Noname manuscript No.
(will be inserted by the editor)

The impact of electricity tariffs on residential demand side flexibility: Results of bottom-up load profile modeling

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Paper published in Energy Systems, suggested citation:
Hayn, M., Zander, A, Nickel, S., Fichtner, W. & Bertsch, V. (2018) The impact of electricity tariffs on residential demand side flexibility: Results of bottom-up load profile modeling. Energy Systems, DOI: 10.1007/s12667-018-0278-8.

Abstract Energy systems based on renewable energy sources require increasing demand side flexibility. Also, changes in the underlying cost structure, i.e., decreasing variable costs and increasing infrastructure investments as well as varying consumer needs should be reflected in the setup of future markets, including retail markets and tariffs. While various studies focus solely on tariffs with variable energy prices to leverage residential demand side flexibility, we incorporate tariffs with capacity-based price components in our analysis. The latter enable electricity providers to offer more differentiated tariffs, considering individual consumer needs and a balanced cost allocation. To compare the impact of different tariffs on residential demand side flexibility, we develop a bottom-up load model. This model not only simulates but also optimizes residential load profiles in the presence of different tariffs. The model is calibrated based on data from a large-scale field trial. Our results show that tariffs with variable energy prices induce larger demand side flexibility, but the impact of tariffs with variable capacity prices is more predictable and reliable from a suppliers perspective. Potential regulatory adjustments are identified enabling sustainable business models, rewarding demand side flexibility and facilitating the technical implementation.

Keywords Residential bottom-up load model · variable energy prices · variable capacity prices · load shifting potential · demand side flexibility

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1 Introduction

Many energy systems tend to rely on an increasing share of power generation from renewable energy sources (RES) [1]. This results in a higher decentralization of generation facilities, a higher fluctuation of power generation and an increasing uncertainty regarding the available power at a specific point in time. As a result, the volatility of the system residual load will increase strongly leading to a growing demand for flexibility [3].

In the context of this paper, flexibility of energy systems shall be defined as the ability to balance demand and supply in order to avoid shortages in the system. These shortages can refer both to generation as well as grid shortages. Generation shortages can occur in case of little RES generation and high energy demand. Grid shortages can arise in case of high RES generation leading to an overload of the power grid [30, 39]. Both shortage situations may negatively influence the economic welfare as either a specific energy demand cannot be fulfilled or a surplus of available energy from RES must be curtailed [30, 26]. Flexibility in energy systems can be provided both from the supply and the demand side. On the supply side, the generation capacity of power plants can be controlled, though most plants using RES cannot provide additional power in case of exceeding demand. On the demand side, consumers can provide flexibility through demand response [6, 10].

While in traditional energy systems with a large share of conventional power plants, flexibility was mainly provided by the supply side, the increasing utilization of RES promotes the need for demand side flexibility [6, 10]. In the industrial sector, demand side flexibility is already partly leveraged through contracts allowing for direct load control, capacity prices in industrial electricity tariffs and their possibility to actively participate in balancing markets [34]. In the residential sector, however, demand side flexibility is hardly leveraged even though various studies indicate a high potential for demand response [34, 32, 12]. Accessing this untapped potential may increase the economic welfare by reducing the curtailment of RES generation [45] and, in the long term, the amount of backup generation capacity through peak load power plants and the need for grid expansion [6, 33].

To access residential demand side flexibility, consumers need some kind of incentive in order to adapt their demand to system requirements. For this purpose, residential electricity tariffs with variable price components can be used. The majority of recent research projects focuses on electricity tariffs with variable energy prices, e.g., time-of-use pricing or real-time pricing, in order to alter residential electricity demand [14, 27]. In addition, tariffs with variable capacity prices, e.g., demand tariffs or curtailable load tariffs, attract the attention of research [48, 24, 43, 52]. In addition to leveraging demand side flexibility, introducing capacity-based price components into residential electricity tariffs may also address changes in the cost structure of the power system. The increasing use of RES for power generation leads to decreasing variable generation costs. Contrariwise, the investment in power infrastructure increases as a result of an enormous amount of RES capacities, grid reinforcements and partly also conventional back-up power plants. Consequently, the fixed costs become more important in future power systems necessitating the reflection of these systematic changes in electricity tariffs as well. On the one hand, electricity tariffs should consider the temporal fluctuations of RES generation, i.e., incentivizing or at least not penalizing demand during times of high RES availability. On the other hand, electricity tariffs need to include the underlying system costs in an appropriate way.

Moreover, the availability and utilization of self-produced electricity, e.g., from photovoltaic (PV) systems, allows traditional consumers like households to reduce their electricity demand from central providers. In systems where consumers pay for costs to build and maintain the system infrastructure on a per unit basis, e.g., grid charges, this means that the consumers that can afford to invest into PV systems contribute less to maintaining the system. At the same time, they still benefit from the security of supply from being connected to the grid. Moreover, a decreasing amount of households that do not or cannot invest into such systems bear the costs of the system which brings about distributional problems [31, 48, 5, 47]. In order to ensure a fair system cost allocation according to the individual needs of different consumers, future electricity tariffs should allow for an appropriate price differentiation. In this context, smart grid technologies can enable electricity providers or aggregators to offer more sophisticated services, allowing not only for a fair cost allocation but also to create tariffs fitting to the individual needs of different consumers [40].

In terms of the impact that different tariffs have on residential demand side flexibility, existing studies focus exclusively on either analyzing tariffs with variable energy prices or tariffs with variable capacity prices. The main contribution of this paper is the comparative analysis of tariffs with variable energy prices and variable capacity prices, as well as a combination of both approaches and their impact on residential demand side flexibility. We therefore developed the **R**esidential **E**lectricity **L**oad profile simulation and **O**ptimization (RELO) model, which combines a technical bottom-up simulation approach with different optimization problems allowing for the analysis of tariffs with variable energy and/or capacity prices. The model takes the perspective of residential consumers, i.e. the consumers in our model choose, within given constraints, how much of their load to shift or reduce in order to meet their demand at minimum costs. In this context, we wish to emphasize that we model a future power system with a significant presence of smart grid technology including smart household appliances, e.g., dishwashers with a smart communication interface. And we assume that an aggregator can use this technology to act on behalf of the consumers and communicate with their smart appliances with the objective of minimizing their electricity supply costs [9, 7, 18]. Households without such appliances or smart communication technology cannot avail of the services offered by an aggregator and therefore need to decide themselves when to shift load. The share of households with / without smart technology is explicitly considered as an input parameter of the RELO model.

Details of the underlying concept of tariffs with variable capacity prices used in this paper are described in [24]. Basically, the tariff represents a curtailable load tariff allowing an electricity provider or aggregator to curtail the electricity demand of an individual household in case of shortages on a contracted guaranteed power level. Besides the power level also the frequency of curtailments, i.e., the number of curtailments per time period, their duration and the advance warning time are assumed to be individually agreed between provider and household. Referring to concepts from service research, these main elements can be described as service level indicators and related service level objectives. Within this paper, the impact of such tariffs on residential electricity demand is analyzed. The two key questions to be answered within this paper are, how different tariffs alter the general household behavior in relation to electricity use and, more specifically, how these tariffs influence the electricity use of households in times of shortages.

The remainder of this paper is structured as follows: Section 2 provides a brief overview of related work and differentiates this paper's bottom-up model from selected existing bottom-up models. Section 3 describes the RELO model. In section 4, the main results of different scenarios focusing on the impact of residential electricity tariffs on demand side flexibility are presented and discussed. Section 5 concludes.

2 Related work

A large number of residential load models has been developed to date following either a top-down or a bottom-up approach [21, 50]. For the analysis of the impact of different residential electricity tariffs on demand side flexibility, technical bottom-up models are most suitable as their high level of detail makes it possible to simulate different household types as well as a large number of different appliances both being relevant with regard to households' behavior towards different tariffs [23]. Within the methodology of bottom-up modeling, technical bottom-up models offer the highest level of detail. In order to simulate households' reaction to different tariffs, several additional aspects need to be considered in the model. As residential demand in general and the load profiles of individual appliances in particular fluctuate continuously, a high temporal resolution is advisable [46]. Additionally, differences between seasons and weekdays should be considered since those aspects influence residential electricity demand [16, 44]. Finally, the model needs to be capable to represent regional specifics, i.e., country specific appliance and household distributions as well as appliance utilization rates. The overview in Table 1 includes only technical bottom-up models allowing for the analysis of demand response effects. Besides the main objective of the reviewed models, key aspects of the models are highlighted, e.g., the geographical focus and the level of detail regarding household and appliance differentiation. Descriptions of more residential bottom-up load models can be found, for instance, in [21, 50, 20].

