10: Real and simulated electricity demand for one week in winter

6 CONCLUSION

In this paper we presented a novel approach to model electricity demand to be used in large-scale energy simulation. Using statistical analysis on officially published data we noticed a strong correlation between the type of day, season, and daily mean temperatures with the actual level of electricity demand. In total we identified twenty groups for the classification of days to account for the specific characteristics of workdays, weekends, holidays, and so on. Additionally we observed that the impact of the daily mean temperature shows a Gaussian-distributed behavior and can therefore be modeled accordingly. To not rely on recorded temperature data we deployed and validated an auto-regressive process to generate a realistic time series of daily mean temperatures.

For validation purposes and as a proof of concept we implemented our model in the simulation framework AnyLogic 6, showing its applicability in the context of hybrid simulation combining System Dynamics and Discrete-Event simulation. Our model is able to realistically produce demand profiles at both small and large-scale and can therefore replace empiric data as input for the simulation of large-scale energy systems.

The developed approach can also be used for any other region worldwide, as long as input parameters such as daily mean temperatures or electricity load profiles are available. In case of all member states of the European Union the electricity load profiles are available on the ENTSO-E website.

Future work includes the scaling of country-wide demand profiles to a smaller scale, e.g., a federal state of Germany.

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