Technische Universität München TUM School of Engineering and Design

Simulation and Optimization of Residential Variable Rates for Integration of Renewable Electricity Generation

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Abstract

The ongoing transition to carbon-free energy in the European energy system requires flexibilization on the consumption side in order to integrate renewable generation into the grid. A potential option for load shifting is demand-side management in the residential sector, which requires appropriate incentives for the affected customers. Thus, a simulation model is developed and analyzed, which allows for the evaluation of the effects of variable electricity rates on consumption patterns and resulting system effects.

To quantify the DSM potential of households, a disaggregation method for measured load curves is developed, allowing the modeling of shifting measures on an individual appliance level. Historical time series of curtailment measures in high spatial resolution are applied to determine the effects of the analyzed approach on the integration of renewables. Survey-based information on the willingness of customers to adjust their consumption behavior and on the acceptance factors of variable rates are applied to model the effects of rate design. Based on these inputs, the developed model allows for the evaluation of a suitable parametrization of the variable rate for the defined goal of curtailment reduction.

The results are mainly assessed regarding the potential reduction of curtailment caused by the modeled load shifting according to the assumed variable rate. A strong regional dependence can be observed, caused by the differences in required curtailment measures. Moreover, sensitivity analyses show the effects of rate parameters on the achieved reduction of curtailment, leading to a resulting potential ranging from 2 % to 5 %. Based on this model, an optimization approach is applied to determine a parameter set that maximizes the curtailment reduction while maintaining approximate cost neutrality from both the customer's and the system's perspectives.

The evaluations show that the developed model chain is suitable for the defined objective, yields plausible results, and can be utilized for the reasonable design of variable rates, which pose sufficient incentive for customers to adhere to system requirements. A legal implementation of the price variability in grid fees mitigates the potential acceptance problems. Thus, residential DSM, according to the developed approach, can provide a relevant contribution to a future energy system.

Kurzfassung

Die laufende Energiewende im europäischen Energiesystem erfordert eine Flexibilisierung der Verbraucherseite, um die erneuerbare Erzeugung ins Netz zu integrieren. Eine mögliche Option für Lastverschiebung ist Demand-Side Management im Haushaltssektor, das geeignete Anreize für die betroffenen Kunden erfordert. Deshalb wird ein Simulationsmodell entwickelt und analysiert, das die Bewertung der Auswirkungen variabler Stromtarife auf Verbrauchsverhalten und resultierender Systemrückwirkungen ermöglicht.

Um das DSM-Potenzial von Haushalten zu quantifizieren, wird eine Disaggregationsmethode für gemessene Lastgänge entwickelt, mit der Verschiebungsmaßnahmen auf der Ebene einzelner Geräte modelliert werden können. Historische Zeitreihen von Abregelungsmaßnahmen in hoher räumlicher Auflösung werden genutzt, um die Auswirkungen des analysierten Ansatzes auf die Integration erneuerbarer Energien zu ermitteln. Umfragebasierte Informationen über die Bereitschaft von Kunden, ihr Verbrauchsverhalten anzupassen, und über die Akzeptanzfaktoren variabler Tarife werden verwendet, um die Auswirkungen der Tarifgestaltung zu modellieren. Basierend auf diesen Eingangsdaten ermöglicht das entwickelte Modell die Bewertung einer geeigneten Parametrisierung des variablen Tarifs für das definierte Ziel der Reduktion von Abregelung.

Die Ergebnisse werden primär in Bezug auf das Potenzial zur Reduktion der Abregelung durch die modellierte Lastverschiebung anhand eines angenommenen variablen Tarifs bewertet. Es zeigen sich starke regionale Abhängigkeiten, die sich durch die Unterschiede hinsichtlich notwendiger Abregelung in den Regionen ergeben. Darüber hinaus zeigen Sensitivitätsanalysen die Auswirkungen der Tarifparameter auf die erreichte Reduktion der Abregelung, was zu einem Potenzial im Bereich von 2 % bis 5 % führt. Basierend auf diesem Modell wird ein Optimierungsansatz angewendet, um Tarifparameter zu bestimmen, die die Reduktion maximieren und gleichzeitig eine ungefähre Kostenneutralität sowohl aus Sicht des Kunden als auch des Systems sicherstellen.

Die Auswertungen zeigen, dass die entwickelte Modellkette für das definierte Ziel geeignet ist, plausible Ergebnisse liefert und für die sinnvolle Gestaltung variabler Tarife genutzt werden kann, die ausreichende Anreize für die Kunden bieten, sich externen Anforderungen anzupassen. Eine gesetzliche Umsetzung variabler Preisbestandteile in den Netzentgelten vermeidet die potenziellen Akzeptanzprobleme. Somit kann DSM im Haushaltssektor gemäß dem entwickelten Ansatz einen relevanten Beitrag zu einem zukünftigen Energiesystem leisten.

Contents

1 Introduction

1.1 Motivation

In response to the world's profound environmental challenges, the European Union (EU) has set ambitious goals to combat climate change. This commitment, defined in the European Green Deal and reinforced by the European Climate Law [1], requires an unprecedented transformation of the continent's energy supply structure to reach the objective of climate neutrality by 2050. The EU's dedication to combatting climate change is embedded in its commitment to the Paris Agreement, which underscores the urgency of limiting global warming to well below 2 degrees Celsius above pre-industrial levels [2]. Achieving this objective involves the evaluation of potential contributions from all sectors of the energy industry, both on the generation and consumption side. Especially the consumption side is expected to make an important contribution since the transition to 100 % renewable generation implies additional demand for flexibilization.

Residential electric energy consumption represents a substantial portion of Europe's total energy demand, accounting for about one-quarter of the total electricity consumption [3]. Thus, the analysis of potential options for flexibilization of this sector's electric demand is substantial to meet the goals. One of the primary options available is the effective management and optimization of the temporal consumption patterns according to system requirements to foster the integration of renewable energy and mitigate grid congestion. Grid congestion arises when the supply of electricity from renewable sources, such as wind and solar, exceeds the capacity of the grid to transport and distribute this energy efficiently [4]. Excess renewable energy may be curtailed without appropriate measures, leading to a loss of clean energy generation.

The flexible adjustment of household electricity consumption by load-shifting measures is denoted as demand-side management (DSM). It offers a viable solution to avoid the curtailment of renewable generation by increasing consumption to utilize otherwise curtailed energy directly. This not only reduces curtailment but also enhances the grid's reliability and resilience [5]. Appropriate energy management systems enable households to align their electricity consumption with the availability of renewable generation [6]. To realize this potential, suitable incentive schemes that make participation beneficial for the customer are necessary. This can be achieved by implementing variable electricity rates that provide monetary advantages by defining adjusted prices for energy consumption dependent on system requirements.

The definition of variable rates is a challenging and complex task since, besides these requirements, customer behavior and preferences have to be taken into account and are decisive factors for such instruments' successful and effective application. Simulation of the expected reaction to variable rates is an option that can contribute to adequate design by modeling the effects on both customers and the energy system, enabling the estimation of the implications of specific rate structures and parameters and drawing conclusions about the optimal implementation in a future energy system.

1.2 Solution Approach

As described, the curtailment of renewable generation can be avoided by increasing consumption at the same time, leading to an overall higher share of usable renewable energy and thus, lower fossil generation and lower GHG emissions. This can be achieved by DSM, in particular by shifting consumption to time intervals with present curtailment measures. Variable electricity rates are a means for incentivizing this behavior by offering a monetary benefit through the difference between high and low prices. Therefore, the optimal design of this kind of variable rate concerning the reduction of curtailment is analyzed in the present thesis.

In order to quantify the possible contribution by this approach, simulation of the expected behavior of residential customers can yield an indication of the potential. Since it depends on many input variables, utilizing a reliable data basis for the models is crucial. Therefore, the combination of surveys, grid, and measured consumption data are applied in the presented approach.

Highly time-resolved consumption data of residential customers allow for modeling the consumption behavior and potential adaptation to DSM measures. Surveys are required to represent the willingness of customers to adhere to potential variable rates and thus, to model the changes in consumption patterns by these rates. Data from grid operators, particularly historical curtailment data in high resolution with respect to both time and space, are applied to calculate the modeled reduction.

Electrical consumption in households is caused by various devices with different consumption patterns and varying potential for load shifting. Thus, the analyses here focus on appliance types with an expected high potential due to comparably high energy consumption, which can also be shifted timely without comfort losses. Electric vehicles are not considered since these require a fundamentally different simulation approach and are covered in various other studies [7]. The same holds for electrical heating systems [8]. Moreover, the flexibilization of these types of appliances according to grid requirements is already covered in the German regulatory system [9, §14a] and defines their grid-oriented operation [10, 11].

1.3 Research Questions

This approach leads to the following central research questions for the thesis:

RQ1 How can the potential for DSM measures with residential appliances be quantified based on measured consumption data?

RQ2 What is the potential contribution to the reduction of curtailed energy by residential DSM?

RQ3 Which share of this contribution can be achieved with acceptance by customers and no additional costs?

1.4 Structure of the Thesis

The overall methodical approach of the thesis is schematically depicted in figure 1.1. This results in four main chapters. Chapter 2 focuses on the analysis of residential load data and the development of methods for the assessment of time-resolved flexible load. To achieve this, section 2.1 describes the identification of potentially flexible and thus relevant appliance types. In section 2.2, an approach for quantification of flexible load based on aggregated load profiles is described, while the detection of flexible appliances in individual household load curves is developed and analyzed in section 2.3. Section 3.1 in chapter 3 shows the preparation and processing of curtailment and

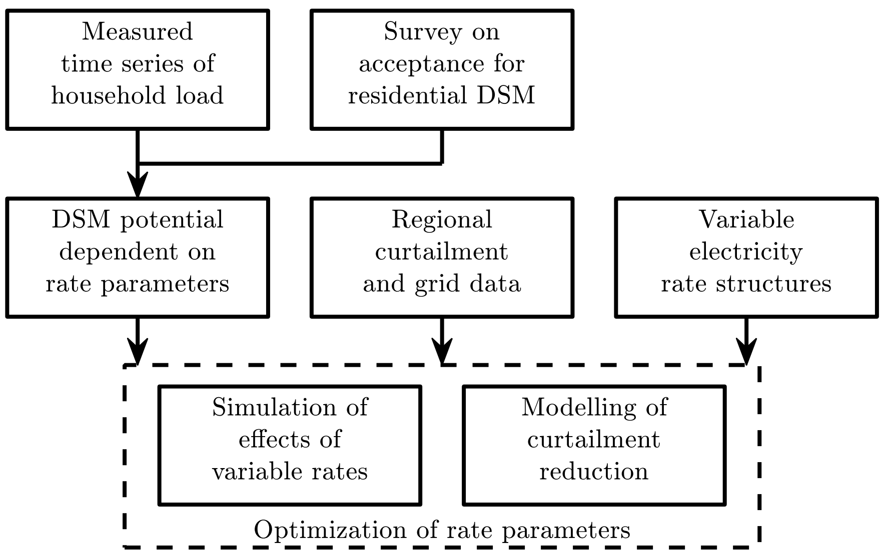


Figure 1.1: Methodical approach of the thesis

grid data to generate regionally resolved time series of curtailed power as an input for subsequent simulations. The approach for the calculation of the monetary value of avoided curtailment is developed in section 3.2.

In chapter 4, the required monetary incentives for residential DSM are presented. A potential variable rate structure suitable for the defined objective is developed and described in section 4.1. Section 4.2 details the current regulatory setting of electricity pricing in the residential sector in Germany. The required simulation parameters for modeling the behavior of residential customers to potential variable rates are acquired by a survey, which is evaluated in section 4.3.

Chapter 5 utilizes these data and findings from the previous chapter for modeling and simulation of variable rates and their effects on consumption patterns and curtailment reduction. Section 5.1 gives an estimate of the flexibility potential and resulting curtailment reduction based on the described aggregate consumption data. Subsequently, a more detailed analysis on an individual basis is carried out in section 5.2. Based on these results, an optimization of the rate parameters with respect to costs from a system perspective and their effects on acceptance of the resulting rate are detailed in section 5.3. Finally, in chapter 6, the findings are summarized, the research questions are answered, and an outlook on potential future research is given.

2 Flexible Household Load

2.1 Suitable Appliances

2.1.1 Scope

Electrical consumption in a residential setting is caused by a large variety of different appliances and devices. These evince different requirements regarding their time of use, user interaction, and controllability. Thus, this section aims to identify suitable appliance types for residential DSM based on these factors.

2.1.2 Methodology

Based on statistical data on the consumption of electrical energy in households and on previous studies on residential DSM, several groups of appliances that are typically present in households are analyzed and evaluated regarding their suitability for DSM measures. As described (cf. section 1.2), the focus is on DSM measures with the intention of increased integration of renewable generation. Thus, the main criteria for this classification are relevant power consumption and the possibility of shifting without substantial loss of comfort for the user.

2.1.3 Results and Discussion

The appliances used in a typical household can be clustered by applications. According to statistics [12], their respective share of the total electricity consumption in the residential sector is given in figure 2.1. This shows that most clusters pose a considerable contribution to the total consumption, and therefore, each cluster is to be analyzed regarding potentially relevant appliance types for load shifting. Acceptance for load shifting measures is assumed if these measures can be performed without noticeable loss of comfort. This will be detailed in the following list.

Information and communication The cluster "Information and communication" consists of communication devices such as phones and computers, as well as consumer electronics like TVs or music systems. All of these appliances require actual user

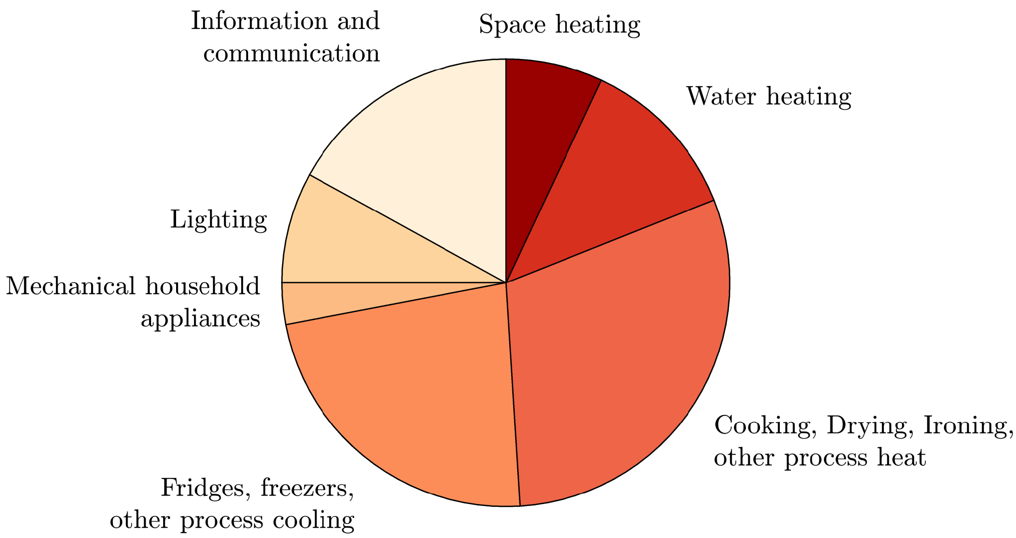


Figure 2.1: Electricity consumption in households per application (data based on [12])

interaction throughout the usage time. Therefore, no acceptance is assumed for load shifting in this sector.

Lighting Similarly, lighting is used and required by the inhabitants of the respective household depending on the current conditions, i.e., lack of natural light and presence in the respective room; therefore, shifting these kinds of appliances is not an option. Thus, lighting is also considered to be non-controllable [13].

Mechanical household appliances This group of appliances evinces similar behavior as before. Mechanical household appliances are mostly not useful without interaction with the customer. Mechanical energy is also required by dishwashers and washing machines, but these will be discussed in the cluster on process heat since this represents their main share of consumption. Thus, this cluster is also excluded from further analyses.

Fridges, freezers, other process cooling Cooling devices in a residential setting are generally considered controllable devices [13]. Fridges and freezers usually evince a regular pattern of periodic consumption, which could be slightly adapted to external incentives without loss of comfort, i.e., without causing damage to refrigerated goods. However, the total load of this group of appliances is relatively small [14], and thus, their potential load increase in case of flexibilization also poses no substantial contribution [15]. Because of these properties, these appliances will not be considered relevant for the simulation of load shifting. Air conditioning, another application within this group, is rarely relevant in the investigated region and, thus, is not considered an option either.

Cooking, drying, ironing, other process heat This group evinces different behavior between the included appliances. Cooking, ironing, and other process heat in kitchen appliances are considered not controllable [13] for the same reasons as above. However, drying enables the decoupling of user interaction and the actual process, i.e., actual electricity consumption. This allows the shifting of a substantial amount of energy consumption to a later point in time. Under the assumption of automated control of this shifting process, this is possible without loss of comfort. Therefore, dryers are identified as a suitable appliance type. Process heat is also required for dishwashers and washing machines. The same observations of decoupling interaction and consumption hold for these types of appliances [16]. Therefore, they are also included for further calculations and simulations.

Water heating and space heating The last two clusters displayed in figure 2.1 are both connected to heating, so they are discussed together. According to literature, water heating and space heating both evince considerable energy consumption and, at the same time, can be automatically controlled and adapted to external influences without loss of comfort with certain temperature limits. This suggests relevance for the discussed use case. Nevertheless, both applications are not considered here since a reasonable simulation of the behavior requires extensive modeling of the thermal properties of residential buildings, which is beyond the scope.

Beyond these clusters of household appliances, there are other potential flexibility options, which are typically connected at the household level. On the one hand, the charging process of electric vehicles can be designed flexibly to comply with external requirements; on the other hand, home storage systems can be charged and discharged accordingly. However, both of these appliances are also excluded from further analyses for the same reason as heating systems since the reliable representation of driving profiles and battery behavior is also beyond the scope of this project.

In summary, this yields three relevant types of appliances for subsequent calculations: dishwashers, washing machines, and dryers. These evince both relevant energy consumption and flexibilization without loss of comfort [17].

2.1.4 Summary

The analysis of suitable appliances for the considered use case of load shifting for reduction of curtailment shows that dishwashers, washing machines, and dryers are identified as relevant for the following investigations. These appliance types evince relevant power, are typically used on a regular basis, and can be shifted without loss of comfort. Thus, to identify the load-shifting potential of the residential sector, it is necessary to identify the operation times and load profiles of these appliances. This is possible on an aggregate level or for individual households. Both approaches are described and analyzed in the following two sections.

2.2 Aggregated Flexibility Load Profiles

This section is partially based on previously published work by the author [18, 19].

2.2.1 Scope

In order to calculate the potential reduction of curtailed energy due to residential load shifting on the level of grid regions without consideration of individual customers, a time series of potentially flexible power of appropriate household appliances is required. The total load of a large number of households is typically modeled using a standard load profile or similar tools deduced from this concept [20–23]. Since evaluations of these standard load profiles suggest that recent changes in consumption patterns are not sufficiently represented, new profiles are to be calculated based on measured load data. Eventually, publicly available data about energy consumption and daily load patterns of relevant appliance types are applied to identify the potentially flexible energy per time step.

2.2.2 Methodology

Measured load profiles of various German regions are used to quantify the potential for load shifting in the household sector. These were recorded over a period of at least six months in 13 local substations with a temporal resolution of 1 min and thus cover all seasons (winter, transition, and summer). The selected substations supply purely residential areas without photovoltaic feed-in and without electrical heating systems and can be used to deduce typical load profiles [19]. These measurement-based profiles are expected to better represent the actual load of current residential customers in Germany since standard load profiles (H0 for households) evince several shortcomings in this respect [20, 22].

The load profiles are calculated according to the structure of German standard load profiles. This means that nine types of days are distinguished: working days, Saturdays, and Sundays for the three seasons mentioned. Public holidays are treated as Sundays [20]. A typical load curve is created for each type of day by normalizing to an annual consumption of 1 MWh and averaging over all relevant days and measurement points. This averaging process approximates the behavior of a larger number of households. In order to smooth out short-term peaks, which can occur due to the measurements of about 30 to 80 households but are no longer to be expected when applied to a region of the considered size, these load profiles are determined in a resolution of 15 min. This corresponds to the usual billing interval in the energy industry and is also used for standard load profiles.

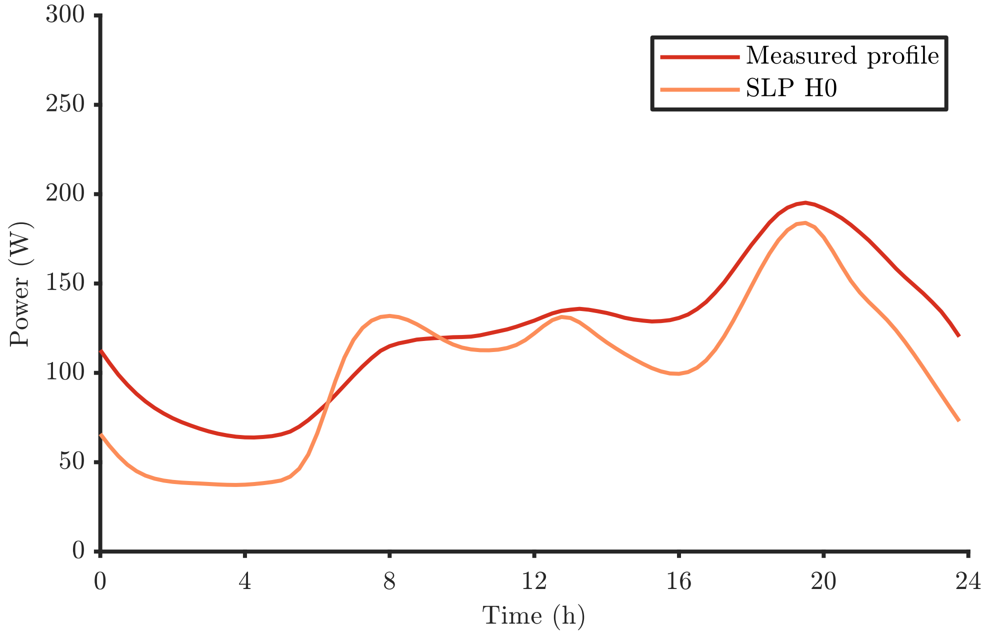
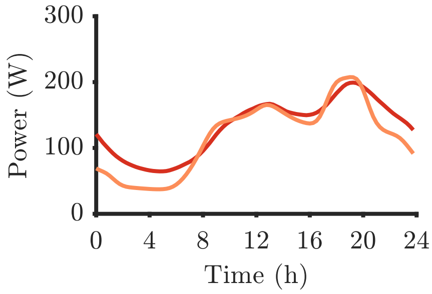


Figure 2.2: Comparison of calculated profile and standard load profile: Workday winter (data based on [19])

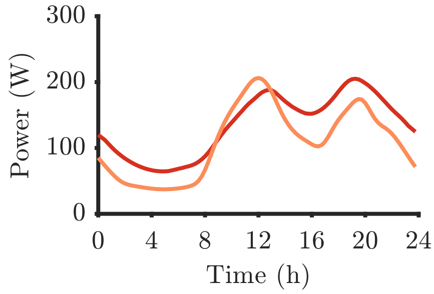
In order to construct annual load curves from these standardized load profiles, the day profiles are lined up according to the distribution of weekdays and holidays. Analogously to the data used to represent curtailment (cf. section 3.1), the year 2018 is applied here. As described before, holidays in the relevant federal state are mapped as Sundays. This results in annual load curves with 35 040 quarter-hour values, which represent a normalized total annual consumption of 1 MWh. These are scaled to the total annual consumption in the respective region.

This annual load curve of all households in the regions under consideration does not allow any conclusions to be drawn about the load-shifting potential in this sector. This potential depends on the share of selected appliances (dishwashers, washing machines, and dryers) in the total load profile.

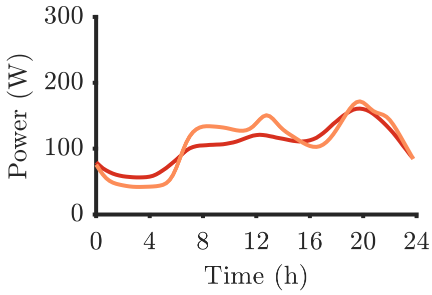
Based on data about the shares of different device types in total consumption, time usage distributions, and equipment levels [24–26], a time-resolved distribution of each day profile to these device types can be calculated. The considered device types are assigned according to their share of the total daily consumption as well as average daily trends from surveys and measurements. These daily curves are only available in hourly resolution, which can be seen in the graphical representation of the result by the resulting steps. Due to the data situation, no better representation is possible here; however, no substantial effect is expected on the results of the calculations.



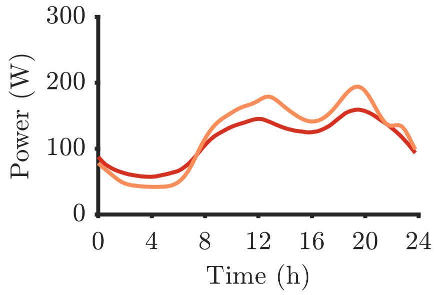
(a) Saturday winter



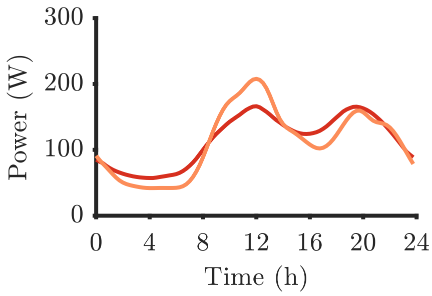
(b) Sunday winter



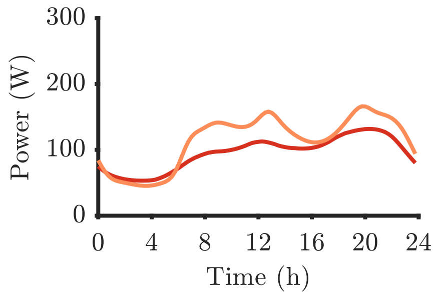
(c) Workday spring/fall



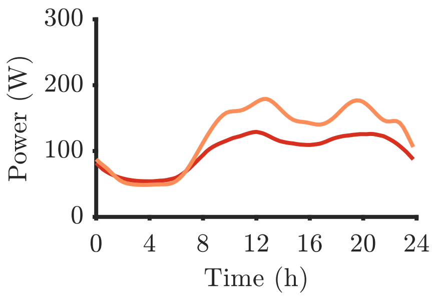
(d) Saturday spring/fall



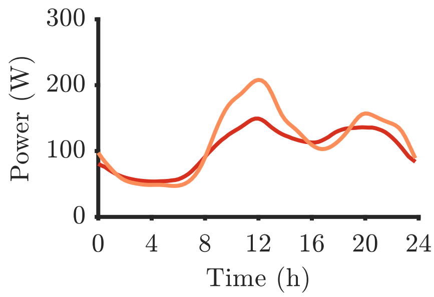
(e) Sunday spring/fall)



(f) Workday summer



(g) Saturday summer



(h) Sunday summer

Figure 2.3: Comparison of calculated profile and standard load profile (data based on [19])

2.2.3 Results and Discussion

Analogously to the established standard load profile, the calculations of new profiles based on the described measured data basis yield load curves in a resolution of 15 min for 9 types of days. Figure 2.2 shows a comparison of the standard load profile H0, which is typically applied for the residential sector, to the new profile deduced from measurements. The load curves for a workday in winter are selected as an example here.

The depicted load curves evince several noticeable differences, which support the assumption that H0 is not suitable for reliable representation of today's household consumption [19]:

- Clearly lower increase in the morning hours
- Less pronounced midday peak
- Raised and slightly shifted evening peak
- Increased base load

The corresponding comparison for the other 8 types of days is given in figure 2.3. These confirm the conclusions listed above and show some additional characteristics that differ from H0 [19]:

- Different seasonal characteristics
- Fewer deviations between Saturdays and Sundays
- Generally, later load increases on weekends

In summary, H0 indeed proves inappropriate for utilization in models regarding residential DSM. Therefore, all the following calculations are based on the newly calculated load profile.

Figure 2.4 depicts the described allocation of the respective shares of the total load to the identified relevant appliance types, exemplarily for one type of day. As expected, it shows that the main operation times of the appliances are during the day, with peaks in the afternoon and the evening. Thus, almost no flexibility potential is to be expected during night hours. Moreover, it can be concluded that the developed method yields plausible results and constitutes a reasonable basis for subsequent calculations.

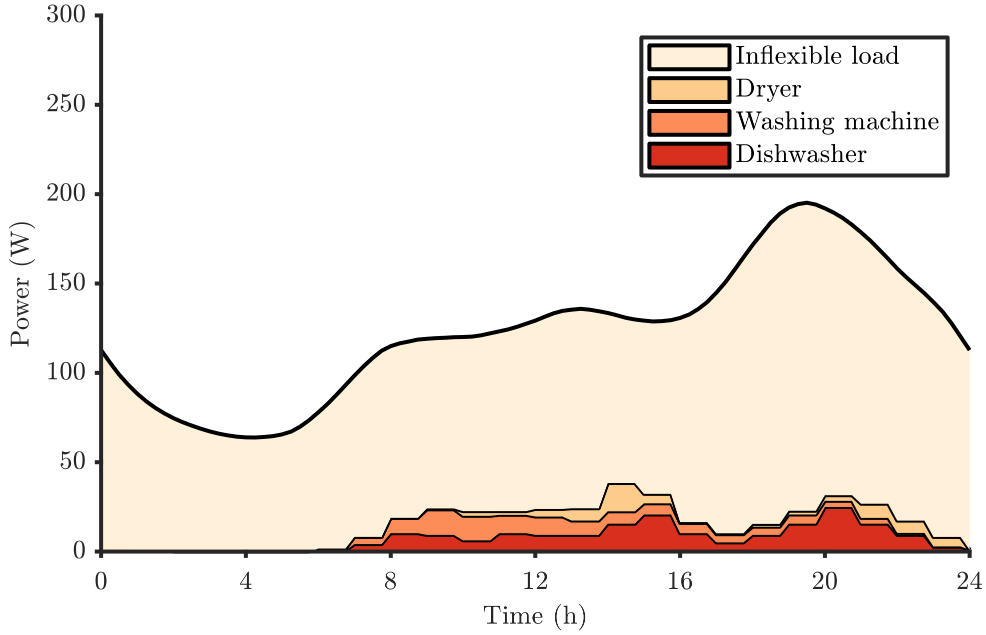


Figure 2.4: Time-resolved share of relevant appliances (based on [18])

2.2.4 Summary

The presented methodology provides a means of determining representative load profiles for the residential sector in Germany. It is based on the established structure of standard load profiles, improved with recently measured data. The comparison to this standard load profile shows several differences, which are assumed to be caused by changes in the daily behavior of residential customers. By additionally utilizing data on the operation of flexible appliances, disaggregation of the profile to the level of these appliances is possible. The resulting profiles enable the construction of time-resolved load curves of potentially flexible consumption in Germany's residential sector. Combined with the survey results discussed in section 4.3, this allows determining the proportion that is actually available for DSM measures. These data are applied in section 5.1 for further analyses.

2.3 Individual Flexibility Assessment

This section is based on previously published work by the author [27].

2.3.1 Scope

The previous section describes an approach to quantify the DSM potential in the residential sector based on aggregate measurements. Naturally, aggregate evaluations cannot fully model individual consumption behavior; therefore, the analysis of individually measured consumption patterns is presented as an alternative approach to obtaining reliable data about the DSM potential of residential customers.