Table 1 Overview of selected technical residential bottom-up load models with demand side management

Source	Objective	Geographical focus	Details (households)	Details (appliances)	Demand side management	Simulation horizon	Seasons	Weekdays	Temporal resolution	Photovoltaic	Electric vehicles	Others
Gobmaier [17]	Development of future residential load profiles	GER	Socio.	n. s.	EP, PVS	1 year	3	3	15 min.	yes	yes	
Gottwalt [19]	Evaluation of demand side flexibility based on variable energy prices	GER	n. s.	8 types	EP, PVS	12 weeks	partly (SH, BL)	partly (BL)	15 min.	yes	yes	BAT
Gottwalt et al. [20]	Evaluation of demand side flexibility based on variable energy prices	GER	Socio.	14 types	EP	1 year	yes	yes	15 min.			
Huang et al. [28]	Evaluation of the profitability of electric vehicles[a]	USA	n. s.	28 types	EP	1 day	2	2	1 h.		yes	
Maier et al. [36]	Evaluation of the maximization of photovoltaic self-consumption	AUT	8 archetypes	12 classes	PVS	1 year	3	3	1 min.	yes	yes	HP
Michalik [37]	Evaluation of load shifting potential with hot water appliances	AUS	24 archetypes	17 types	EP	1 day	1	1	15 min.			
Paatero and Lund [41]	Evaluation of load shifting potential as a function of grid frequency	FIN	Socio.	17 types	Grid	1 year	3	2	1 h.			
Ruiz et al. [43]	Evaluation of demand side flexibility based on variable capacity prices	ESP	n. s.	5 types	CP	1 day	partly (SC)	n. s.	15 min.			
Widén et al. [51]	Combination of existing models and enabling for demand side management	SWE	Socio.	9 types	EP, PVS	1 day	partly (L)	2	1 min.	yes		
Own model	Evaluation of demand side flexibility based on variable energy as well as capacity prices	GER	Socio.	17 types	CP, EP, PVS	1 year	3	3	15 min.	yes		

[a] Model based on Paatero and Lund 2006
Abbreviations: BAT = Battery; BL = Base load; CP = Capacity price; EP = Energy price; HP = Heat pump; L = Lighting; n. s. = not specified; PVS = Photovoltaic self-consumption; SC = Space cooling; SH = Space heating; Socio. = Socio-demographic characteristics

In comparison to existing developments, the RELO model offers several enhancements. First, RELO is able to demonstrate the effect of residential tariffs with variable energy and capacity prices as well as a combination of both. Additionally, the model can maximize the use of self-produced PV electricity (self-consumption). Second, the RELO model is calibrated with empirical data from a large-scale field trial with more than 1,000 participating households for the simulation of manual demand side flexibility. More information on the field trial is given in [27, 44]. Using empirical data on the probability of manual load shifting improves the model's ability to simulate real life behavior of households instead of considering only technical restrictions of electric appliances. Third, the model developed creates weekly profiles instead of daily ones offering the possibility to shift the utilization of appliances across daily limits, e.g., for dish washers. As most reviewed models create only daily profiles, this option does not apply for these.

The strongest similarities regarding the methodological modeling approach exist with the model developed by [20]. The major improvement of their approach is seen in the consideration of tariffs with variable capacity prices. Furthermore, the underlying data base was enhanced, using empirical distribution functions for the utilization of different appliance types in order to determine their start time instead of calibrating the model with empirical load profiles [42]. However, as already mentioned, we calibrate the likelihood of manual demand side flexibility with empirical data. Consequently, the outcome of the RELO model relates closer to the demand side flexibility achievable in reality instead of a purely theoretical potential. Additionally, we implemented typical load profiles for different appliance types in the model based on [49].

In terms of the content, the strongest similarities exist with the model developed by [43] as their model is the only one able to describe the effect of residential tariffs with variable capacity prices. However, even here, differences exist. On the one hand, different electricity tariffs are modeled. First, the impact of tariffs with variable capacity prices is considered differently. While [43] minimize the electricity bill by applying a capacity price function, i.e., households receive a bonus payment if their electricity demand remains below or above a certain threshold, our applied tariff with variable capacity prices curtails households' electricity demand to a pre-defined household specific level in shortage situations. Hence, the approach from [43] is more similar to tariffs with variable energy prices just applying the price incentive on power instead of energy. Second, as already mentioned, the RELO model is able to simulate both variable energy and variable capacity prices which is its major enhancement. On the other hand, the modeling approach significantly differs, e.g., the longer simulation horizon of one year in our model versus one day and the representation of seasonal and diurnal differences in household's energy demand.

3 The RELO model

This section describes the main characteristics of the **R**esidential **E**lectricity **L**oad profile simulation and **O**ptimization (RELO) model, which we developed to analyze the impact of different tariffs on residential demand side flexibility. To illustrate its work flow, Fig. 1 shows a simplified flow diagram. RELO combines a simulation with an optimization approach, allowing us to reflect household specific differences regarding electricity demand on the one hand, and model rational household or appliance reactions on external price or control signals on the other hand.[1] After reading the required input data, e.g., the number of simulated households I, their distribution of sizes and appliances, all individual households are generated and described with specific characteristics. Then, weekly load profiles with a 15 minutes resolution for every week $w \in W$ for each household $i \in I$ are simulated. Concatenating these profiles over all weeks creates a yearly profile for each household. The accumulation of these across all households is used to determine relevant energy demand indices. Finally, the load profiles and indices are written as output files for further analysis.

The model is able to reflect the reaction of households on external price or control signals. For instance, households can shift their power demand as a reaction to tariffs with variable energy prices. Therefore, the tariff structure, i.e., which price applies at what time, must be given as an input to the model. Control signals can be used to indicate shortage situations to the households, through which the supplier activates pre-defined electricity demand limits. Both, the electricity demand limits and the point in time at which the activation takes place, are exogenous model parameters.

The core of the model itself covers the simulation and optimization of weekly load profiles. First, the number of appliance utilizations in a specific week and the related start times are simulated for each household. The simulated start time represents the point in time when the household would, under normal circumstances, use the appliance. Subsequently, the optimization regarding the respective tariff takes place. When using tariffs with variable energy prices, the start times or energy demand of appliances at a specific point in time are optimized, if possible, to minimize the related costs. The nomenclature for the developed model is presented in Table 2.

For tariffs with variable capacity prices, the optimization ensures that the power used does not exceed the pre-defined limit. In case the limit is exceeded, a penalty term applies. The objective of the optimization is to minimize these penalties. If a household has a tariff with variable energy and capacity prices, both optimizations are performed. In this case, the results of the variable energy price optimization are used as the initial solution for the capacity price optimization. As described in section 3.3 below in further detail, the initial solution will only be altered if the power demand at a certain point in time

[1] RELO was used on a computer with the operating system Win Server 2008, two AMD Opteron 6134 processors with 2.3 GHz and 64 GB RAM.

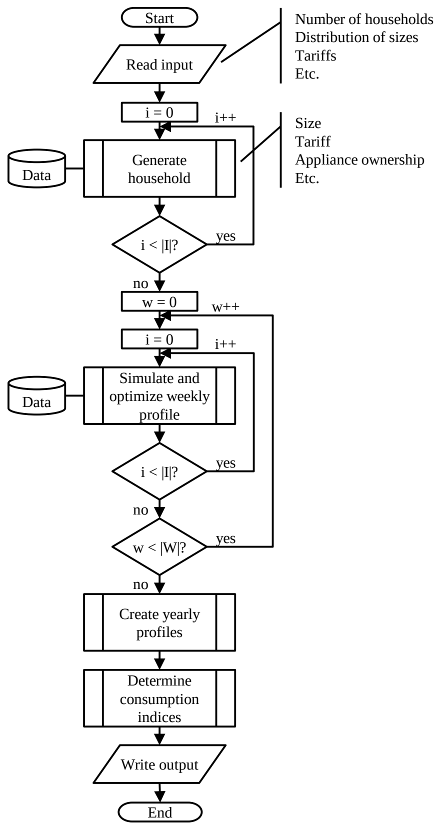

Fig. 1 Simplified flow diagram of the RELO model

exceeds the pre-defined limit during a shortage situation. After the optimization, the final weekly load profile of the household is created based on the final start times and energy demand of all appliances.

