Applied Energy 210 (2018) 1290–1298

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Large-scale demand response and its implications for spot prices, load and policies: Insights from the German-Austrian electricity market

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HIGHLIGHTS

- We model the large-scale impact of demand response systems with real-world data.
- Our key measures include electricity price, grid load and financial savings.
- The average spot price, as well as the peak price, decrease considerably.
- However, the volatility of the price can rise, impairing non-flexible customers.

ARTICLE INFO

Keywords:
Demand response
Load shifting
Financial savings
Electricity price
Load
Policy implications

ABSTRACT

Active load shifting of the electricity demand unlocks a variety of benefits. Examples of such advantages include the increased stability of energy systems, reduced electricity costs and financial savings in the transmission as well as generation infrastructure. Although the technology necessary for demand response has been extensively studied for individual appliances or at the micro-grid level, evaluations of its nationwide impact are scarce. Yet governments and policy-makers require quantitative assessments in order to understand the underlying value and derive appropriate policies. For this purpose, this paper utilizes real-world data from the German-Austrian electricity market in order to calculate ex post the impact of demand response on electricity spot prices and load. As a result, we find that a 25% adoption rate of the available potential for load shifting could have decreased nationwide electricity expenses by approximately €500 million, or 6%, in 2014. At the same time, we observe that the price volatility rises under this scheme and thus impairs non-flexible electricity customers. This observation entails significant implications in terms of designing effective policies.

1. Introduction

For many years, the electricity market has predominantly offered energy derived from fossil resources, which, conveniently, represent a highly controllable form of power generation. However, the advent of renewable energy has shifted the focus towards intermittent sources, such as solar and wind power [1]. Since solar and wind power are highly dependent on weather conditions, they cannot be operated according to electricity demand. Conversely, the increasing availability of smart and connected devices enables a better control of electricity demand [2–4].

This paradigm shift has given rise to the concept of *demand response* (DR) as a means of controlling demand [5]. Demand response has been defined by the U.S. Department of Energy and the Federal Energy Regulatory Commission as "*a tariff or a program established to motivate changes in electric use by end-use customers in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized*" [6]. Within the field of DR, the term *load shifting* refers to moving the electricity consumption of devices to a different point in time such that the monetary expenditures for electricity generation are minimized [7]. In this respect, electricity consumption is merely postponed or shifted to an earlier point in time, while the overall electricity demand remains the same.

While DR has been the focus of many research publications, little is known about the changes caused by load shifting on a national level or its financial implications: prior research has discussed different DR programs [8], based on which theoretical frameworks have been developed for classifying the benefits and costs of DR [9,10]. Multiple studies analyze findings from field trials across electricity markets in the United States [11–14], Japan [15] and Europe [16–19]. For instance, with regards to a European implementation, research has

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http://dx.doi.org/10.1016/j.apenergy.2017.08.039
Received 30 March 2017; Received in revised form 6 August 2017; Accepted 9 August 2017
Available online 26 August 2017

calculated the infrastructure investments required to enable DR, but provides only rough estimates of the potential benefits [20]. Among the few quantitative evaluations, the long-term effects of different demand response policies have been studied on the basis of a simplified model [21]. In addition, stochastic Nash-Cournot competition models have demonstrated that demand response lowers the electricity price, generation and emissions [22]. However, the latter work does not explicitly distinguish between cases with and without Demand Response and thus fails to precisely evaluate the benefits from DR usage. Various papers describe and model implementations of DR for small sub-grids with a focus on residential communities [23], real-time markets [24], fast-acting response [25] or centralized scheduling [26]; however, their approaches are not applicable to nationwide studies. A decision model for the large-scale impact of DR is proposed in [27], but this work provides merely an example evaluation for a single day. Hence, it is the contribution of our work to extend such a simulation to a long-run time horizon.

Our paper shows how the electricity spot market and electricity expenses change at market level due to demand response usage, as this question has been largely neglected in previous works. This research gap is confirmed by a recent literature review of 117 publications conducted in [28], which explicitly states that future research on demand response should (1) focus on system-wide analysis and (2) include a wide range of end-uses, such as industrial, commercial and private households. Hence, we take both requests into account and perform an in-depth calculation of the nationwide impact of load shifting.