As previously described, dishwashers, washing machines, and dryers are considered relevant here. To investigate the exact DSM potential, certain information about the appliances is necessary:

- How many appliances are present in a household?
- How often are the appliances used?
- Which characteristics do the load profiles have?
- What is the energy consumption per use?
- How long does a program last?
- When are the appliances used?

To gather this information, three approaches are possible: a survey, measuring the appliances directly, or the disaggregation of the household's power consumption. Due to some disadvantages of the first two listed procedures (e.g., survey: inaccuracy, measuring: great effort), disaggregation is the preferred variant here.

There are various existing and proposed algorithms to perform this disaggregation, primarily denoted as non-intrusive load monitoring, which can be used for a wide variety of applications [28]. Although different approaches are applied, most of them require consumption data in a temporal resolution in the range of 1 Hz up to the kHz range [29,30]. Since the available data set here is recorded in 1 min intervals, these are not applicable. Thus, the methodology is developed to fit these circumstances.

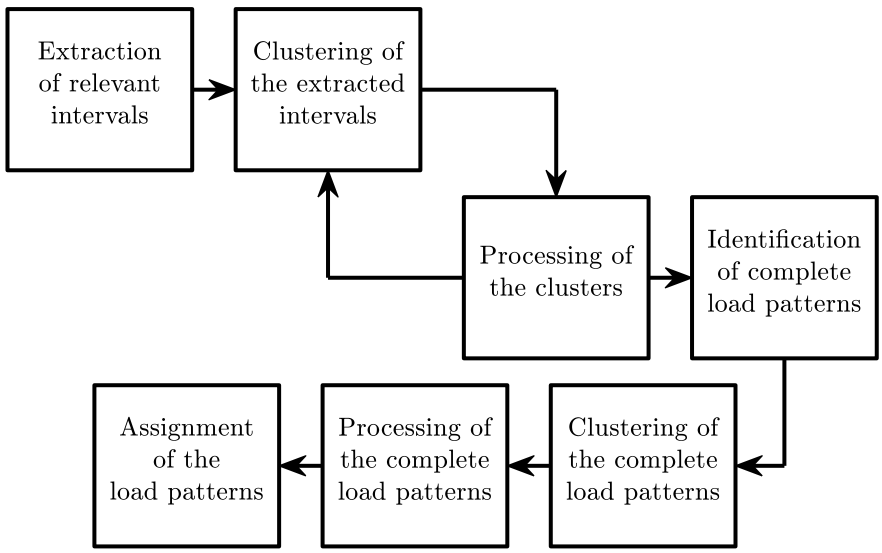


Figure 2.5: Method for disaggregation (based on [27])

2.3.2 Methodology

In order to obtain valuable and representative data, the developed algorithm is to be applied to a large number of households. Due to the installation of smart meters, the required consumption data in high temporal resolution becomes available for this kind of analysis. The available data basis consists of around 2500 German households. Due to partially incomplete recordings, these are reduced to 565 data sets with good data quality from August 2014 to July 2015 for further analyses.

Existing approaches often rely on a known load profile of the appliance to identify. Therefore, all different appliances' programs have to be measured. Based on these data, algorithms that recognize this load profile are implemented. This approach is impractical for a large number of households due to the effort of measuring every single appliance and program. [31] [32]

Therefore, the goal is to design an algorithm that can disaggregate the power consumption without prior knowledge about the present appliances. The method consists of two parts that are applied separately for every household: Recognition of load profiles, which occur repeatedly, and assigning them to an appliance type depending on defined properties.

2.3.2.1 Identification of Dishwashers and Washing Machines

In figure 2.5, seven steps are illustrated, which are applied to disaggregate the total power consumption. The first six steps identify regularly appearing load profiles. The last step includes the assignment of determined load profiles to appliance types. Ultimately, the result is none, one or more load profiles per appliance representing different programs. In detail, this is reached by:

Extraction of relevant intervals In the first step, the whole year's data are reduced by extracting intervals from the total power consumption, which potentially are household appliances of the considered types. Therefore, the load profile needs to exceed both a defined minimal power and a minimal duration after subtracting the base load from the household's load profile. In order to take the alternating load profiles, especially from dryers, into account, an additional time variable is specified. It defines how long the load profile may be lower than the minimal power so that the interval is still extracted as one coherent sequence.

Clustering of the extracted intervals Similar load profiles are grouped by clustering of all extracted intervals. The correlation coefficient is applied as a metric for clustering the load profiles. Due to high computational effort, this process is applied to only three months of data (November–January). This does not influence the analyses of actual uses. This step results in a certain number of clusters containing a minimum number of similar load profiles. Clusters that don't reach the minimum of included patterns are deleted because it is assumed that the three considered household appliances are used regularly.

Processing of the cluster After clustering the intervals, they exhibit different lengths due to possible disturbances like simultaneously running appliances. During this step, unnecessary information is deleted. The clustering step, as well as the processing, is repeated twice in order to improve the quality of the results.

Identification of complete load profiles The first three steps may lead to partially incomplete load profiles. Some appliances may contain a heating phase that occurs later than the distance defined for extracting the intervals. Therefore, the determined load profiles are used to identify similar intervals during the whole year's load data. As soon as an interval with the same length exceeds the selected correlation coefficient, an interval with a fixed length (here: 150 min) is extracted. The maximum program duration of the three considered appliances is expected to amount to approximately 150 min.

Clustering of the complete load profiles All extracted intervals of the previous step are clustered again. It occurs that different programs start with the same energy consumption, and the rest of the complete profiles vary.

Processing of the complete load profiles This step contains the same procedure as the first processing step, but now the clusters of the whole year are edited and adjusted.

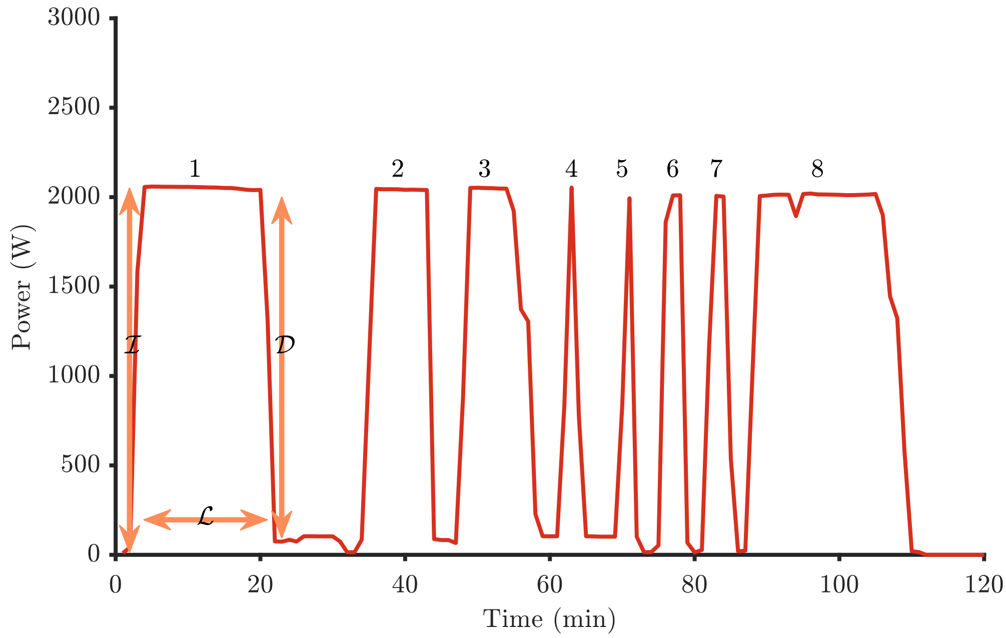


Figure 2.6: Exemplary visualization of defined properties (based on) [27])

Assignment of the load profiles At this point, several load profiles exist for every household, which occur regularly. To finish the disaggregation, assigning these load profiles to one of the three household appliance types is necessary. For this purpose, a few known appliances' load profiles are available. A conceivable brute-force approach would be possible by looking for matches between measured and extracted load profiles. Due to a small data basis and a large number of households, this approach is expected to lead to inadequate results. Therefore, the load profiles are used to realize a more general approach. Five properties (depicted in figure 2.6) are defined, which describe the load profiles' characteristics more abstractly and are used to assign the determined load profiles to the appliance types:

- Number of peaks: The number of peaks or rather heating phases included in the load profile (1 to 8)
- Power increase: The amount the power increases at the beginning of a peak (I)
- Power decrease: The amount the power decreases at the end of a peak (D)
- Relation of peak duration and whole duration: The sum of the duration of all heating phases divided by the whole length of the profile

- Longest peak's duration: For this load profile, the first peak is the longest (L)

These five features are computed for the measured household appliances. Due to differences in the individual appliances, this yields an interval per appliance type for every property. To prevent double or triple assignment, at least one property of two appliances must be disjointed. A load profile is neglected if it does not fulfill all properties for one appliance type.

Analyses show that this approach does not work for dryers. For the 565 households, nearly no load profile is identified as a dryer. For less than 5 % of the households, a dryer is assigned, which is significantly smaller than the value of the federal statistical office (42.6 %) [33]. Detailed investigation of the dryers' load profile characteristics shows why a separate procedure is necessary to identify those appliances.

With the method described above, none, one, or more than one load profiles are assigned to an appliance for every household. The load curve for the whole year is analyzed for uses by comparing the correlation coefficient between the extracted load profile and the energy consumption pattern. In contrast to the clustering algorithm, the expected correlation coefficient is smaller to also identify disturbed appliance uses. Accordingly, the difference in the two intervals' energy consumption is also considered to ensure reliable assignments.

As an additional plausibility check, the identified appliances are evaluated regarding their number of uses per year. Appliances that are beyond the range of plausible values (e.g., for dishwashers between 52 (once per week) and 730 (twice per day)) are considered incorrectly recognized and removed from the results.

As soon as more than one load profile is assigned to one appliance, two operations are required to ensure correct results. If one identified profile is part of another, this could lead to double counts or wrong energy calculation. For analyzing the frequency of uses, the following steps are applied:

- Sorting the load profiles by length: This step is necessary to identify the correct amount of consumed energy. Searching for the shorter profile first would prevent any matches of the longer profile afterward and, therefore, underestimate the energy and duration of the operation. Thus, the load profiles have to be sorted by length in descending order.

- Partly deletion of detected matches: To avoid duplicate uses, the appliance load profile is subtracted from the load curve, so after a match has been detected, there cannot be another match for the shorter profile at the same time step.

2.3.2.2 Identification of Dryers

As mentioned, the described method does not work for dryers because nearly no load profile is recognized. Dryers are typically characterized by a strongly alternating load profile. As soon as there is any disturbance like a measurement inaccuracy or shift, the load profiles of two dryers are precisely opposite. Consequently, the correlation coefficient gets relatively small or even negative, so these intervals are not clustered.

Therefore, a separate method is required to identify dryers. Two additional assumptions are used here to reduce the solution space: Firstly, a dryer only exists if the household owns a washing machine, and secondly, the dryer is used subsequently to the washing machine. According to the second criterion, only 4-hour intervals after washing machines are considered to identify dryers. In order to avoid the problem of inaccurate matches, the load curve is smoothed by converting to a time resolution of 3 min. After that, the same processing steps as described can be applied and yield plausible results.

2.3.2.3 Extraction of Representative Sample

The data basis consists of 565 measured households with varying consumption behavior and equipment state regarding the considered appliances. Therefore, it cannot be assumed that the results for this complete set are in accordance with statistical data about German households in general. Therefore, the results are not considered representative. However, for reliable calculations about potential contributions from the residential sector, an approximately representative sample is required.

The approach of generating such a representative sample is the optimized selection of households from the complete set to reduce the deviations between statistical values for the selected sample and statistical values which are published for Germany [26, 33]. To find a suitable trade-off between a sufficiently large remaining sample and enough combination opportunities to fit statistical data, a sample size of 100 is defined. Therefore, the goal is to select 100 of 565 data sets that provide the best possible approximation.

Since $\binom{565}{100}$ is way too large to perform an exhaustive search for the selection of the appropriate sample, the selection is carried out by optimization. The selection of a sample of objects from a more extensive data set can be reasonably represented as a bitstring, i.e., a series of zeros (not selected) and ones (selected). According to previous research, genetic algorithms are suitable for this kind of optimization problem [34]. Therefore, the selection of the sample utilizes the MATLAB implementation of genetic optimization. Since the result of the algorithm is non-deterministic, the process is conducted repeatedly to identify the optimal solution.

As already mentioned, the goal of the optimization process is the reduction of deviations from statistical data. These are evaluated for all three relevant appliance types. The

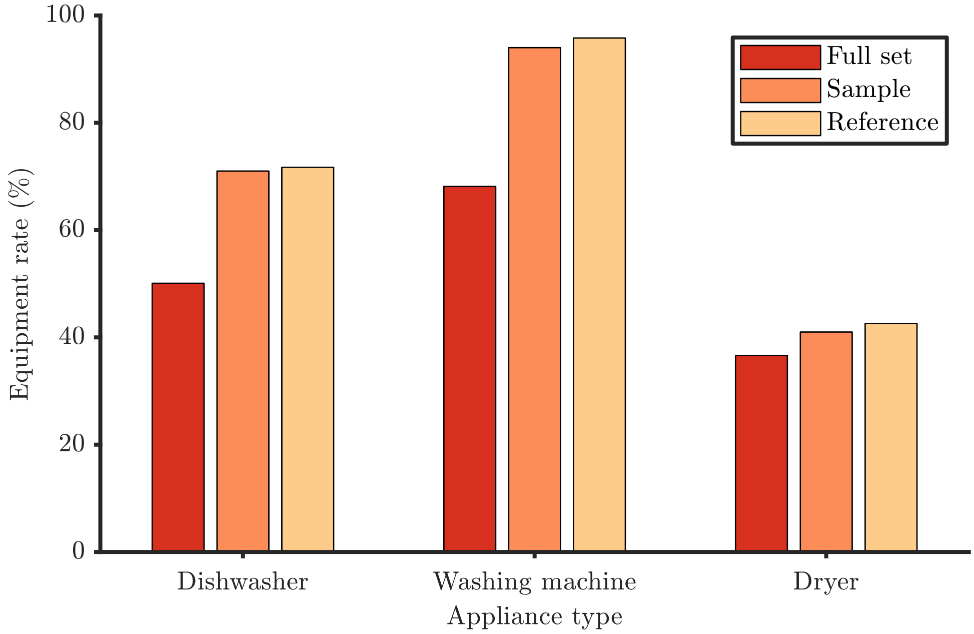


Figure 2.7: Equipment rate of identified appliances (based on [27])

following indicators for representative consumption behavior and DSM potential are chosen:

- Equipment rate
- Mean uses per year
- Mean energy consumption per use

Therefore, nine indicators are applied in total. The objective of optimization is the reduction of the mean squared error of these nine values.

2.3.3 Results

2.3.3.1 Number of Appliances

As a first result, the amount of households with a specific type of appliance is evaluated. The red bars in figure 2.7 represent the number of households in the complete set for which the respective appliance has been assigned. By application of the described optimization process, the sample of 100 households is chosen and depicted in the second bar per set. As a reference, statistical values that are applied as the optimization goal are also given [33].

The determined values for the equipment rate are smaller than the statistical values but in the same range. This suggests that the identification method generally yields valid

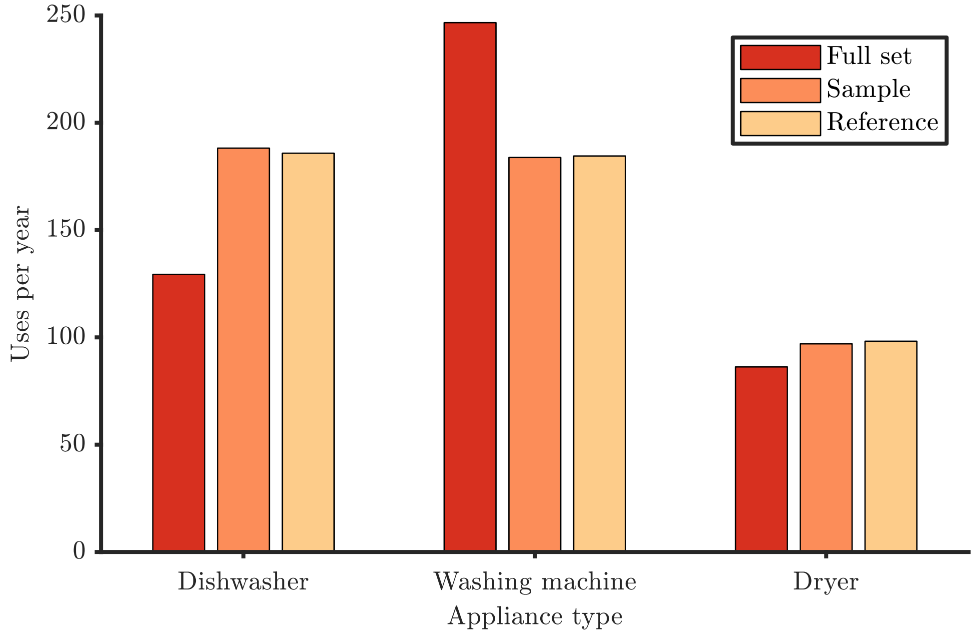


Figure 2.8: Mean uses per year of identified appliances (based on [27])

results, but not all occurrences are recognized. This might result from the relatively small data basis of appliance load profiles.

The sample selection process yields a viable method to create a data set that almost fulfills the statistical demands. A very good approximation of the reference value can be observed for all three types of appliances. Therefore, the selection method yields plausible results on the first indicators and will be analyzed further.

2.3.3.2 Frequency of Operation

The frequency of operation, i.e., the number of uses per year, is already applied as a criterion in the identification of plausible appliances. In figure 2.8, the mean value for every appliance is illustrated in the same structure as before.

This analysis confirms the developed methodology for sample selection. For every appliance, the sample values are very close to statistics [26], whereas the complete set differs considerably. As before, the values differ slightly from the statistically determined ones but are close enough to consider the results reliable.

2.3.3.3 Energy Consumption

The energy consumption per use is essential for determining the DSM potential. Moreover, these results can again be used to check the plausibility of the applied method. Figure 2.9 shows the appliances' mean energy consumption per use.

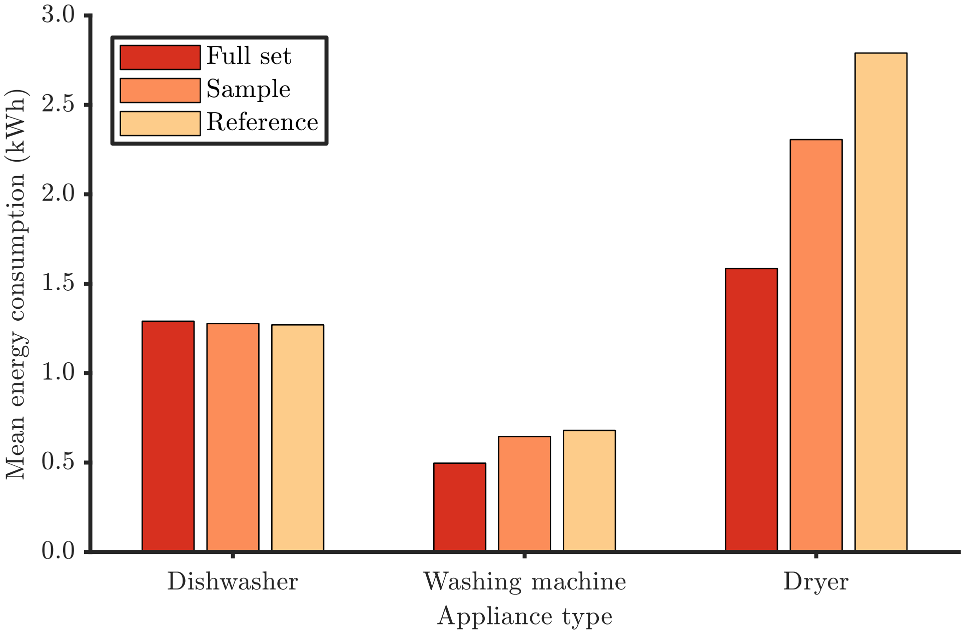


Figure 2.9: Mean energy consumption of identified appliances (based on [27])

Previous studies mention the mean energy consumption for dishwashers with 1.25 kWh, for washing machines with 0.75 kWh, and for dryers with 1.6 kWh [35]. The comparison of these values and those depicted in figure 2.9 (mean 1.01 kWh/0.42 kWh/1.58 kWh, median 0.90 kWh/0.43 kWh/1.38 kWh) leads to the result that the determined mean energy consumption is slightly smaller but reasonably close. A possible explanation for the deviation might be that households tend to use eco programs, which is not considered in the computation of the mean literature values.

2.3.3.4 Duration of Operation

The duration of the programs is the next value, which belongs to the appliances' characteristics. According to the source above [35], program durations for dishwashers are in the range of 60 min to 80 min, for washing machines between 70 min and 120 min and for dryers between 80 min and 120 min. The calculation confirms that most of the recognized dishwashers and dryers are in these ranges (mean 65 min/18 min/83 min, median 66 min/17 min/77 min). However, washing machines differ significantly. The analysis of the identified load profiles suggests that the described algorithm only recognizes the initial heating phase for washing machines but not the subsequent spin cycle since it is below the chosen power threshold. Since energy consumption is the crucial quantity for evaluating DSM measures, the results can nevertheless be used despite these shortcomings.

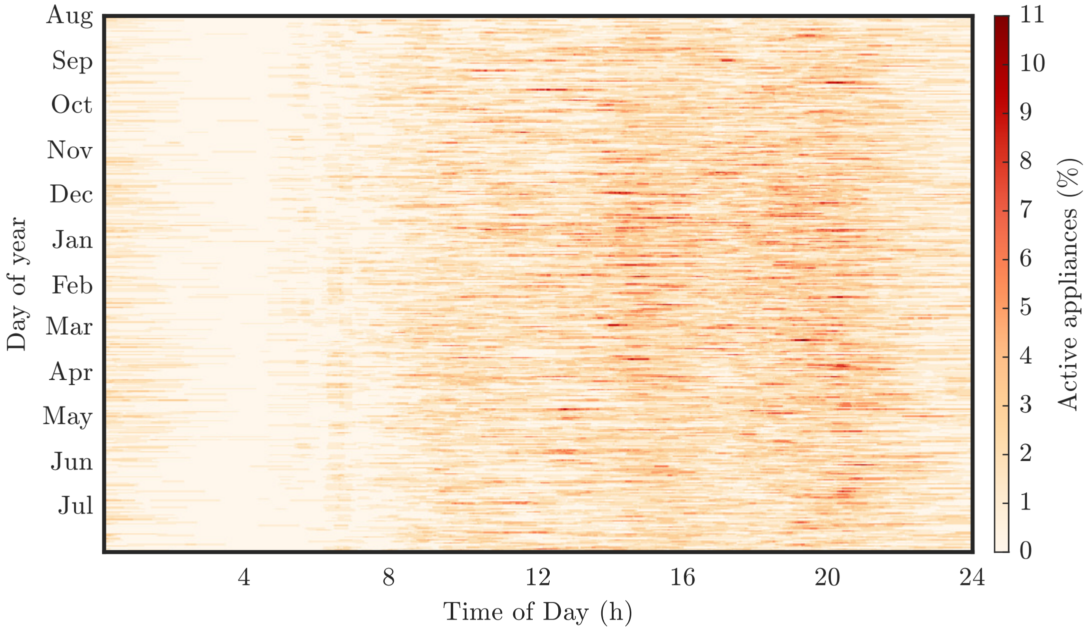


Figure 2.10: Raster plot of dishwasher usage (based on [27])

2.3.3.5 Time of Operation

The last important subject of investigation is analyzing the user behavior, i.e., the typical operation times of these appliances. These results are also essential for assessing the DSM potential. In this context, raster plots are used to visualize the distribution. The generated plots consist of 1440 columns (minutes of the day) and 365 rows (days of the year). Each cell contains the normalized number of identified uses of the selected sample of households during the relevant minute. This means that minutes with no uses are marked white, and the maximum is displayed in dark red. Figure 2.10 shows the distribution for dishwashers for the year from Friday, August 1 2014 until Friday, July 31 2015.

This kind of visualization evinces some notable characteristics:

- Focus during evenings: It shows that most dishwashers are used in the evenings, especially during working days. Using the dishwasher after work is the expected user behavior for employed people.

- Focus during winter: The second finding is the focus of uses from November until March. The results show a highly frequent use of dishwashers in this season, specifically on weekends. A higher probability of being at home might be a conclusive explanation for this observation.

Closer inspection of the resulting data leads to additional conclusions:

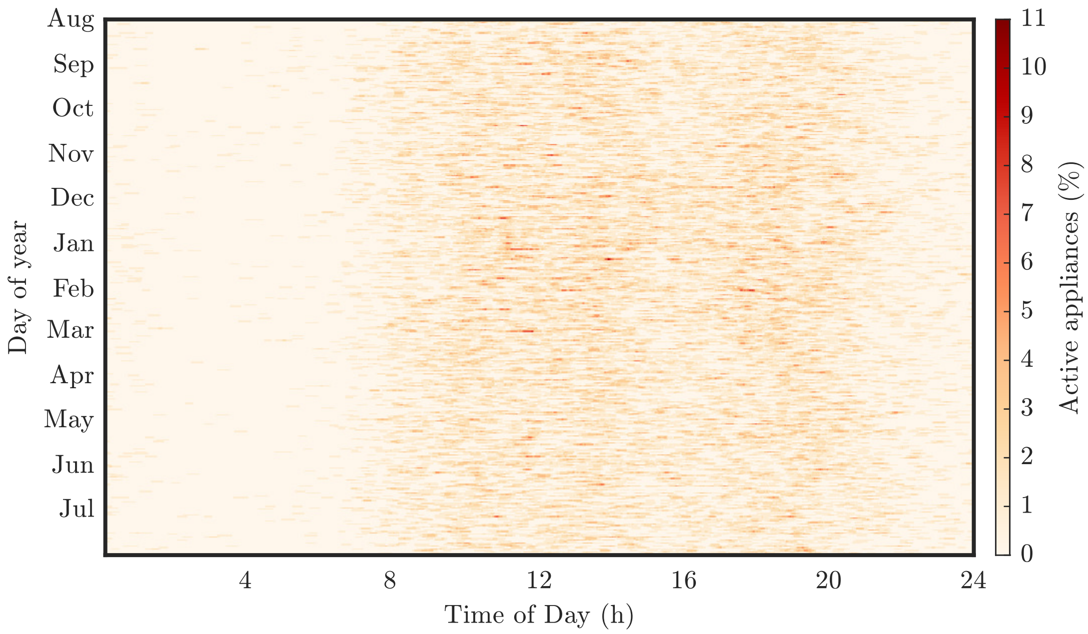


Figure 2.11: Raster plot of washing machine usage (based on [27])

- Public holidays: Several public holidays like Christmas Days, New Year, or Ascension Day evince substantially increased appliance usage compared to non-holidays with similar seasons and weekdays. Since people tend to be at home more often on these days compared to working days, this supports the plausibility of the method.

- Vacation periods: In school vacation periods like, e.g., easter vacation, the distribution of dishwasher uses is much smoother compared to the rest of the year. This can be explained by the assumption that more people are on vacation, which reduces the after-work peak in the evenings.

All of these observations are in accordance with typically expected customer behavior. This is, therefore, another plausibilization step for the presented algorithm.

The raster plots for washing machines and dryers are depicted in figures 2.11 and 2.12. As presented, both the equipment rate of washing machines and the number of uses per year are the highest of the considered appliances. In contrast, the dryers' plot is much lighter, which implies a lower equipment rate and the lowest number of uses per year.

For both appliances, the focus of use can be observed during weekends, especially for dryers in winter. This again seems plausible because people are doing their laundry rather on weekends. Moreover, higher dryer usage during winter makes sense because some households have alternative options to dry their laundry, e.g., air drying outside.

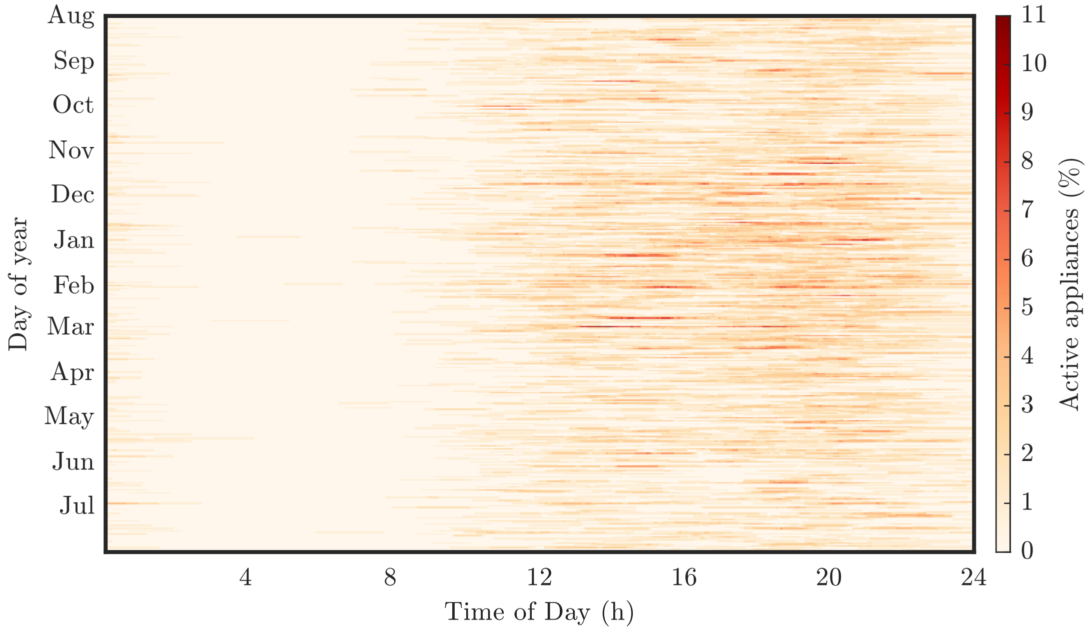


Figure 2.12: Raster plot of dryer usage (based on [27])

2.3.4 Summary

The presented method intends to develop an algorithm for disaggregating the load curve of various households without having data about individual equipment states or load profiles of the respective appliances. Load profiles are identified and extracted based on several criteria, such as power thresholds and durations. Measured load profiles for some appliances are used to derive these criteria, which allow assigning the identified load profiles to appliance types. Therefore, this method can be applied to a large number of data sets without the necessity to perform individual analyses or measurements.

The results show plausible characteristics. All investigated quantities, like equipment rates, energy consumption, or number of uses, are reasonably close to literature values. The investigation of the temporal user behavior even evinces noticeable differences for special days like holidays, confirming the method's plausibility. Therefore, the identification of dishwashers, washing machines, and dryers is considered suitable for further simulations in the subsequent chapters.

3 Curtailment Data

3.1 Regional Curtailment Data

This section is partially based on previously published work by the author [18].

3.1.1 Scope

Curtailment of renewable generation is one of the measures for grid congestion management available to grid operators. The curtailed energy is lost for the energy system since it cannot be fed into the grid. Therefore, reducing curtailed energy can increase the overall share of renewably generated energy and decrease the total greenhouse gas (GHG) emissions caused by the generation of electric energy. Since October 2021, it is implemented in the German redispatch process [9, § 13a]. Previously, it constituted a separate process called feed-in management [36].