The main criterion for the differentiation of households is their size [22]. Based on their size, households are randomly equipped with different electric appliances and have a different user behavior regarding the number of utilizations as well as heat and hot water requirements. Additionally, each household uses a specific electricity tariff. The considered appliance types and clustered sets are described in Table 3. Appliances with significantly fluctuating power demand during their utilization, e.g., fridges and washing machines, are characterized through simplified load profiles [49]. In the following, these general appliance types are indicated by the index $\dot{g}$ and the respective set $\dot{G}$. When referring to a specific appliance of a household and not to the general appliance type the index g is used. Within each set, appliances may be available for load shifting, i.e., either appliances with smart communication interfaces

Table 2 Nomenclature

Parameter and variables		Index sets	
b	Binary decision variable	A	Days
c	Costs	G	Appliances
D	Duration of utilization	H	Hours
e	Energy	I	Households
M	Big M Parameter	S	Shortages
q	Power	T	Points in time
γ	Power level	U	Number of utilizations
τ	Penalty term	W	Weeks
ϕ	Price		
λ	Load		
ν	Power supply from PV-system		
ψ	Load factor		
Accents		**Other indices**	
$\dot{}$	Appliance type	d	Point in time during utilization
$\tilde{}$	Already simulated value	$Flex$	Manual or automated shifts possible
$\dddot{}$	Already optimized value	max	Upper bound/ maximum
		min	Lower bound/ minimum
		$Start$	Starting point

Table 3 Overview of clustered appliance sets

Parameter	Appliance set	Clustered appliance types
G	All considered appliances	All appliances mentioned below and telecommunication appliances, circulation pumps, residual category
G^{Active}	Appliances with active participation of people	Washing machines, tumble dryers, dish washers, stoves, TV, DVD/video, audio, PC/laptop, lighting
G^{Heat}	Appliances used for room or water heating	Night storage heating, direct hot water heating, hot water heating with storage
G^{Cold}	Appliances used for cooling	Fridges, freezers

that can be used for automated demand response (ADR) or appliances with or without smart communication infrastructure that can be manually shifted such as washing machines or dish washers. The set of shiftable appliances is marked by the superscript index Flex (see Table 2).

The model makes use of data from different sources during the simulation in order to reflect the characteristics of German households. In addition to statistical information on the distribution of household sizes and different appliance types [11], the main input data are cumulated distribution functions (CDF) used to determine the start time of appliances. The CDF consider seasonal and diurnal variations in appliance utilization as well as hourly ones [42]. For validation and calibration purposes of the simulated load profiles without demand response, the BDEW H0 standard load profile is used [16], for load profiles with demand response, data from the already mentioned field trial are considered [27]. The full overview of data used is given in Table 4.

Table 4 Overview of data used

Data	Description	Source
Household distribution	Statistic distribution of number of occupants in households in Germany (household size) [in %]	Destatis [11]
Appliance distribution	Statistic distribution each appliance type for different household sizes (saturation) [in %]	Destatis [11]
Appliance stock	Number of appliances of each appliance type available in 100 households for different household sizes [in units]	Destatis [11]
Average household electricity demand	Average electricity demand of households for different household sizes and the respective standard deviation [in kWh]	Frondel et al. [15]
Average appliance electricity demand	Average electricity demand as percentage of total residential electricity demand [in %]	Bürger [8]
Average appliance utilization	Calculated average utilizations per year of active appliances for different household sizes [in use times]	Gottwalt et al. [20]
Simplified appliance load profiles	Simplified load profiles of all appliance types in 15 minutes steps for an average use cycle [in W]	Stamminger [49]
Average appliance peak load	Average peak load of appliance types [in W]	Beer [2]; Stamminger [49]
Daily appliance electricity demand	Share of yearly electricity demand of active appliances distributed to each weekday for winter and summer [in %]	Prior [42]
Hourly appliance electricity demand	Share of abovementioned daily electricity demand of active appliances distributed to each hour of a day [in %]	Prior [42]
Average heating days per season	Average number of heating days in Germany for different seasons [in days]	IWU [29]
Average days with hot water demand	Average number of days per year when households require hot water [in days]	Beer [2]
PV generation profiles	PV generation time series for different system sizes for the year 2011 [in W]	Bertsch et al. [4]
Load shifting potential	Relative load shifting potential under tariffs with variable energy prices [in %]	Hillemacher et al. [27]
BDEW H0 standard load profile	Standard load profile representative for household samples with more than 150 households [in W]	Fünfgeld and Tiedemann [16]

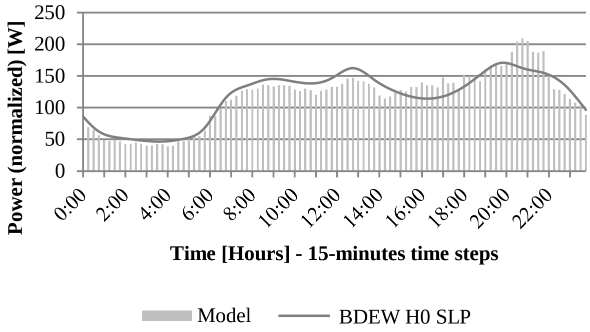

Fig. 2 Visualization of modeled load profile of 1,000 households and BDEW H0 standard load profile of a summer weekday

3.1 Load profile simulation

The first step of the model consists of the creation of household objects, each described through a household's size, i.e., the number of occupants, the equipment with electric appliances, their specific utilization rates and an electricity tariff. Furthermore, each appliance is characterized with a specific peak load determining its electricity demand during utilization. Mathematically, this definition of household objects is based on pseudo random numbers combined either with the inverse function of the cumulative distribution function (quantile function), e.g., for the household's size, or with Bernoulli-experiments, e.g., for the ownership of different appliance types. Several characteristics of a household object are dependent on the household size, for instance the ownership of different appliance types, the number of owned appliances per appliance type and the utilization rate of different appliances. The underlying data for this differentiation stems from empirical studies and statistical data from Germany (see Table 4). If the corresponding data from other countries is at hand, it is easy to adapt the model accordingly allowing for the generation of load profiles for households of the respective country.

The simulation of individual load profiles takes place on a weekly basis, taking seasonal and diurnal variations in the probability of appliance utilizations into account. The start time of each utilization of a household's appliance is allocated to a specific 15-minutes time step of a week based on empirical quantile functions per appliance type [42]. Subsequently, the appliance specific load profile is allocated to that start time. By aggregating the electricity demand of each appliance in every time step of a week, the household's load profile can be constructed (see Fig. 2 for an example of a summer weekday). A basic version of the simulation approach is described in [23]. However, the model described in this paper goes beyond [23] in that it allows for analyzing demand side flexibility as a response to variable energy prices (see section 3.2 below) and variable capacity prices (see section 3.3 below).

Table 5 Indices for the comparison of simulated load profiles to the BDEW H0 standard load profile

Number of simulated households	Correlation with BDEW H0-SLP	RMSE [in W]
1	0.203	162.3
10	0.652	52.8
100	0.895	22.7
1,000	0.929	17.5
10,000	0.931	17.1

Standard load profiles are accepted as good approximations of cumulated load profiles for more than 400 households [13]. The correlation coefficient of the standard load profiles and the simulated load profiles for an increasing number of households simulated with the model developed (see Table 5) can therefore be used to validate the model for large numbers of households. While individual households show only a low correlation to the BDEW H0 standard load profile (SLP), the correlation coefficient strongly increases when analyzing more households (see also Fig. 2). Also the root mean square error (RMSE) supports the increasing fit of the simulated load profiles with an increasing number of households.

3.2 Optimization with variable energy prices

The RELO model is not only able to simulate the effect of residential tariffs with variable energy prices but also the effect of self-consumption of self-produced electricity from PV systems. In both cases, the energy price for households is time-dependent as electricity from PV is only available with a limited amount at certain points in time. The model assumes that the household knows for the entire simulated week at what time which price is valid and how much power from its PV system can be used. We are aware, that in reality this information might rather be available on a day-ahead basis. However, the effect of this information discrepancy is mostly negligible as neither the initial start time of the individual appliances relies on this knowledge, nor can any appliance be shifted by more than 24 hours. Hence, the model implicitly applies a day-ahead logic. On this basis, the household aims at minimizing its electricity bill by shifting utilizations of certain appliances. Only certain types of appliances can provide demand side flexibility, either when they are equipped with a thermal storage or when they operate rather independently from household's occupants once started [32, 38]. The former are fridges, freezers, electric heating systems and hot water systems with storage reacting on price signals through ADR. The latter are dish washers, washing machines and tumble dryers which can either react to price signals through ADR or can be shifted manually in their utilization by household occupants delaying their start time. For each appliance, type specific restrictions constraining their flexibility are considered. These are summarized in Table 6.

Table 6 Overview of appliance specific load shifting restrictions

	Load shifting range		Time of day restrictions
	Earliest start	Latest start	
Fridges[a]	Up to 1 hour earlier	Up to 1 hour later	None
Freezers[a]	Up to 1 hour earlier	Up to 1 hour later	None
Dish washers	Simulated start time[c]	Up to 12 hours later[b]	None
Washing machines	Simulated start time[c]	Up to 4 hours later[b]	Not later than 10 p.m. [b]
Tumble dryers	Simulated start time[c]	Up to 4 hours later[b]	Not later than 10 p.m. [b]
Night storage space heatings[c]	Simulated start time	Up to 24 hours later	None
Hot water heatings (Storage)[c]	Simulated start time	Up to 24 hours later	None

[a] Cf. Klobasa [32]; [b] Cf. UBA [35]; [c] Own assumptions

An optimization takes place for every shiftable appliance utilization within one week. Shiftable appliance utilizations are those of appliances with ADR and those for which households are willing to react on price signals manually. The probability for manual load shifting is derived through calibrating the model with measured data from the field trial already mentioned. The probability takes seasonal, diurnal and hourly differences into account. The objective of the optimization is to minimize the energy costs.

