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Demand side management—A simulation of household behavior under variable prices

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ABSTRACT

Within the next years, consumer households will be increasingly equipped with smart metering and intelligent appliances. These technologies are the basis for households to better monitor electricity consumption and to actively control loads in private homes. Demand side management (DSM) can be adopted to private households. We present a simulation model that generates household load profiles under flat tariffs and simulates changes in these profiles when households are equipped with smart appliances and face time-based electricity prices.

We investigate the impact of smart appliances and variable prices on electricity bills of a household. We show that for households the savings from equipping them with smart appliances are moderate compared to the required investment. This finding is quite robust with respect to variation of tariff price spreads and to different types of appliance utilization patterns.

Finally, our results indicate that electric utilities may face new demand peaks when day-ahead hourly prices are applied. However, a considerable amount of residential load is available for shifting, which is interesting for the utilities to balance demand and supply.

1. Introduction

Due to environmental concerns governments foster the use of clean, renewable electricity generators. The European Commission set for their member countries a share of 20% by 2020 as target for the generation of electricity from renewable energy sources (EU Commission, 2009). Triggered by the disaster in Fukushima, German politics force the exit of nuclear electricity generation and promote a fast change towards renewable electricity generation.[1] The existing power grid is designed to distribute electricity from few large, constantly generating power plants. Hence, the increasing share of renewable energy sources, which are decentralized, small units with variable capacity, conflicts with the current power grid control infrastructure (Jansen et al., 2005). A reliable electricity supply in a grid with a large share of volatile generators can only be guaranteed with adequate balancing power reserves being available as backup. This results in high investments for storage technologies like flywheels, pumped storage water plants or compressed air storages to compensate the fluctuations. Another, less capital intensive, approach to address this problem is the use of demand side management (DSM) (Klobasa, 2009). DSM relies on "smart home" automation technology to shift loads over time in order to better match demand with output of generation capacities. Flexible demand allows for better integration of variable generation capacities such as those from renewable energy sources.

Large field projects are underway to evaluate technological readiness and economic effects of smart grid technology (e.g. Hirsch et al., 2010). Key components in these projects are DSM systems which control household appliances (e.g. washing machines) and optimize their operation. Field tests provide important real-world data on the effects of introducing DSM systems, but they can evaluate only a small number of new technologies and control strategies at the same time to keep costs within a reasonable limit. For this reason, it remains to be researched how households equipped with many smart appliances will react when faced with time-based electricity tariffs.

To address this lack in research we have developed and validated a household model that generates realistic electricity load profiles that are close to empirically measured profiles. Based on these load profiles, our model simulates electricity consumption of households that are (1) equipped with smart appliances, and (2) are billed based on time-based electricity tariffs. We then

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[1] www.bundesregierung.de/Webs/Breg/DE/Energiekonzept/energiekonzept.html

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estimate electricity bill savings and additional (equipment) costs in order to evaluate the incentives for households to invest in smart appliance technology. Further we investigate the effects of DSM in combination with time-based electricity prices on the utilities level.

Of especial interest in our simulation is the development of peak loads and the aggregated amount of load that is available for shifting. Our results show how variable pricing will likely affect consumer behavior under realistic environment conditions. Variable pricing alone cannot level the demand curve, and there is a minimum amount by which prices have to vary to have a "significant" impact. This is important because electricity retailers need to know how to position themselves in the market as a result of pricing decisions.

The paper is organized as follows. In Section 2 we review relevant literature. Section 3 describes our household model and its two main components a load profile generator, and scheduler that optimally shifts household appliances given an arbitrary tariff. Section 4 validates our artificially generated load profiles against synthetic profiles. In Section 5 we present simulation results from our household model. Finally, we conclude with directions for future research.

2. Related work

2.1. Demand side management

In theoretical research and practical field tests different aspects of DSM have been investigated. A great number of research papers focus on the benefits of DSM. Denholm and Margolis (2007) concentrate on the effect of DSM to enable the use of a large share of solar photovoltaic systems. Strbac (2008) mentions the benefits of DSM to balance demand and supply in systems with a high share of intermittent renewable generators, including combined heat and power plants. DSM can reduce the cost of generation by providing balancing power and substitute expensive gas-fired power plants that are used only a few hours per year. Furthermore DSM improves the investment in transmission and distribution grid through an increased utilization. Shaw et al. (2009) suggest benefits that can be achieved with the technologies that have to be installed for DSM, e.g. a smart meter enables more accurate billing and detailed customer information increases awareness of electricity consumption.

We focus on time-based electricity rates in form of day-ahead hourly time-of-use (TOU) tariffs as incentives for DSM adoption. Under such a tariff pricing regime customers pay each hour a different price for electricity and they receive the price information 1 d in advance. This is also referred to as quasi real-time pricing (RTP). Other major DSM techniques are for example direct load control or demand bidding (Strbac, 2008).

Several field studies have tested time-based electricity rates for household customers. In the 1990s some regions in Germany introduced time-of-use (TOU) or real-time pricing (RTP) (Morovic et al., 1997). Progress in the manufacturing of household appliances, and changes in information and control technology make it difficult to apply these results today. In particular, smart metering and demand side management technology had not been introduced in these projects. In the U.S. approximately 70 utilities offered voluntary RTP programs until 2004 but unfortunately the evaluation of customer's "*price response had not been formally evaluated*" (Barbose et al., 2005).

2.2. Smart home decision support

Advanced metering and displays for feedback on electricity consumption have been widely investigated as a tool for customers to better control their consumption and save electricity (Darby, 2001; Wood and Newborough, 2003; Fischer, 2008). Only recently smart household appliances and their potential for load shifting attracted interest. Different research communities prioritize various aspects of smart appliances. Computer scientists focus on the architecture to integrate appliances in a household energy management system (Becker et al., 2010; Kugler et al., 2011; Son et al., 2010). Other researchers analyze demand response options provided by smart household appliances on an aggregate level (Stamminger et al., 2008; Klobasa, 2009) or investigate consumer acceptance (Mert and Tritthart, 2008).

Silva et al. (2009) evaluate the potential benefits of smart appliances for balancing intermittent wind power generation. They assess the value of smart appliances for shifting and the benefit in case of network congestions. Based on these results Timpe (2009) states that two-thirds of the total demand response potential of smart appliances is economically available. Their model targets simulations at the country level, hence smart appliances and their shifting potential are modeled in a very simple way and the individual household level is beyond their scope. Additionally, no assessment of incentive-based demand response of households is included in this simulation model; instead, shifting of appliance operation is controlled directly.

2.3. Load profile generation and simulation models

Two distinct modeling approaches for private household electricity consumption can be identified: top-down and bottom-up (Swan and Ugursal, 2009). The first approach models total residential sector electricity consumption to trace consumption back to characteristics of the housing sector. Bottom-up models create load profiles on the appliance or household level and then project these results to represent a region.

Armstrong et al. (2009) present a model which is based on publicly available statistical data related to annual power consumption of appliances, average number of appliances per household, specific appliance characteristics (power, cycle duration, cycles per year), and probability distributions for time of use. They use these data as input to generate domestic load curves for different types of households.