In order to quantify the potential reduction achieved by demand-side flexibilization measures, like in this case, load shifting of household appliances, the potential effect on the grid is to be estimated. Since previous analyses show that the majority of individual curtailment measures are caused by congestion on the transmission grid level [37], lower voltage levels and grid structures will be neglected here, which also circumvents the problem of severely limited data availability on a national scope.

Another simplification applied here is the assumption that load increase at a particular grid node on the transmission level prevents curtailment of the equivalent amount of energy [18]. This neglects the potential effects on other nodes but is considered a reasonable approximation since no data about the actual line sections that cause curtailment are publicly available. Therefore, a way of allocating historical curtailment measures to appropriate grid nodes is required to model potential reductions. Based on that, the actual curtailed energy per grid node and time step can be determined.

3.1.2 Methodology

The first step here is the acquisition of data about the geographic location of all grid nodes in the German transmission grid. Since the grid data published by the transmission system operators (TSOs) are not sufficient in this respect, this analysis is based on a grid model developed in a previous project [19], which in turn utilizes several free data sources and processing tools [38–41].

As already mentioned, grid data for underlying grid levels are not available with the required coverage to be used for allocation to grid nodes. Therefore, the allocation is based on the geographic proximity of the curtailed plant to the node. This procedure yields a tesselation of the considered area, i.e., of Germany, in regions, each of which contains one node and consists of the geographic area with the smallest distance to this specific node, compared to all other nodes [42]. Mathematically, this is called a Voronoi diagram.

The initial Voronoi tesselation yields neighboring regions; therefore, each node's neighboring nodes can be deduced. This allows calculating the distance between each pair of neighboring nodes. These distances evince a wide range of values. Therefore, the lowest decile is chosen as a threshold value. This choice cuts the extremal values but still leaves most of the assumed grid in its original state.

The aggregation of nodes to the described new "nodes" is performed by identification of clusters, i.e., two or more nodes within a distance below the threshold of each other. These nodes are then replaced by one new node at the center of gravity of the original nodes.

Currently, there is no central data set of curtailment measures or curtailed energy for Germany. These data are only partially published by the respective distribution system operators (DSOs). The curtailment data consist of a list of individual curtailment measures, which include the time stamps of begin and end of the respective measure, the level of curtailment (relative to the installed capacity), and the affected plant. All renewable plants funded by EEG are included in a register of installations, which additionally gives location, installed capacity, and the energy carrier. In order to determine the actual curtailed power and, therefore, deduce the curtailed energy, it is necessary to estimate the generation power at a given point in time. Since no data about this are available in a per-plant resolution, the time series is approximated by the total power of the respective energy carrier in the control area where the plant is located. This is referred to as "dynamic approach" in literature and evinces good results compared to alternative approaches [43].

3.1.3 Results and Discussion

3.1.3.1 Grid Data

As a result, the locations of 490 German grid nodes can be deduced. The analysis of these grid nodes also shows several clusters of nodes with very low distances, which would produce very small regions compared to others. In order to achieve a tesselation in regions with areas on a comparable scale, neighboring nodes with a distance below the defined threshold are combined and considered only one node for subsequent calculations.

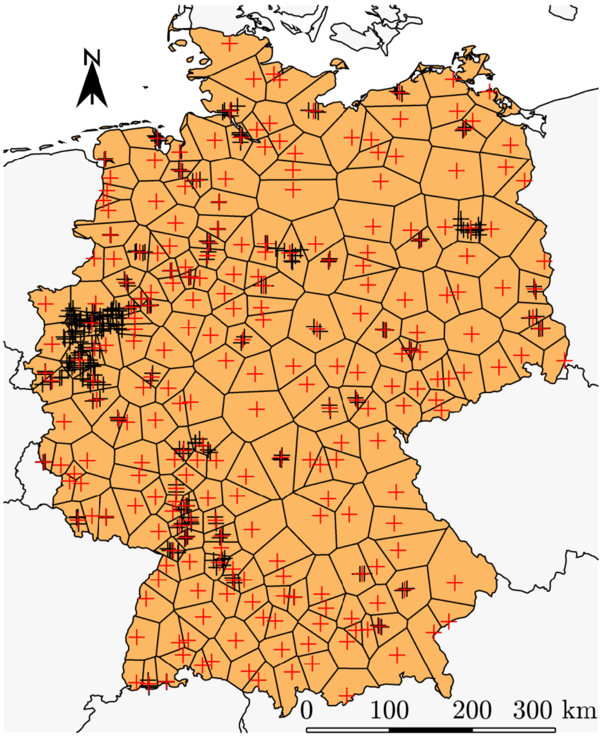


Figure 3.1: Grid regions for subsequent simulations (based on [37])

This approach is also supported by the assumption of a highly meshed distribution grid in regions with a high density of transmission grid nodes [42]. The threshold value cannot be deduced from actual distribution grid data, so the described alternative approach is applied and yields 5.14 km as the threshold value.

Based on the resulting set of 251 nodes, the Voronoi tesselation is computed again, yielding 251 grid regions for Germany, which are shown in figure 3.1 and will be the basis for regional evaluations and charts.

3.1.3.2 Curtailment Time Series

For the presented evaluations, data from Bayernwerk, Netze BW, Mitnetz, Avacon, E.DIS, WEMAG, and Schleswig-Holstein Netz for the year 2018 are available and used.

The described methodology is applied to the identified 251 grid regions, resulting in 251 time series of curtailed energy in a resolution of 1 min for 2018. For this, the plants are allocated to the respective administrative districts according to their locations and then aggregated to the level of grid regions. Figure 3.2 shows the calculated sum of curtailed energy per grid region, displayed on a log scale due to a wide magnitude range. The distribution evinces high amounts of curtailment in northern and northeastern Germany, whereas considerably less energy is curtailed in the south. Grid regions displayed in

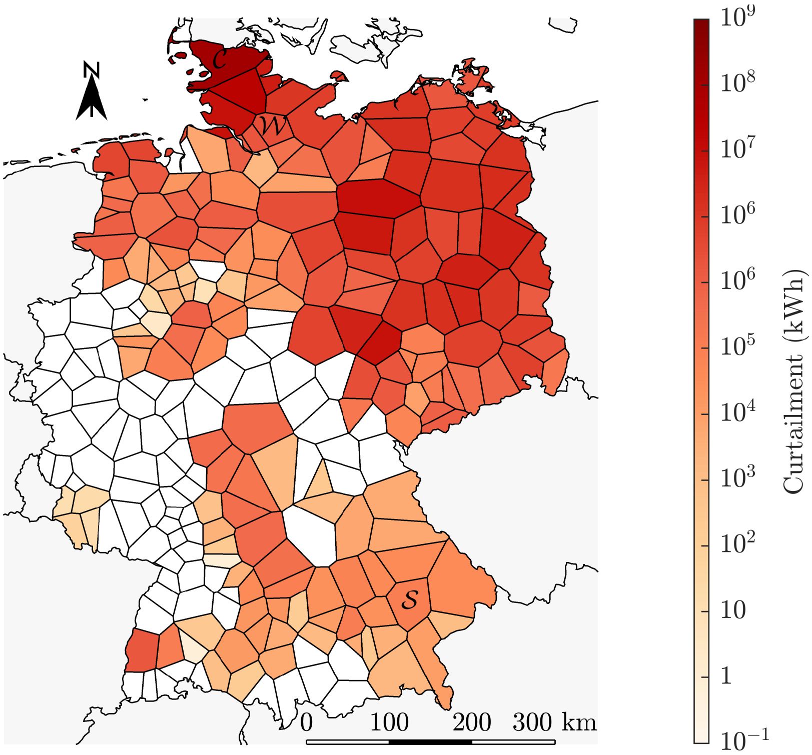


Figure 3.2: Curtailed energy per grid region in 2018

white do not necessarily mean zero curtailment but also include regions with no available data.

The total curve of curtailed power in Germany is given in figure 3.3. It is calculated as stated before and summed over all grid regions. The graph in a resolution of 1 min shows that curtailment is necessary throughout the year and sums up to several gigawatts for peak events. Total curtailed energy amounts to 2.34 TWh according to the calculations, which represents about 43.3 % of the published values [44]. 421 610 time steps of the year, i.e. 80.2 %, evince curtailment in this aggregate analysis. Therefore, both a seasonal evaluation and an evaluation on the grid region level make sense for identifying and understanding potential characteristics and patterns.

Figure 3.4 shows the total curtailed energy per month of the year 2018. In order to get fully comparable values, "month" is not used in its usual calendrical definition, but rather as $^1/_{12}$ of the whole year, i.e., 730 h. It is evident that the curtailed energy follows a seasonal pattern since there is considerably less curtailment in the summer months from May to August. This confirms the assumption that most of the curtailment is caused by wind power rather than by PV plants since these have their production peak in months with high solar irradiance.

Three grid regions are selected for detailed analyses. The first one is located in the north of Germany, so the renewable generation mix is dominated by wind power, and

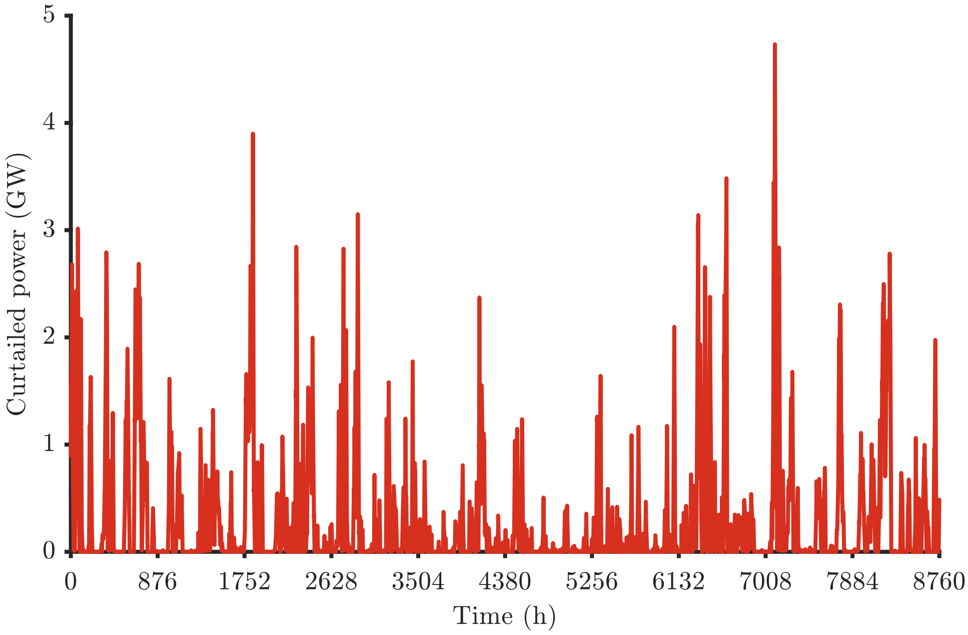


Figure 3.3: Total curtailed power in 2018, resolution 1 min

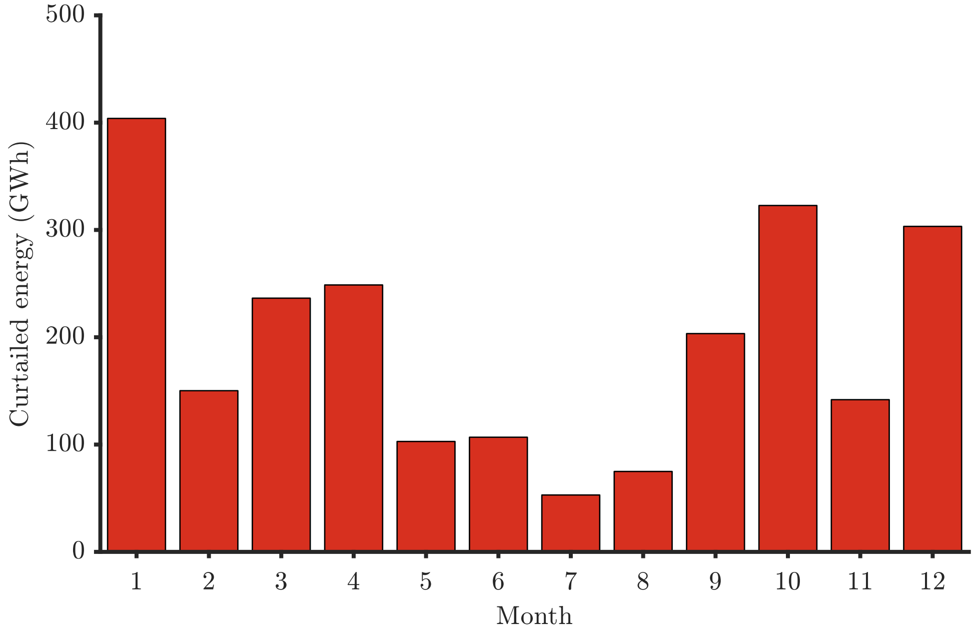


Figure 3.4: Total curtailed energy in 2018 per month

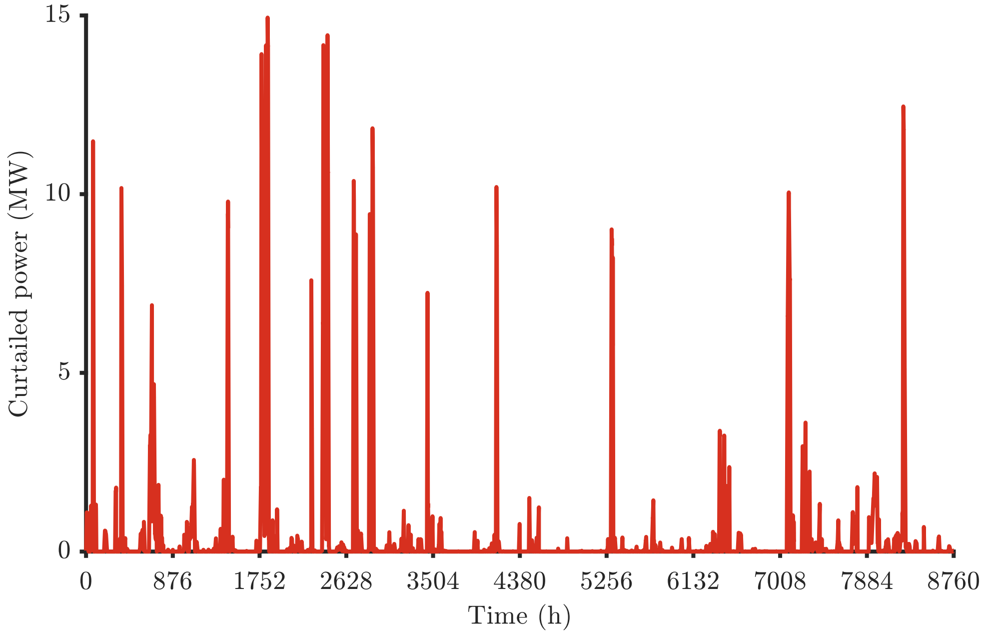


Figure 3.5: Curtailed power in region $\mathcal{W}$ in 2018, resolution 1 min

the amount of curtailed energy is comparably high. The chosen grid region is denoted by $\mathcal{W}$ in figure 3.2 and represents a part of the project region evaluated in [45].

The second selected grid region complements this by representing the southern German grid situation with high shares of solar PV and considerably less curtailment than in the north. Here, the grid region which contains the field trial of [46, 47] is chosen and denoted by $\mathcal{S}$.

The third region, denoted by $\mathcal{C}$, is chosen to include the maximum occurring curtailment in the present data set. It is also located in northern Germany and still shows considerably higher amounts of curtailed energy compared to $\mathcal{W}$, so its detailed analysis is expected to yield additional insights.

Detailed analysis of the times series of curtailed power in grid region $\mathcal{W}$, displayed in figure 3.5, yields a total amount of curtailed energy of 3.00 GWh, reaching peaks of over 10 MW. Curtailment measures are active for 39.9 % of the year, so in 209 941 time steps in the applied resolution of 1 min. This shows that wind-dominated grid regions require curtailment measures frequently, which in turn shows relevant potential for reduction of curtailment.

For comparison, figure 3.6 shows the analogous graph for grid region $\mathcal{S}$. Here, the total curtailed energy in 2018 amounts to 108 MWh, so approximately $^1/_{28}$ of region $\mathcal{W}$. Correspondingly, curtailment measures occur far less frequently, as only 4296 time steps, or 0.8 % of the whole year 2018, are affected. By contrast, the peaks of curtailed power are in the same order of magnitude as for region $\mathcal{W}$. Therefore, grid regions dominated by

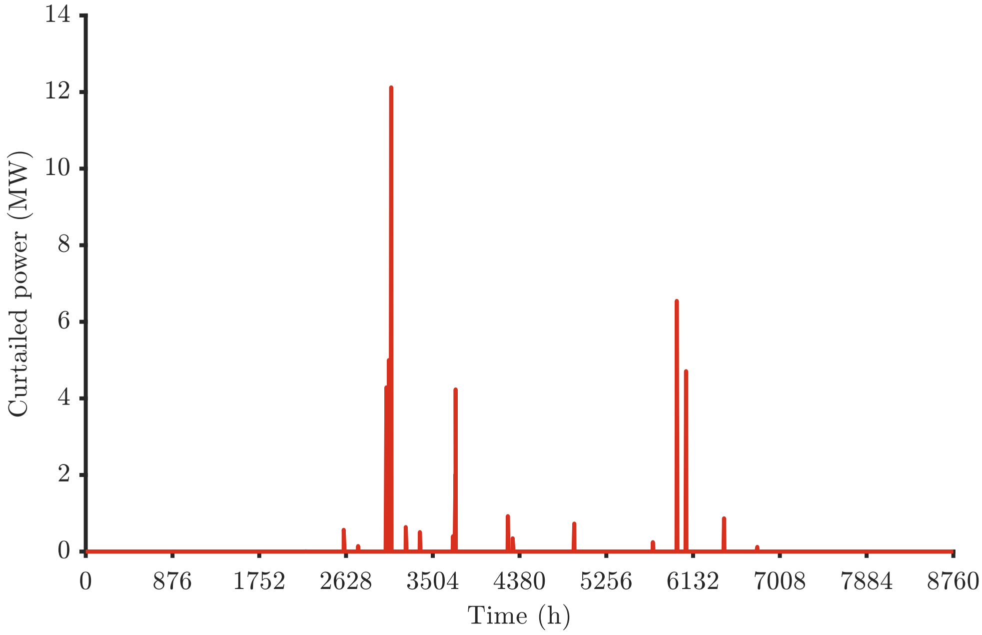


Figure 3.6: Curtailed power in region $\mathcal{S}$ in 2018, resolution 1 min

solar PV require considerably less consumption adjustment to reduce necessary curtailment but still require comparable flexible power in the event of adaption.

As expected, the highest values can be seen in figure 3.7 for region $\mathcal{C}$. Here, the peaks exceed values of 1 GW, leading to 1.26 TWh of total curtailed energy over the year. Thus, about half of the curtailed energy in the data is attributed to this grid region. 72.1 % of the year, or 378 744 time steps, evince curtailment measures.

3.1.4 Summary

In summary, the developed methodology allows the partitioning of the area of Germany into smaller regions, which are geographically associated with one or more nodes of the transmission grid. This allocation of generation or consumption by geographical distance is considered a reasonable approximation since no comprehensive data set of lower grid levels is available. Historical data of individual curtailment measures are converted to time series by applying the dynamic approach, which considers publicly available generation data of renewables to improve data quality. The procedure yields time series of curtailed energy in a resolution of 1 min for 251 regions.

The evaluation of these time series evinces substantial differences between the selected example regions, $\mathcal{W}$ as a typical wind-dominated region in the north, $\mathcal{S}$ as a region in the south with a substantial share of solar PV, and $\mathcal{C}$ as the region with maximum curtailed energy. $\mathcal{W}$ undergoes curtailment measures for approximately 40 % of the whole year, whereas in $\mathcal{S}$ less than 1 % of all time steps are affected. The evaluated total

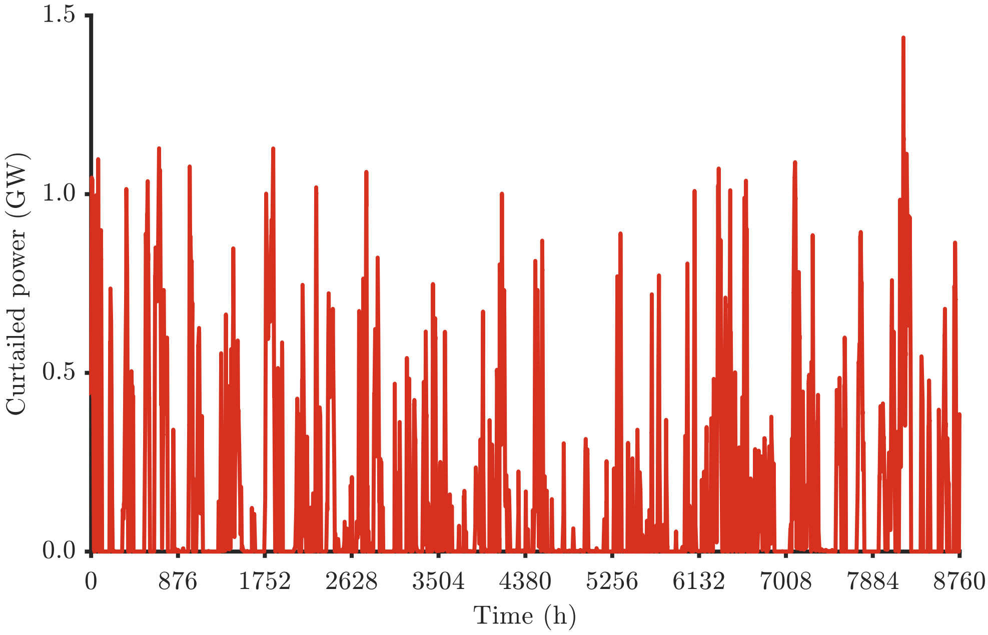


Figure 3.7: Curtailed power in region $\mathcal{C}$ in 2018, resolution 1 min

curtailed energy throughout the year shows similar behavior. Region $\mathcal{C}$, however, evinces considerably higher curtailed power for about $^{3}/_{4}$ of the year. Thus, it is concluded that the detailed modeling and evaluation of regions with different characteristics is essential for a comprehensive assessment of rates for the defined use case.

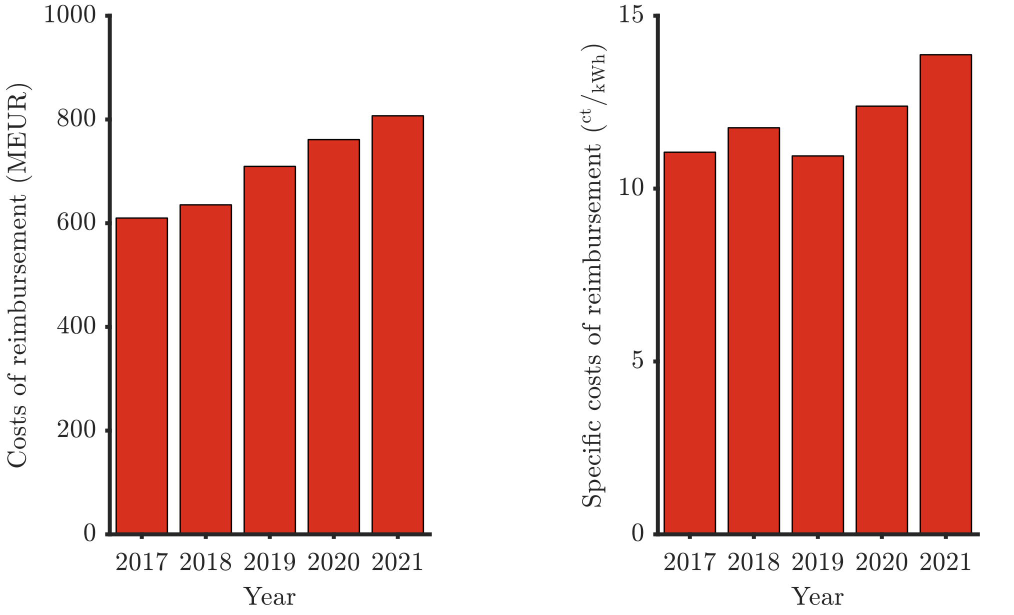
3.2 Value of curtailed energy

3.2.1 Scope

The previous section described the developed method to represent curtailed energy in the required temporal and regional resolution. Since the overall goal includes the design of a cost-neutral electricity rate, it is also necessary to define the monetary value of these measures, or more precisely, the value of avoided curtailment from an energy system perspective. Thus, this section aims to deduce a suitable definition of said value for the subsequent simulations.

3.2.2 Methodology

The assessment of the value of curtailed energy is performed in two steps. First, the usual literature approach is presented and discussed. After that, the proposed shifting process is analyzed more thoroughly regarding potential additional or saved costs due



(a) Estimated total costs **(b)** Estimated specific costs

Figure 3.8: Costs for curtailed energy (data based on [48])

to the DSM measure. Thus, this leads to a valuation method for avoided curtailment by DSM.

3.2.3 Results and Discussion

One key figure usually applied to describe the total costs of curtailment in the German energy system is the sum of reimbursements for the curtailment measures. Operators of curtailed renewable assets are reimbursed for their lost revenue compared to the uncurtailed operation [9, § 13a]. This value is typically evaluated yearly and can be applied to describe the value of curtailment per energy unit. Figure 3.8 shows these values for recent years, both in total (figure 3.8a) and per curtailed energy (figure 3.8b) [48]. This can be considered a comparatively simple first approach. However, it has two substantial weaknesses: it does not reflect the time-dependency of the value and describes the costs of curtailment, not the value of avoided curtailment.

Based on that, one possible improvement to the approach would be to use time-dependent costs in the calculation. Since reimbursements are partially coupled to market prices of the respective time frame, this would yield an hourly time series representing the costs of curtailed energy. Nevertheless, this still cannot be considered a helpful definition of the value of avoided curtailment in the context of this thesis. Moreover, data availability is another problem for this approach since these time-dependent reimbursement costs are not published.

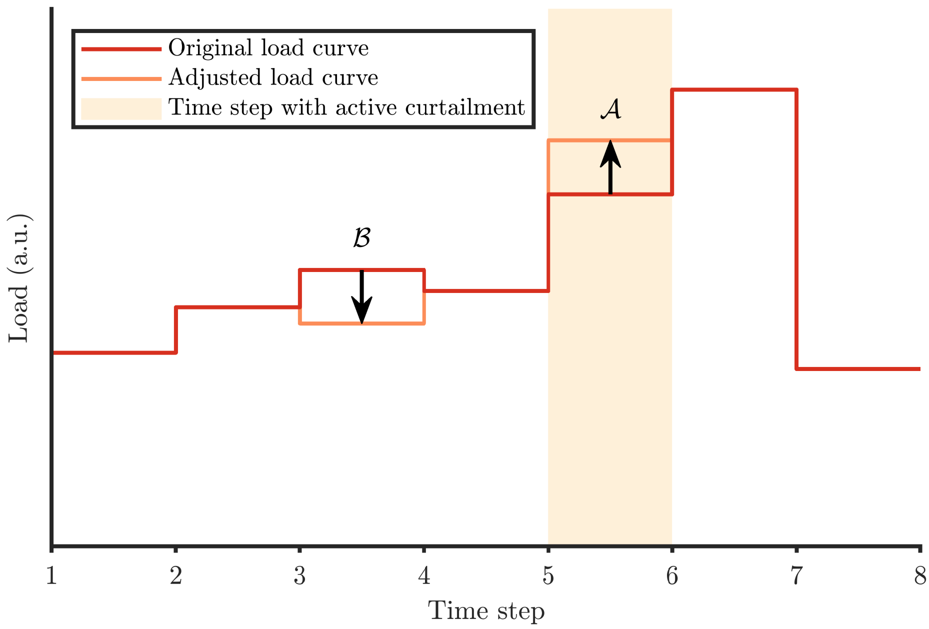


Figure 3.9: Qualitative illustration of curtailment-driven load shifting

In order to reasonably assess the value of avoided curtailment by a DSM approach, the load-shifting process also has to be taken into account. Thus, two time intervals are to be considered: one with potentially reduced curtailment by increasing load (discussed in the two previous approaches, interval $\mathcal{A}$), and a second one with corresponding load reduction (interval $\mathcal{B}$). This means that a load-shifting measure from interval $\mathcal{B}$ to interval $\mathcal{A}$ is assumed. This is schematically depicted in figure 3.9.

In interval $\mathcal{A}$, curtailment is reduced by increasing load. This means that the additional shifted load within this interval is covered by generation that would be curtailed otherwise. Thus, the accruing costs in interval $\mathcal{A}$ remain unchanged by DSM measures.

In interval $\mathcal{B}$, the load is reduced compared to the unshifted state. This means that the coverage of the load in interval $\mathcal{B}$ after the shifting process causes less costs since less energy has to be supplied. This cost reduction depends on the market prices within this interval and is determined by the day-ahead prices.

Reduced load, in theory, also causes feedback effects on these prices, which in turn also affects the reduction in costs. This effect can be quantified by energy system modeling or by analyzing the historical bid curves of the day-ahead spot market. Both approaches are compared in a previous paper [49]. The results show that the expected price changes are relatively small in general, and for the discussed application of DSM with household appliances, they can be considered negligible. Moreover, it would introduce additional non-linearities in the resulting model, causing substantially increased runtimes of the simulations and optimizations in sections 5.2 and 5.3. Thus, these feedback effects are not modeled within the scope of this thesis.

3.2.4 Summary

The analysis of the cost effects of DSM measures shows that, on the one hand, increased load, which reduces curtailment, can be considered cost-neutral, whereas, on the other hand, load reduction in uncurtailed intervals reduces the total system costs. Thus, the load-shifting measures, designed with the primary purpose of curtailment reduction, also contribute to cost reduction. This provides additional financial leeway for the optimization of rate parameters.

4 Rate Structures and Parametrization

4.1 Rate Structure

This section is partially based on previously published work by the author [50].

4.1.1 Scope

The overall goal of the flexible operation of household appliances for this thesis's scope is the reduction of curtailed energy. In order to achieve this, sufficient monetary incentives have to be offered for the expected behavioral adjustments of the customers. Thus, the scope of the present section is the analysis of existing rate structures and their specific features and influences, leading to a structure designed to meet this goal's requirements. This structure is seen as a general pattern, where several variables are to be defined by subsequent simulations to define the concrete implementation. The analyses within this section are conducted regarding the resulting total retail price from the customer's perspective. The question of implementability in specific price components like grid fees is discussed in the subsequent section (cf. section 4.2).

4.1.2 Methodology

Various options for residential electricity contracts are collected, analyzed, and compared to identify suitable rate structures. This includes both theoretical concepts for variable pricing and experiences from actual projects or electricity suppliers. This overview allows the identification of the essential elements of a variable electricity rate for the use case of load-shifting for the reduction of curtailment. Thus, it allows the definition of the general rate structure, which will be applied in subsequent calculations and simulations.

4.1.3 Results and Discussion

In order to incentivize the behavioral adaptation of customers to the system's demand for flexibility, several rate elements can be applied and combined. Electricity rates generally consist of one or more of three fundamental elements, which can also be designed in various variable ways. The term variable here is used to represent all kinds of pricing structures that vary the resulting price according to defined influences, so no terminological distinction between variable and dynamic pricing is applied.