The linear (integer) optimization problems are solved with IBM ILOG CPLEX for appliances with thermal storage and with exhaustive enumeration for appliances with active participation of occupants but independent operation (dish washers, washing machines, tumble dryers).[2] In the latter case, a solver does not have any computational advantages due to the non-linear structure of tariffs with variable energy prices and the problems are rather simple since the only decision variable is the specific start time of a utilization. In the former case, however, the decision variable is the specific electricity demand of an appliance at every point in time leading to more complex optimization problems, thus necessitating a solver. This difference results in two different optimization problems – one for dish washers, washing machines, tumble dryers, i.e., active appliances, and one for appliances with thermal storage.

The objective function and the related cost function for shiftable active appliances $G^{FlexActive}$ are given in formulas (1) and (2). The decision variable in the optimization is the specific start time t of each utilization $u \in U_{w,g}$ of an appliance $g \in G^{FlexActive}$ in a week $w \in W$. The lower and upper bound ($t^{min}_{w,g,u}$ and $t^{max}_{w,g,u}$) for the start time, i.e., the shifting range, depend

[2] The number of variables and constraints varies significantly depending on the appliance type and its considered shifting ranges, which also affects the computing time. For instance, the optimization of fridges and freezers typically requires about 16 variables and 17 constraints while domestic hot water or space heating requires about 192 variables and 288 constraints. The default configuration of IBM ILOG CPLEX was used.

on the appliance specific restrictions given in Table 6. The costs of a specific utilization $c_{w,t,g,u}$ are cumulated over its duration $D_{\dot{g}}$, where g is of type $\dot{g}$. The costs are influenced through the given energy price from the tariff $\phi^{Tariff}_{w,(t+d)}$, where d counts through the duration of an appliance utilization, and the power used from a PV system $q^{PV}_{w,(t+d),g,u}$ which is available at a lower price ϕ^{PV}[3] (cf. constraint (2)). The usable power from a PV system is restricted through the power $v_{w,t}$ initially available at a specific point in time reduced by the already simulated electricity demand $\tilde{q}_{w,t,g,u}$ of other appliances (cf. constraint (3)). If the remaining PV power is larger than the appliance load, the appliance can use PV power only. Otherwise, the appliance load will be partially covered by PV and the rest will be covered by electricity from the grid. Since the covered appliances follow a specific load profile, their electricity demand during the utilization can be determined through a load factor $\psi_{\dot{g},d}$ and the appliance peak load λ^{max}_g. As the price is given per energy unit, the electricity demand is converted to its corresponding energy demand in the specific 15-minutes time step.

$$\min_{t \in \{t^{min}_{w,g,u}, \dots, t^{max}_{w,g,u}\}} c_{w,t,g,u} \tag{1}$$

$$c_{w,t,g,u} = \frac{1}{4} \sum_{d=0}^{D_{\dot{g}}-1} \left(q_{w,(t+d),g,u} \cdot \phi^{PV} + (\psi_{\dot{g},d} \cdot \lambda^{max}_g - q^{PV}_{w,(t+d),g,u}) \cdot \phi^{Tariff}_{w,(t+d)} \right)$$
$$\forall t \in \{t^{min}_{w,g,u}, \dots, t^{max}_{w,g,u}\}, g \in G^{FlexActive}, u \in U_{w,g}, w \in W \tag{2}$$

$$q^{PV}_{w,t,g,u} = max \left(0, min \left(v_{w,t} - \sum_{g \in \tilde{G}} \sum_{u \in \tilde{U}_{w,g}} \tilde{q}_{w,t,g,u}, \lambda^{max}_g \right) \right)$$
$$\forall t \in \{0, 1, \dots, |T_w|\}, g \in G^{Flex}, u \in U_{w,g}, w \in W \tag{3}$$

Shiftable appliances with thermal storage ($g \in G^{FlexHeat} \cup G^{FlexCold}$) follow a different optimization approach, represented through the objective function and the related cost function in formulas (4) and (5). In this case the decision variables are the power used from a PV system $q^{PV}_{w,t,g,u}$, if available, and the power used from the grid $q^{Grid}_{w,t,g,u}$. Combined with the specific price ϕ^{PV} and $\phi^{Tariff}_{w,t}$ respectively, the utilization costs can be determined. Divergent from the previous optimization problem, the utilization is not dependent on a specific start time. While cold appliances are continuously in use throughout a week and their optimization takes place on an hourly basis, heating appliances are optimized on a daily basis, depending on whether or not they are used on a specific day.

[3] In many applications, ϕ^{PV} may be assumed to be zero. However, there may be cases where $\phi^{PV} > 0$, e.g., if those who live in the house do not own the PV modules but pay a fee for each kWh of PV power as defined in an agreement with the owner of the PV modules.

$$\min_{(q^{PV}_{w,t,g,u},\, q^{Grid}_{w,t,g,u})} \quad c_{w,g,u} \tag{4}$$

$$c_{w,g,u} = \frac{1}{4} \sum_{t=t^{min}_{w,g,u}}^{t^{max}_{w,g,u}} \left(q^{PV}_{w,t,g,u} \cdot \phi^{PV} + q^{Grid}_{w,t,g,u} \cdot \phi^{Tariff}_{w,t} \right) \qquad \forall g \in G^{FlexHeat} \cup G^{FlexCold}, u \in U_{w,g}, w \in W \tag{5}$$

The given optimization problem is subject to several constraints. Independent from the specific appliance type, the electricity demand from the grid may not exceed the peak load λ^{max}_g of the specific appliance. Additionally, other constraints need to be considered depending on the optimized appliance type.

Fridges and freezers are implemented with a short shifting range of plus/ minus one hour. The main constraint in this case is that within every hour $h \in H_w$ in week w the initially simulated electricity demand $\tilde{q}_{w,g,h}$ needs to be covered during the optimization time span from $t^{min}_{w,g,h}$ to $t^{max}_{w,g,h}$ through power used either from the PV system $q^{PV}_{w,t,g,h}$ or from the grid $q^{Grid}_{w,t,g,h}$ (see equation (6)).

$$\sum_{t=t^{min}_{w,g,h}}^{t^{max}_{w,g,h}} \left(q^{PV}_{w,t,g,h} + q^{Grid}_{w,t,g,h} \right) = \tilde{q}_{w,g,h} \qquad \forall h \in H_w, g \in G^{FlexCold}, w \in W \tag{6}$$

Due to this hourly approach, consecutive optimizations overlap. In order to adhere to the appliance specific minimum and maximum loads λ^{min}_g and λ^{max}_g, an additional constraint is considered. The sum of the already set electricity demand from previous optimizations $\ddot{q}_{w,t,g}$ and the two decision variables of the current optimization $q^{PV}_{w,t,g,h}$ and $q^{Grid}_{w,t,g,h}$ must remain within the appliance specific load limits (see constraint (7)).

$$\lambda^{min}_g \leq q^{PV}_{w,t,g,h} + q^{Grid}_{w,t,g,h} + \ddot{q}_{w,t,g} \leq \lambda^{max}_g \qquad \forall t \in \{0, 1, ..., |T_w|\}, h \in H_w, g \in G^{FlexCold}, w \in W \tag{7}$$

For shiftable heating appliances $G^{FlexHeat}$, the electricity demand throughout a day a is optimized. The main constraint in this case is that the minimum required heat $e^{min}_{w,t,g,a}$, from the beginning of the day until the current time period, of a household is supplied by the appliance at every point in time of that day. Therefore, the cumulated electricity demand of the appliance, from the starting point of the optimization $t^{min}_{w,g,a}$ to the current time step t, must be greater or equal to the minimum required heat (see constraint (8)). Again, similar to the optimization of fridges and freezers, the sum of used power from a PV system and from the grid must remain within the appliance specific load limits.

$$\frac{1}{4}\sum_{j=t^{min}_{w,g,a}}^{t}\left(q^{PV}_{w,j,g,a}+q^{Grid}_{w,j,g,a}\right)\geq e^{min}_{w,t,g,a} \qquad \forall t\in\{0,1,...,|T_a|\}, g\in G^{FlexHeat}, a\in A_{w,g}, w\in W \tag{8}$$

The described optimization results in cost minimal load profiles for every shiftable appliance in a specific week. This profile replaces the initially simulated one and will be used in case of an additional optimization with variable capacity prices which will be described in the next section.