Paatero and Lund (2006) develop a bottom-up tool to artificially generate domestic electricity consumption time series that are well correlated with empirically measured reference data. They use a simple DSM simulation and only estimate the effects on peak load from shifting. Furthermore they do not take time-based pricing as DSM strategy into account.

Esser et al. (2006) use a two step model. First the load curve of a household under a flat electricity tariff is generated using an approach similar to Armstrong et al. Then the household's resulting electricity consumption is optimized taking price differences for different times of a day as well as customer (dis-) utility from load shifting of appliances into account. They assume shifting disutility to increase with the shifting distance, which is not necessarily true for all types of appliances.

In contrast to the approaches described above we apply day-ahead hourly electricity prices to incentivize demand response of residential households. Furthermore, we model different classes of appliances, each implementing its own load shifting logic adhering to the objective of not harming customer convenience.

3. Model description

Our simulation model consists of two main components, the generator and the scheduler. The generator creates artificial load profiles for household appliances and optionally aggregates

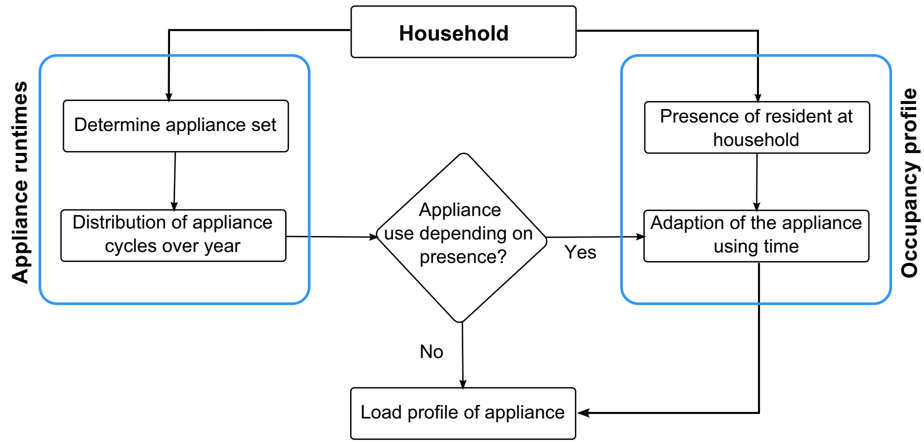

Fig. 1. Structure of the model to generate household load profiles.

Table 1
Electrical appliances included in the model and the corresponding statistical average values for Germany as input parameters for the simulation. Values for the saturation level were obtained from Bundesverband der Energie- und Wasserwirtschaft (2009), for appliance shares from Bürger (2009), for standby share, power and cycle duration from Bürger (2009); Stamminger et al. (2008).

Appliance (i)	Saturation (l_i) (%)	Consumption share ($\tilde{c}_i$) (%)	Standby share (e_i) (%)	Power ($\tilde{p}_i$) (W)	Cycle duration (d_i) (min)	Smart scheduling
Refrigerator	99	9.0	0.0	140	15	Auto
Freezer	54	7.1	0.0	106	15	Auto
Dishwasher	66	3.7	0.0	530	135	Semi
Washing machine	97	3.5	2.0	600	105	Semi
Dryer	42	2.5	1.5	1410	105	Semi
Storage water heater	8	5.2	0.0	3000	120	Auto
Space heating	4	17.0	0.0	7000	210	Auto
Stove	85	8.1	0.0	1840	30	–
Consumer electronics	98	13.0	35.0	100	90	–
ICT	98	5.0	60.0	150	90	–
Instant. water heater	12	7.8	0.0	12,000	15	–
Circulation pump	92	6.0	7.0	90	975	–
Light	100	8.0	0.0	350	120	–
Others	100	4.1	20.0	500	15	–

these profiles to the household level. This component is bootstrapped with statistical data on appliance availability in households, work and holiday patterns of household inhabitants, etc. and described in more detail in Section 3.1. The resulting load profiles serve as input for the scheduler, which calculates optimal shifting of the original appliance operation schedules given a time-based electricity tariff. This component is described in more detail in Section 3.2.

3.1. Generating residential load profiles

In our bottom-up model we generate electricity consumption profiles on a per-household-appliance basis and then aggregate these to create artificial but realistic household load profiles at 15-min time resolution. We have used empirical electricity consumption data from Germany to calibrate our model.

The basic model structure for generating a load profile of a single household is shown in Fig. 1. The model is built on two influence factors: (1) publicly available statistical data are used to determine the utilization of appliances, and (2) resident presence at home is used to adapt this usage.

First, a set of electric appliances for each household is determined and, based on aforementioned statistical reference data, the number of yearly uses for each appliance is calculated. The specific appliance run times for a single household are then distributed over the simulation year. Further, occupancy profiles for the households are simulated. These are required as usage of some of the simulated appliances, e.g. stove, in reality is concentrated to hours when residents are at home.

3.1.1. Allocating appliance runtimes

To allocate appliance runs we start with determining a set of appliances for the household. Applying saturation levels of household appliances as probability of availability creates an individual set for each household. The electrical appliances included in the simulation and their saturation levels are shown in the first two columns of Table 1.

For each appliance i of this set M_i is the number of usage cycles per year and determined as follows:

$$M_i = \frac{h_k \cdot \tilde{c}_i}{l_{k,i}} \cdot (1-e_i) \cdot \frac{1}{d_i \cdot \tilde{p}_i} \tag{1}$$

where h_k is the average annual electricity consumption in kWh of a household with k residents, $\tilde{c}_i$ is the share of appliance i in the annual consumption of a household, $l_{k,i}$ is the saturation level, e_i is the standby share,[2] d_i the duration of one cycle and $\tilde{p}_i$ the power consumption for appliance i in Watt. Table 1 shows mean values as input parameters for consumption share, standby share, power and cycle duration. Table 2 depicts the input values for the

[2] Appliances consume electricity while they are switched off or in standby mode. Electricity consumption due to appliance operation is reduced by this standby consumption. Standby power is allocated to all hours of a day.

Table 2
Size and average annual electricity consumption of households in Germany.

	Persons in a household				
	1	2	3	4	> 4
Share (%)	39	34	13	10	4
Avg. annual consumption (h_k) (kWh)	1973	3261	4240	4902	6147

average annual electricity consumption of households in Germany.

We assume the average input values for the share in annual consumption of a household and the power consumption of an appliance to be normally distributed. We then use these normally distributed numbers to generate the profiles of the appliances. Load profiles for all appliances of a household then ad up to individual electricity consumption profiles on a per household basis. The model is calibrated such that the average power consumption of a household (calculated as mean from a large number of artificially generated load profiles) is in line again with the statistical base data. The electricity consumption of a household in the model depends on the number of persons living in the household. For the sake of simplicity we do not incorporate other influence factors for the electricity consumption, e.g., household income.[3]

In the simulation we use discrete points in time, which we refer to as time slots, to allocate the appliance runs. One hour is represented by four time slots, hence, a time slot represents a 15 min period. The individual runs for each appliance must then be distributed over the year. For this, a slot s_n (i.e. the appliance start) has to be selected. A time slot within a year has the probability $P(s_n,m_i)$ of being selected as a start slot for run number m_i of appliance i

$$P(s_n,m_i) = P_{season,i} \cdot P_{day,i} \cdot P_{daytime,i} \tag{2}$$

where $P_{season,i}$ is the probability of a cycle of appliance i to occur in a season, taking into account seasonal changes in load, $P_{day,i}$ the probability for a day, modeling differences in consumption between days of the week and $P_{daytime,i}$ the probability for a time during the day. Load for a cycle is added beginning from the selected starting time.