Retail customers can be charged per grid connection point, per capacity, and per consumed energy. This is implemented by three different fundamental rate elements, which can be combined:

Basic fee The basic fee is a constant amount that accrues per unit of time, usually per month or year, and is charged per grid connection point. It is, therefore, independent of the actual consumption behavior and poses no incentive for load shifting or energy saving.

Demand charge A demand charge can represent the necessary capacity for the energy supply of the respective customer [51]. It is determined by the maximum demand in a given time frame. Therefore, this can motivate behavioral changes (load shifting and energy saving) to smooth the load curve.

Energy price The third fundamental element is the energy price, which is charged per consumed unit of energy. This represents the cost for the generation of electrical energy and is the element commonly viewed as "electricity price". It can be interpreted as an incentive to avoid energy consumption but is irrelevant for load-shifting measures.

In the German retail market for the residential sector, usually a combination of a basic fee and an energy price is applied. Both elements are constant in this system. As already pointed out, this is a suitable approach to cover the costs but is not helpful in utilizing the flexibility potential of residential customers. Therefore, additional variability is to be included.

The overall aim is to incentivize household load-shifting measures by varying rate elements dependent on external parameters. Therefore, the basic fee is unsuitable for this purpose, which leaves demand charge and energy price as relevant elements.

The specific implementation of these price adjustments is typically clustered in the following types of variable rates: [52]

Time of use pricing Time of use (ToU) pricing applies two or more price levels, predefined based on time of day, day of week, or season. This segmentation and the respective price levels are deduced from historical data regarding, e.g., consumption, wholesale prices, or generation. Therefore, it is impossible to represent short-term pricing requirements but only to incentivize flexibilization based on long-term patterns. Typical implementations include ToU rates with high prices during the day and low prices during the night, leading to a smoothed consumption curve of the affected customers. Low prices around noon may also be helpful to shift consumption to the expected time of high PV consumption.

Critical peak pricing This concept is extended with Critical peak pricing (CPP). As before, the price levels are predefined, but to provide additional short-term flexibility, the actual time frames where these price levels apply are determined on short notice, typically between one day and some minutes. The share of time affected by the peak price level (i.e., the high price) can be restricted. Variable rates with this pattern are often applied to reduce grid load during critical events. The structure can also be combined with additional ToU elements. A variant of this pricing approach is called Peak time rebate (PTR) or Critical peak pricing with rebate (CPR), which incentivizes load adjustment with rebates for load reduction during peak events rather than high prices.

Real-time pricing The direct representation of wholesale prices in the retail price is denoted as Real-time pricing (RTP) and yields price adjustments in short intervals, typically hourly or quarter-hourly. This structure passes the price risk of energy procurement to the customer and, therefore, incentivizes load adjustment according to the current market conditions. However, RTP does not represent influences other than market prices in the resulting price, which requires the introduction of additional principles to achieve, e.g., grid-friendly behavior (assuming that prices do not represent the grid state, which would be possible with, e.g., nodal or, to a lesser extent, zonal pricing).

These general structures describe the price levels, the intervals of price adjustments, and the lead time of price information. They can be applied to represent a variety of external influences in the resulting retail price and, thus, to achieve load adjustment for several different purposes [53]:

Time Both demand charges and energy prices can be time-dependent. Daily and weekly energy price patterns with two price levels are relatively common since they can be implemented with conventional double-rate meters. Further options are seasonal differences or a higher number of different price levels. Strictly time-dependent rates (also called time of use rates) usually define the time frames at least one month ahead, which can be considered convenient for customers to adapt to.

Load Load dependency is another form of variable rate. This means that the applicable price level depends on the current total load of the customer's household. Again, several price levels or a continuous increase can be implemented.

Energy consumption Similarly to load dependency, the current price level can also depend on the cumulative energy consumption within a defined time frame, e.g., within a day or month. Rates with increasing prices at higher cumulative consumption are also called "‘progressive"’ and pose an incentive for energy-efficient behavior.

Grid state Prices can be adjusted based on the current or expected grid state to avoid grid problems. Since the prediction horizon is relatively small, these kinds of rates are usually implemented as CPP. This means customers get information about higher or lower prices for critical situations on short notice.

Renewable generation Another influence that can be represented as CPP (and in approximate form with ToU) is renewable generation. This is aimed at consuming as much renewable energy as possible and thus avoiding curtailment by reducing prices (energy or demand) at times with high renewable generation.

Spot market Prices at the EPEX SPOT wholesale market change hourly and can also be directly passed on to the retail customer as a part of the energy price. This structure is called real-time pricing and assigns the price risk entirely to the customer, not the energy supplier, as is the case with the other variable rate possibilities. There are also market-based implementations that do not directly forward the market price to the customer but involve adjustments like minimum and maximum prices, fixed time frames, or longer lead time.

The described variants of variable rates show a variety of potential rate structures for residential customers. In order to suit the discussed objective of increased integration of renewable generation by reduction of curtailed energy, the options are analyzed regarding the specific requirement for this use case. This yields a general rate structure with several parameters, which can be optimized and determined by simulation.

Fundamental rate elements The necessity for curtailment is not directly linked to the maximum demand of the customers. Therefore, a demand charge is not included in the considered rate structure. As described, the monthly basic fee is generally considered constant since it represents fixed costs per customer. Therefore, it has no relevance regarding incentives for DSM and is also neglected for simplicity. This leaves energy prices for further investigation, which can be adjusted according to the requirements defined by the use case.

Rate structures Occurrences of curtailment measures do not follow a reliable daily or seasonal pattern (cf. section 3.1). Thus, ToU pricing is not an option for this use case. Wholesale prices do not represent curtailment necessities either since the grid congestion does not directly affect the resulting price (again, not considering approaches like nodal pricing). Therefore, an adjusted version of CPP pricing is suggested here as a suitable approach. Since the objective of reducing curtailment requires increasing the load in times with active curtailment measures rather than decreasing for traditional CPP implementations, the “peak” price interval is defined as the low price level to incentivize load shifting to this interval. Intervals that are not affected by curtailment evince a higher price.

Influences As already pointed out, time, load, and wholesale prices do not represent the necessity for curtailment. Renewable generation can potentially correlate but still does not include all necessary information. Therefore, the predicted grid state is the selected control variable since it directly allows for determining the potentially required curtailment measures and, therefore, identifying appropriate "peak" intervals with low prices.

In summary, the chosen rate structure consists of an energy price with two price levels. The "normal" energy price, denoted as N, applies for time intervals without predicted congestion. In case of expected curtailment, a lower price L is defined to increase attractiveness for load shifting to this interval. Since the "peak" events are advantageous for the customer, no restriction regarding their occurrences is considered. However, the minimum duration of a price interval can be decisive for acceptance of the resulting variable rate. Therefore, the rate structure includes this as a third parameter M. According to these preliminary investigations, numerical values for these three parameters are to be determined optimally to achieve the highest possible reduction while maintaining the economic viability of the whole concept. In subsequent analyses, this rate structure will be denoted as *NLM rate*.

4.1.4 Summary

Potential features of variable electricity rates are collected and discussed in three dimensions. Concerning the use case, a CPP variant with a low "peak" price as an incentive for load increase is selected. The time interval with low prices is directly deduced from predicted curtailment necessity, which yields the duration of a price interval as an additional parameter since it defines to what extent the actual requirements can be represented in the rate structure. Demand charges and basic fees are neglected for the model, leading to three parameters for the resulting rate structure: normal price level N, low price level L, and minimum duration of price intervals M.

4.2 Regulatory implementation

This section is based on previously published work by the author [50].

4.2.1 Scope

Retail electricity rates in Germany consist of several components like power generation costs, grid fees, electricity tax, VAT, and concession fees [54]. In today's market setting, all these components are usually charged per unit of energy; therefore, a constant energy price applies to the energy consumption of retail customers, which poses no incentive for adjustments of the consumption behavior to external requirements.

However, utilization of the residential flexibility potential can be enabled by variable electricity rates with elements like time-dependent pricing, peak pricing, real-time pricing, or demand charges (cf. section 4.1). Recommendations for functional rate design can be deduced by simulation based on measured consumption data (cf. chapter 5). This raises the question: Which price components should be charged variably to reproduce the optimal rates with necessary spreads and assign price risks to the appropriate market players?

4.2.2 Methodology

Based on the legal and regulatory definitions of the price components of retail energy prices in Germany, the structure is analyzed regarding potential variability and possible spreads, both in the current implementation and potentially adjusted settings. For each component, this yields a potential contribution and suitability to implementing variable rates in the German system.

4.2.3 Results and Discussion

4.2.3.1 Current Electricity Price Components

German retail electricity prices consist of several components beyond the costs of procurement and sales. Most of them have a fixed price per consumed unit of energy. They are defined by some kind of regulatory entity, which means the involved stakeholders have no possibility of adapting these components to current necessities.

Currently, the electricity price for German households consists of 8 components, displayed in figure 4.1 for 2023 and summing up to a mean total of 45.73 ct/kWh. Due to unusual circumstances in recent years regarding the pandemic and the global political situation, retail prices underwent a substantial increase compared to previous ones and do not necessarily pose a representative basis for the presented evaluations. Thus, the price composition for January 2020 is also displayed and subsequently discussed for comparison, at that time consisting of 10 components and totaling at a mean value of 31.37 ct/kWh. The reported values proportionately include base fees. [54, 55]

Procurement and sales The first component covers the costs for the actual generation or purchase of electrical energy, the expenses for sales and marketing, and the potential profits for utilities. Its mean value increased from 7.18 ct/kWh [55] to 23.83 ct/kWh [54]. The amount of this component is solely set by the energy supplier; therefore, variable design is possible here. Since the mean amount more than tripled in the considered time period, this also relevantly increases the possible price spreads in this component.

In the current German market, several suppliers offer variable rates based on this component. However, these mostly depend on market prices and do not reflect grid requirements, as discussed here. [56]

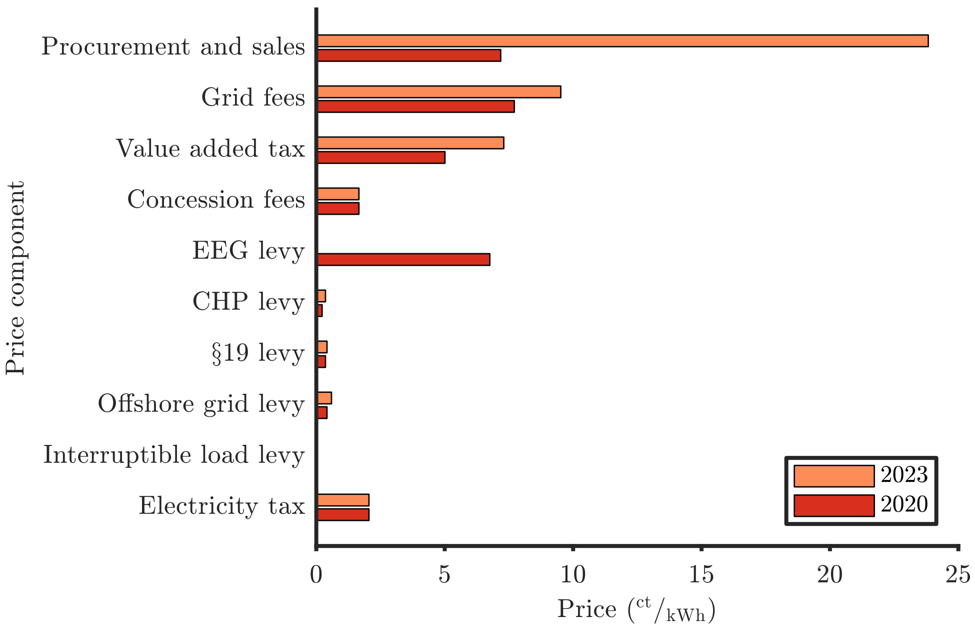


Figure 4.1: Price components of German retail electricity prices for households (data based on [54, 55])

Grid fees Grid fees are charged by the respective grid operators for the construction and maintenance of the electric grid on both distribution and transmission levels. The regulator defines the calculation of the amount, so individual grid operators have no possibility to vary this component. The cost component caused by the transmission grid is unified [9, § 24], whereas distribution grid components depend on the local DSO. However, both are essentially charged per unit of energy.

For larger customers, grid fees usually include a demand charge, which at the moment is not applicable for residential customers [57, § 17]. The component also includes the costs for metering point operation. This leads to a mean value of 7.71 ct/kWh for 2020 [55], increasing to 9.52 ct/kWh for 2023 [54].

There are already possibilities to reduce grid fees for customers with grid-friendly consumption patterns [57, § 19]. Although these measures, called "atypical grid usage" or "intensive grid usage," are not relevant for residential customers, this shows that the general concept of variable or at least individual grid fees is a valid option.

For customers with controllable devices like electric vehicles, heat pumps, and electric storage systems which are obliged to comply with grid-oriented operation according to [9, § 14a], reduced grid fees are legally implemented [11]. Beginning in April 2025, a variable grid fee with ToU structure can be chosen voluntarily by operators of said devices [11]. This can be considered a first approach to improved integration of renewables, as discussed here. However, it is currently focused on local grid overload by consumption and thus might be complemented by the presented concept.

Value-added tax This tax is applied as a general consumption tax, so it is not specific to electricity distribution. It is defined by a fixed percentage (19 %) of the total net price, i.e., the sum of all other components [58, § 12], which yields 7.30 ct/kWh at the moment for Germany [54], up from 5.01 ct/kWh in 2020 [55]. Adjusting this component would require major modifications to the whole system of taxation, making it quite complex to vary.

Concession fees Concession fees are paid by the grid operator to the respective municipality for the concession to operate the electricity grid; therefore, they are also charged to the customer. The amount is defined in the particular concession contract but is subject to upper limits defined by law [59, § 2]. This yields a current mean value of 1.66 ct/kWh [54], which remained constant for the past years [55].

Concession fees can only be charged per kWh according to applicable law [59, § 2]. Therefore, the flexible design of this component would require adjusted legislation. Moreover, the exact formulation would still depend on the individual contracts between the parties involved.

With the so-called "low load fee", it already includes an incentive for variable rates and load shifting, which applies to rates with at least two price levels. However, the achievable spread is relatively low due to the small total amount of this component. Moreover, free adjustment depending on current requirements is impossible, so it will not be considered sufficiently flexible for these investigations.

EEG levy Before July 1, 2022, the expenses caused by the differences between EEG remuneration and actual market revenues of the generated energy were reallocated via the EEG levy by the transmission system operators [60, § 60]. It was recalculated annually and amounted to 6.756 ct/kWh in 2020 [55]. Since these costs are now covered by tax money, it is no longer present as a price component for retail prices.

According to the relevant law, it was charged per kWh, so a flexible EEG levy would not have been possible within this regulatory framework. Changes to this system have been proposed several times [61], [62], and were expected to significantly impact customer behavior. Due to the abolition of the levy, this flexibilization potential is no longer relevant for further investigation.

CHP levy Similarly to the EEG levy, extra costs for the promotion of CHP systems are reallocated by the CHP levy [63, § 26]. Compared to the former EEG levy, the amount is low with 0.226 ct/kWh [55] for 2020 and 0.357 ct/kWh for 2023 [54], but the system of calculating and allocating the costs is identical to the EEG [63, § 26a]. As before, the regulation demands billing per unit of energy and needs to be adjusted to design variable implementations.

Further levies As mentioned before, atypical or intensive grid usage allow for reduced grid fees under certain conditions [57, § 19]. The resulting missing revenues for grid operators are reallocated by this levy, which is named by the paragraph of the respective law. Its value is 0.417 ct/kWh for 2023 [54], up from 0.358 ct/kWh in 2020 [55], and analogously to the previous levies, flexibilization would require regulatory changes.

The same also holds for the offshore grid levy, which covers the costs for missing connection of offshore wind power plants [9, § 17f], which amounts to 0.416 ct/kWh for 2020 [55] and 0.591 ct/kWh for 2023 [54]. Another levy with similarly designed calculation and billing was the interruptible load levy, which covered the costs for specific industrial demand response measures [64, § 18] (0.005 ct/kWh in 2020 [55]), but disappeared with the expiration of the underlying regulation [64, § 20].

Electricity tax As a last component, the electricity tax is charged by the government and constantly accounts for 2.05 ct/kWh [54, 55]. The amount is defined by law [65, § 3] and not assigned to a specific purpose.

4.2.3.2 Analysis of Status Quo

As described in the previous subsection, all components of German retail electricity prices are currently charged per energy and are usually constant over time. They can be clustered into three different groups based on the current price formation mechanism:

- Price is defined by the energy supplier
- Fixed price defined by law or regulation
- Price is dependent on other components

These groups are described and analyzed in the following.

Procurement and Sales The first group consists of the component "Procurement and Sales". As pointed out, its function is to cover the costs of electricity generation or purchase and for all other processes of the energy supplier that are necessary to supply energy to its retail customers. Therefore, the exact pricing structure and price level are up to the energy supplier, making it a perfect candidate for implementing variable rates.

Since this component accounts for about 24 ct/kWh, spreads of just under 50 ct/kWh are possible in a conservative implementation of time of use rates. Conservative here means an approximately uniform distribution of time intervals with high price level and intervals with low price level, a nonnegative low price level, and (at least approximately) revenue neutrality for both energy supplier and customer (provided that the customers' behavior remains unchanged).

However, none of these assumptions are legally necessary, so in theory, arbitrarily high peak prices can be implemented as an incentive for load reduction or load shifting in critical situations. Analogously, negative values of this component can provide an incentive to increase the current consumption. Therefore, potential price spreads are not limited by the current mean value. Demand charges are currently not explicitly allowed but also seem to be in accordance with the law since they are mentioned for a particular group of retail customers [9, § 37].

However, a completely free rate design is not advisable from an economic point of view. Cost savings on the customer side have to be compensated for by the energy supplier by cost reduction on the wholesale market or other financial benefits. Moreover, rate structures that are too complicated or include very high price spreads might receive little acceptance in today's highly competitive retail electricity market.

As described, the component is defined and charged by the energy supplier. Therefore, grid requirements cannot be represented due to unbundling laws [9, § 6a]. This means that theoretically, most flexibility requirements in retail electricity pricing could be mapped to the component, but in practice, the necessary information is not available.

Regulatory components The second group consists of all components defined by some kind of law or regulation and typically fixed for at least one year. This includes all kinds of fees and levies, as well as the German electricity tax. These components are charged per energy, so demand charges are impossible in the current setting. Due to the static definition, they are unusable for dynamic pricing approaches. Thus, using these components as additional incentives for load shifting and other changes in behavior requires regulatory changes. For grid fees, variable design is possible beginning in 2025 but is limited regarding the maximum spread and requires yearly predefined price levels [11]. Thus, it is not suitable for the desired CPP design but can pose a basis for further development.

VAT The third "group" also consists of only one component: the value-added tax. This component is defined by federal law and amounts to 19 % of the sum of all other components. Since this ratio is fixed, no flexible design of the component itself is possible, but price spreads in other components are increased by 19 % due to the VAT. Therefore, this introduces additional leverage to incentivize changes in consumption behavior.

The analysis of the current situation shows that only the energy supplier has the possibility to adjust prices dynamically. Therefore, only about 52 % of the total retail price can be influenced. All other relevant stakeholders, like grid operators and the regulator, have no means to vary their respective components according to the defined goal under current legislation. Including all relevant influences and dependencies (cf. section 4.1) in the final retail price requires appropriate adjustments. These will be discussed in the following section.

4.2.3.3 Potential regulatory adjustments

In general, there are three possible approaches to redesigning the system to overcome the described drawbacks:

- Price signals by other stakeholders to the energy supplier
- Legislative redesign of components
- Introduction of new components

All of these approaches require substantial adjustments to existing laws or regulations, and therefore, market players in energy economics cannot implement them without the legislator's support.

Price signals As already pointed out, the influence of grid operators or possibly other stakeholders on the actual price for energy supply, so on the component defined by the energy supplier, would allow including all relevant factors in the price formation process. Therefore, adjustments of further price components can be avoided, which could potentially reduce legislative implementation efforts. On the downside, new processes for aggregation of all signals have to be defined to establish measures to deal with conflicting interests, e.g., between grid operators and energy suppliers or between grid operators on different voltage levels. Similar challenges are currently being addressed in the field of CLS management [66].

Legislative redesign Changing the respective regulations that define grid fees, concession fees, or several levies could enable dynamic design and adjustments of these components. Thus, grid operators or the regulator have a direct influence on the final retail price and are able to include their requirements in this price. Depending on the current situation of the energy system, this could raise the total price spread seen by the customer, increasing the variable rate's incentive effect.

However, the adjustments might cancel out in other situations with contradicting flexibility requirements of the respective market players. Moreover, the price spread that can be realized with one component directly depends on the current value; therefore, the spreads might be too low to sufficiently incentivize load shifting. Besides procurement and sales, only grid fees pose the opportunity of creating spreads larger than a few cents (cf. subsection 4.2.3.2).

Grid fees could potentially include demand charges that allocate the costs of grid construction and maintenance to the respective cause, potentially leading to awareness regarding load peaks. CPP variants representing the current grid requirements on a local or regional scale are also an option. Since a large share of the grid fees is assigned to the DSO, this would enable the local grid operator to react flexibly to local congestion situations. Thresholds and prices can be dynamically adjusted depending on the actual grid state. The introduction of variable grid fees with a ToU structure, beginning in 2025, can be considered a first step.

New components For increased spreads and, therefore, additional leverage, it can be helpful to include additional components that incentivize behavioral changes. Several variants have been proposed [67, 68].

This new price component is denoted as the flexibility component. Usually, it is adjusted based on current flexibility demand. To pose an incentive for increased consumption, it can be 0 or negative; to cause a reduction of consumption, it is positive and therefore increases the price per unit of energy.

Therefore, with this instrument being regulatory possible, virtually arbitrary energy prices could be defined by the energy supplier or the grid operator. Given the assumption that there is the same flexibility demand in both directions, this could be designed revenue-neutral for the grid operator [68].

With the usual approach to a flexibility component system, it is impossible to include demand charges for utilizing flexibility potential. This might require another new component with the goal of a smoother consumption behavior. To avoid additional financial burdens for customers, other components might be reduced. This could be applied as an instrument to avoid load peaks in critical situations.

4.2.4 Summary

The analyses show that in the current regulatory setting, only the amount for procurement and sales of the energy supplier can be designed in a variable and flexible way to pose an incentive for residential customers for behavioral changes. This evinces two main disadvantages: the potential spread is restricted by external factors, and other stakeholders in the energy system have no means of influencing the final retail prices.

Possible improvements to the system include three different approaches. The first one is the regulatory introduction of price signals from other stakeholders to the energy supplier, providing an opportunity for, e.g., grid operators to react to their specific requirements. This could also be achieved by the flexible design of further price components like grid fees. As a last option, implementing new price components, e.g., a flexibility bonus, yields the highest flexibility for customized rate structures. Therefore, further development of the regulatory environment in one or more of these directions is recommended to tap the full potential of residential flexibility in the electricity sector.

4.3 Survey

This section is partially based on previously published work by the author [69].

4.3.1 Scope

For the simulation of customer behavior under the effect of variable electricity prices, it is essential to model their decisions regarding rate acceptance, price interval duration, and actual load shifting. In order to determine the respective parameters for the intended target group, a survey is conducted among German customers to collect current data regarding their preferences and attitudes towards variable electricity rates, leading to input parameters for the model that characterize their behavior and participation.

4.3.2 Methodology

To obtain an overview of load-shifting potential in the residential sector, a variety of previously conducted pilot projects and studies is analyzed regarding suitable appliances and load-shifting potential first. Since these projects cover various rate structures, appliance types, and regional scopes, a survey was conducted to create reliable and recent data on the relevant parameters for the defined NLM rate and a German target group. This survey is designed as an online questionnaire with the main focus on the following areas of questions:

- Which decision criteria are relevant for the acceptance of an electricity rate?
- Which monetary savings are required per use to choose a variable rate and to shift the operation of appliances?

4.3.3 Results and Discussion

Figure 4.2 gives an overview of several field trials and research projects regarding residential DSM in the form of a bubble chart [70–94]. It shows the dependency of the overall load shifting potential (on the ordinate) to the spread between the highest price and the lowest price (converted to Eurocents, on the abscissa) which apply in the respective variable rate. The size of the bubbles corresponds to the analyzed participants, and the color represents the type of variable rate (cf. section 4.1).

The chart shows that the determined potential varies vastly among the analyzed projects. There are cases that evince no load shifting at all, whereas others lead to shifting rates of over 40 %. The majority of results lies within approximately 10 % to 30 %. This observation leads to the conclusion that the actual achieved load shifting depends not only on the price difference but also on other influences, which are not covered here.

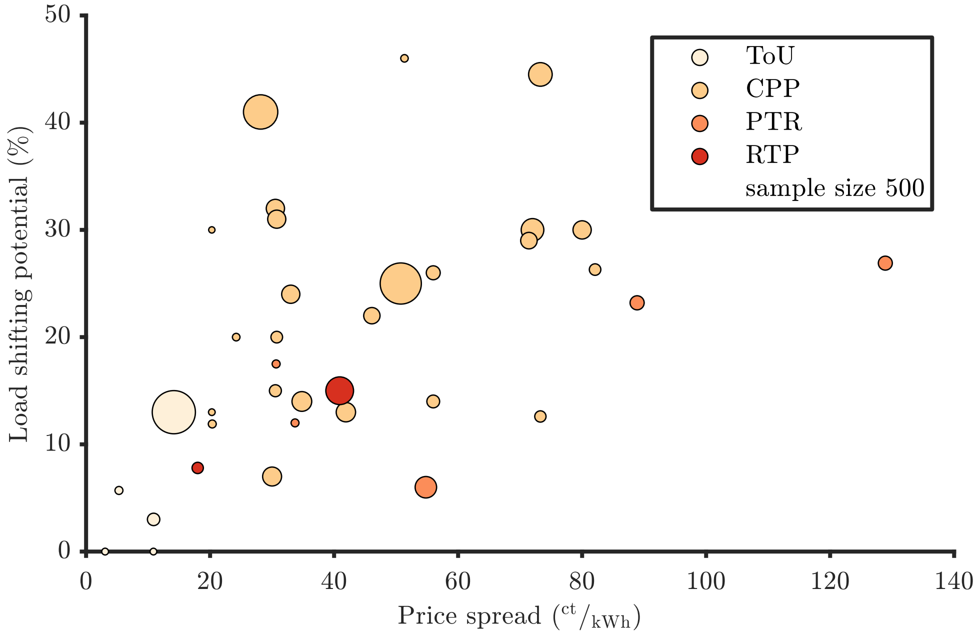


Figure 4.2: Overview of pilot projects and field trials regarding residential DSM (based on [69])

Moreover, the distribution of data points with a high number of participants also shows no clear pattern. Therefore, it cannot be deduced that outliers are caused by a smaller sample size.

However, the overall tendency suggests that higher price spreads generally enable higher shifting rates, which is in accordance with expectations. Therefore, a survey is helpful to determine this correlation with respect to the intended target group.

The sample group that is analyzed in the survey is described by some key figures in table 4.1. This shows that all relevant groups of customers concerning gender, age, and housing situation are represented in the sample group. The mean number of persons per household is slightly above the statistical mean value for Germany, which might correlate with a high share of house owners in the sample group. Nevertheless, due to the number of participants and the described coverage of relevant clusters of customers, the survey results are considered to be a reliable approximation of customers' behavior. Relevant findings for the simulation are discussed in this section.

As a first result, figure 4.3 shows the importance of several potential decision criteria for the customers' rate selection and switching process. This is implemented in the survey by a numerical rating from 1 (not important) up to 5 (very important), which allows the calculation of the mean importance per criterion within this scale.

The figure suggests that criteria regarding the structure of the potentially variable rate (integration in everyday life and comprehensible rate structure) and resulting costs (total electricity costs, price cap, potential monetary savings) are essential. Ecological factors

Number of participants	130
Male : female participants	50 % : 50 %
Age of participants	up to 25: 8 % 26–35: 19 % 36–45: 12 % 46–55: 29 % 56–65: 20 % above 65: 11 %
Mean number of persons per household	2.4
Housing situation	Owner of house: 45 % Owner of flat: 16 % Main tenant: 35 % Subtenant: 4 %

Table 4.1: Key figures about the survey sample group (based on [69])

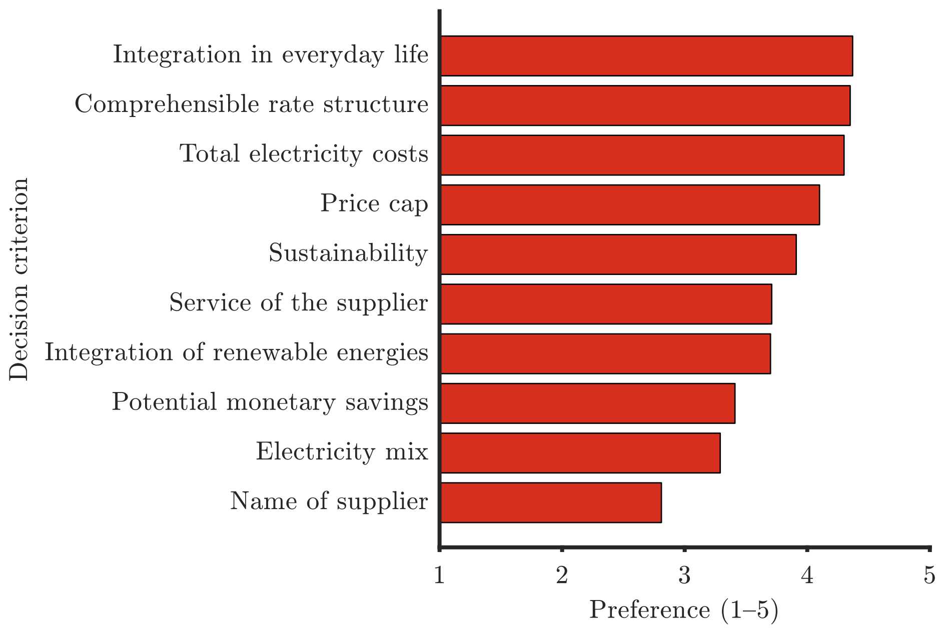


Figure 4.3: Decision criteria for electricity rates (based on [69])

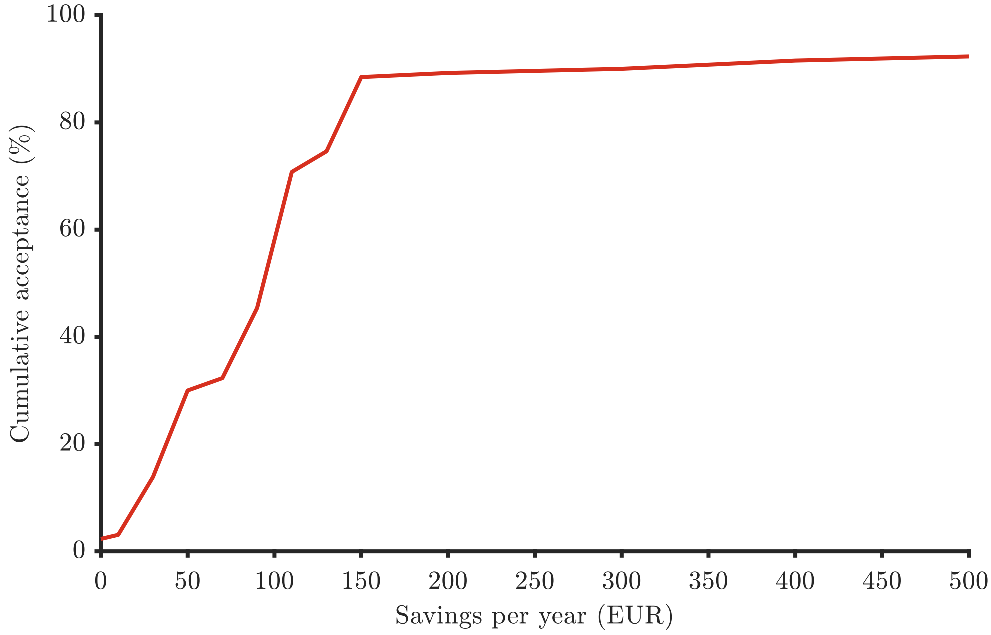


Figure 4.4: Acceptance of variable rates depending on yearly savings (based on [69])

like sustainability and integration of renewables are also considered to be important. However, according to the survey, the actual supplier is relatively insignificant for the choice. Therefore, a transparent, comprehensible, and comparable rate structure is recommended. Sustainable rate design, e.g., by procurement of renewable generation, can be a USP.