Based on the described optimization with variable energy prices, the model is calibrated with data from the already mentioned field trial in order to reflect manual load shifting of households appropriately. In the field trial, a modified time of use tariff with three price levels was used from very low (SNT) over low (NT) to high (HT) [27]. Every evening, the consumers received the information which price level would apply in which hour of the following day. Additionally, around 25% of the participating households were equipped with smart appliances (some of which were controlled through ADR), mainly smart freezers, some smart dish washers and washing machines and few smart tumble dryers. The objective of the calibration is to represent the load shifting behavior, observed in the field trial, appropriately within the model. Therefore, the field trial data is used to derive probabilities for hourly Bernoulli distributions. It is assumed, that the observed load shifting behavior based on the modified time of use tariff is an appropriate basis for simulating reactions to real time tariffs as well, which will be analyzed in the scenarios in section 4.

In Fig. 3, the indicated range represents the minimum and maximum load shifting potential achievable within the model using the abovementioned configuration from the field trial. The minimum is achieved when only the existing smart appliances react on the given price signals, the maximum when, in addition, all households manually shift all utilizations of their dish washers, washing machines and tumble dryers to the optimal start time.

In order to avoid an overestimation of the load shifting potential, three aspects need to be considered in the calibration. First, a few households in the field trial had an additional battery storage leading to an increased load shifting potential which is not covered in the model. Second, the model setup used for the calibration may differ from the real situation in the field trial, e.g., the distribution of household sizes and electric appliances. Third, the results from the field trial may be biased due to the voluntary participation of the households having an increased interest in this topic and maybe a higher willingness to react on price signals [27]. Consequently, following a more conservative approach, the calibration should result in a slightly lower load shifting potential from the model than observed in the field trial.

The calibration takes place through the definition of probabilities for hourly Bernoulli distributions of every season weekday combination ranging from zero

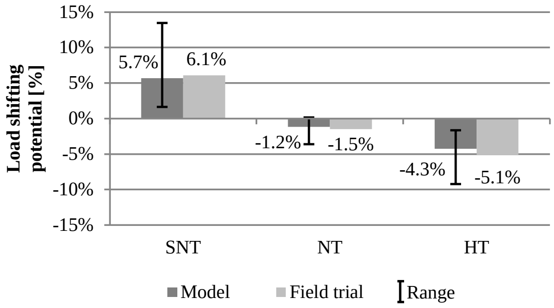

Fig. 3 Comparison of the modeled load shifting potential to the results from a field trial [27]

(no manual load shifting at all) to one (full manual load shifting). In Fig. 3, the columns show the achieved load shifting potential with the finally chosen Bernoulli distributions of the model in comparison to the observed load shifting potential within the field trial. Based on the underlying likelihood, the model determines for every utilization of dishwashers, washing machines and tumble dryers if manual load shifting takes place. The hourly probabilities are given in Table 9 in the appendix.

3.3 Optimization with variable capacity prices

Similar to the optimization with variable energy prices, the optimization with variable capacity prices is influenced through the use of a related tariff and the existence of a PV system. Again it is assumed that households know for one week in advance at what time how much power from their PV systems is available and at what time and for how long a curtailment will occur. The considered appliance types remain the same as in the optimization with variable energy prices having the same shifting restrictions already presented in Table 6. This time, however, the optimization does not take place for single appliances but for every shortage situation during the week considering all appliances in use during the shortage. The mixed integer linear problems are solved with the IBM ILOG CPLEX solver.[4] The maximum available power level of households $\gamma_{w,t}^{max}$ depends on the contracted guaranteed power level $\gamma_{w,t}^{Tariff}$ and, if available, additional power from a PV system $v_{w,t}^{max}$ at a specific point in time (see equation (9)).

$$\gamma_{w,t}^{max} = \gamma_{w,t}^{Tariff} + v_{w,t}^{max} \forall t \in \{0, 1, ..., |T_w|\}, w \in W \tag{9}$$

[4] The number of variables, binary decision variables and constraints differs significantly between shortage situations depending on the appliance types and their shifting ranges. For instance, a model run with 1,000 households, a maximum power level restricted over one year and 100% smart households requires approximately from 100 to 17,000 constraints, 30 to 11,000 variables and 30 to 8,500 binary decision variables.

The objective of the optimization is to remain below the maximum power level in every shortage situation announced by the electricity provider, given as exogenous input for the model. Therefore the utilizations of all shiftable appliances can be optimized within the lower and upper bound of a shortage ($t_{w,s}^{min}$ and $t_{w,s}^{max}$), both depending on the considered appliances shifting ranges. In order to reduce possible negative impacts on households' comfort, appliance types are prioritized based on a penalty term $\tau_{\dot{g}}^{Flex}$. Whenever possible, smart heating appliances $G^{FlexHeat}$ are used first, then smart fridges and freezers $G^{FlexCold}$ and finally shiftable active appliances $G^{FlexActive}$. If a household is not able to remain below its maximum available power level during a shortage situation, a much bigger penalty term τ^{Tariff} is applied. In this case, it can be chosen if the model shall allow the household to consume more power than contracted or if the electricity demand is reduced on the contracted power level after the optimization. The former represents a possible tariff structure where consumers would have to pay a penalty price when exceeding their power level during shortages. The latter represents a tariff where technical restrictions hinder households in exceeding their power level. In reality the latter would mean for households that they would need to provide additional demand side flexibility, e.g., by switching of other appliances than considered as shiftable in this model.

The objective function (10) includes two binary decision variables $b_{w,t,s}^{Tariff}$ and $b_{w,t,s,g,u}^{Flex}$ linking this function with the main constraints of the optimization problem. The first decision variable is part of a big-M constraint turning one if the cumulated electricity demand of all appliance utilizations exceeds the maximum available power level $\gamma_{w,t}^{max}$ at any point in time during the duration of the shortage $s \in S_w$ in week $w \in W$ from $t_{w,s}^{min}$ to $t_{w,s}^{max}$ (see constraint (11)). Otherwise $b_{w,t,s}^{Tariff}$ is null.

$$\min_{(b_{w,t,s}^{Tariff},\, b_{w,t,s,g,u}^{Flex})} \left(\sum_{t=t_{w,s}^{min}}^{t_{w,s}^{max}} \left(\tau^{Tariff} \cdot b_{w,t,s}^{Tariff} + \sum_{g \in G^{Flex}} \sum_{u \in U_{w,g}} \tau_{\dot{g}}^{Flex} \cdot b_{w,t,s,g,u}^{Flex} \right) \right) \tag{10}$$

subject to:

$$\left(\sum_{g \in G} \sum_{u \in U_{w,g}} q_{w,t,g,u} \right) - \gamma_{w,t}^{max} \leq b_{w,t,s}^{Tariff} \cdot M^{Tariff} \tag{11}$$
$$\forall t \in \{t_{w,s}^{min}, ..., t_{w,s}^{max}\}, s \in S_w, w \in W$$

The second binary variable of the objective function turns one if an appliance utilization is changed during the optimization in comparison to the initially simulated load profile. For heating appliances as well as fridges and freezers a deviation from the initially simulated electricity demand $\tilde{q}_{w,t,g,u}$ can exist through an over- or under-consumption at a specific point in time. Consequently, the binary variable equals the sum of two other binary variables

$b^{Flex+}_{w,t,s,g,u}$ for the over- and $b^{Flex-}_{w,t,s,g,u}$ for the under-consumption (see equation (12)). The related big-M constraints to penalize the corresponding deviation are given in (13) and (14).

$$b^{Flex}_{w,t,s,g,u} = b^{Flex-}_{w,t,s,g,u} + b^{Flex+}_{w,t,s,g,u}$$
$$\forall t \in \{t^{min}_{w,s}, ..., t^{max}_{w,s}\}, g \in G^{FlexHeat} \cup G^{FlexCold}, u \in U_{w,g}, s \in S_w, w \in W \tag{12}$$

$$\tilde{q}_{w,t,g,u} - q_{w,t,g,u} \leq b^{Flex-}_{w,t,s,g,u} \cdot M^{Flex}_{\dot{g}}$$
$$\forall t \in \{t^{min}_{w,s}, ..., t^{max}_{w,s}\}, g \in G^{FlexHeat} \cup G^{FlexCold}, u \in U_{w,g}, s \in S_w, w \in W \tag{13}$$

$$q_{w,t,g,u} - \tilde{q}_{w,t,g,u} \leq b^{Flex+}_{w,t,s,g,u} \cdot M^{Flex}_{\dot{g}}$$
$$\forall t \in \{t^{min}_{w,s}, ..., t^{max}_{w,s}\}, g \in G^{FlexHeat} \cup G^{FlexCold}, u \in U_{w,g}, s \in S_w, w \in W \tag{14}$$