The probabilities of equipping a household with an appliance and the appliance operations are independent from each other, except for the washing machine and dryer. Only households equipped with a washing machine can have a dryer and the dryer can only be used after a run of the washing machine. The fraction $M_{washing}/M_{dryer}$ defines how often a dryer is applied after a washing machine.

3.1.2. *Determining occupancy profiles*

Appliances such as a dishwasher, can only be used when at least one person is at home, therefore we simulate occupancy profiles for a household. The start time selected in the first part of the model is then delayed until someone is present at home. Different individual residents are part of a single household. Presence-dependent appliances cannot be started when all residents are away from home at the same time. Fig. 2 depicts the structure for determining the occupancy profile for one household. Computation of an individual occupancy pattern starts with all resident being at home for the whole time.

In the following the simulation randomly selects several intervals of consecutive days for vacations as well as single days for public holidays within a year. Public holidays are single days within a year, on which all residents of the household do not go to work. For simplicity, days for public holidays are randomly selected, with each day having equal probability. The number of public holidays within a year is 10 in the simulation, which equals the annual number in Baden-Württemberg.[4]

Vacations are consecutive days during which all residents of a household do not go to work. To consider a distinct number of vacation days for households, the annual average is normally distributed. The mean value for the normal distribution is 28 and equals the German average available in a study of Mercer. For the standard deviation a value of three is assumed. The duration of a vacation period is selected randomly.[5] All vacation periods within a year sum up to the total number of vacation days for a household. The start of a vacation period is a randomly selected day, with each day having equal probability. Sunday, Saturday and public holidays within the vacation time prolong the vacation period.

Household residents can spend holidays away from home. During this time, the household will only consume standby power. In addition, intervals of consecutive days within the year are selected randomly, when a resident is sick. During a day of sickness the resident stays at home. Subsequently times for leaving home because of work and leisure activities are introduced and the individual's occupancy pattern is updated accordingly.

Based on a survey of the federal statistic office in Germany different types of household residents have been identified that can be distinguished according to their working habits (Statistisches Bundesamt, 2009). We allocated a type to each household resident and assume empirical average values for the time a resident starts to work and the duration of work to be normal distributed for each type. We then use normally distributed numbers to determine the individual daily resident absence because of work for each day.

Household residents leave home also for leisure activities, e.g. shopping, sports or cinema. In the simulation this is incorporated by defining a number of such activities for each week which are then distributed over the week. The number of activities differs between the types with different working habits. We integrate individual leisure activities, also by using normally distributed numbers for the starting time and the duration. Table 3 shows the input parameters for the three types of household residents.

Different elements of customer absence simulation have different priorities. A day selected as holiday cannot be a working day. During a sickness day, neither work nor a leisure activity is possible. In addition, leisure activities can take place only outside working hours.

Fig. 3 shows a sample load profile for 1 day of a household. It can be seen that the load profile is composed out of the individual appliance load profiles.

3.2. *Smart scheduling of household appliances*

Based on the generated load profiles under a flat tariff, the model can simulate changes in customer electricity consumption under time-variable electricity tariffs through rescheduling of

[3] Given the low penetration of electric space heating in Germany we can also ignore the built forms of the houses which primarily influence heating energy requirements.

[4] cf. FTG - Feiertagsgesetz, Baden-Württemberg (Act on Sundays and public holidays in Baden-Württemberg).

[5] The duration is uniformly distributed in the interval from 0 and the total number of days. After drawing and allocating the duration of the first period, the number of days to allocate is decreased. The duration of the next period is uniformly distributed between 0 and the remaining days to allocate. This is repeated until all days have been allocated.

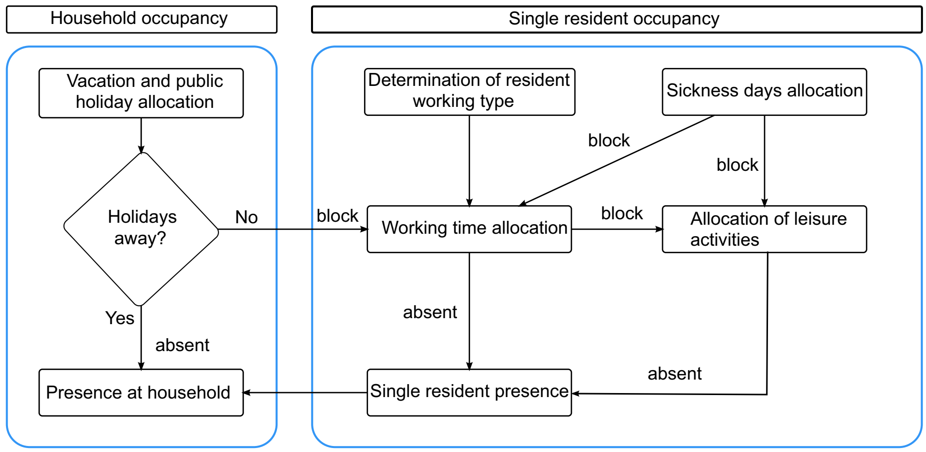

Fig. 2. Influence factors for the generation of occupancy patterns.

Table 3
Different working types and input parameters. Working types and their share are, based on Statistisches Bundesamt (2009), start of work and absence for work based on data of TNS Infratest Sozialforschung, (http://de.statista.com/statistik) values for number of activities are assumptions.

Working type	Periodically present	Mostly present	Randomly present
Persons included	Employee, pupil, worker, student	Retired, homemaker, children, unemployed	Shift worker
Share in population (%)	53	40	7
Start work (h)	7	–	0–23
Absence for work (h)	8	–	8
Number of activities	4	7	3

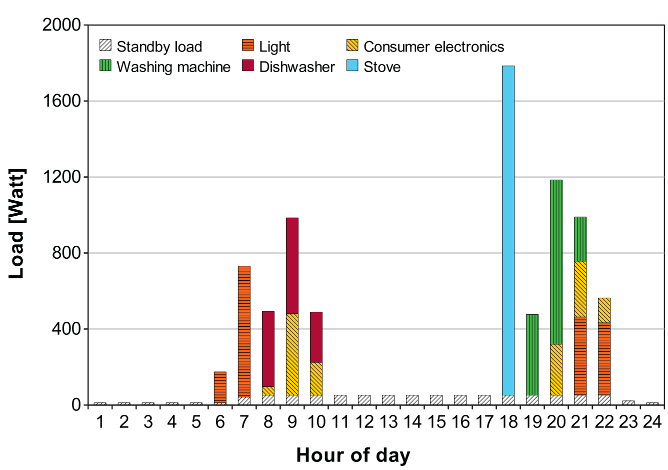

Fig. 3. Example of a load curve for an individual household.

household appliance runtimes given appliance-specific constraints (Paatero and Lund, 2006). Thus, we first identify and classify appliances that can be shifted. Then, depending on the service an appliance provides, we define a shifting interval in which an appliance agent shifts the start of a cycle to the cheapest time. We assume that shifting the operation of an appliance does not change the electricity consumed by the appliance run.