Within the defined general rate structure (cf. previous sections), both costs and integrability are represented by the parameters that are to be optimized. The resulting costs are directly affected by the normal price level, the low price level, and the spread of these two. Easy integration and a comprehensible structure are assumed to correlate with longer duration of price intervals, e.g., price intervals of 24 h require less adaptation effort than intervals of 1 min. Therefore, both of these criteria are analyzed in detail throughout the following survey questions.

The potential savings with the new, possibly variable, rate can be a decisive criterion for rate switching and acceptance decisions. Thus, figure 4.4 shows the acceptance of switching to a variable rate dependent on the expected monetary savings per year. The chart is depicted in cumulative form, which means it shows the total share of customers who are willing to switch to a variable rate with respect to their savings.

The results lead to several interesting conclusions:

- A small share of customers 2.3 % is willing to switch to a variable rate at projected savings of 0. However, as expected, the vast majority only accept "new" structures if they benefit monetarily.

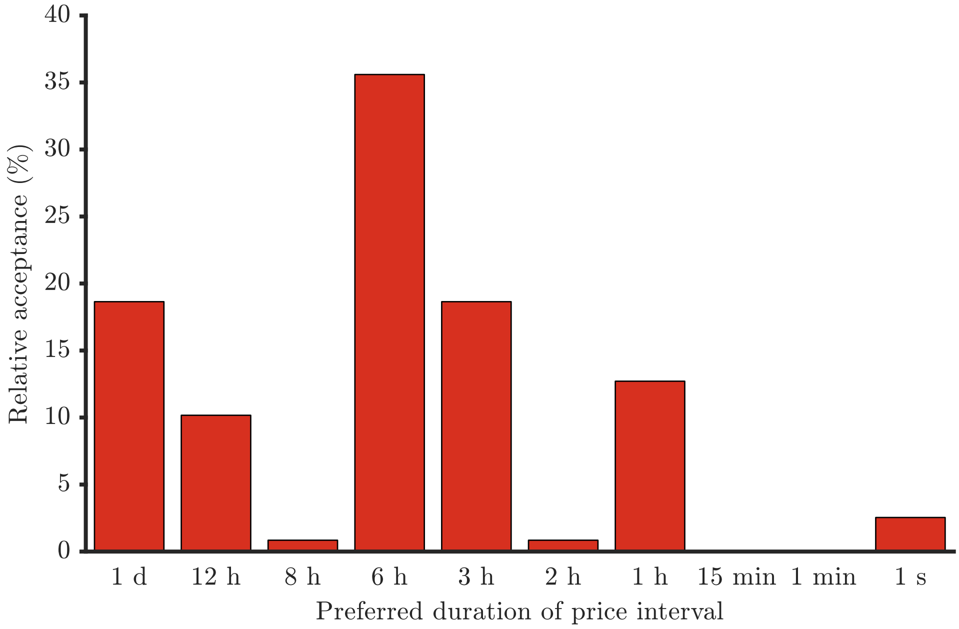


Figure 4.5: Preferred price interval duration (based on [69])

- The cumulative curve evinces a steep increase to about 150 EUR, where already 88.5 % of participants are willing to switch to the respective variable rate.

- Customers, which still reject a new rate at this value, are also unlikely to accept it at considerably higher savings since at 500 EUR, the resulting cumulative acceptance is still only 92.3 %.

The depicted data is used for acceptance analysis of modeled customers in section 5.3. Customers who do not accept variable rates even at potential savings of 500 EUR are assumed to be indifferent to variable rates and, therefore, are not expected to switch at all based on monetary incentives. Values between the grid points are interpolated linearly.

As mentioned, the second identified cluster of criteria, easy and comprehensible integration in everyday life, is affected by the rate parameter M, the minimum duration of a price interval. In order to quantify these effects, the preferred price interval duration of each participant of the survey is determined. The results are depicted in figure 4.5, in this case not cumulated.

The distribution shows that more than 95 % of respondents prefer rate structures with interval duration of at least one hour. The categories 6 h and 3 h cover over 60 % of the sample group, suggesting that attractive rate design should at least consider price interval duration in this range. Nevertheless, a considerable number of customers prefer their price to be constant for at least half a day or even a day.

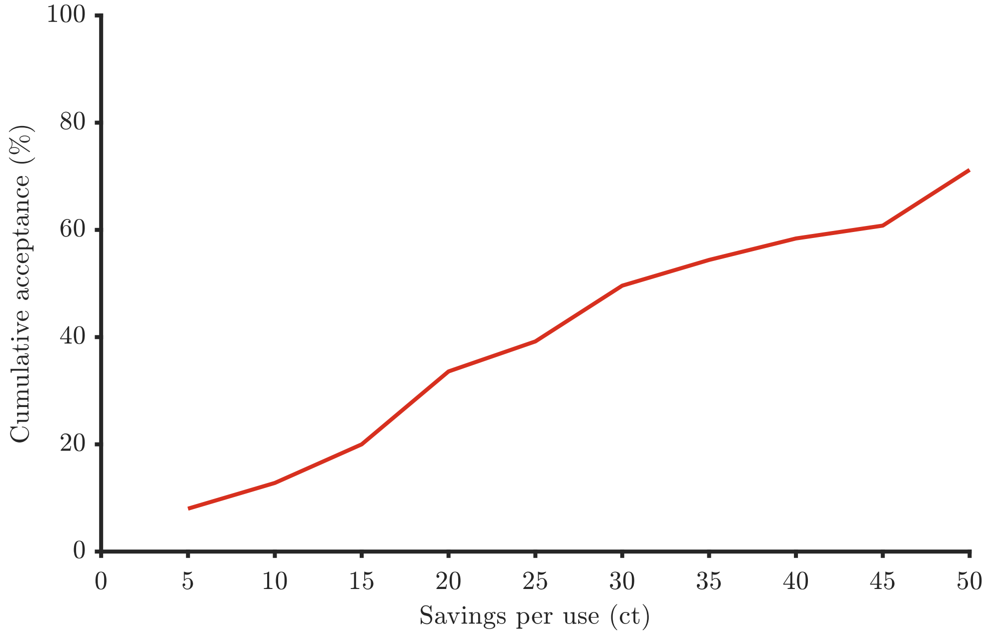


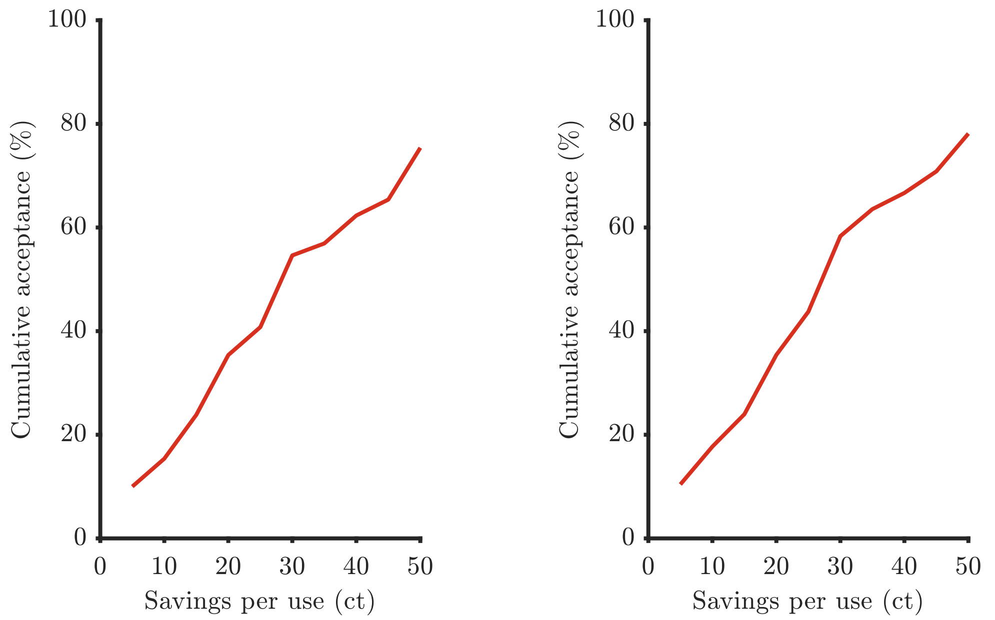
Figure 4.6: Acceptance of DSM for dishwashers dependent on savings per use (based on [69])

For utilization in the evaluations, this decision is also considered to be cumulative, i.e., customers are assumed to also accept durations above their chosen answer. As an example, a customer with a preferred duration of 6 h is assumed and modeled to also accept price interval durations of more than 6 hours. This leads to a quantified share of customers willing to accept a potential NLM rate dependent on the parameter M of this rate.

These two described coefficients allow modeling the acceptance decision of simulated agents to potential variable rates depending on the current parameters of this rate. However, the actual load-shifting measures still require sufficient monetary incentives.

This evaluation is given in figure 4.6 for dishwashers as one of the identified appliance types. Similar to figure 4.4, acceptance of shifting measures is depicted cumulatively as a function of monetary savings. The chart shows a pretty uniform increase of acceptance over savings, up to 71.2 % for 50 ct less energy costs per use. Here, the specified savings are calculated per use of the respective device.

Therefore, the implementation in the model requires translation of price spreads induced by the rate (difference between N and L) to these actual savings per use, which are additionally dependent on the device's energy consumption. Values between the grid points are also linearly interpolated here. For potential savings of 0 ct, the share of shifted appliances is assumed to be 0 % since the defined rate model solely relies on external price signals as incentives for load shifting. Customers who demand higher



(a) Washing machines **(b)** Dryers

Figure 4.7: Acceptance of DSM dependent on savings per use (based on [69])

savings than 50 cents in the survey are considered to be unwilling to participate in load-shifting measures.

Figure 4.7a and figure 4.7b show the analogous evaluation for washing machines and dryers, respectively. The overall characteristics are pretty similar to those discussed for dishwashers since they commence at about 10 % acceptance for low savings values and evince an approximately uniform increase to more than 70 %. Again, the savings are given per use of the respective appliance, so the described translation of price spreads to saving values is applied here. All further assumptions discussed for dishwashers are also utilized for these appliance types in order to convert the survey result to appropriate input data for the model.

4.3.4 Summary

The survey results show that the general acceptance of variable rates depends on simple rate design and monetary benefits for the customer. Closer inspection of these criteria with respect to the defined rate parameters suggests that a majority of respondents are generally willing to accept variable rates and also to adapt their behavior accordingly, provided that the structure complies with their preferences regarding price spreads and interval duration. Thus, the survey evaluation yields input data for the modeling process described in section 5.2.

5 Modeling of DSM and Optimization of Rate Parameters

5.1 Aggregate Potential Estimation

This section is partially based on previously published work by the author [69].

5.1.1 Scope

The previous chapters described both the data basis and the additional assumptions required for modeling the potential benefits of residential DSM regarding curtailment measures. In the subsequent sections, these effects are modeled in detail on an individual appliance level and in high temporal resolution. However, to get a first estimate of the overall potential of a nationwide implementation and a general basis for plausibility checks, the effects are simulated on an aggregate level first. This allows evaluation of the general concept and yields preliminary results about the usefulness of the described pricing approach.

5.1.2 Methodology

5.1.2.1 Load and Curtailment Data

For modeling potential residential DSM measures, aggregate load curves for the residential sector are calculated based on the load profiles that are determined in section 2.2. By concatenating the daily profiles dependent on the type of day and on the season, load curves for a whole year are constructed. The described distribution of the time-resolved total load to different types of appliances can also be extended from daily profiles to yearly curves. This yields the possibility of approximately determining the potentially flexible share of the residential load.

As previously explained, these resulting load curves are normalized. Simulations within this section are spatially resolved based on the grid regions identified in section 3.1. Therefore, the load curves are scaled to the total residential electricity consumption in the respective region, yielding an approximation of the actual consumption patterns per region. Since this procedure is applied to both the flexible and the inflexible components of the load curve, the total flexible load per time step can be determined.

Since the underlying load profiles are calculated in a temporal resolution of 15 min (cf. section 2.2), the model employs the same resolution. Although curtailment data are available in higher resolution, calculations on this level are not reasonable here since no additional precision is to be expected. Therefore, curtailment data are converted to values in time steps of 15 min by calculating the mean value per respective interval. Due to this averaging process, the results can be considered an upper estimate of the actual potential since peaks below the resolution are not represented.

In order to determine the potential for reducing curtailed energy based on the acquired data regarding curtailment measures and consumption profiles, it is assumed that load reduction is generally possible without causing additional curtailment. This simplification is necessary since data for a more precise mapping are not available. Again, the results are thus regarded as an upper estimate since this assumption is not generally valid in actual grid situations.

5.1.2.2 DSM measures and Curtailment Reduction

The general methodology for modeling DSM measures is based on the assumption that flexible load from time intervals with price N is shifted to time intervals with price L. Here, the shifting process is modeled per day without considering a maximum accepted shifting period and also without the possibility of shifting between days. These simplifications are justified due to the simulation of a very large number of households per region. Nevertheless, this again contributes to interpreting the results as an upper estimate.

As already described, the electricity grid within the regions is not considered. Therefore, it can be assumed that load increase in intervals with active curtailment reduces the amount of curtailed energy accordingly. This is yet another reason for interpreting the result as an upper estimate since, in some cases, this can be prevented by congestion in the distribution grid. However, as already mentioned, this effect is not expected to be substantial [37]. Flexible load is reallocated optimally to L-intervals, i.e., in a way that covers as much curtailed energy as possible. Since no individual appliances with a fixed duration of operation are considered, this optimal allocation can be implemented on independent time steps. Thus, the total possible reduction results on the one hand from the flexible share of the calculated load curve and on the other hand from the total amount of curtailed energy on the respective day.

Since the goal here is to approximate the total potential for curtailment reduction with the identified rate structure, the price spread between N and L intervals is assumed to be large enough for all customers, which complies with all previously mentioned assumptions in terms of getting an upper estimation of the potential. The parameter

M, representing the minimum duration of price intervals, is varied to get an indication of the effects depending on the curtailment characteristics of different regions.

The rate levels for each day are determined based on curtailment data. It is assumed that these are known precisely in advance. In reality, a slightly lower effect can be expected due to forecasting inaccuracies. As described in section 4.1, the lower price level L applies to all intervals with active curtailment. No upper bound on the total duration of L-intervals is applied.

5.1.2.3 Parametrization

In order to assess the influence of accepted DSM measures, four assumptions regarding the flexible load are compared. A1 represents the assumption that the total consumption of flexible appliances (i.e., washing machines, dryers, and dishwashers) is flexible and shiftable. For A2, the flexible load is reduced to the ratio, which is generally accepted according to the survey in section 4.3, assuming a price spread that is large enough. Due to the representation of survey results, this is considered the reference scenario. For simplified estimation of lower acceptance, A3 and A4 assume that this share is further reduced to $^2/_3$ and $^1/_3$, respectively.

For the examination of the required resolution of price intervals, M is varied from 15 min over 1 h, 2 h, 4 h up to 6 h. Higher values are not considered since they would cause implausible results due to the day-by-day model structure.

5.1.3 Results and Discussion

5.1.3.1 Regional Characteristics

The simulation result for minimal M under assumption A2 is depicted in figure 5.1, which is subsequently considered the reference case for this section to evaluate differences in reduction potential. For every region with available curtailment data (cf. section 3.1), the relative reduction potential is represented by the coloring of the region. The relative reduction potential is defined as the amount of curtailed energy that can be avoided by the modeled DSM measures divided by the total curtailed energy in the respective region. As a first observation, the map evinces substantial regional differences regarding this indicator. The relative potential varies from 0.4 % up to 100 %, i.e., a complete avoidance of curtailment necessity due to DSM measures. For comparison of the assumptions, figure 5.2 shows the regional difference in relative reduction potential between A4 and A2. This shows that most regions evince low differences below 20 % between the assumptions, especially those with very high or very low reference (A2) values. Relevant differences due to the reduced flexibility potential under A4 are observed for mid-range regions since these are comparably affected more by changes in flexibility potential.

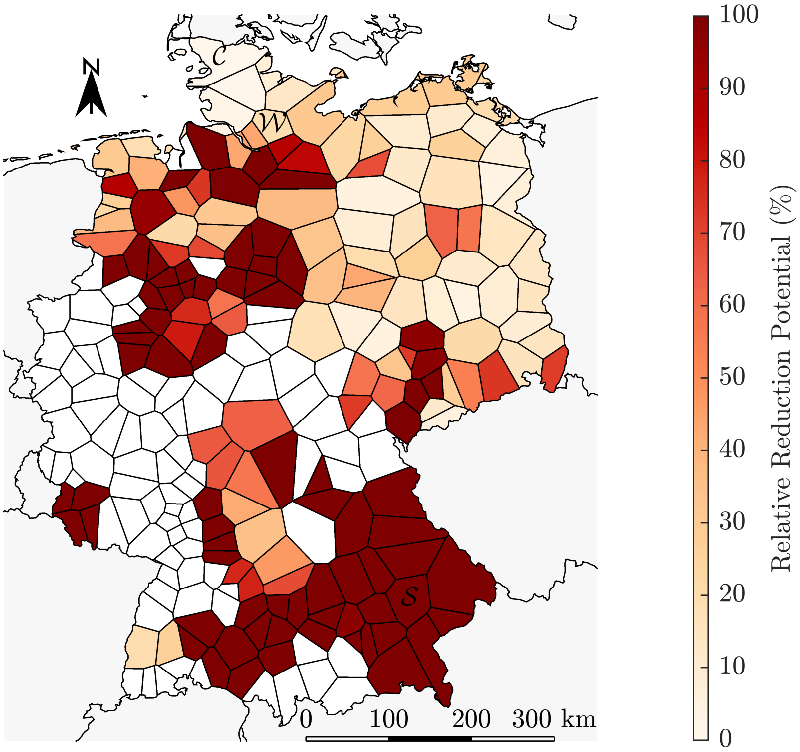


Figure 5.1: Relative curtailment reduction potential per region, A2, $M = 15\,\text{min}$ (reference case)

Assumption	Relative Reduction(%)
A1	5.0 %
A2	4.6 %
A3	3.3 %
A4	2.1 %

Table 5.1: Relative curtailment reduction for $M = 15\,\text{min}$

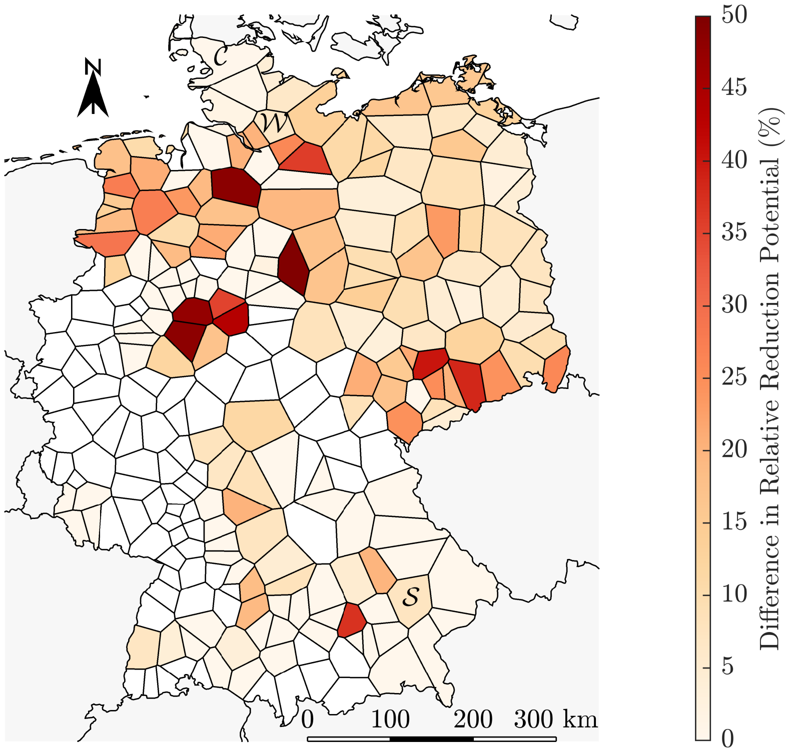


Figure 5.2: Difference in relative curtailment reduction potential per region, A4, $M = 15\,\text{min}$, compared to reference case

Comparison with the total curtailed energy depicted in figure 3.1 shows that these differences are mainly caused by the amount of curtailed energy, leading to the conclusion that residential consumption and, thus, the amount of flexible load per region is only a minor influence. Therefore, detailed analyses of selected regions are essential for valuable results. Overall, A2 leads to a nationwide curtailment reduction of 4.6 %. The respective values for different assumptions are given in table 5.1. Two main findings can be deduced here:

- The difference between the total flexible load (A1) and the accepted flexibilization (A2, reference case) is rather small. In contrast, the effect of further reduction of the assumed potential in A3 and A4 reduces the overall benefits considerably. Thus, rate design, which leads to high acceptance among the participating households, is crucial for the whole approach.

- In the optimal case, the achievable curtailment reduction is a low single-digit percentage. Therefore, no real decisive contribution to the whole energy system can be expected, but the effect is nevertheless non-negligible.

5.1.3.2 Detailed Analysis of Focus Regions

A detailed analysis of daily curtailment values and potential reduction for region $\mathcal{C}$ under A2 is depicted in figure 5.3. The chart displays one bar per day, which represents the total curtailed energy in the respective region on this day. In order to visualize both range and distribution, these bars are sorted by magnitude. The calculated potential reduction of curtailed energy compared to the residual amount, which the simulated measures cannot avoid, is shown by the color of the bars. Depending on the region, only one of the two colors might be visible in the graphical depiction.

It shows that almost every day of the year (332 days) evinces curtailment measures, totaling to 1.3 TWh. About half the year (180 days) evince over 1 GWh curtailed energy per day, with a range of up to 25 GWh. The potential relative reduction, as already apparent from figure 5.1, is very small. Most days evince no visible reduction since only 12 days allow a reduction of more than 0.1 GWh, whereas 154 days evince a non-zero value below this threshold. However, the total amount of potentially avoidable curtailment sums up to 5.2 GWh, leading to a relative reduction potential of 0.42 % for A2.

Figure 5.4 depicts the effects of varied flexibility assumptions. Similar to the values in table 5.1, the difference between A2 (accepted DSM) and 0.48 % for A1 (total flexible load) is relatively small. However, further decreased flexibility for A3 and A4 lead to a considerable, approximately linear reduction of the calculated potential.

Figure 5.5 shows analogous charts for region $\mathcal{S}$. Here, the overall number of affected

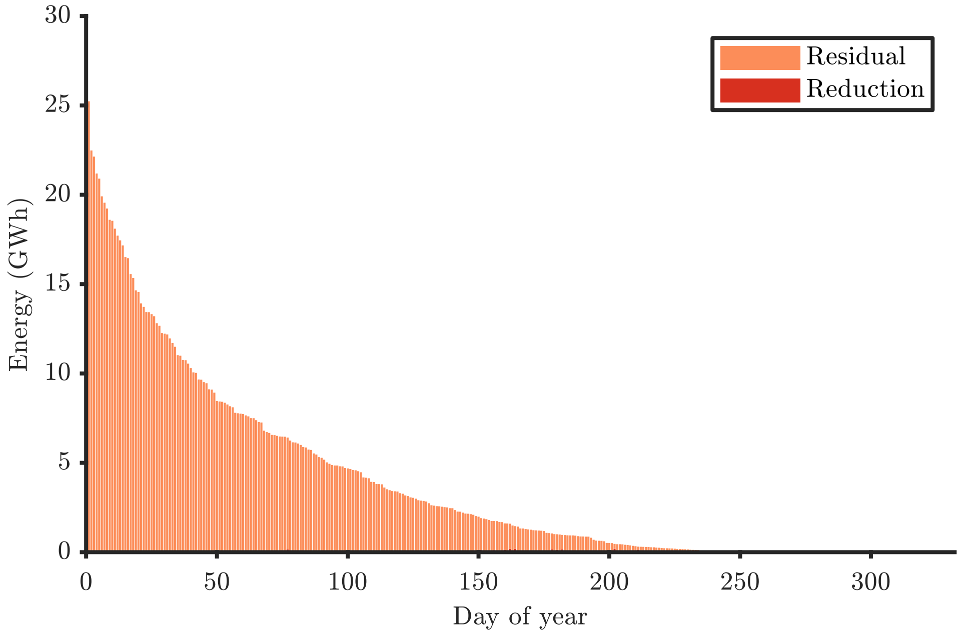


Figure 5.3: Sorted daily curtailment reduction potential for region $\mathcal{C}$, A2

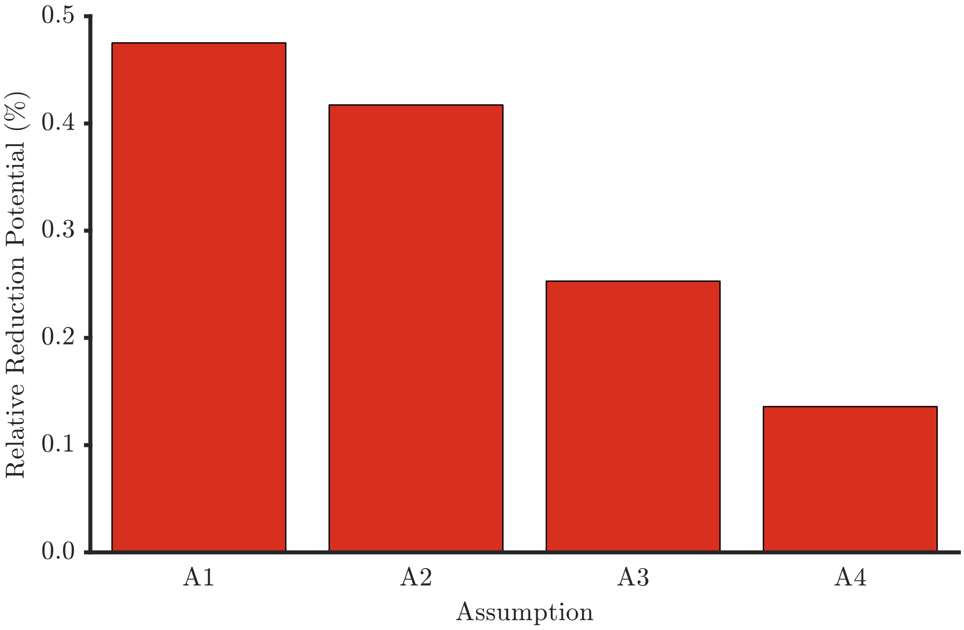
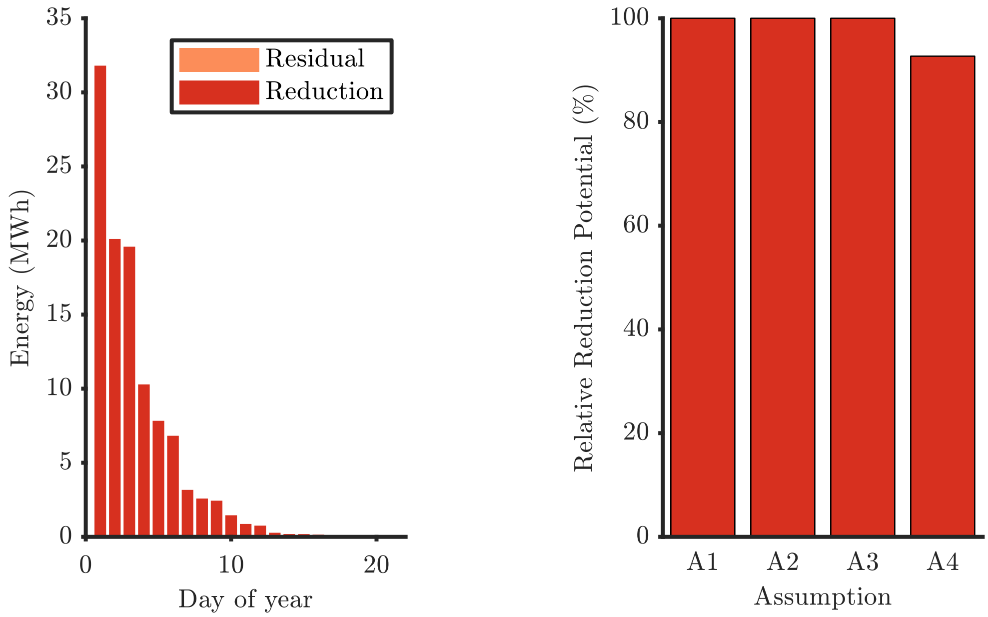


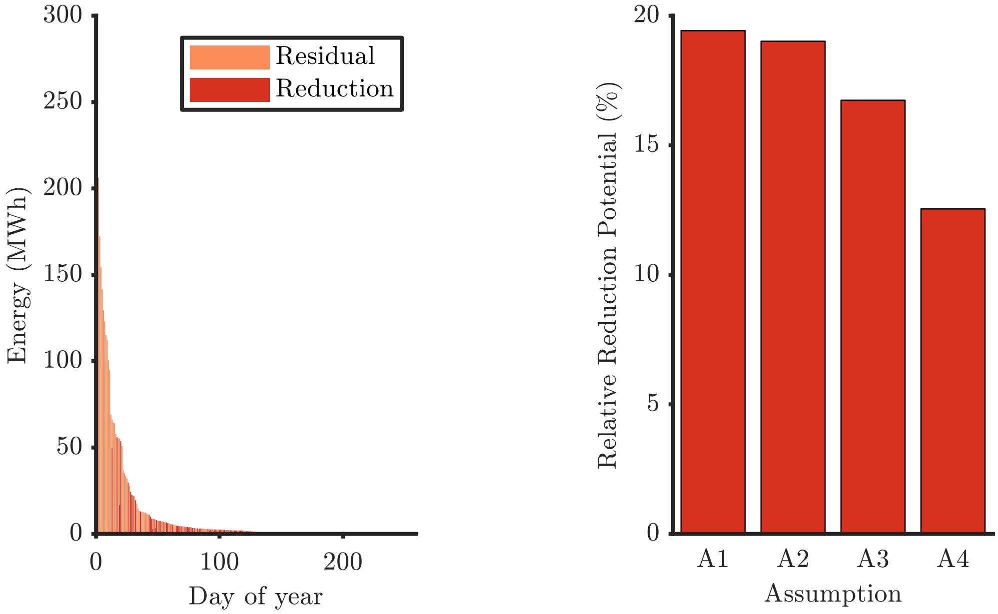
Figure 5.4: Relative curtailment reduction potential for region $\mathcal{C}$



(a) Sorted daily reduction, A2

(b) Relative reduction

Figure 5.5: Curtailment reduction potential for region $\mathcal{S}$



(a) Sorted daily reduction, A2 **(b)** Relative reduction

Figure 5.6: Curtailment reduction potential for region $\mathcal{W}$

days, i.e., bars in figure 5.5a, is comparably low with 22. The figure also shows that for all days, the total amount of curtailed energy can be avoided by DSM measures. Therefore, this region's total value of potential curtailment reduction amounts to 0.11 GWh.