For shiftable active appliances, the specific start time of the utilization $t^{Start}_{w,g,u}$ is the determining factor for its electricity demand since, after the start, a fixed load profile is followed. To reflect this appliance behavior appropriately in the optimization problem, every step of the load profile is represented with a dedicated binary variable $b^{Profile}_{w,t,s,g,u,d}$ during the shifting range of the appliance utilization. This variable is set to one if, at a specific point in time t, the specific value of the appliance load profile at position d is used. In combination with a load factor $\psi_{\dot{g},d}$ of that specific position and the appliance peak load λ^{max}_{g}, the electricity demand can be calculated accordingly (see equation (15)).

$$q_{w,t,g,u} = \sum_{d=0}^{D_{\dot{g}}-1} b^{Profile}_{w,t,s,g,u,d} \cdot \psi_{\dot{g},d} \cdot \lambda^{max}_{g} \tag{15}$$
$$\forall t \in \{t^{min}_{w,s,g,u}, ..., t^{max}_{w,s,g,u}\}, g \in G^{FlexActive}, u \in U_{w,g}, s \in S_w, w \in W$$

Constraint (16) connects the single steps of the load profile, constraint (17) ensures that every step of the appliance load profile is used only once per utilization. Finally, constraint (18) is used to avoid a temporal overlap of two utilizations of the same appliance.

$$b^{Profile}_{w,t,s,g,u,d} = b^{Profile}_{w,(t-s),s,g,u,(d-1)}$$
$$\forall t \in \{t^{min}_{w,s,g,u}, ..., t^{max}_{w,s,g,u}\}, g \in G^{FlexActive}, u \in U_{w,g}, \tag{16}$$
$$d \in \{1, ..., D_{\dot{g}} - 1\}, s \in S_w, w \in W$$

$$\sum_{t=t_{w,s,g,u}^{min}}^{t_{w,s,g,u}^{max}} b_{w,t,s,g,u,d}^{Profile} = 1 \qquad (17)$$

$$\forall g \in G^{FlexActive}, u \in U_{w,g}, d \in \{0, ..., D_{\dot{g}} - 1\}, s \in S_w, w \in W$$

$$\sum_{u \in U_{w,g}} \sum_{d=0}^{D_{\dot{g}}-1} b_{w,t,s,g,u,d}^{Profile} \leq 1 \qquad (18)$$

$$\forall t \in \{t_{w,g,u}^{min}, ..., t_{w,g,u}^{max}\} g \in G^{FlexActive}, s \in S_w, w \in W$$

If the utilization of an active appliance is delayed during the optimization, the start time changes and consequently the first step of the appliance load profile takes place at a different point in time. The corresponding binary variable $b_{w,t_{w,g,u}^{Start},s,g,u,0}^{Profile}$ is linked to the penalty binary variable $b_{w,t_{w,g,u}^{Start},s,g,u}^{Flex}$ for active appliances (see constraint (19)), with $t_{w,g,u}^{Start}$ being the previously simulated start time.

$$1 - b_{w,t_{w,g,u}^{Start},s,g,u,0}^{Profile} \leq b_{w,t_{w,g,u}^{Start},s,g,u}^{Flex} \qquad (19)$$

$$\forall g \in G^{FlexActive}, u \in U_{w,g}, s \in S_w, w \in W$$

Other constraints considered in the optimization with variable capacity prices relate to the minimum heat and cooling requirements and are very similar to those already explained in the previous section. Therefore, they are not explained in detail again. After the optimization, the already created weekly load profiles of the household are adapted accordingly and the next week can be simulated until a full annual load profile is available.

4 Results and discussion

The described model is used for a comparative analysis of the impact of different electricity tariffs on residential demand side flexibility. Therefore, four different scenarios will be defined, evaluated and discussed in the following.

4.1 Scenario description

The RELO model offers a wide range of setup options, e.g., with regard to the simulated household characteristics, the share of smart appliances in households and the applied electricity tariffs. As the objective of this paper is to analyze the impact of different tariffs on residential demand side flexibility, the scenarios must be identical except regarding the applied tariff.

Table 7 Guaranteed power levels for different tariff options

	Lower need for supply security	Higher need for supply security
1-person-households (HH1)	2,000 W	4,000 W
2-persons-households (HH2)	2,500 W	4,500 W
3-persons-households (HH3)	3,000 W	5,000 W
4-persons-households (HH4)	3,000 W	5,000 W
5 or more-persons-households (HH5)	3,500 W	5,000 W

The reference for the following analysis is a scenario with a classic electricity tariff without any variable price components representing the status quo for most German households. For the tariff with variable capacity prices, the service level objective for three out of four service level indicators, i.e., the guaranteed power level, the frequency of curtailments and the duration, must be defined for different household sizes as the household size is a major impact factor for residential electricity demand [22]. Furthermore, since households shall only be curtailed in case of shortage situations, it must be defined when these shortage situations occur. As this is an exogenous parameter to our model, we use hourly EEX prices of 2011 as a reference. Based on these prices, ten shortage situations with a maximum duration of four hours are defined in every month at times when the EEX prices are the highest. The frequency of ten shortages per month with a maximum duration of four hours is taken from the results of a representative survey with more than 1,000 German households indicating that this combination of service level objectives is accepted by the majority of households [25]. The survey results additionally indicate that households have different needs for supply security – some households have a higher, some have a lower need for supply security. Hence, based on the survey results and some sensitivity analyses with the model, the guaranteed power levels for different household sizes are set as shown in Table 7. With regard to the shown values it must be kept in mind that the model operates on a basis of 15-minutes time steps. Thus, higher inrush currents that might occur from specific electric appliances or other peaks become leveled in the model, leading to an underestimation of peak loads.

In order to achieve consistent scenarios, the tariff with variable energy prices is based on the same EEX data and information on the composition of average German residential electricity prices, given in Table 8. By substituting the average value for generation (the 5.112 Ct/kWh in the second but last row of Table 8) by the EEX electricity price for each hour, a real-time-price tariff with hourly values is constructed.[5] The chosen methodology ensures consistency in the effects of the tariff with variable energy and variable capacity prices since curtailments and high energy prices coincide.

Beyond the tariffs, further setup options must be defined for the scenarios. In all scenarios 1,000 households are simulated reflecting the German distribution of household sizes as well as the corresponding equipment with electric

[5] The hourly EEX prices for 2011 are available at www.eex.com.

Table 8 Composition of average German residential electricity prices in 2011

Price components	Value 2011	Unit	VAT relevant
Concession feeds	1.79	Ct/kWh	Yes
Surcharge under EEG	3.53	Ct/kWh	Yes
Surcharge under KWKG	0.03	Ct/kWh	Yes
Electricity tax	2.05	Ct/kWh	Yes
Surcharge under section 19 StromNEV	0	Ct/kWh	Yes
Surcharge for offshore liability	0	Ct/kWh	Yes
Generation, sales, transport & distribution	13.8	Ct/kWh	Yes
Net electricity price	21.2	Ct/kWh	Yes
Value-added tax (VAT)	19	%	No
VAT absolute	4.028	Ct/kWh	No
Gross electricity price	25.228	Ct/kWh	No
Net network tariff (transport & distribution)	20	%	Yes
Net network tariff absolute	5.046	Ct/kWh	Yes
Generation, sales	8.754	Ct/kWh	Yes
Generation (Average spot price)	5.112	Ct/kWh	Yes
Sales	3.642	Ct/kWh	Yes

appliances [11]. Only appliances for electric hot water and space heating are excluded for two reasons. First, only a minority of German households uses electric appliances for hot water and space heating. Second, the high electricity demand of these appliances would require different tariffs with variable capacity prices which would be beyond the scope of this paper. Note that even today's residential standard load profile is not valid for households with electric space heating [16].

The model is able to reflect manual reaction of households and ADR on price or control signals. For ADR, smart appliances are required. As a first set of results of our model, Fig. 4 illustrates the effect of different shares of smart appliances in combination with the time-of-use tariff of the already mentioned field trial. Fig. 4 also differentiates between households with and without hot water and space heating appliances. Each household owning at least one smart appliance is denominated as a smart household.

In the field trial, about 25% of smart households participated. With an increasing share of smart appliances, the number of smart households increases as well, leading to a higher load shifting potential (cf. Fig. 4). Especially the utilization of smart hot water and space heating appliances allows households to significantly increase their demand side flexibility, due to the associated thermal storages and the high energy demand of these appliances. Since nowadays, residential electricity tariffs with variable price components are hardly available, we analyze potential future scenarios. Therefore, we assume a share of 50% smart appliances, representing a possible scenario in the mid-term future. As a consequence, around 90-95% of all simulated households own at least one smart appliance.