We classify household appliances in three categories according to their technical specification and the effect (utility or disutility) of a time shift on a household member. Washing machine, dishwasher and dryer are controlled *semi-automatically* in our model. Their cycles can be shifted, but interaction with the consumer is needed, e.g., a dishwasher must be loaded. The next class of appliances includes storage water and space heating, refrigerator and freezer. These appliances possess a natural thermal storage so they do not work continuously. Within constraints they can be controlled *fully automatically* without noticeable differences in utility for consumers (Timpe, 2009). Some household appliances are *not included* in the load shifting model presented here.[6] Individually modeled appliances like stove, light and instantaneous electric water heater are used on demand. They have in common that electric energy is needed exactly at the moment when the appliance provides its service. Shifting of these appliances is only possible when consumers change their schedule. An algorithm cannot support shifting. Moreover, a delay in the service provided by these appliances decreases customer utility. The categories others, consumer electronics, and information and communication technology contain several appliances. Some of them might be available for shifting, e.g. air conditioning (others) or notebook (ICT) , but, as they only have a small share on total electricity consumption in Germany, their potential for shifting is limited and they are not modeled as shiftable appliances. Other appliances, e.g., TV, radio (consumer electronics) or coffee machine (others), are used on demand and are not modeled for the aforementioned reasons.

When determining the shifting interval we consider the specific characteristics of the service each appliance provides, so that customers do not experience a loss in convenience due to shifting of the appliance runtime. In our model a household member can set semi-controlled appliances into a ready mode (after loading them) and determine the latest feasible finishing time. We explain the determination of the shifting interval for an operation of this class of appliances using a dishwasher as an example.

We choose the starting time for a dishwasher cycle from the load profile under a flat tariff to be the loading point for the smart

[6] cf. appliances in the lower part of Table 1.

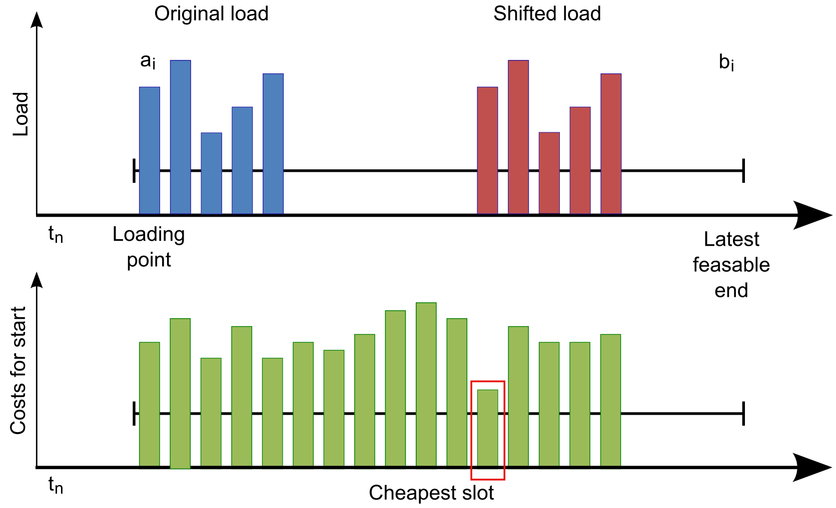

Fig. 4. Shifting of a dishwasher operation.

dishwasher. At the loading point the dishwasher is filled and ready to run, so it defines a_i the lower boundary of the shifting interval. The customer then either starts the dishwasher directly or selects a "smart start". Probability for the use of a smart start has to be assumed as there are no reliable empirical data available. In our simulation we use distinct scenarios for the probability of smart start use.

Selection of a smart start sets the latest feasible end of the cycle, which is the upper boundary for the shifting interval b_i. For the dishwasher three smart start modes can be chosen in the model: in mode one the machine has to finish within 5 h, in mode two within 10 h or in mode three the machine has to finish until the next day at 6 am. Fig. 4 depicts the shifting interval and the cost minimizing shift of a dishwasher operation.

The idea for modeling smart dish washers like this stems from a survey in the context of a research project on smart appliances, where one of the most widely accepted scenarios was that users define when the operation has to be finished latest (Timpe, 2009). The specific design of the three modes is a function of the dishwasher's flexibility as cycles can often be shifted without violating customer convenience and the efforts to keep use of a smart dishwasher easy. Selection of a mode for a cycle is based on the presence of the residents. Mode one and two can be selected, if during 2.5 h after the end of the respective mode someone is at home. This is based on the assumption that some customers need to have the dishwasher ready at the same day, e.g., they need clean dishes for their next meal. Mode three always can be selected, when a customer uses smart mode. The 6 am constraint is chosen to enable shifting of a dishwasher operation to night hours, at the same time guaranteeing clean dishes the next morning.[7] If more than one mode is selectable, the mode for a specific cycle is randomly chosen with equal probability.

We shift cycles of fully automatically controlled appliances in order to maintain customer utility, e.g., for a refrigerator or freezer the inner temperature should not exceed a threshold value, to guarantee that food quality is not harmed due to the temperature changes. In the literature the interval to delay or postpone their use varies from 15 to 30 min (La Cascia and Miceli, 2008; Timpe, 2009). To increase shifting ability for the simulation the maximum time interval from literature is chosen, hence refrigerator or freezer cycles can be shifted 30 minutes before and after the original runtime set by the load profile generator. A cooling cycle for refrigerator and freezer lasts 15 minutes (Stamminger et al., 2008). If several time slots have the same costs, the algorithm randomly selects one of the cheapest slots. Within the shifting interval $[a_i, b_i]$ the appliance shifting algorithm identifies the cost minimizing start slot. In short, the appliance shifting algorithm needs to solve the following optimization problem:

$$\min \sum_{s_j = s_{n,i}}^{s_j + d_i} \pi(s_j) \cdot p_i(s_j) \cdot \frac{\tau}{60} \quad \text{s.t. } a_i \le s_{n,i} \le b_i - d_i \tag{3}$$

where $s_{n,i}$ is the slot in which the appliance starts, d_i is the duration of one run of appliance i in number of slots, τ the length of a slot in the simulation in minutes, $\pi(s_j)$ is the electricity price per kWh and $p(s_j)$ the power consumed by the appliance i in kilowatt, both in slot s_j.

4. Verification of generated electric load profiles

Due to the lack in high resolution individual household consumption data, an industry standard load profile describing residential electricity consumption over time is used as a benchmark to evaluate the load profiles generated for an average German household. Esser et al. (2006) apply the same approach to evaluate load profiles generated by a simulation. The Federal Association of Energy and Water Industries (BDEW) in Germany provides this profile, called H_0, in a 15-minute resolution for the average electricity consumption of a norm German household.