As expected, the comparison of assumptions in figure 5.5b shows that total usage of the flexibility potential (A1) does not affect the relative reduction potential since A2 already achieves 100 % reduction. This is still possible for A3, whereas A4, i.e., utilization of only 1/3 of the accepted potential, evinces a slight reduction to 93 %. This shows that for regions with few required curtailment measures and small amounts of curtailed energy, the actually utilized share of flexibility is comparably insignificant since A4 still avoids over 90 % of curtailment. A second finding is that regions with very high values in the relative perspective, e.g., depicted in figure 5.1, affect the overall reduction only slightly since high relative values correlate with small absolute amounts of curtailed energy.

For the third focus region $\mathcal{W}$, the analyses are given in figure 5.6. Here, on 259 days of the year, a total amount of 3.0 GWh is curtailed, with daily values of up to 0.26 GWh. Nevertheless, only 42, i.e., a minority of days exceed 10 MWh. This allows a total reduction of curtailment for a large number of days (195) and a partial reduction for several more but shows that the residential contribution is insufficient for days with high curtailed energy. This is in accordance with the results for region $\mathcal{C}$. Overall, this leads to a potential reduction of 0.57 GWh and, therefore, a relative reduction of 19.0 %.

The assumption-dependent evaluation shows similar characteristics as identified before for region $\mathcal{C}$. The additional flexibility, which could be assumed for A1, facilitates

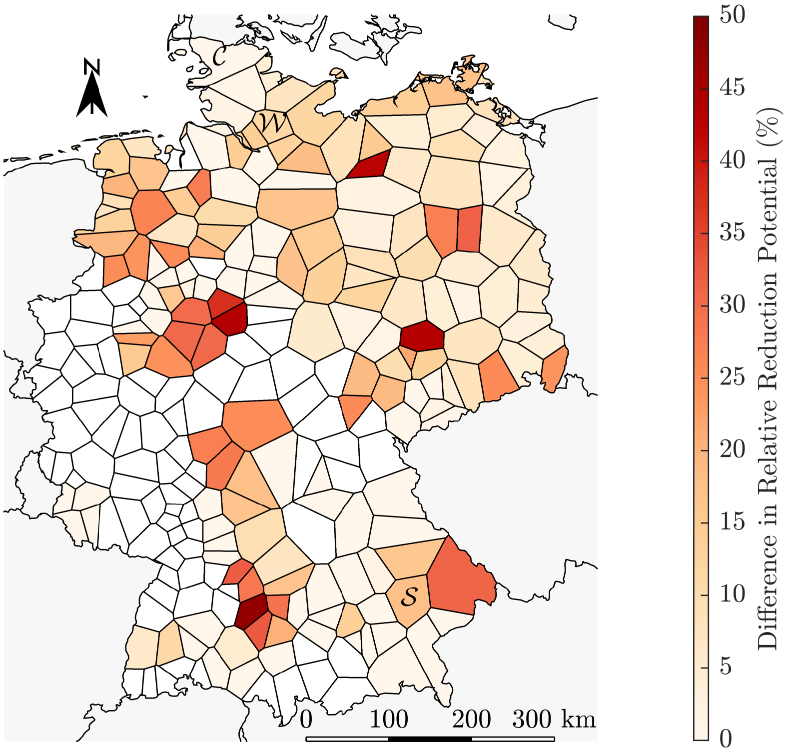


Figure 5.7: Difference in relative curtailment reduction potential per region, A2, $M = 6\,\mathrm{h}$, compared to reference case

only a minor increase to 19.4 %, whereas the reduced scenarios evince considerably less potential.

In summary, these analyses show that the individual potential for curtailment reduction is highly dependent on the regional characteristics and amounts of curtailed energy and also on the assumed flexibility potential in the residential sector.

5.1.3.3 Rate Structure

Previous analyses within this section assumed optimal reallocation of flexible load in a quarter-hourly grid. Since the chosen NLM rate depends on M, defining the minimal duration of price intervals, the achieved flexibilization can also be smaller for higher values of M. Figure 5.7 exemplarily shows this dependency for $M = 6\,\mathrm{h}$, compared to the previously displayed reference case in figure 5.1. As before, assumption A2 is applied for the displayed evaluation.

The map suggests a rather small effect of different M-values. For many regions, the relative potential is only slightly reduced. However, in some cases, especially in the middle and higher range of relative reduction potential, the resulting potential is clearly affected and reduced by an increase of M. As before, a detailed analysis of selected

M	Relative Reduction(%)
15 min	4.6 %
1 h	4.3 %
2 h	3.9 %
3 h	3.5 %
6 h	2.7 %

Table 5.2: Relative curtailment reduction for A2

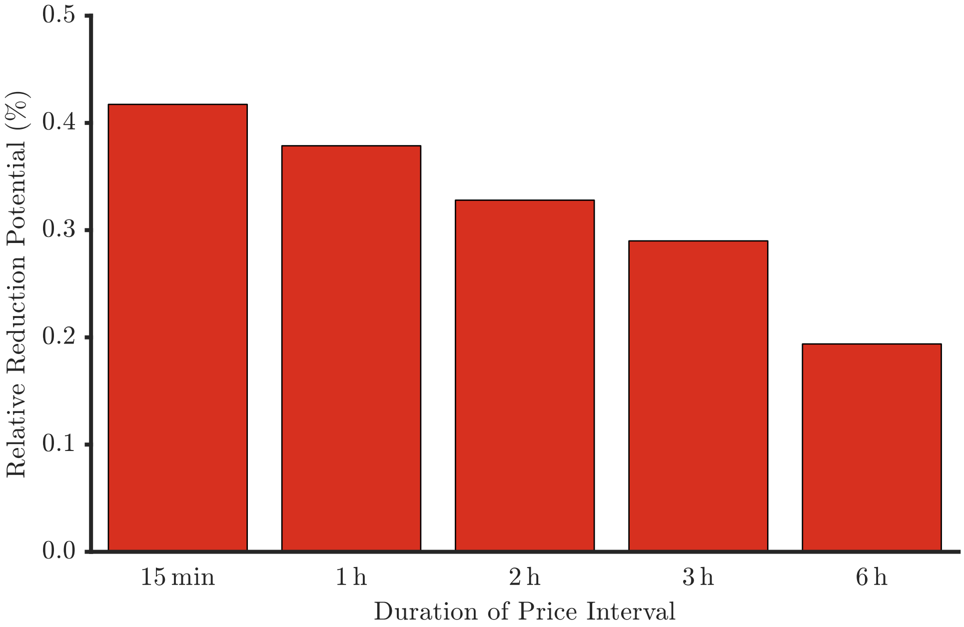
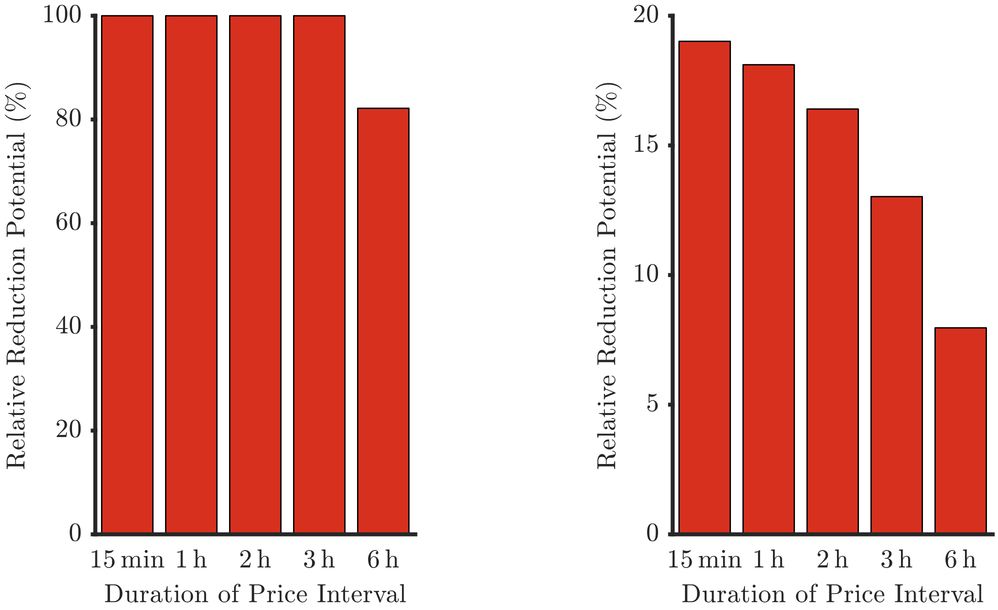


Figure 5.8: Relative curtailment reduction potential dependent on M for region $\mathcal{C}$

focus regions seems appropriate for further insights. On a nationwide scale, the achieved relative reduction of 4.6 % for $M = 15$ min changes as given in table 5.2. Higher values for M are not considered here since no useful results can be expected due to the day-based modeling. The table shows that overall, a 6 h grid for price levels would cause a decrease of potential by approximately 40 %. However, the survey results (cf. figure 4.5) show that higher values lead to generally higher acceptance. This confirms the importance of M as a rate design parameter.

The dependency of relative reduction potential from M for the region with the highest curtailed energy $\mathcal{C}$ is depicted in figure 5.8. The chart suggests an approximately linear descent of relative reduction potential with interval width, from 0.42 % in the base case down to 0.19 % for the maximal value of $M = 6$ h, leading to an approximate halving of the potential due to adjusted interval width.

Analogous charts for the other focus regions are given in figure 5.9. In region $\mathcal{S}$, the relative reduction potential is not affected up to 3 h. As already pointed out, the flexibil-



(a) Region $\mathcal{S}$ **(b)** Region $\mathcal{W}$

Figure 5.9: Relative curtailment reduction potential dependent on M

ity potential is high enough compared to the necessary curtailment, so additional slight restrictions are not visible in the results. Only for $M = 6\,\text{h}$, a reduction by about 20 % is observed.

By contrast, region $\mathcal{W}$ (figure 5.9b) again shows quite a strong correlation between interval duration and relative reduction. The relative potential decreases from 19.0 % for 15 min to 8.0 % for 6 h. Thus, the region-specific charts support the previous observations.

5.1.4 Summary

The described model for assessment of the effects of potential residential DSM measures on the curtailment of renewables on an aggregate level proves helpful for an approximate indication of the viability and utility of the general flexibilization approach. It allows for simulation of the expected effects on a regional level based on load profiles of flexible appliances, assumptions about their utilization, and historical data about curtailment measures. The results are considered to be plausible and explainable.

Estimating the relative reduction potential of curtailment on this aggregate level shows clear differences between the defined regions. In regions with high amounts of curtailed energy, the absolute potential is considerably higher, as observed for regions $\mathcal{C}$ and $\mathcal{W}$; however, depending on the assumptions, only 0.14 % to 0.48 % curtailment reduction can be achieved for region $\mathcal{C}$, and 8.0 % to 19.0 % for region $\mathcal{W}$. The comparison to region $\mathcal{S}$

shows that under given assumptions, no curtailment would be necessary if DSM measures were implemented as described. Here, the differences between assumptions are almost negligible.

Similar observations apply also to the sensitivity analyses regarding the rate parameter M, which defines the minimum duration of a price interval. Regions with low total curtailment, such as region $\mathcal{S}$, are considerably less affected than regions with medium or high amounts, like regions $\mathcal{W}$ and $\mathcal{C}$, respectively. However, since regions with high curtailment also present high absolute potential for reduction and, therefore, more contribution to the total relative reduction of curtailment, a suitable choice of M is essential for viable results.

In summary, the presented results indicate that residential DSM can contribute considerably to the reduction of curtailment and therefore, to the increased integration of renewable generation. Thus, detailed investigations on the level of individual households and appliances and in higher temporal resolution are reasonable for more precise results. These are given in the subsequent sections.

5.2 Modelling of Individual DSM Potential

5.2.1 Scope

As described in the previous section, the simulation of the potential contribution of residential flexibility to reducing curtailment requirements with an aggregate model shows that the discussed approach can be beneficial. In order to improve the quality and precision of the results, the following section presents an alternative methodology for modeling flexible customer behavior based on individual load curves and appliances. Due to the more detailed data basis, this also allows for refining the temporal resolution.

Therefore, this leads to the following objectives for this section:

- Development of a model for load-shifting processes of household appliances based on measured load data
- Application of this model to calculate the potential reduction of curtailment
- Definition of realistic model parameters
- Sensitivity analyses of influence factors

5.2.2 Methodology

5.2.2.1 Load and Curtailment Data

Analogously to the simplified model in the previous section, the data basis for modeling curtailment measures is deduced from historical data for the year 2018 as described in section 3.1. In contrast to before, the generated time series of curtailed energy with a temporal resolution of 1 min remain unchanged here since this matches the model resolution of the individual DSM model. The previously described regional partitioning according to proximity to grid nodes is also applied here.

The consumption patterns are modeled based on the load curves described and analyzed in section 2.3. These are also available in a temporal resolution of 1 min and thus allow the development of the whole model in this resolution, leading to a more detailed representation of both consumption patterns and the potential effects of flexibilization on the consumption side. In order to extrapolate conclusive results from the available data set, the extracted representative sample of households, which is constructed to meet statistically collected data for Germany, is used here.

For the simulation of DSM measures, i.e., load shifting of individual household appliances, the identified operation times and load profiles of relevant appliances are applied. These allow to individually reallocate the electricity consumption caused by said appliances based on the influences considered in the model, such as price differences and acceptance parameters of the simulated customer. Consequently, these data are also reduced to the approximately representative sample as described.

5.2.2.2 Parametrization of Agents

Every modeled household, denoted as an agent in the simulation, is described by three parameters that define its behavior towards load shifting of considered appliance types. These parameters represent the minimal monetary savings the respective agent demands to shift the specific appliance type, i.e., dishwasher, washing machine, and dryer. Since these requirements differ between the appliance types according to the discussed survey (cf. section 4.3), the behavior cannot be reasonably modeled with a single threshold value but requires distinction by appliance type.

These three parameters are deduced from the survey and represent the distribution gathered from these results. Since the 100 load patterns of the extracted sample differ considerably regarding present appliances and individual consumption behavior, the sensible matching of survey data and load data to define one of 100 agents is crucial for helpful results. In order to define this matching, a large number of calibration simulations have been carried out with random configurations, i.e., randomly permuted assignment of price thresholds according to the survey and load data. These calibration simulations cover all regions and a variety of rate parameters in order to achieve meaningful results. The potential reduction of curtailed energy (cf. subsequent sections) is calculated for each configuration since this is the most relevant indicator in the subsequent application of the model and, therefore, is chosen as the criterion to identify a representative configuration.

Since the "true" configuration or the actual reduction of curtailed energy is unknown, the median value of the calculated reduction is chosen as an approximation for the expected outcome. Therefore, the configuration that meets the median value best over all simulated parameter sets is chosen as a basis for all subsequent simulations and considered roughly representative of the given purpose.

5.2.2.3 Modeling of Load Shifting Processes

In section 4.1, the applied NLM rate structure, characterized by three parameters N, L, and M, is deduced and explained. This structure also applies to the simulations in this section. Therefore, time series of prices can be constructed from given curtailment data and these parameters for each region. In accordance with the model structure, these time series are generally defined in a resolution of 1 min. All calculations are carried out for one year.

For the simulation of the load-shifting processes, every agent is handled individually. For each identified usage of an appliance, the costs for the operation are calculated from a customer perspective. These costs are given by the sum over the product of energy consumption and energy price per minute of operation. This baseline is used to evaluate potential savings achieved by the shifting process.

Within a specific shifting interval, i.e., the time window that is assumed to be acceptable for load shifting, the potential costs for operation are calculated for all possible starting points. This can be illustrated by moving the load profile of the appliance minute by minute through the shifting interval and evaluating the costs that would apply for every possible position. The difference between baseline costs and potential costs at this position defines the potential savings that can be achieved by shifting.

In case these savings reach or exceed the individual threshold value of this agent for the respective appliance type, load shifting of this appliance usage is assumed. The shifted position is defined by the minimum resulting costs of operation, i.e., the maximum savings for the agent. Positions where the same appliance type is already in operation are excluded to prevent implausible results with, e.g., two dishwashers running simultaneously while only one is present in the respective household.

Due to the given rate structure with two price levels, in the general case, several possible positions meet this criterion of minimum costs. In that case, one of the possible positions is chosen randomly in order to reflect the potentially unknown behavior of home energy management systems. This introduces an additional probabilistic element to the simulation, potentially affecting the results.

5.2.2.4 Evaluation of Potential Curtailment Reduction

The potential reduction of curtailed energy is calculated analogously to the previous section. This means that an increase in consumed energy within a particular region in a time interval with active curtailment is assumed to reduce the curtailment by the amount of additional consumption, whereas the decreased consumption in other time intervals does not affect the necessity for curtailment.

As explained before, this is a slightly simplified approach, which is necessary due to restricted data availability and to maintain a feasible computational effort. Thus, the results are still considered an upper estimate while presumably closer to reality than the aggregate simulation before.

5.2.2.5 Handling of Probabilistic Model Structure

In order to deal with the probabilistic model structure, the calibration simulations mentioned above are evaluated regarding the effects of random positioning of appliance operation. Repeated simulations with identical parameters evince a distribution of results regarding the potential curtailment reduction. As before, the median value of relative curtailment reduction over a large number of simulations is chosen as an indicator.

The calibration simulations show that comparably few repetitions allow approximating this median value quite well. Since the overall simulation is computationally very intensive and will become even more complex (cf. section 5.3), this is crucial for maintaining a feasible runtime of the model. The evaluations show that 10 repetitions are necessary to approximate the median value of relative curtailment reduction to a deviation of less than 0.05 with a probability of more than 95 %.

This precision is considered sufficient for the described application; therefore, all subsequent evaluations of curtailment reduction will be repeated 10 times. Since the optimization procedure in section 5.3 requires more data than curtailment reduction, the result of this repetition process is not calculated just by taking the median value but by choosing the simulation result that meets the median value best. This allows for additional output of the “median” resulting load curve.

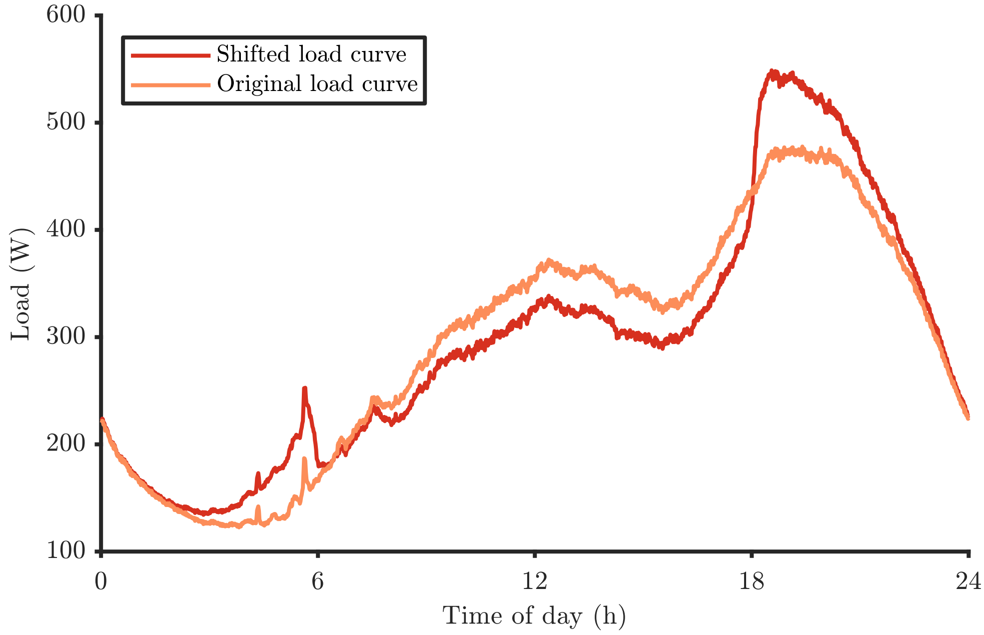


Figure 5.10: Mean daily load curve for exemplary ToU rate

5.2.3 Results and Discussion

5.2.3.1 Exemplary Time of Use Rate

Although the considered rate structure is defined as dependent on curtailment data, a simple time of use (ToU) rate is chosen here as an example for illustrative purposes to demonstrate the model capabilities and results. This rate is defined as follows:

- Two price levels as an incentive for load shifting from high prices to low prices
- A price spread of 100 ct/kWh between the levels for full utilization of the potential
- High price level from 06:00 to 18:00, low price level for the rest of the day

Since the model component, which simulates the individual load-shifting processes, can flexibly take time series with prices as an input, this rate structure can be modeled despite the fact that it does not comply with the rate structure generally considered here.

For this exemplary evaluation, a shifting interval of 6 h|6 h is assumed. This means that each individual usage of an appliance can be shifted by 6 h in both directions, i.e., the appliance can be operated up to 6 h before the original time of operation as well as up to 6 h after this time.

The simulation of load shifting based on this ToU rate results in an adjusted load curve for the modeled year. The mean daily load curve, calculated by averaging the resulting load values per minute of the day over all days of the year, is depicted in figure 5.10.

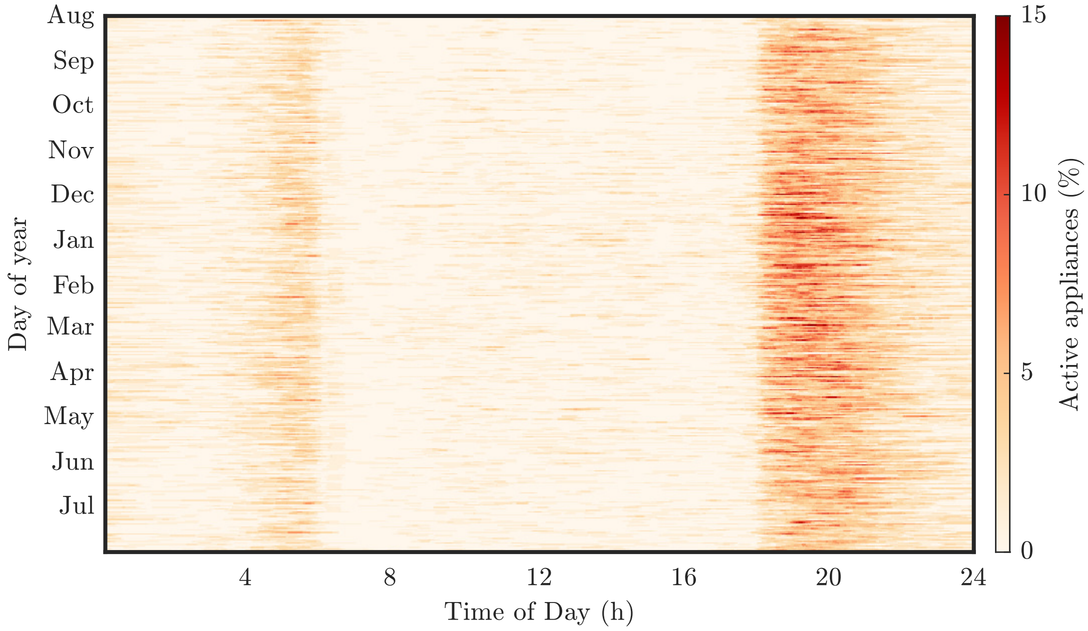


Figure 5.11: Raster plot of modeled dishwasher usage with ToU rate

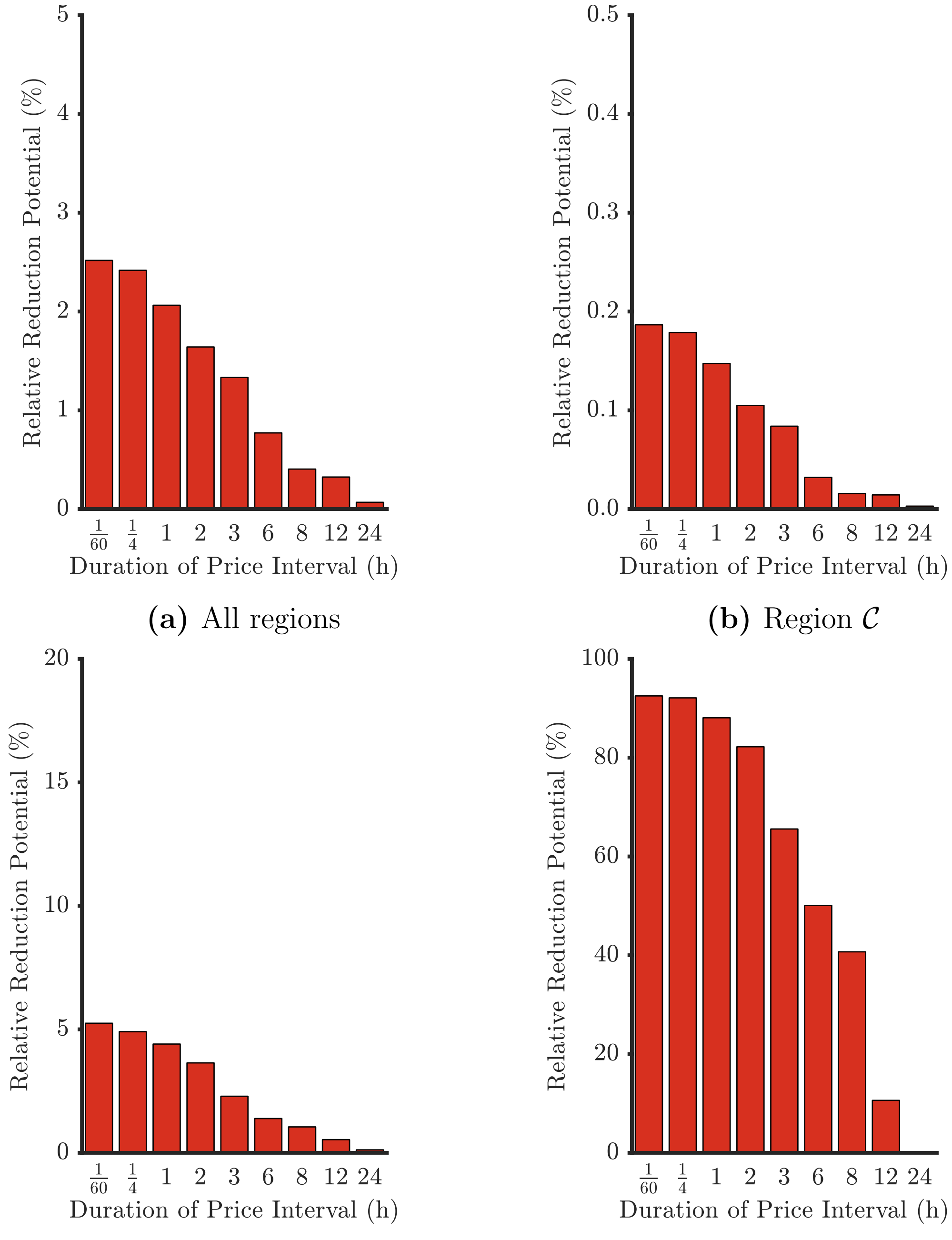
This evaluation shows the general principles of the load-shifting model. Within the time interval from 06:00 to 18:00, the load curve is decreased due to appliance operation being shifted from this high price interval. Consequently, load increase is observed in the remaining intervals, with peaks developing at the borders between high and low prices. Since the shifting interval is chosen as 6 h—6 h and the high price level is applied for a time window of 12 h, appliance usage from the high price interval can be shifted entirely, leading to considerably high differences in the resulting load curves.

These effects can also be observed in the raster plot depicted in figure 5.11. It shows the share of active appliances within the modeled sample of households per minute of the year, analogously to figure 2.10. Compared to the initial state, load decreases in the high price interval and load increases at times with low prices are clearly visible.

The chart also confirms the peaks as mentioned above, which evolve at the borders of the price intervals, i.e., at 06:00 and 18:00. Additionally, it shows that the load is shifted steadily throughout the year, so there are now observable seasonal effects. These exemplary model results show that the simulation of load-shifting processes works as expected.

5.2.3.2 Effects of Price Intervals

Applying the described methodology to the actual rate structure under investigation allows the evaluation of several influence factors on the potential contribution of the residential sector to a reduction of curtailment. As detailed before, the NLM rate structure



(a) All regions **(b)** Region $\mathcal{C}$ **(c)** Region $\mathcal{W}$ **(d)** Region $\mathcal{S}$

Figure 5.12: Relative curtailment reduction potential dependent on M

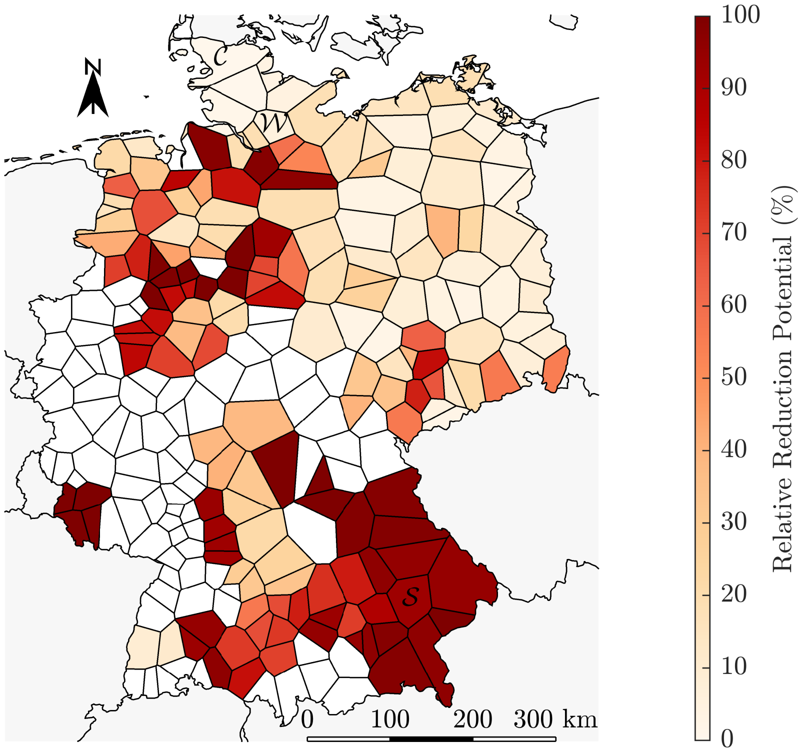


Figure 5.13: Relative curtailment reduction potential per region, $M = 1\,\text{min}$, $6\,\text{h}|6\,\text{h}$, spread $100\,{}^{\text{ct}}/_{\text{kWh}}$ (reference case)

is defined by three parameters, which define two price levels and the minimum duration of price intervals.