The results of the conducted survey indicate that around 75% of the participants are willing to use a tariff with variable capacity prices [25]. However,

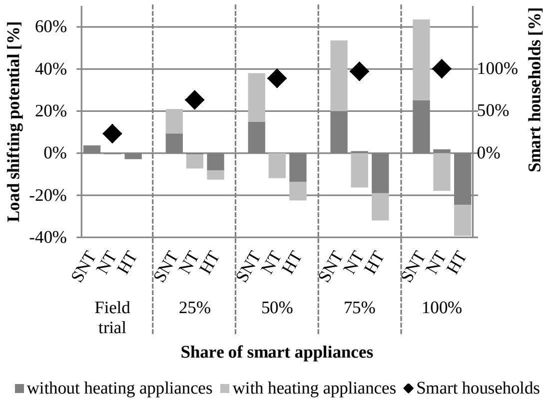

Fig. 4 Sensitivity analysis for the impact of smart appliances on demand side flexibility

	Reference scenario	Variable capacity prices (var. CP)	Variable energy prices (var. EP)	Variable energy and capacity prices (var. EP + CP)
Distribution of household sizes	Germany			
Distribution of appliances	Germany (except exclusion of heating appliances)			
Share of smart appliances	50 %			
Utilization of variable tariffs	0 %	100 %		
Energy price	Fix		Variable (EEX)	
Capacity price	Fix	Variable	Fix	Variable

Fig. 5 Characteristics of the four considered scenarios

for the purpose of this paper, we assume that all households use the same tariff within one scenario. Besides the reference scenario without variable price components, three more scenarios are analyzed. One scenario with variable energy prices, one with variable capacity prices and one with variable energy and capacity prices. Fig. 5 summarizes the main characteristics of the four scenarios and the corresponding model setup.

4.2 Scenario analysis

As the defined scenarios differ only with regard to the applied tariffs they can be used to analyze the impact of different residential electricity tariffs on demand side flexibility. In this context, two questions are of major interest:

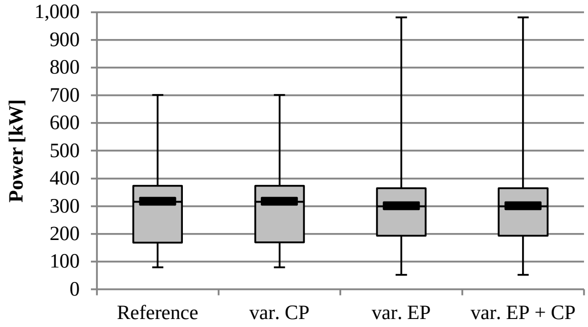

Fig. 6 Box plots for the electricity demand of 1,000 simulated households

– How do different tariffs alter the general household behavior related to electricity use?
– How do these tariffs influence the electricity use of households in times of shortages?

Fig. 6 shows the box plot per scenario for the electricity demand of 1,000 simulated households during one simulated year. In terms of the first question, Fig. 6 shows that the box plot of the scenario with variable capacity prices is almost the same as that of the reference scenario. The scenario with variable energy prices, however, shows a completely different structure than the reference scenario (variable energy prices lead to more extreme peak values as well as to a smaller interquartile range and median compared to the reference scenario). And then, the box plot of the scenario with both variable energy and capacity prices is almost the same as that of the scenario with variable energy prices only. In other words, variable energy prices have a significant impact on residential electricity demand while the impact of variable capacity prices is negligible. This suggests that under variable energy prices, the related load profile is smoothened during most times of the year but it shows extreme values at certain times. In contrast, the impact of tariffs with variable capacity prices is only visible in the absolute values being too small to be visible in the chart. Basically, tariffs with variable capacity prices slightly reduce the maximum demand when used in combination with variable energy prices.

The described results can be explained through the different tariff structures. While tariffs with variable capacity prices, as used within this paper, only influence households' electricity demand during shortages, which is for a maximum of 40 hours per month and only aiming at power reduction, the applied tariff with variable energy prices constantly incentivizes households to adapt their electricity demand in both directions. Additionally, tariffs with variable energy prices always incentivize all households in the same way while in tariffs with variable capacity prices only those households are constrained that initially intended to use more power than contracted as their guaranteed

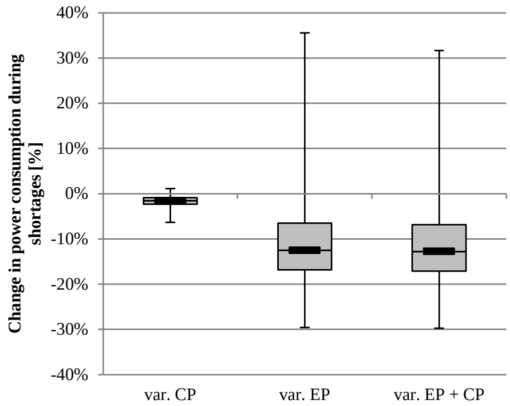

Fig. 7 Box plots for the change in electricity demand during shortages of 1,000 simulated households

power level. In the chosen setup of power levels this is only a fraction of the total number of simulated households, hence the visible effect is smaller.

Since the objective of the tariff with variable capacity prices is to reduce residential electricity demand during shortage situations, the following analysis considers only those time steps where a shortage has been simulated. Fig. 7 shows the box plot per scenario for the change in electricity demand during the shortages of 1,000 simulated households. The maximum power reduction of tariffs with variable capacity prices is approximately -6%, varying in a very narrow interquartile range around the median of -2%. In very few situations a slight power increase can be observed indicated by the top whisker in the box plot of variable capacity prices. This phenomenon occurs mainly during long shortages when load shifting activities result in small power increases in single time steps of the shortage still obeying the effective power levels.

The maximum power reduction of tariffs with variable energy prices, illustrated by the bottom whisker in the second box plot, exceeds the one of tariffs with variable capacity prices with almost -30% by far. Even the median, with almost -13%, is about twice as big as in the former case. However, Fig. 7 also shows two drawbacks. First, tariffs with variable energy prices may lead to strong power increases of more than +30% during some shortage situations aggravating the criticality (see top whisker). Second, the interquartile range is much bigger for tariffs with variable energy prices resulting in a higher uncertainty about the effective power reduction in shortage situations.

The power increase occurs again during long shortages over several hours. Since the energy prices vary on an hourly basis, even small price reductions during the shortage result in lower energy costs incentivizing the households to shift appliance utilizations to that point in time. As all households react simultaneously on price signals in the model these power increases appear.

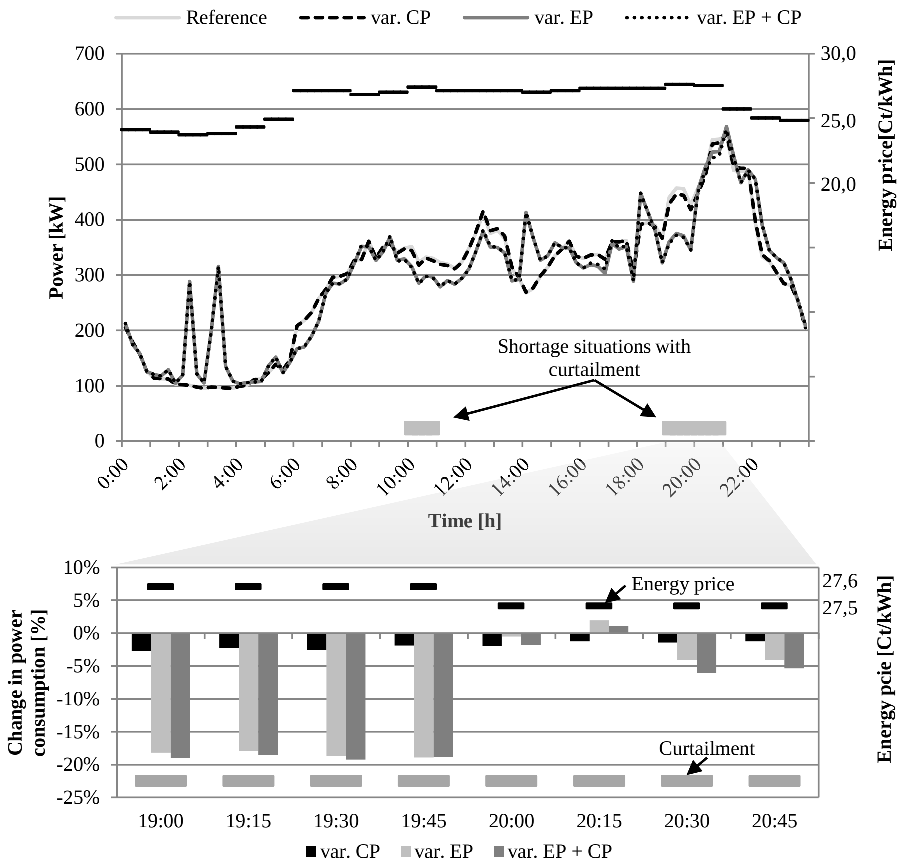

Fig. 8 Load profiles and changes in electricity demand on a summer Sunday with shortage situations and high energy demand

Even though this effect occurs only in about 5% of all time steps in shortage situations, it can still be critical for energy systems, when the majority of power shall be provided through renewable energy sources. Combining variable energy and capacity prices slightly improves the described drawbacks, but the impact of variable energy prices still predominates (cf. box plot of both variable energy and capacity prices in Fig. 7).