As the H_0 profile describes *average* electricity demand ruling out individual demand peaks, we create populations of households using our model with input parameters for Germany. We then compare the average load data for this population with the scaled-up standard load profile of BDEW. The number of households of a specific size in a population depends on the distribution of the household size in Germany (see Table 2). The simulated period is one year.

BDEW emphasizes with the H_0 profile two important aspects of residential loads. First, the amount of electricity consumed differs between seasons, and second, load profiles show significant differences between day types. A realistic simulation of residential load profiles should be able to take these aspects into account.

Table 4 shows the share of load in each season for two simulation runs and the H_0 profile as a benchmark. For both

[7] 6 am is chosen rather arbitrary. Another time in the morning, e.g. 7 am has the same effect.

Table 4
Seasonal load distribution of the H_0 profile and the test runs.

Season	H_0 (%)	100 Households (%)	1000 Households (%)
Winter	36.9	36.9	37
Transit	36.8	36.6	36.7
Summer	26.3	26.5	26.3

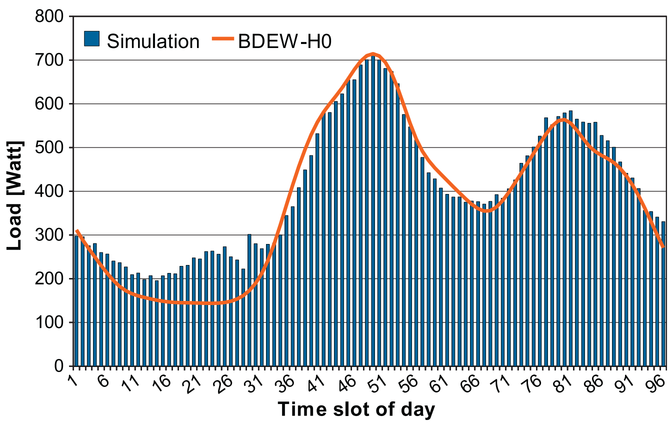

Fig. 5. Sunday load curve.

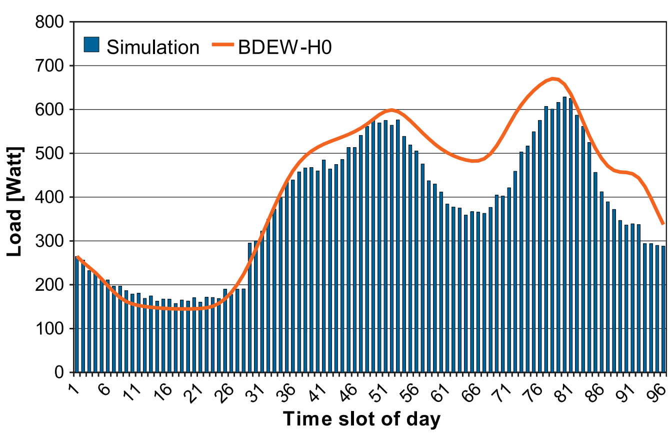

Fig. 6. Saturday load curve.

populations the seasonal load distribution fits well to H_0. Population size does not have a high impact on seasonal load distribution, as already for a small population values from the simulation are very close to the benchmark.

The H_0 profile defines 3 day types: working days (Monday to Friday), Saturdays, and Sundays. Figs. 5–7 shows the load profiles for these day types from the simulation and the H_0 profile. In the diagrams, time slot one corresponds to the time from 12:00 am to 12:15 am, time slot 96 to the time from 11:45 pm to midnight.

Table 5 shows the Pearson correlation coefficient between the H_0 profile and load profiles of the test runs calculated by incorporating all time slots of the simulation period. Correlation increases with population size. As some input parameters are normally distributed, for small populations their deviation from average values might be higher. With increasing population size, this deviation decreases and simulation results converge to the H_0 profile. We use a sample size of 1000 households, which provides a good trade-off between correlation and computational overhead.

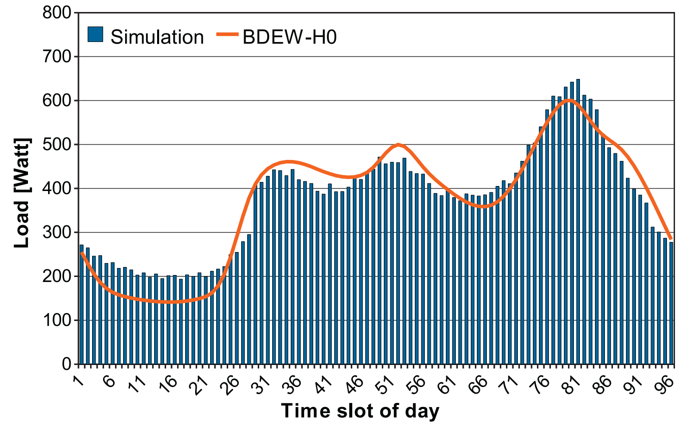

Fig. 7. Working day load curve.

Table 5
Correlation of the H_0 profile with load simulated household populations.

Number of households	10	100	1000	10,000
Correlation	0.29	0.77	0.88	0.90

Table 6
Parameter of the simulated scenarios.

Number scenario	Auto shift	Smart start probabilities (%)			Price
		Dish	Wash	Dryer	
1	Yes	0	0	0	EEX
2	Yes	30	30	30	EEX
3	Yes	60	60	60	EEX
4	Yes	90	90	90	EEX
5	Yes	90	90	90	EEX spread −10%
6	Yes	90	90	90	EEX spread +10%

5. Evaluation

5.1. Simulation settings

Based on these realistic load profiles under flat tariffs we simulate load shifting of residential homes. In our simulation households are equipped with smart appliances as described in Section 3.2. As an incentive scheme for shifting, households face time-based electricity prices in form of day-ahead hourly TOU pricing. Hourly prices are taken from the European Energy Exchange (EEX). The EEX offers hedging auctions (between 6 years and current month), day ahead auctions (1 day ahead) and spot market auctions (1 day–75 min ahead) [European Energy Exchange (EEX), 2010]. For shifting the average clearing price from the EEX spot market is used. Within the current market structure EEX spot market prices are the best approximation to hourly electricity prices.

To identify effects of different parameters we conduct a sensitivity analysis. First we change the probability of selecting the smart start option for semi-automatically controlled appliances as shown in Table 6. Two variations of the original 2008 EEX prices have been applied where the spread is reduced and increased by 10%. Automatically controlled appliances are shifted in all scenarios.

In total we simulate six scenarios, and 20 populations in each scenario. In accordance with Section 4 each population consists of

1000 households. In the following we analyze the simulation results of these scenarios and show the economic effects of load shifting for households, the impact on peak load and the flexibility gain utilities can expect.

5.2. Economic effects for households

In 2008 German households paid an average electricity price of 21.72 EuroCent/kWh (Goerten and Ganea, 2008, 2009). To evaluate the savings "Smart Homes" can achieve under a day-ahead hourly TOU pricing regime, we first value the load of a household under a flat regime with the average electricity price. Then we upscale the hourly EEX prices so that a household which does not shift any appliance operation schedule has the same electricity bill regardless if paying the flat tariff or the day-ahead TOU price. The distribution and the hourly average of the upscaled prices for one population can be seen in Figs. 8 and 9. With the adapted prices we finally value the shifted load to estimate the electricity bill a household has to pay when a day-ahead TOU tariff is applied. Respectively, a decrease in the electricity bill for shifted load is the savings for a household. Boxplots in Fig. 10 show the average electricity bill savings of a household for different input parameters.