In order to assess the effect of this interval duration M, the price levels N and L are assumed to be $100\,{}^{\text{ct}}/_{\text{kWh}}$ and $0\,{}^{\text{ct}}/_{\text{kWh}}$, respectively, to create a maximum price spread and, therefore, to tap the full potential of load shifting in the modeled data set. The shifting interval is again set to $6\,\text{h}|6\,\text{h}$ as a good estimation of the actually accepted intervals. The relative curtailment reduction potential, given by the potentially reduced amount of curtailed energy divided by the total amount of curtailed energy, is used as an indicator for comparison.

Figure 5.12a shows overall relative curtailment reduction for the described parameter for regions modeled. It can be observed that higher values of M lead to a considerable reduction of the potential, which is in accordance with the results in section 5.1. The difference between 1 min and 15 min is relatively small, but each subsequent step, starting from $M = 1\,\text{h}$, decreases the result clearly. Price intervals with a duration of 1 d, i.e., an assignment of high or low price levels to whole days, prove not beneficial according to the evaluation.

This effect is also confirmed by a more detailed view of the individual regions in figure 5.13 for $M = 1\,\text{min}$, used as a reference case for this section, and the comparison to

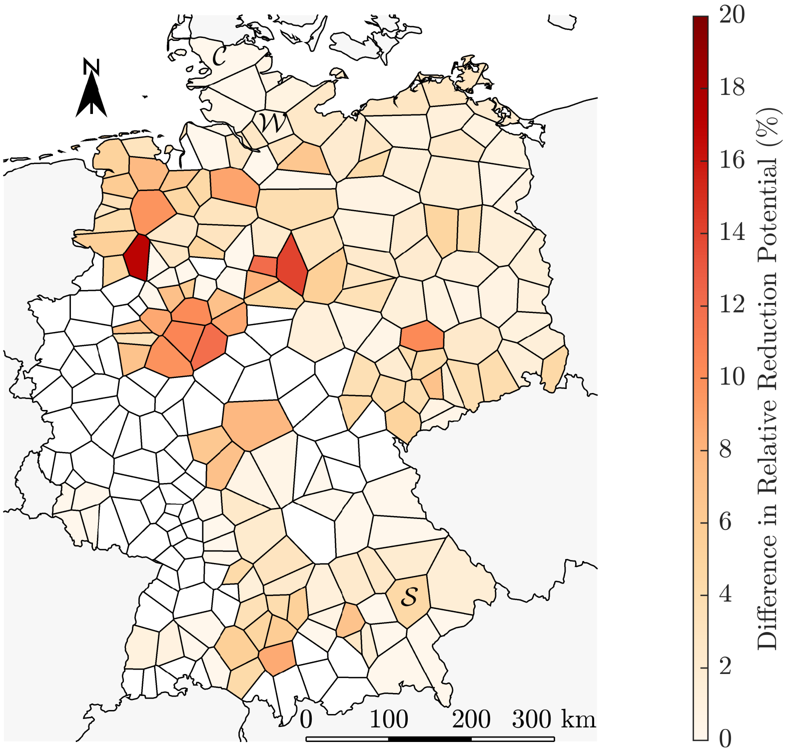


Figure 5.14: Difference in relative curtailment reduction potential per region, $M = 1\,\text{h}$, $6\,\text{h}|6\,\text{h}$, spread $100\,\text{ct/kWh}$, compared to reference case

$M = 1\,\text{h}$ in figure 5.14. Most regions evince a noticeable decrease in relative reduction potential, especially those in the middle range regarding their potential.

Regions with very high reduction potential in the first case often appear to be virtually unaffected by the parameter change, leading to the conclusion that their load-shifting potential by far exceeds the required flexibility for curtailment avoidance. Due to the color scale, the effects on regions in the very low range cannot be reasonably deduced from the map. Therefore, the previously defined focus regions will be analyzed in more detail.

The relative curtailment reduction potential for varied values of M in region $\mathcal{C}$ is depicted in figure 5.12b. It shows that compared to the baseline for 1 min, the variation of M considerably affects the resulting reduction potential. As explained, this is not visually represented in the maps due to the generally low level and the wide range of values, which is to be visualized with one color scale.

The bar plot shows that similarly to the nationwide evaluation in figure 5.12a, the transition from 1 min to 15 min is relatively small, whereas subsequent steps lead to substantially decreasing results. The observation that a daily price structure is not to be recommended can also be confirmed in this detailed analysis of region $\mathcal{C}$.

Figure 5.12c gives the analogous evaluation for region $\mathcal{W}$. It evinces a very similar pattern, only starting from a different level for the base case. Moreover, a notable difference is the comparably slight deviation between 15 min and 1 h.

As expected, region $\mathcal{S}$ shows a different picture due to the generally lower required curtailment. The first differences from 1 min up to 1 h are relatively small to negligible, and the resulting values on a generally high level, starting around 90 % relative reduction potential. This means that the detailed simulation described here still confirms the observation from section 5.1 that curtailment in this solar-influenced region could almost be entirely avoided by residential flexibilization measures.

Starting from a high initial value, the following decreases are more pronounced than for the previously analyzed regions, again confirming that a daily price structure is not helpful for the considered use case. Values of M in the range of several hours evince stronger effects on the result than for the previously depicted focus regions. However, due to the overall small contribution of this region, the effect on the total result is virtually irrelevant.

Overall, the analyses show that the parameter M considerably affects the potential reduction of curtailed energy and, thus, is to be chosen carefully. Smaller interval duration generally increases the potential contribution to curtailment avoidance, whereas larger intervals prevent the full potential from being used. These effects will also be analyzed in section 5.3.

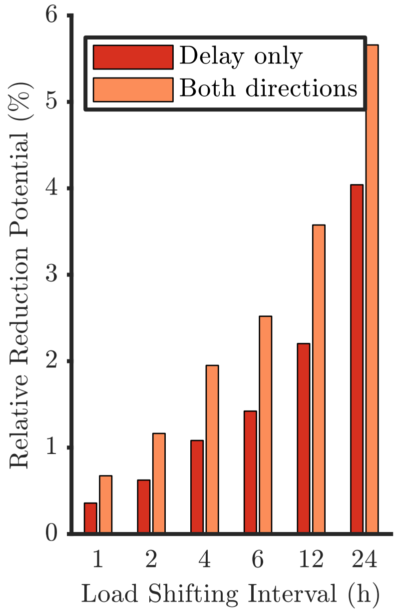
5.2.3.3 Effects of Shifting Intervals

As previously defined, the shifting interval is the time window that is assumed to be accepted and possible for DSM measures, i.e., for load shifting. Since this parameter was not covered in the survey, it is to be chosen according to previous studies. These evince a wide range of assumptions, from a few hours to days. Due to this, a value in the middle range, 6 h in both directions, is chosen as the base case, which is thus applied in the previous calculations regarding the variation of M.

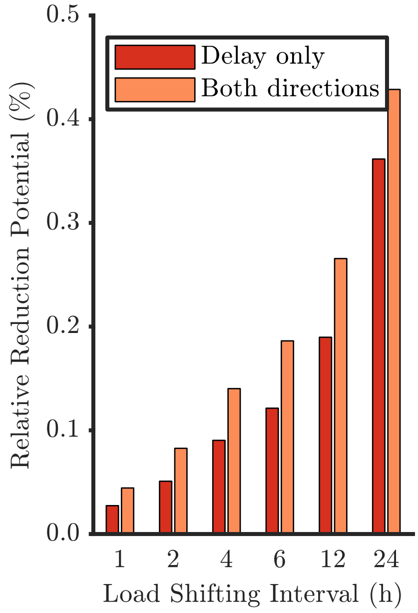
Nevertheless, the effect of smaller or larger shifting intervals is to be analyzed since it vastly affects the potential operation times of flexible appliances and, therefore, the possibilities to temporally meet curtailment measures with these appliances. For this section, M is chosen as 1 min to achieve conclusive results. For the same reason, the modeled price spread remains 100 ct/kWh.

Figure 5.15a shows the potential relative reduction of curtailment over all regions for different values of the shifting interval. Two general cases are distinguished:

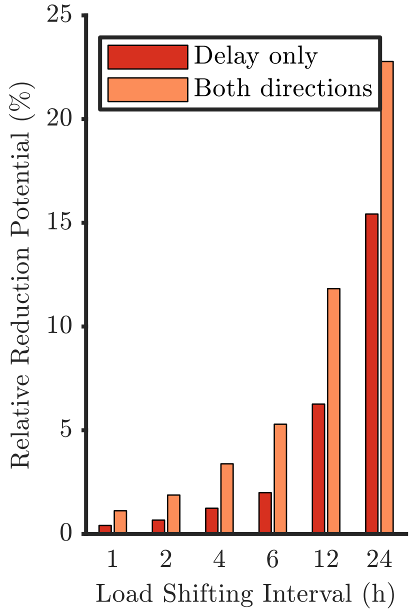
- Delay only: The operation of an appliance can only be postponed. This is motivated by the fact that the operation of considered appliance types requires user interaction beforehand, e.g., filling the dishwasher. Therefore, this case needs few or no behavioral changes on the customer side.



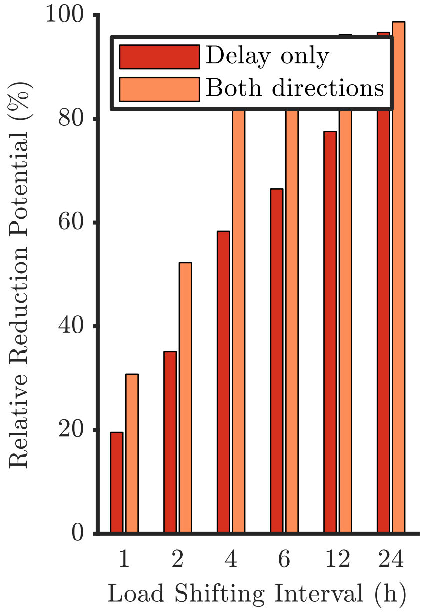
(a) All regions



(b) Region $\mathcal{C}$



(c) Region $\mathcal{W}$



(d) Region $\mathcal{S}$

Figure 5.15: Relative curtailment reduction potential dependent on shifting interval

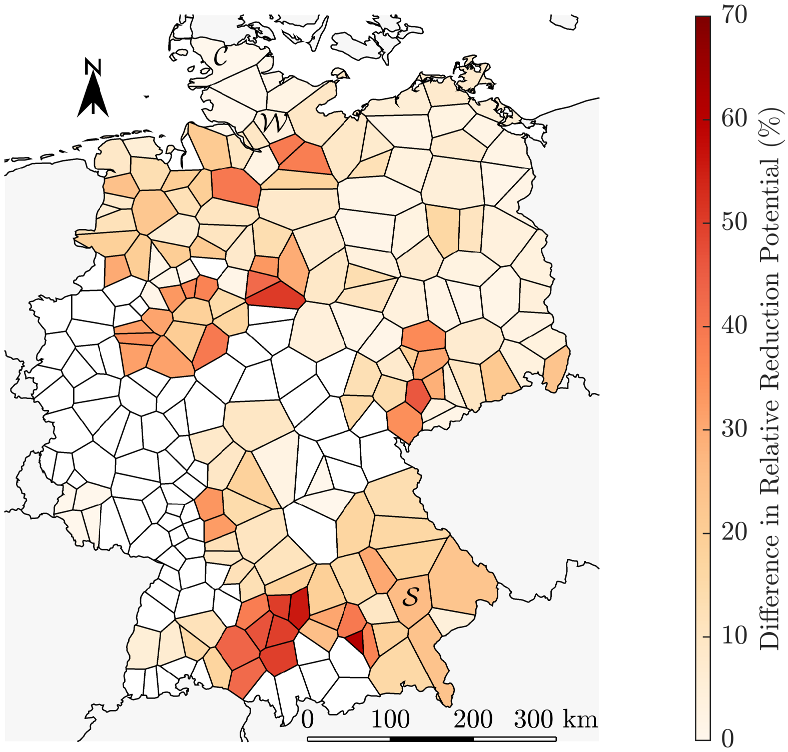


Figure 5.16: Difference in relative curtailment reduction potential per region, $M = 1\,\mathrm{min}$, 0 h|6 h, spread 100 ct/kWh, compared to reference case

- Both directions: Besides postponing the operation, it is also possible to start the appliance prior to the original time of operation. Naturally, this increases the possible flexibility and, therefore, the adaptability to rates and represented curtailment requirements.

For both cases, several intervals are analyzed. It is important to note here that 1 h in both directions means the appliance can be started up to 1 h earlier and up to 1 h later, leading to a total time window of 2 h.

As expected, the chart shows that the assumed shifting interval substantially influences the result. The calculated relative reduction potential covers a range from 0.4 % up to 5.7 %. It is observed that the extension of the shifting interval to both directions increases the potential considerably but does not reach twice the value for unidirectional shifting, as might be assumed due to the doubled time window.

For an overview over all modeled regions, figure 5.16 shows the results for a shifting interval of 0 h|6 h compared to the reference case with an interval of 6 h|6 h. The map evinces a quite uniform decrease of reduction potential due to the restriction to delay, except for some regions that still achieve very high values for the delay-only case. These confirm both main conclusions so far for a vast majority of regions: Larger shifting intervals substantially increase the potential reduction of curtailment, and so does the possibility of shifting the load in both directions.

The detailed chart for focus region $\mathcal{C}$ is given in figure 5.15b. It evinces similar features compared to the total evaluation in 5.15a, but as expected from previous calculations, on a generally lower level of relative reduction. However, the increasing effects of larger shifting intervals and allowing earlier operation of appliances are clearly visible, confirming the previous conclusions.

This also holds for region $\mathcal{W}$ in figure 5.15c. However, in this case, the relative increase for higher values (more than 4 h) is substantially larger, hinting at curtailment events that occur less frequently than for region $\mathcal{C}$, but still require high load increases in order to be avoided.

By contrast, region $\mathcal{S}$ in figure 5.15d evinces higher increases in the lower range, whereas it reaches some saturation effect for higher shifting intervals, especially in the case of shifting to both directions. Again, this can be traced back to the fact that the overall demand for curtailment measures in regions like this is comparably low, leading to an almost complete reduction of curtailed energy already with limited flexibility.

In conclusion, the analyses and charts prove that the shifting interval is an essential determinant for calculating potential curtailment reduction. Variation of this parameter causes considerable deviations in the resulting values of relative reduction. Considering the problem that no reliable, generally valid statistical data regarding this parameter are available, it is essential to consider variations and sensitivity analyses in subsequent simulations.

5.2.3.4 Effects of Price Spreads

Besides the duration of price intervals and possible shifting intervals, the price spread between the price levels N and L is the third main influence factor to the resulting reduction of curtailment measures since it directly affects the willingness of customers and, therefore, of modeled agents, to adhere to the given price signals.

The described survey (cf. section 4.3), used for parametrization of agents in the model, already shows that the price sensitivity is quite high. In order to verify this simulatively, the effects of price spreads between 0 ct/kWh and 100 ct/kWh in the simulation results are evaluated in steps of 5 ct/kWh. For this purpose, M is again set to 1 min, and the shifting interval is defined as 6 h|6 h.

The relative reduction potential over all regions for varied price spreads is depicted in figure 5.17a. As before, the relative reduction potential is plotted on the ordinate, whereas the abscissa shows the independent variable, in this case, the price spread.

As expected, no curtailment reduction is observed for a price spread of 0 ct/kWh since no incentive for load shifting is present. In the range from a spread of 5 ct/kWh to about

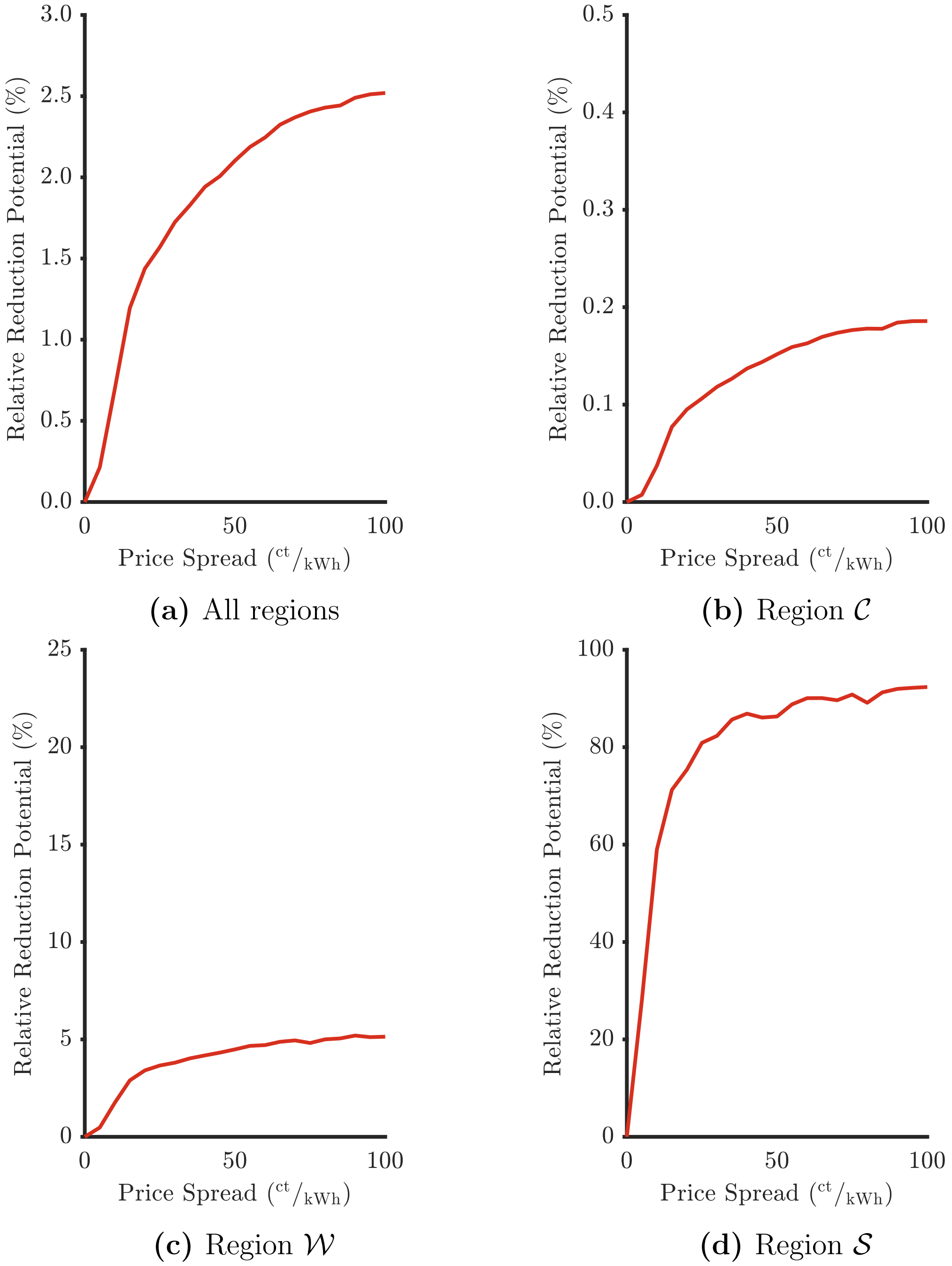


Figure 5.17: Relative curtailment reduction potential dependent on price spread

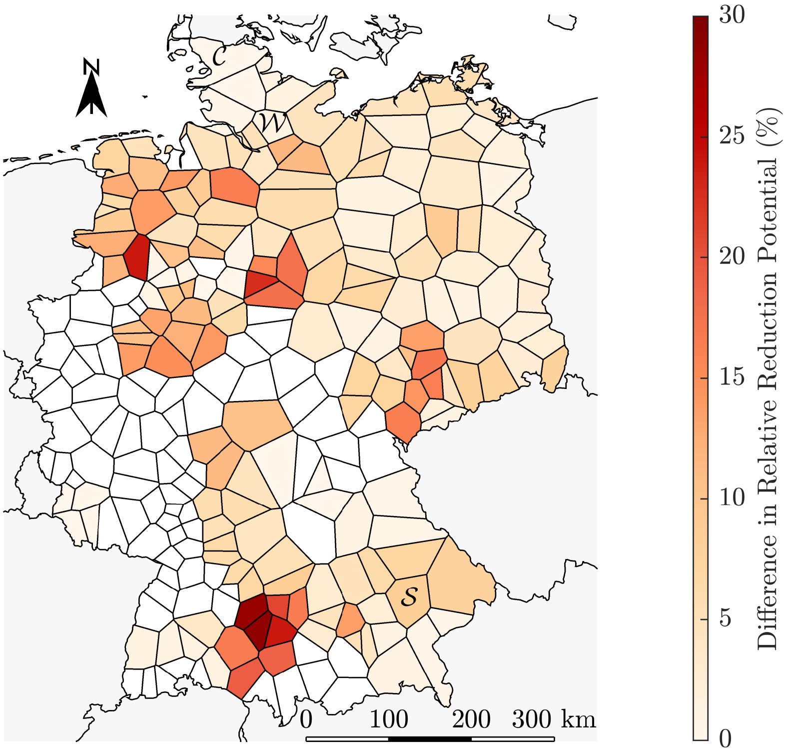


Figure 5.18: Difference in relative curtailment reduction potential per region, $M = 1\,\text{min}$, 6 h|6 h, spread 30 ct/kWh, compared to reference case

30 ct/kWh, a steep increase of the potential is observed with every step, showing that a substantial share of the total flexibility can already be activated with these comparably small spreads. Above that, the slope decreases, eventually showing an effect of saturation when approaching the highest value of 100 ct/kWh. Thus, the effect of an additional price spread is relatively small in this range.

A spatially resolved illustration of the effect of price spreads is given in figure 5.18 for a spread of 30 ct/kWh. This value is chosen since it represents the steeper part of the relation between price spread and relative reduction potential and is considered a realistic estimate of an implementable price spread (cf. section 4.2).

Similar to the previously analyzed influence factors, the difference map shows a relatively uniform decrease of relative reduction potential for a majority of regions due to the reduced price spread. Especially in the regions with generally low curtailment necessity, a spread of 30 % already reaches similar values as the reference case.

Another observation also corresponds to the previous analyses: Regions with a generally low value of relative reduction potential evince less or no apparent decrease. As before, this is caused by the color scale of the map, which cannot fully represent the details in all ranges of values. However, a closer investigation of region $\mathcal{C}$ in figure 5.17b and $\mathcal{W}$ in figure 5.17c shows that both evince an apparent decrease in relative reduction potential between the compared cases.

The general characteristics for region $\mathcal{C}$ match the relation for the sum of all regions quite well. This is expected behavior since a majority of curtailment measures are located in this region, thus affecting the overall evaluations proportionally. This means that a steep increase for smaller spreads can be observed, followed by a decreasing gradient and leading to a saturation effect, where the potential flexibility is almost fully utilized.

The chart for region $\mathcal{W}$ shows a similar relation with the difference that the saturation takes effect already for smaller price spreads. This can also be observed for region $\mathcal{S}$ in figure 5.17d and can be explained by the generally lower levels of curtailed energy for these regions.

Bot region $\mathcal{W}$ and $\mathcal{S}$ evince another notable feature in their respective charts. As described, the curve is expected to increase monotonically since higher price spreads enable more flexibilization and, thus, higher values of relative curtailment reduction potential. However, both charts show one or more small dips in the range of almost constant values, i.e., for higher price spreads with very small changes between the simulated steps.

This is caused by the aforementioned probabilistic structure of the model. Load-shifting processes are not modeled as totally deterministic but involve a random choice of operation time if equivalent alternatives occur. As described, repeated model runs are applied to alleviate this approach's distorting effects. Nevertheless, a slight uncertainty in the simulation results remains, leading to artifacts like the ones described. Since these do not affect the overall results and conclusions, they are considered unproblematic.

5.2.4 Summary

The developed model of load-shifting measures on individual appliance level for modeled agents proves helpful and generates plausible results. It considerably increases the precision of the simulation compared to the aggregate model discussed before due to better temporal resolution, better data basis, and much more detailed modeling of shifting processes.

For a realistic parametrization of agents, a probabilistic approach is applied to meet a larger group's expected median behavior. The modeling of load-shifting processes introduces another probabilistic element since the objective of minimal costs can be achieved for more than one shifted position. In this case, a random choice is used in the model. In order to avoid model distortions caused by this randomness, repeated model runs are applied to generate stable and representative results. Calibration runs show that 10 repetitions are enough for reasonable precision.

The analyses of three main influences on the relative curtailment reduction potential show that price interval duration, shifting interval, and price spread all affect the result considerably, as expected from previous calculations and investigation. For a configuration of $M = 1\,\mathrm{min}$, a shifting interval of $6\,\mathrm{h}|6\,\mathrm{h}$ and a maximum price spread of

100 ct/kWh, which is assumed to be roughly comparable to the aggregate calculations in the previous section, a relative reduction potential over all regions of 2.5 % is simulated, compared to 4.6 % in the aggregate case. Clearly, this difference is partially caused by different parametrization, but it also shows the increased model precision due to better temporal resolution and more detailed modeling of shifting processes.

Price spread and price interval are identified as relevant influences to the effect of the described rate structure. Therefore, these are chosen as optimization variables for the subsequent section, where a model is presented to choose the optimal parameter set for the given objective. Besides that, the shifting interval is a property of customer behavior. Therefore, this cannot be defined from a system perspective but is considered an input value. Since no reliable data is available, the strong dependence of results on this factor suggests that sensitivities are also to be considered in further analyses.

To conclude, the detailed appliance-level simulation model confirms the main conclusions from the previous section. The residential sector can contribute to reducing curtailment and, thus, to better integration of renewable generation in the energy system. This contribution is comparably small but non-negligible. In order to tap this potential, the choice of rate parameters is crucial to meet the requirements both from a system perspective and the customers' view. Therefore, this problem will be addressed in the following section.

5.3 Optimization of Rate Parameters

5.3.1 Scope

In the previous section, the methodology for the simulation of load-shifting processes based on the described input data is described and applied to assess the potential for curtailment reduction dependent on assumed rate parameters. These parameters are varied to examine different sensitivities and influences, but requirements regarding costs and acceptance of the resulting rates are not considered. Thus, this section presents an approach to determine the defined rate parameters in a way that does not cause additional costs from a system point of view and investigates the resulting rate structure in the context of the collected acceptance data from the survey (cf. section 4.3). This raises the following core questions for the section:

- Is it possible to maintain cost neutrality by appropriately calculating the parameters of an NLM rate?
- Which curtailment reduction potential can be achieved by the resulting rate?
- Is there a substantial difference between regionally defined NLM rates and nationwide ones?
- Can the resulting rates be expected to be accepted by customers?

5.3.2 Methodology

Based on the load shifting model and subsequent evaluation of curtailment reduction described previously, an optimization model is applied to determine the parameters for an NLM rate. This allows the inclusion of all defined requirements and conditions in a comprehensive model and, thus, the calculation of the optimal parametrization for the defined application.

Since the overall model structure is highly nonlinear due to the simulation of individual customers and their consumption patterns, choosing an appropriate optimization method is crucial to achieving reliable results in a manageable runtime. A considerable number of conventional methods are not applicable to this problem structure. Previous analyses of the optimization of related problems in the field of electricity rates suggest that genetic optimization is the appropriate choice for this application [95, 96]. Besides the handling of nonlinear problems, also integer-valued, i.e., discrete, variables are supported by this approach, which is required for the integration of M in the model. The implementation of the optimization is built upon the standard MATLAB implementation since it is assumed to be fully developed and easily adaptable, and it features built-in parallelization, which is necessary for complex optimization problems [97].

The overall objective of the optimization is the maximization of reduced curtailment, i.e., the difference between the curtailed energy in the base case and the curtailed energy in the optimized case. With the described model and simulated customer behavior, this naturally leads to a maximum difference between N and L in order to tap the full potential of load shifting [97]. This leads to considerably fewer expenses by the customers due to the time intervals with free energy, which can also be interpreted as an increase in costs from a system perspective, which is unfavorable since the costs of generation and distribution still have to be covered. Therefore, an additional condition is to be defined to yield viable resulting rates from a cost perspective.

In general, this condition can be described as cost neutrality of the resulting rate. This means that the total purchasing costs of the modeled customers do not change due to the applied new NLM rate compared to the base case with fixed energy price. Thus, for every configuration, the potential purchasing costs are to be calculated and compared with the base case in order to decide on the viability of said configuration. Since this calculation is too complex to be represented in the constraints of an optimization problem, it is also included in the objective, leading to a multi-objective problem that intends to maximize the reduction of curtailed energy as long as cost neutrality is maintained.

As described, cost neutrality is seen as equality of purchasing costs in the base case of a constant energy price and the respective costs in the NLM case. However, equality conditions are computationally hard to implement in an optimization problem, potentially causing infeasibility of the resulting model. Thus, the equality condition is reformulated to incorporate an accepted tolerance range that is still considered sufficiently "equal" for the model. This tolerance range is chosen as 5 % of the total costs. For the fixed

Variable	Lower bound	Upper bound	Type
N	31.37 ct/kWh	100 ct/kWh	Continuous
L	0 ct/kWh	31.37 ct/kWh	Continuous
M	1	9	Integer

Table 5.3: Definition of optimization variables in the model

energy price, the value 31.37 ct/kWh is chosen based on the data discussed in section 4.2 for 2020 [55], assuming that this value is more representative for long-term insights than recent values for 2023.

In the optimization, three parameters for the NLM rate are to be determined. In accordance with the previous sections, the maximum difference between N and L is considered to be 100 ct/kWh. Thus, 100 ct/kWh and 0 ct/kWh are chosen as upper and lower bounds of these parameters, respectively. Since cost neutrality is an additional condition for feasible solutions, N cannot be lower than the fixed energy price in the base case, whereas L cannot be higher than this value. This is represented in the boundary values to reduce the solution space and, thus, computational effort. The parameter M can be discrete time intervals as defined in section 4.1. To represent this in the optimization, these intervals are mapped to the integer range 1 to 9. This leads to the definition of optimization variables summarized in table 5.3.

The optimization as described can be applied either to each region individually, leading to separate sets of rate parameters per region, or to the sum of all regions, yielding a "nationwide" optimized parametrization. In the first case, the objective considers the reduced curtailment of one region, whereas in the second case, the sum of all regions is taken.

As a result of this approach, a parameter set is deduced that is expected to contribute to the reduction of curtailment while maintaining cost neutrality when applied to all customers. Since there are various options for the actual implementation of such rates in the retail market (cf. section 4.2), it is also important to assess whether such rates are attractive to customers if they are introduced as an alternative option besides the existing conventional rates with constant energy prices. Based on the findings from the survey in section 4.3, this can be evaluated by the expected savings that are required for a switching decision as well as the minimal price interval that is accepted by the customer. There are more complex methods to assess the diffusion of novel electricity rates described in literature [97–100]. However, these sophisticated models require a high number of assumptions that are not backed by real-world data. Thus, the described more straightforward approach to acceptance is preferred here.

5.3.3 Results and Discussion

5.3.3.1 Optimized Rate Parameters

Applying the described optimization model to the present data representing residential consumption and curtailment measures yields optimal parameter sets for NLM rates that maximize the reduction of curtailed energy while maintaining (approximate) cost neutrality. Naturally, the achieved relative reduction is lower than in the previous section with maximum price spread between N and L due to the additional constraints. For the general case of nationwide optimization, i.e. no individual rate parameters per grid region, the results regarding relative reduction potential over all regions are displayed in figure 5.19a.