Fig. 8 shows a specific example for a summer Sunday with two shortage situations highlighting the impact of the analyzed tariffs on demand side flexibility. The selected day is characterized through a comparably high electricity demand in the reference scenario. In the upper part of the figure, the load profiles of the four scenarios as well as the energy price and shortage situations are shown. The lower part zooms in on one shortage situation showing the change in electricity demand per 15-minutes time step. The results described beforehand are supported by this figure. The scenarios with variable energy prices lead to a much stronger decrease in electricity demand in the first hour of the shortage, but result in a small increase in one time step of the second hour. The scenario with variable capacity prices shows only a power reduction of about -2% but this potential is rather constant over time.

4.3 Discussion

The presented results show that electricity suppliers can influence residential demand through different tariffs. The specific impact on demand side flexibility, however, is strongly dependent on the characteristics of the tariff used.

Tariffs with variable energy prices always incentivize all participating households at the same time. Hence, the achievable change in electricity demand is higher. The main drawback is the occurrence of unwanted power peaks during shortage situations due to the simultaneous reaction of households and smart appliances on small price changes. Additionally, the fluctuation of demand side flexibility varies more. Both effects make it more difficult for electricity providers to predict households' power demand. To overcome the mentioned issues of tariffs with variable energy prices, either a more sophisticated price signal needs to be created or the operating mode of smart appliances needs to be adjusted accordingly to avoid unwanted power peaks.

Also, the setup of tariffs with variable capacity prices influences the measurable demand side flexibility. Even though all households in the corresponding scenario use such a tariff, only those households are curtailed in their electricity demand which have a higher demand than covered through their guaranteed power level. With the current set of power levels, the probability for a household to be curtailed by the model is rather low. Therefore only a limited number of households contributes to the shown effects. Lowering the guaranteed power levels would increase the number of households being curtailed, hence increasing the change in electricity demand. However, due to the temporal resolution of 15 minutes and the related underestimation of power peaks, we do not recommend this approach. The main advantage of tariffs with variable capacity prices is the high predictability and reliability of the achievable change in electricity demand during shortage situations allowing electricity providers to use the resulting demand side flexibility in their planning. Besides these quantified advantages, tariffs with variable capacity prices additionally allow for a fair allocation of system costs based on the individual consumer needs for security of supply. Furthermore, the tariff design with curtailments only in shortage situations avoids the penalization of system-supporting behavior of households in case of excess supply from RES.

In tariffs with variable energy and capacity prices, the impact of the former still predominates the simulated load profiles. The chosen power levels still allow households to increase their power demand in accordance with lower energy prices even in shortage situations without being curtailed. However, an improvement with regard to unwanted power peaks can be achieved. Also the non-quantified advantages mentioned before are still valid.

Critically reflecting our approach, the presented results are subject to certain limitations, mainly related to the chosen model and tariff setup. The main limitation of the RELO model is its temporal resolution of 15 minutes which results in an underestimation of peak loads. Increasing the temporal resolution, e.g., to one minute or even seconds would help to better simulate appliance peak loads such as inrush currents which are leveled with lower temporal resolutions. Consequently, the actual power demand of households can exceed the model results. We also note that our approach optimizing each appliance individually may, theoretically, lead to suboptimal solutions as opposed to an approach optimizing all appliances at the same time. However, this can only happen if self-produced PV power shall be considered for self-consumption, which was not part of the case study in this paper. Moreover, this never turned out to be a problem in a number of test runs. Furthermore, the RELO model includes only 17 different appliance types, therefore not covering the full range of available appliances in households. Including additional appliances has the potential to further increase the reliability of the modeled load profiles. Finally, the data used for the seasonal, diurnal and hourly appliance utilization is based on a field trial from the 1990s. Thus, changes in daily routines of the last 25 years are not considered. To overcome the mentioned model limitations, more detailed data needs to be made available.

5 Conclusions and outlook

Within this paper, we have developed the RELO (**R**esidential **E**lectricity **L**oad profile simulation and **O**ptimization) model capable to simulate the impact of different electricity tariffs on residential demand side flexibility. With regard to the tariffs, both variable energy prices and variable capacity prices are considered in the analysis, hence enhancing existing modeling approaches. In addition, we calibrated our model using data of a large-scale field trial on load shifting. To analyze the impact of different tariffs on residential demand side flexibility, four scenarios with different tariff setups were compared. While the reference scenario has no variable price components, all other scenarios incentivize households to change their behavior related to electricity use. We have used one scenario based on a tariff with variable energy prices only, one based on a tariff with variable capacity prices only and one based on a tariff with a combination of variable energy and capacity prices. Our results show that variable energy prices induce a higher demand side flexibility than variable capacity prices. However, with regard to the predictability and reliability of the resulting impact on the demand side flexibility, tariffs with variable capacity prices are superior to those with variable energy prices. Moreover, tariffs with variable capacity prices allow electricity providers to introduce tariffs that take into account consumer needs for security of supply and the corresponding impact on energy system costs. As the curtailment in these tariffs is limited to shortage situations only, a penalization of system-supporting behavior of households, e.g., in times of high power supply from RES, is avoided.

Going forward, two research areas are of major interest with regard to the topics addressed in this paper. First, the market integration of new tariffs, both with variable energy as well as with variable capacity prices, is an important topic for future analyses. Therefore, a thorough evaluation of possible business cases, from a provider and a consumer point of view, is required, considering new retail market designs rewarding demand side flexibility. This evaluation should include the definition and discussion of the aggregator role in future energy systems. Second, the impact of different tariffs on entire energy systems should be explored quantitatively. By incorporating residential demand side flexibility in energy system models, the impact on generation, transportation and distribution capacities can be assessed. Especially from a supplier's point of view, this is very relevant in order to evaluate the potential benefits of new electricity tariffs.

From a policy perspective it becomes obvious that the regulatory framework needs to be adjusted in order to allow electricity providers and aggregators to develop sustainable business models and offer new tariffs. On the one hand, policy makers can facilitate the roll-out of new tariffs by including required technical specifications in guidelines for advanced metering systems. For instance, in Germany the technical guideline TR-03109 of the Federal Office for Information Security could be adapted, specifying the need for a technical curtailment function in advanced metering systems. On the other hand, residential demand side flexibility needs to be rewarded. Policy makers need to adjust existing regulations in order to increase the incentive for residential consumers and electricity providers providing demand side flexibility.

Acknowledgements Valentin Bertsch acknowledges funding from the Energy Policy Research Centre of the Economic and Social Research Institute. The usual disclaimer applies.

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Appendix

Table 9 Hourly probabilities for the Bernoulli distributions of manual load shifting

	Winter			Summer			Transition		
	Mo.-Fr.	Sa.	Su.	Mo.-Fr.	Sa.	Su.	Mo.-Fr.	Sa.	Su.
0	10%	10%	10%	10%	10%	10%	10%	10%	10%
1	10%	10%	10%	10%	10%	10%	10%	10%	10%
2	10%	10%	10%	10%	10%	10%	10%	10%	10%
3	10%	10%	10%	10%	10%	10%	10%	10%	10%
4	10%	10%	10%	10%	10%	10%	10%	10%	10%
5	20%	20%	20%	20%	20%	20%	20%	20%	20%
6	20%	20%	20%	20%	20%	20%	20%	20%	20%
7	50%	40%	40%	30%	30%	30%	30%	30%	30%
8	50%	40%	40%	30%	30%	30%	30%	30%	30%
9	50%	40%	50%	30%	30%	30%	30%	30%	30%
10	50%	40%	50%	40%	30%	40%	40%	30%	40%
11	50%	40%	50%	40%	30%	40%	40%	30%	40%
12	50%	50%	50%	40%	30%	40%	40%	30%	40%
13	50%	50%	50%	40%	30%	40%	40%	30%	40%
14	50%	50%	50%	40%	30%	40%	40%	30%	40%
15	50%	40%	50%	40%	30%	40%	40%	30%	40%
16	50%	40%	50%	40%	30%	40%	40%	30%	40%
17	40%	40%	40%	30%	30%	30%	30%	30%	30%
18	40%	40%	40%	30%	30%	30%	30%	30%	30%
19	30%	30%	30%	20%	20%	20%	20%	20%	20%
20	30%	30%	30%	20%	20%	20%	20%	20%	20%
21	20%	20%	20%	20%	20%	20%	20%	20%	20%
22	10%	10%	10%	10%	10%	10%	10%	10%	10%
23	10%	10%	10%	10%	10%	10%	10%	10%	10%