This figure captures four different settings for smart start probabilities. A large share of electricity bill savings is already realized in Scenario 1 where only the four fully automatically shifted appliances are available for demand side management. A more intensive use of the smart start option for semi-automatically controlled appliances decreases electricity costs. The median for average cost savings per household range from about 50 Euro per year in Scenario 1 up to about 65 Euro per year in Scenario 4.

Fig. 11 shows the results for the Scenarios where the spread of the underlying EEX price has been varied. In Scenario 5 the spread has been deceased by 10%, in Scenario 6 the spread has been increased by 10%. For the three, Scenarios 4–6, the smart start probability is the same. Higher price spreads decrease prices in already cheap hours where load is shifted to and vice versa. Hence, boxplots in Fig. 11 show that savings of a household increase with higher spreads and decrease when price spreads are lowered.

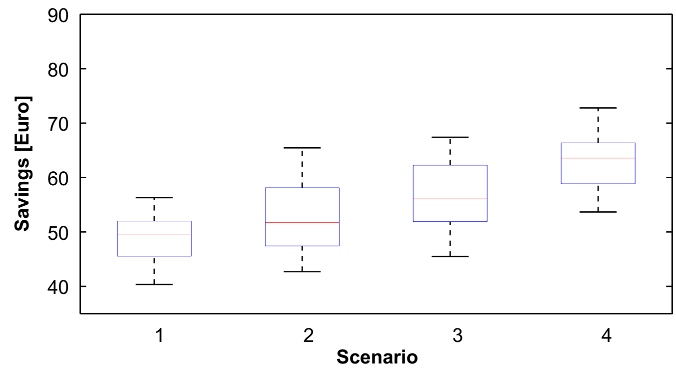

Fig. 10. Annual savings of a household for varying smart start probabilities (see Table 6).

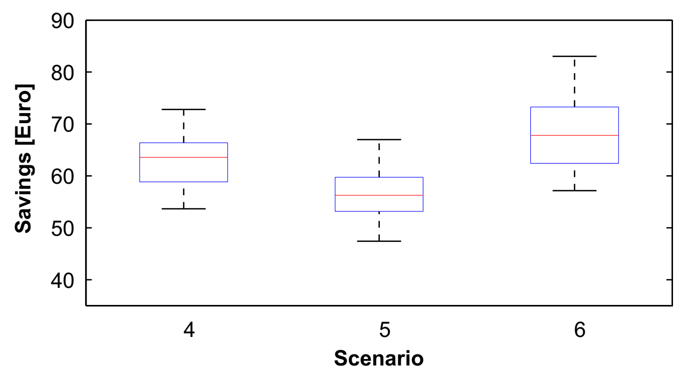

Fig. 11. Annual savings of a household for different price spreads (see Table 6).

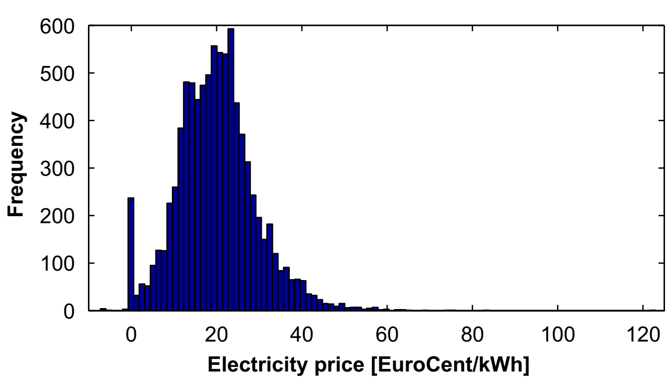

Fig. 8. Distribution of upscaled EEX prices in 2008.

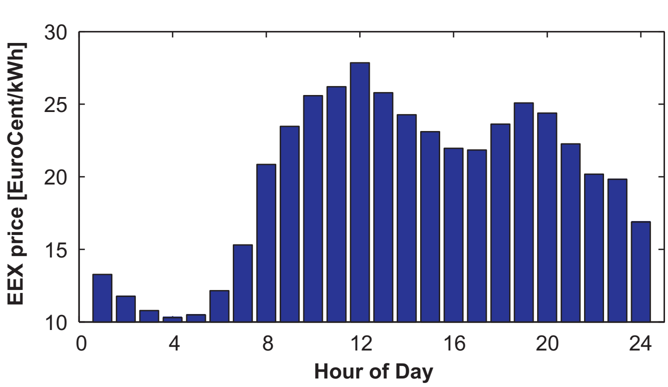

Fig. 9. Average upscaled EEX prices in 2008 by hour of day.

Table 7
Average annual savings (EUR) per appliance for the scenarios (negative values indicate savings).

Scen.	Savings in Euro for						
	Dish	Wash	Dryer	Fridge	Freezer	Water	Heating
1	3.0	1.9	1.0	−3.8	−4.9	−141.0	−1253.6
2	−1.6	0.9	−0.2	−3.8	−5.0	−139.8	−1230.6
3	−6.1	−0.2	−1.6	−3.8	−4.9	−146.4	−1223.1
4	−10.8	−1.2	−2.9	−3.8	−4.9	−139.0	−1270.3
5	−9.6	−1.1	−1.9	−3.8	−4.8	−116.5	−1117.7
6	−11.6	−1.5	−3.6	−4.2	−5.5	−153.1	−1375.9

Table 7 depicts the savings on an appliance a basic household can expect when investing in smart responsive appliances and at the same time day-ahead TOU prices are applied. Warm water heaters and even more space heaters facilitate the highest savings. These two appliances operate mainly during night. Fig. 9 shows that during night hours in average the electricity prices are much lower than before. Electrical warm water and space heaters benefit in large extent from these lower prices. Despite the high savings these two appliances do not seem to be very important for load shifting. First, because only very few households possess an electric space heating (4%) or a storage water heater (8%).

Second, in these two appliances high quality electricity is wasted to provide low quality energy and the specific CO_2 emission is high. In Germany financial incentives exist to substitute electrical warm water heating and space heating by other technologies. In future their role in Germany can be expected to decrease further.

In our simulation a smart refrigerator saves about 4 Euro, a freezer about 5 Euro per year. Savings are constant in the first four Scenarios where only the shifting probability varies, which do not affect refrigerators and freezers. A small increase can be observed in the case of higher price spreads. For the semi-automatically shifted appliances we observe the highest savings for dishwashers. They range from plus 3 Euro to −11.6 Euro. Higher electricity costs compared to the base case can be explained with the increase in average electricity prices during the day when these appliances are mainly used and at the same time no or hardly any operation of the appliance is shifted. With a more intensive use of the smart mode savings increase.