As before, the calculations are performed for assumed shifting intervals from 1 h to 24 h. The different parameters in this regard also result in differences in the optimal rate parameters. Thus, for every displayed case, the individually optimal rate parameter set is applied in order to determine the relative reduction potential in said case.

As expected, load shifting in both directions still evinces higher relative reduction potential than delayed operation only. Moreover, the general trend to higher reduction potential with increasing shifting intervals is also as expected and in accordance with previous evaluations. However, the step from 4 h|4 h to 6 h|6 h unexpectedly shows a slight decrease in reduction potential. As already explained before, this kind of seemingly inconsistent behavior is caused by the probabilistic model structure, which incorporates randomness in the modeling methods and thus, cannot generate fully comparable results for different inputs.

Looking at the actual resulting values, the exemplary case of 6 h|6 h evinces a relative reduction potential of 1.31 %, whereas the delay-only case of 0 h|6 h results in 0.90 %. Compared to the previously calculated values of 2.52 % and 1.42 % (cf. figure 5.15a), respectively, the additional constraint of cost-neutral implementation considerably reduces the potential. However, under the given assumptions, the contribution to increased integration of renewables by reduction of curtailment is still present and non-negligible.

Overall, this evaluation shows that the optimization model works as designed, as it still yields a non-zero reduction potential with the applied constraints. Therefore, it is theoretically possible to design electricity rates that pose sufficient incentives for load shifting while still ensuring cost neutrality.

The results for a shifting interval of 6 h|6 h are also regionally depicted in figure 5.20. Similar to the previous section, large differences between the regions can be observed, which are assumed to be mainly caused by the total amount of curtailed energy.

Detailed analysis of focus region $\mathcal{C}$ in figure 5.19b shows the same behavior as described before between 4 h|4 h and 6 h|6 h. Since most curtailed energy occurs in this region, it considerably affects the overall result. Thus, it can be deduced that the described probabilistic effect leading to seemingly inconsistent results occurs within this region. Apart from that, the general pattern of increasing reduction potential with increasing shifting intervals remains present as expected.

Regarding the resulting values, the decrease of relative reduction potential is in the same range as for all regions. In the 6 h cases, the reduction potential decreases from 0.19 % and 0.12 % (cf. figure 5.15b) to 0.09 % and 0.07 % for 6 h|6 h and 0 h|6 h, respectively.

Similar observations hold for regions $\mathcal{W}$ and $\mathcal{S}$ in figures 5.19c and 5.19d. Both evince the plausible pattern of increasing reduction potential with increasing shifting intervals, and both show a considerable reduction compared to previous analyses depicted in figures 5.15c and 5.15d. However, for region $\mathcal{S}$, a saturation effect for high shifting intervals can be observed, caused by the fact that the comparably low total curtailed energy can be avoided to a high share of up to 96 %.

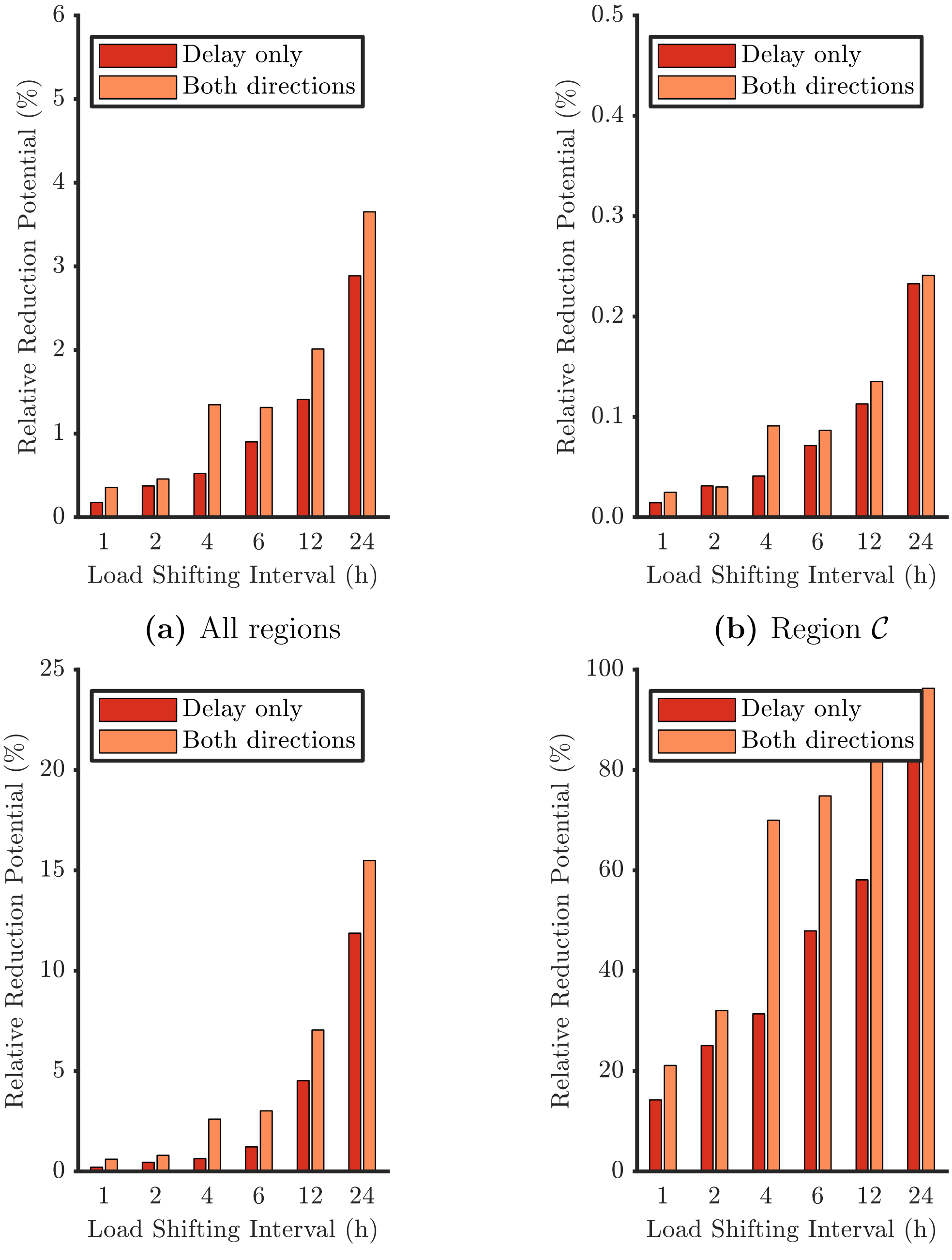
5.3.3.2 Variation of M

The optimization model is designed to return the optimal rate parameters for an NLM rate regarding curtailment reduction. Without additional constraints besides cost neutrality, it is expected to consistently yield a value of 1 min for M, regardless of the specific configuration, because the lowest duration of price intervals allows for the best representation of load shifting needs. However, the model results in a $M = 15$ min for three of the simulated cases. Since these results contradict plausible expectations, a detailed analysis is necessary.

Figure 5.21 depicts the relative reduction potential according to the optimization result for these three cases 2 h|2 h, 6 h|6 h and 0 h|12 h. Compared to these, the results of the comparison runs with identical N and L values, but $M = 1$ min, are also shown.

It can be observed that the cases that result in unexpected M-values cannot be assigned to a specific group since both low and high shifting intervals are affected. Also, shifting to both sides and delay-only shifting is present in the sample.

The results of the comparison run evince a slight increase in relative reduction potential for all three cases. This means that the optimization in these cases does not return the actual optimal result since adapted parameters increase the objective value. This effect can be caused by the structure of the complex optimization problem since minor deviations in the objective when adjusting variables lead to increasing difficulty in solving the optimization. Thus, it can be deduced that the optimization does not yield the best solution in all cases, but considering other inaccuracies and probabilistic effects in the model, it provides a sufficiently precise and plausible result for the present application. The model structure which causes the described effect is analyzed in more detail in a subsequent subsection.



(a) All regions **(b)** Region $\mathcal{C}$

(c) Region $\mathcal{W}$ **(d)** Region $\mathcal{S}$

Figure 5.19: Relative curtailment reduction potential for optimized rate parameters

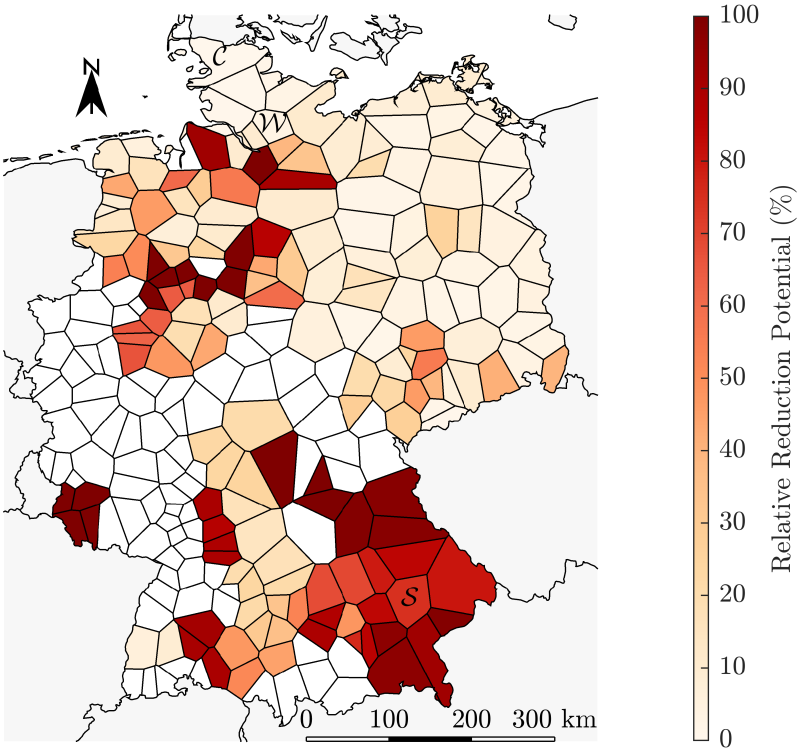


Figure 5.20: Relative curtailment reduction potential per region with optimized rate parameters for a shifting interval of 6 h|6 h

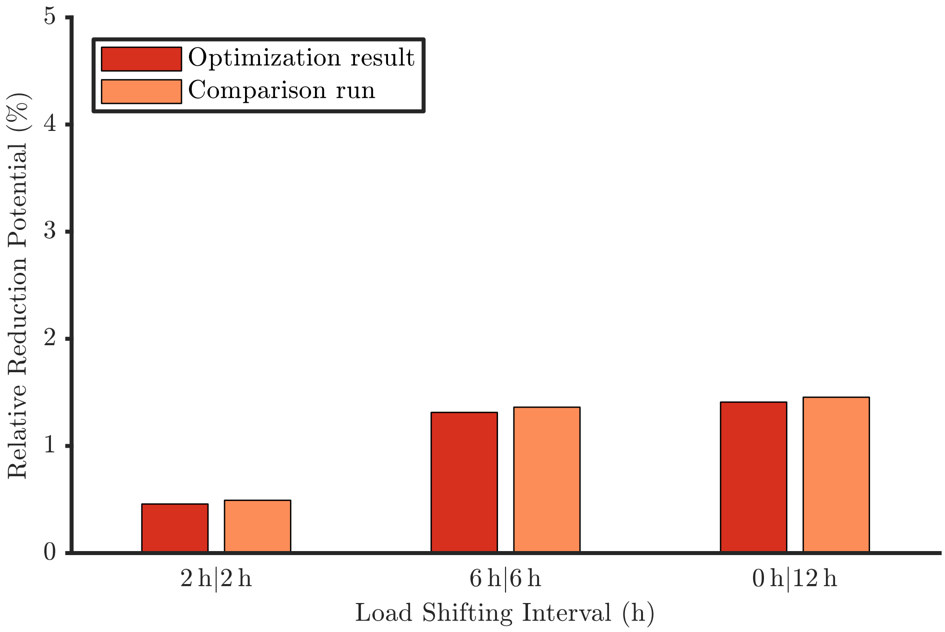


Figure 5.21: Relative curtailment reduction potential with optimized rate parameters and $M = 1\,\mathrm{min}$

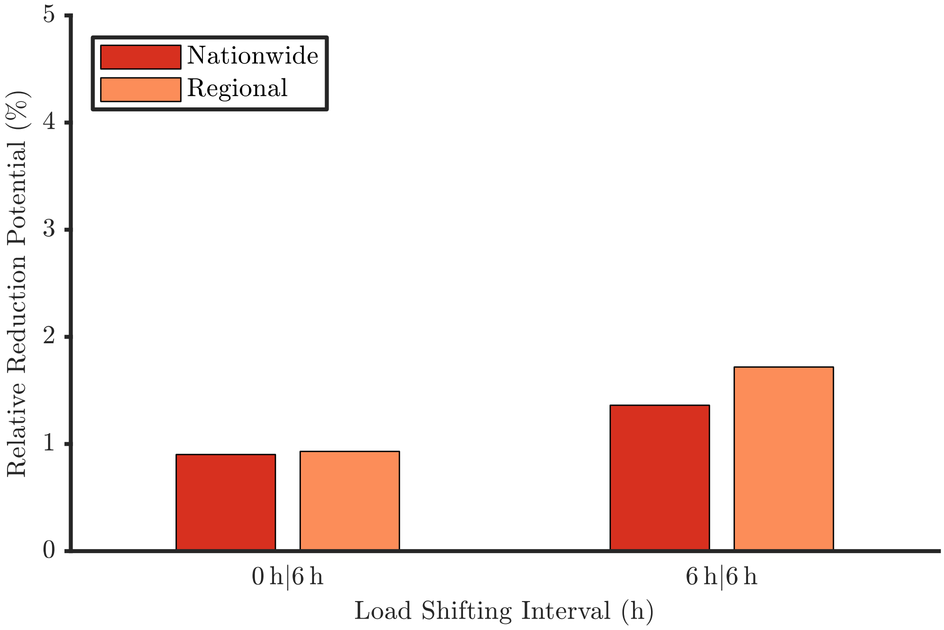


Figure 5.22: Relative curtailment reduction potential with regionally optimized rate parameters

5.3.3.3 Regional Optimization

As mentioned above, the depicted optimization results are calculated for a nationwide uniform NLM rate. Thus, this rate does not represent regional characteristics or differences, which might be caused by the generation structure within respective regions. However, the advantage of easier implementation and communication due to lower complexity seems preferable. In order to assess the effects of regionally optimized rate parameters, the optimization model is applied to the defined grid regions individually, as described in the methodology.

The result for two exemplary load shifting intervals is depicted in figure 5.22. As expected, the regional optimization yields slightly better results regarding relative reduction potential since the regionally distinct definition of rates allows for adaptation to specific requirements. Compared to the nationwide optimization, the resulting relative reduction potential is higher by up to about one quarter. Thus, individually designed rate parameters seemingly are the superior option for implementation.

However, several observations contradict this conclusion. The proper design of an NLM rate and the determination of optimal rate parameters is dependent on a large amount of data, which has to be collected in high quality and for long time periods since the precision of an optimization result naturally depends strongly on the input data. This is much easier to ensure for a nationwide rate than for several hundred subregions. Moreover, as explained before, the optimization method itself can partially cause the

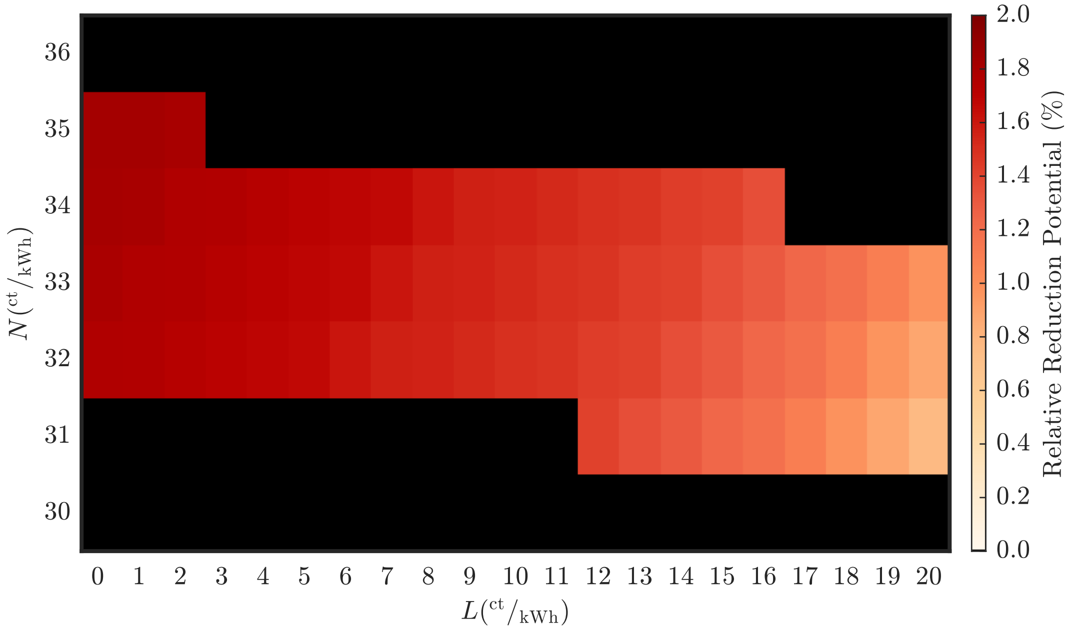


Figure 5.23: Structure of the optimization problem for 6 h|6 h

difference between the two results by not finding the actual optimum. Thus, for the present data, a nationwide implementation is considered preferable.

5.3.3.4 Structure of the Optimization Problem

As observed above, the optimization model does not always yield the best possible solution but might also return a parameter set that is near the best value. This is caused by the structure of the optimization problem, which evinces small gradients, i.e., the difference in the objective value is small for marginal adjustments of the variables. However, in the general case, the obtained solution can be considered good enough and valid for further evaluations and conclusions.

In order to depict the described effect, figure 5.23 shows the dependency of the calculated relative reduction on two of the three defined variables, N and L. The relative reduction is represented by the color value at the intersection of L on the abscissa and N on the ordinate, yielding a raster plot of the results. The calculations in the depicted case use a value of $M = 1\,\text{min}$, a shifting interval of 6 h|6 h and are evaluated in steps of 1 ct/kWh. Combinations of N and L which do not fulfill the cost-neutrality criterion are marked in black instead of the color-coded reduction potential.

The figure demonstrates two main findings: The solution space that maintains cost-neutrality is relatively small, and both N and L evince a narrow parameter range due to this additional condition. However, within this area, the difference between adjacent values is relatively small to negligible, leading to the difficulty of the optimization as

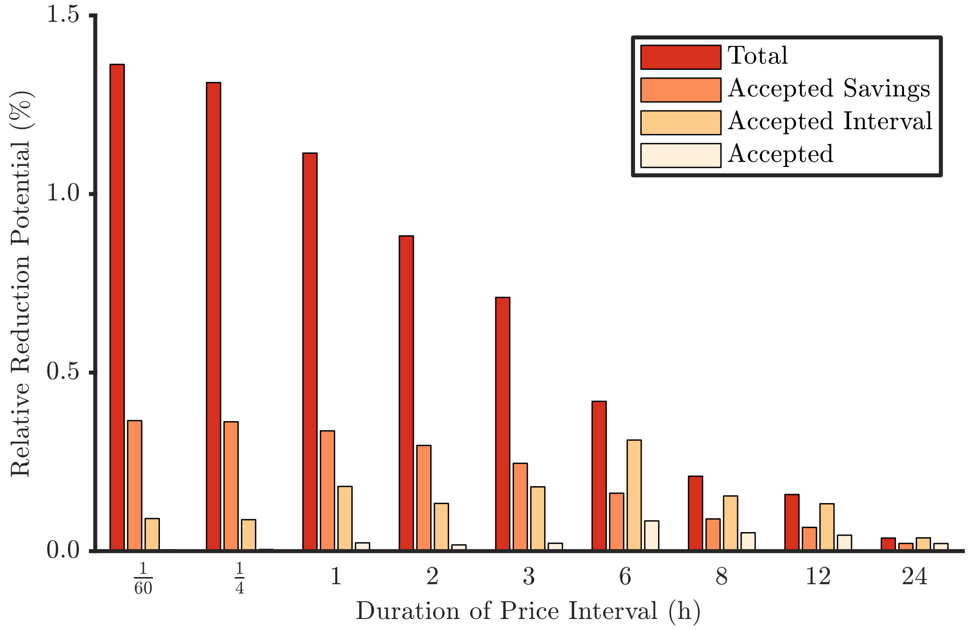


Figure 5.24: Relative curtailment reduction potential for accepted parameters according to survey data

mentioned above and, thus, to results that do not reach the actual optimum but an adequate approximation. Due to the uncertainties regarding the input values, this accuracy is considered sufficient for the evaluations within the scope of this thesis and still allows evaluation of the general effects and correlations.

5.3.3.5 Acceptance of Resulting Rates

The described and evaluated methodology allows for designing variable retail electricity rates, which pose sufficient incentive for load shifting while not causing additional costs. However, depending on the actual implementation in the market, the rate may be competing with conventional rates with fixed energy prices. Thus, in this case, this incentive only comes into effect for customers who actively decide to choose this rate because it meets their needs and expectations.

Besides criteria focusing on sustainability, which might be convincing enough for some even if there are few additional advantages, according to the survey discussed in section 4.3, this decision is mainly based on two properties: Monetary savings and simple rate structure. The first one can be calculated for modeled customers based on their shifted load curve, whereas the second one here is mainly defined by the parameter M. Therefore, these criteria are determined for the optimized rate structure from subsection 5.3.3.1 in order to decide whether a specific modeled customer chooses the NLM rate. If not, no load shifting is expected from the respective customer; therefore, there is no contribution to curtailment reduction.

The results of this evaluation are depicted in figure 5.24. It shows that by including the criterion of sufficient savings, of accepted price interval M, or both (denoted by "accepted" in the plot), the relative reduction potential substantially decreases, leaving little to no relevant contribution to curtailment reduction. This demonstrates that a rate like this cannot be expected to have high enough acceptance for the defined goals. Moreover, if it is only used by those who achieve substantial savings, whereas the others stay with a conventional rate, the calculated cost neutrality no longer holds. In conclusion, it is necessary to implement incentives in price components that affect all customers, like e.g. grid fees or electricity tax.

Summary

Based on the DSM model described and analyzed in the previous section, an optimization method is developed that determines suitable parameters for the chosen rate structure, which fulfills the criterion of cost neutrality and, at the same time, maximizes the reduction of curtailed energy. The model implementation based on genetic optimization shows this problem's general feasibility, enabling the analysis of the potential effects of such optimized rates.

The results evince similar behavior in dependence of the load shifting interval as observed previously without optimization. However, the overall reduction potential substantially decreases compared to the unconstrained values in the previous section, in the exemplary case of 6 h|6 h to about 1/2.

A detailed investigation of the focus regions supports these conclusions. The effect of varied shifting intervals yields plausible and expected results, and the cost-neutrality criterion generally decreases the reduction potential. Due to the low absolute curtailed energy, a saturation effect can be observed again for region $\mathcal{S}$.

In theory, $M = 1\,\mathrm{min}$ is expected to yield the best possible curtailment reduction. However, for some simulated cases, the optimization result does not reflect this. Closer inspection of this effect evinces that the difference between the optimization results for $M = 15\,\mathrm{min}$ and the shortest possible interval is almost negligibly small in some cases, causing the optimization to not find the optimal solution, but a close enough approximation regarding the reduction potential.

The comparison of nationwide to regional optimization of rate parameters shows that regional adjustment yields slightly better reduction potential due to better adaptation to regional characteristics. However, the calculated improvement is relatively small, while causing considerable additional effort regarding data collection and implementation. Thus, a nationwide definition of rate parameters is recommended.

The analysis of potential acceptance of the resulting rates based on the previously discussed survey results regarding preferred rate structure and expected savings shows that the reduction potential decreases to almost no relevant contribution to the goal. Therefore, to achieve a considerable effect, the price variability has to be implemented in a way that equally affects all customers, not as an additional rate choice.

6 Conclusion

6.1 Summary and Key Findings

The transition of the European energy system to renewable and decarbonized generation poses a major challenge to all stakeholders for the next decades. A diverse combination of measures and technologies can support and enable progress towards this overall objective. One of these, the utilization of demand-side flexibility in the residential sector, is described and analyzed in the present thesis, focusing on the additional integration of renewable energy in the grid. To quantify this contribution, the potential reduction of curtailment from renewable generation units is chosen as an appropriate objective since curtailed energy is currently lost for the system.

For the evaluation and calculation of the potential contribution to this objective, the first step is to determine the flexibility potential of the residential sector. The analysis of the consumption structure in typical German households yields the conclusion that washing machines, dryers, and dishwashers are the relevant appliance types for this kind of application since they evince comparably high consumed power and energy while also being shiftable without loss of comfort for the customer. Cooling devices (fridges, freezers) are excluded since their potential is considered to be too low due to low power demand. Additional loads like electric vehicles and electric heating systems are not considered within the scope of this thesis since their modeling and analysis require fundamentally different approaches.

Two approaches for quantifying the time-resolved flexibility potential are presented based on the identified appliance types. The first one utilizes measured data of several German distribution grid areas with exclusively residential customers, enabling the calculation of aggregate load profiles based on the established standard load profile system. In combination with literature data of usage profiles for the appliances in question, the resulting profiles can be distributed to the appliance types in question, leading to a value of flexible load for each time step. Thus, two possible solutions for **RQ1** are developed and analyzed, providing input data for subsequent modeling steps.

By contrast, the second approach is based on measured data from individual households, utilizing the installed smart metering infrastructure. In order to quantify the flexibility potential in this case, a pattern-matching methodology is developed, which allows for identifying the operation times of the relevant appliances in the yearly load curve. Thus, the resulting flexibility is defined by the time steps and load profile of the recognized usage of said appliances, presumably leading to considerably higher accuracy than the previous approach.

In order to calculate the potential reduction of curtailed energy by the modeled DSM measures, regionally allocated curtailment data are required. This is achieved by processing historical data on individual curtailment measures and assigning the resulting time series to grid regions. These grid regions are based on the nodes of the German transmission grid, slightly adjusted where distances are too low. The resulting data show that the need for curtailment measures varies vastly between different German regions, with the highest values for grid regions with high installed wind capacity and lower for grid regions with a focus on solar PV. The analysis of the systemic value of avoided curtailment shows that in the considered application, it depends on the market value of the energy that is shifted to reduce said curtailment.

The implementation of DSM measures in the residential sector requires appropriate incentive structures. Monetary incentives for load shifting can be posed by suitably designed variable electricity rates, which enable savings for the customer by adhering to the present price signals. The investigation of the regulatory setting for residential retail prices in Germany shows that in the current system, variable price signals can only be set by the energy supplier, demonstrating the need for a redesign of the price components to enable including grid requirements. In order to develop a variable rate for the considered problem, the range of possible rate structures and designs is analyzed, leading to a CPP-type rate with low prices for time intervals with present curtailment. Based on this finding, a survey is conducted in the form of an online questionnaire to collect data on the willingness of customers to accept variable rates and to adhere to these by load shifting in dependence of rate properties and potential savings.

The modeling of the potential for curtailment reduction by application of the defined rate structure is again demonstrated in two variants. On the one hand, an upper estimation of the potential is possible by using the time series of flexible load on an aggregate level, whereas on the other hand, modeling of individual load shifting processes allows simulating the potentially reduced curtailment in more detail, higher temporal resolution and presumably increased accuracy. The results show that the relative reduction potential differs vastly between the defined grid regions, confirming that regionally differentiated calculation is important for reliable conclusions. Moreover, the effects of different assumptions regarding accepted load shifting intervals, price spreads, and duration of price intervals can be quantified. Regarding **RQ2**, the models evince a relative reduction potential of between 2 % and 5 %, depending on the assumptions. Thus, the potential contribution to the overall integration of renewable generation is rather small but still substantial.

By adding the additional criterion of approximate cost neutrality from a system perspective, determining suitable rate parameters requires an optimization approach to suffice the requirements and, thus, to answer **RQ3**. The methodology is based on genetic optimization, enabling the finding of close-to-optimal sets of rate parameters that achieve maximum curtailment reduction while maintaining the additionally introduced constraint of cost neutrality. As expected, this constraint causes further decreased curtailment reduction to about one-half of the previous case. The calculation of regionally defined rate parameters evinces a slight improvement but is not recommended due to increased effort regarding data and implementation. Adding customer acceptance as a further criterion, the potential curtailment reduction decreases to almost negligible values. This demonstrates that for actual regulatory implementation, it is necessary that the price variability applies to all customers in the form of suitable price components like grid fees and not to provide the variable rate as an additional choice opposed to conventional rates. Since the transition of grid fees to a more variable design is currently ongoing with a voluntary ToU structure starting in 2025 for operators of, e.g., electric vehicles and heat pumps, future extension and dynamization of this approach constitutes an opportunity for implementation.

6.2 Limitations and Outlook

The presented methodology proves to be a good foundation for both estimating the potential effects of variable rates in the residential sector regarding load shifting measures and for the reasonable design of said variable rates. The discussed results confirm the feasibility and plausibility of the developed model but also show potential for further research in this field. A first possible improvement is the extension of the scope to further appliance types like cooling devices or to flexible loads of customers beyond the residential sector like small businesses. This allows the model to yield a more comprehensive view of the expected results of specific regulatory changes and their resulting rates, thus providing improved insight into the requirements for rate design. Regarding said rate design, the investigated rate structure is specific for the defined purpose of curtailment reduction by load-shifting measures. This also poses potential for future model enhancements, covering a more comprehensive range of possible rate features and applications.

The developed optimization approach is applied to find the optimal choice regarding curtailment reduction while maintaining cost neutrality, with evaluation of the acceptance afterwards. A potentially substantial improvement is the integrated optimization under additional consideration of acceptance of the resulting rate, enabling an improved workflow for rate design. This is not implemented in the current optimization model due to high computational complexity caused by the probabilistic model structure, but is expected to be feasible with appropriate assumptions.

Besides that, model coupling is an option for future development. On the one hand, integrated interaction with simulation models for the load-shifting behavior of electric heating systems and electric cars enables a more detailed understanding of residential load curves under present and potential future circumstances. On the other hand, coupling with an energy system model or with grid simulation software provides additional capabilities regarding the modeling of feedback effects on energy markets or electricity grids, as well as their consideration in the modeling methodology.

Since the results vastly depend on the quality of input data, a last point to be mentioned here is the enlargement and improvement of the utilized data basis. This applies to all described input data but primarily to curtailment and consumption data. Especially for the last one, more recent data in higher temporal resolution are expected to substantially improve the quality and usefulness of the model results and should become available soon with the ongoing rollout of intelligent metering systems.

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List of Abbreviations

CHP .... Combined heat and power
CPP .... Critical peak pricing
DSM .... Demand-side management
DSO .... Distribution system operator
EEG .... Erneuerbare-Energien-Gesetz ("Renewable Energy Source Act")
EU .... European union
GHG .... Greenhouse gas
H0 .... SLP for households
PTR .... Peak time rebate
RQ .... Research question
RTP .... Real-time pricing
SLP .... Standard load profile
ToU .... Time of Use
TSO .... Transmission system operator
VAT .... Value-added tax

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