Table 8 depicts the additional costs a household faces for the introduction of smart appliances as estimated an research project on smart appliances on European level. Three different costs are linked with the introduction of smart appliances. The additional communication and control technology within the appliances increase especially in short term the production costs. Eventually, in a mass market economies of scale reduce these costs. Communication equipment include the smart meter and the information technologies to connect with the appliances from the outside, e.g., wireless router. In medium term households can be expected to be equipped with this additional communication infrastructure and costs decrease. Additionally, ongoing communication requires appliances to be in stand-by mode the whole day or at least several hours and increases standby electricity consumption of the appliances.

Excluding electrical water and space heating, which are irrelevant in the German market, the economic incentive for an investment in smart appliances is today very low. If we assume an average responsive customer (Scenario 3 in Table 6) a household can expect savings of about 16.6 Euro per year. In contrast the annual increase in costs for the lowest expected costs in short term are about 13.6 Euro, when assuming a depreciation period for additional production and communication costs of 10 years. In 2025 estimated additional costs drop at best to 0.95 Euro, in worst to 7.25 Euro per year. Which still leads to electricity bill savings that do not give high incentives for customers to invest in smart appliances and the communication technology required. Based on our findings we claim that at least the pro-active replacement of existing household appliances never pays off.

5.3. Effects for electric utilities

In this section we focus on two interesting aspects of load shifting from a utility's point of view: (i) potentials for peak load reduction, and (ii) flexibility of loads through price-responsive smart appliances.

Table 8
Low and high additional cost cases for smart appliances (Seebach et al., 2009; Timpe, 2009).

Additional cost	Unit	Short term		2025	
		Low	High	Low	High
Production cost	EUR/device	17.00	34.00	1.70	3.40
Communication equipment	EUR/home	50.00	100.00	0	0
Standby consumption	EUR/year/device	0.02	1.10	0.02	1.10

5.3.1. Peak load development

Fig. 12 shows the loads of the 100 hourly demand peaks in the simulated year for the six simulation scenarios defined in Table 6. Additionally, the original load peaks from the flat tariff pricing scheme are included (marked as "Flat"). In all scenarios where demand side management is possible peak value increases compared to the "Flat" scenario. The reason for this surprising increase is avalanche (also called herd) effects, which originate in the simple price optimization model that the different smart appliances implement. In essence, day-ahead TOU tariffs introduce a sequential game where the utility moves first by setting electricity prices for the next day given their beliefs about consumer behavior. Afterwards the household optimizes its electric energy usage based on the previously announced prices and potentially supported by automatically operating load shifting appliances. Like this, original demand peaks are eliminated but alternative peaks occur usually in those hours where off-peak pricing takes over-from peak-pricing. In our simulations these alternative load peaks increase with the adoption rate of "smart" appliances.

Today, there is a common perception that electric utilities will benefit from DSM, for example, in the form of a reduction in the generation costs, less balancing power transportations and thus less transmission grid investments, and increased operation efficiency. In our setting these benefits do not emerge due to the increase in peak load.

5.3.2. Load flexibility

Smart appliances react to price incentives. Electric utilities can influence electricity consumption of households via prices and make parts of the load flexible (de Weerdt et al., 2011). Beyond peak loads, the simulation shows how much electric power is shifted between hours of a day. Bars in Fig. 13 indicate how much electricity is shifted in Scenario 1 from 1 h to another. Values shown are the average for all 20 populations simulated for the scenarios. As a reminder: in Scenario 1 only automatically controlled appliances are shifted. Shifting patterns of appliances can be identified in this figure. High bars in the diagonal of the diagram base mainly on shifting of refrigerator and freezer. They can only be shifted in an interval of 30 min. Such a small shifting interval of fridge and freezer leads to a selection of a new start slot that is close to the original one. Nevertheless, due to automated shifting every operation can potentially be shifted and in total a large amount of electric energy is shifted.

Load shifting during night bases on a more efficient allocation of electric warm water and space heating operations. Their operation is shifted from more expensive night hours to the cheapest starting time during night.

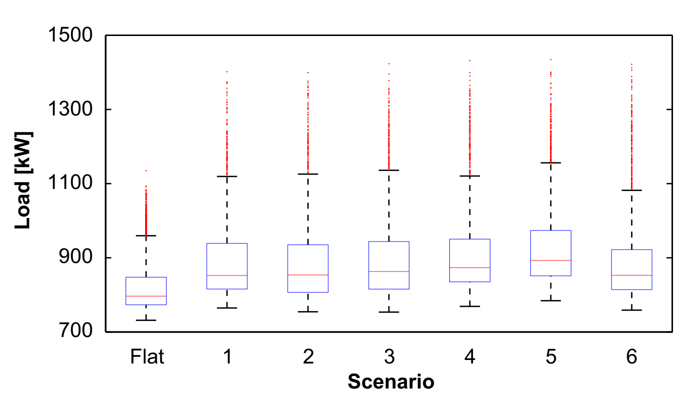

Fig. 12. Distribution of the 100 peak load values for each scenario.

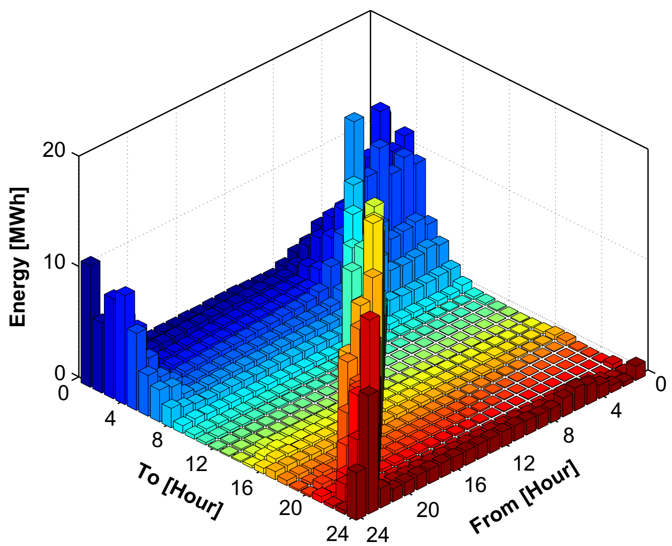

Fig. 13. Shifting for fully automatically controlled appliances.

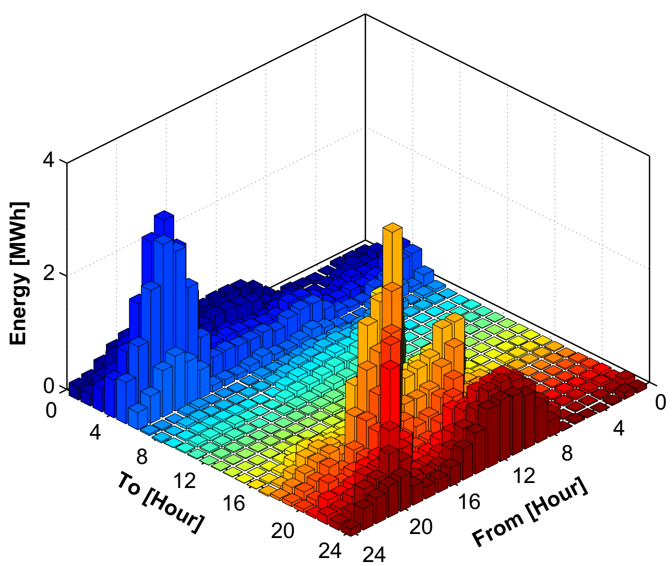

Fig. 14. Shifting for semi-automatically controlled appliances.

Fig. 14 shows shifting for semi-automatically controlled appliances. Two areas where electric energy is shifted can be identified here. An increase in electricity consumption can be observed during night. A large amount of this load originally arises in the late evening hours. In contrast to refrigerator and freezer, washing machine, dishwasher and dryer can accommodate larger distances for shifting.

Further, the amount of flexible load available in each hour is of interest for utilities. Fig. 15 compares the load curve of households equipped with smart appliances paying a time-based tariff (Scenario 4) with their original electricity consumption when shifting was not possible. On average the load is shifted from the high price hours in the afternoon and the evening to the cheaper hours during night. Changes in hourly load are more closely investigated in Fig. 16. This figure depicts the net changes in load per hour for Scenario 4. Net load change is the difference of load shifted to and from 1 h. Underlying data for the boxplot is the net load change in each hour for 20 populations.

Despite the likely emergence of alternative demand peaks (see Section 5.3.1) smart appliances applied conjunction with

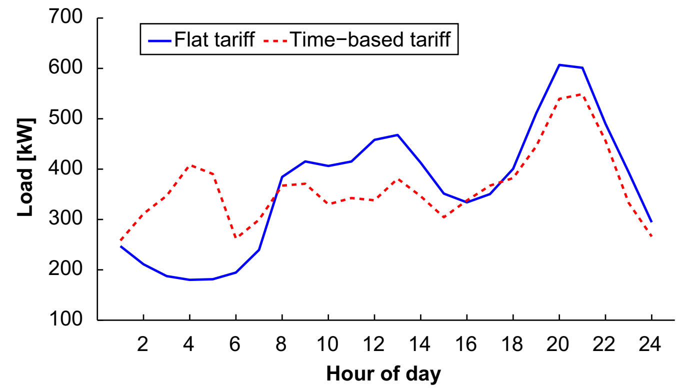

Fig. 15. Comparison of average load for the flat tariff scheme and households with smart appliances paying a time-based tariff (Scenario 4).

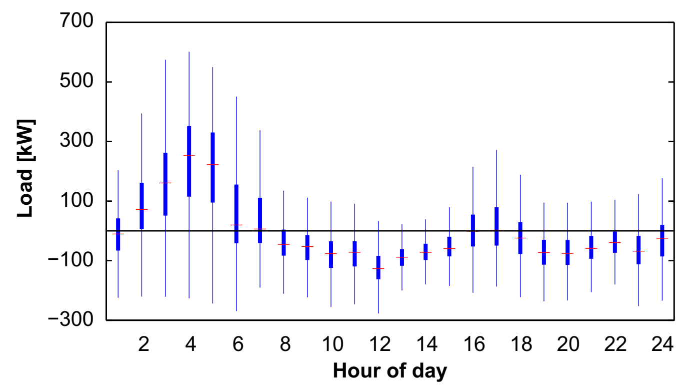

Fig. 16. Hourly net load changes explaining the differences in the load curves in Fig. 15.

day-ahead hourly TOU tariffs make a large amount of the overall residential load flexible and available for demand shifts. This is of interesting for electric utilities who need to balance demand and supply in systems with high penetration of intermittent renewable generators.

6. Conclusions

Our model generates realistic residential load profiles, which are highly correlated to empirically measured historic household electricity consumption data. We presented an algorithm that simulates residential load shifting under time-of-use regimes using previously generated profile data. To model realistic demand response behavior, different groups of household appliances are included into the model with their technical and practical usage patterns and operation constraints.

We show that an individual household can expect rather low benefits of an investment in smart appliances. Especially in the beginning savings in electricity bill hardly exceed additional costs and make investments in smart appliances unattractive. Nevertheless, smart appliances make a large share of the hourly residential load flexible which could support the balancing of demand and supply in distributed power systems and systems with a high share of intermittent renewable sources. With regard to the expansion targets of renewable generators in Europe flexible load is attractive for energy utilities and offers a high value to them.

A simple change of existing flat tariffs to time-based prices does not necessarily provide enough monetary incentives for households to invest in smart appliances and DSM technology.

Still, these investments are necessary as they increase demand responsiveness (and thus adjustment to intermittent supply).

Incentive mechanisms have to be designed that transfer parts of the benefits from more flexible and controllable residential loads from utilities to households. Concrete measures might include reduced average electricity prices for households that invest in smart appliances and DSM or a fixed premium for consumers that provide flexible loads.

Our simulation produced avalanche effects, i.e. the shifting of appliance runs to hours with a cheaper price, which introduced new peak loads while eliminating the original ones. Before applying day-ahead TOU tariffs in real world for a large amount of households it is important to closer investigate how these effects can be avoided. This would at the same time make the whole range of DSM accessible to electric utilities.

For the sake of simplicity we limit our simulation to German households and their typical appliance set. In many economically developed countries, penetration rates for fridge, dishwasher and washing machine are comparable to Germany. Moderate differences in the saturation rate can be observed for dryer and freezer. For electrical space and water heating we identify high potential savings in the simulation. In contrast to Germany, high penetration levels for these appliances can be found in Australia, the United States and Southern Europe. For example in the US about 40% of the homes are equipped with electrical water heating and about 17% with electrical space heating (Energy Information Administration, 2009). In Germany the respective shares are 12% and 4%.

We did not include air-conditioning in our model due to the low share in residential electricity consumption in Germany. Air-conditioning involves thermal storage similar to space heating; room temperature can vary in a certain range without violating customer convenience, and the operation of an air-conditioning can be shifted. In other economically developed countries the penetration of air conditioning in the residential sector is very high: in Southern Europe about 30% of the homes posses an air conditioning in the US and Australia penetration is respectively 83% and 90%. Economic benefits from smart appliance control in residential homes can be expected to increase with higher penetration of electric space and water heating and air conditioning. It might be beneficial to evaluate economic benefits and flexible load for residential homes in these countries.

There are ample opportunities to expand and improve our simulation of load shifting in response to time-based electricity prices. In future research we are interested to investigate potential counter measures for peak loads which include (i) consumer clustering so that different consumer groups obtain different time-of-use tariffs and (ii) the introduction of real time pricing where end consumers are exposed to electricity market prices that are *not* committed in advance but change over time reflecting changes in demand and supply. Real-time-pricing at the same time enables DSM for system stabilization by reacting to short-term fluctuations in the power grid. In a real-time pricing environment, customers (or their home automation) might want some ability to predict future prices, for example as described in Ketter et al. (2009), in order to maximize their utility.

In our simulation, the probability for selecting a smart start mode for the operation of an appliance is independent of the price level. It would be interesting to connect these probability with the savings a customer can realize by selecting smart start. Further, the potential of domestic demand side management on the economic and technical integration of intermittent renewable energy generators needs to be assessed more closely.

The presented household model is incorporated in Power TAC, a simulation of regional electricity markets. Power TAC aims to establish a testbed in the spirit of other trading agent competitions and incorporates a flexible plugin architecture that allows researchers to replace modules such as the wholesale market and also to add modules such as new customer models (Ketter et al., 2011).

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