In order to analyze the system-wide impact of load shifting, we first need knowledge of the available load shift potentials. We can then insert the potential into an optimization formulation to simulate the ex post impact of load shifting. Effectively, we determine the best decisions with respect to load shifting by minimizing the overall electricity expenses. To account for an increasing adoption of load shifting in the future, we perform our calculations for three scenarios representing different volumes of available demand response potentials. In addition, we utilize actual data from the electricity market of Germany and Austria to ensure realistic results. Based on this, our results reflect the impact of load shifting on both the electricity spot price and load.

The remainder of this paper is structured as follows. Section 2 presents a literature review concerning the expected benefits of demand response. Subsequently, Section 3 describes our models and datasets for analyzing the impact of load shifting on the electricity spot market. In Section 4, we show the corresponding results from our analysis based on actual market data. We then use our findings to derive implications and discuss policy trade-offs in Section 5. Section 6 concludes.

2. Review of financial benefits of demand response

Related literature generally concludes that demand response triggers many positive developments. These include economic and environmental benefits, as well as improvements in pricing, risk management, reliability and market efficiency [10,29–31]. We restrict our literature search to materials concerning the immediate savings from more cost-effective electricity purchases. For any other financial savings, we refer to related research.

Electricity retailers achieve cost savings if they optimize the volume and timing of their electricity purchases in the most economically efficient manner. This finding has been suggested by conceptual works [10]. Simulated results quantify the financial savings from market-based trading of DR potential [32]. Such studies have also been extended to incorporate different pricing schemes [33].

Besides these savings from optimized electricity purchases, electricity retailers could also pursue other business models. For example, one option is the provision of flexible demand in ancillary or control reserve management [34,35]. To this end, a focus has been put on the underlying optimization techniques for load balancing [36]. Interestingly, this market scenario yields greater financial savings as compared to offering demand response potential as balancing energy or for ancillary services [37]. Because of this, our study also addresses a market-based scenario and this is later reflected by our choice of appliances (e.g. white goods), which do not entail the fast response rate needed for grid stabilization.

In order to realize the aforementioned benefits, electricity retailers alter the consumption behavior of their customers through special programs or tariffs and pass some of their savings on to their customers. Here a shift of a few hours is often sufficient to realize savings and does not usually represent an inconvenience for the customer [38], e.g. if a freezer's compressor runs at night instead of during the day. Interestingly, demand response flattens the overall demand curve, leading to price reductions also for consumers not participating in demand response [26]. The savings for electricity retailers and their customers come at the cost of reduced profits for vendors of expensive peak reserve generation capacities [39,40].

Quantitative results from a macro-level study [41] indicate that financial savings from smart meters, in combination with dynamic tariffs in the European Union (almost 200 million households), could range between €14 billion and €67 billion. This amounts to savings between 2.5% and 11.9%, given a total spending of €561 billion. The outcome ultimately depends on customer adoption of demand response, i.e. the extent to which end-consumers engage in DR activities. The previous study assumes peak demand at a transmission level of 467 GW, while the cost of smart meters in the European Union accounts for approximately €51 billion, which is partially offset by an economic surplus between €26 billion and €41 billion. The authors of [42] optimize the mix of renewable energy sources and find no significant impact of DR at an hourly level. However, in a later study they project cost savings of €27 million for the year 2024 in the investigated Western Interconnection grid [43].

3. Methods and materials

This section presents our methodology for determining the impact of nationwide load shifting. First, we show how we model the electricity price on the basis of both actual demand and supply curves from the electricity auction. This calculation includes optimal load shifts based on a quadratic optimization that minimizes electricity expenses. Finally, we describe the market data serving as the basis of our calculation and discuss the load potentials.

3.1. Modeling load shifting

Electricity retailers purchase power on the market via different products, which differ in their time horizon. Market participants use the derivative market to purchase electricity on a relatively long time-horizon and thus ensure supply. In contrast, the spot market allows one to balance day-to-day variations in supply and demand. In this paper, we focus on the spot market, namely, day-ahead auctions, its most important product.

We assume that the market price $price_t$ for electricity depends on the actual trading volume (i.e. market cleared quantity) vol_t at time t. Both exhibit an approximately linear relationship within the observed neighborhood and we thus introduce the following model

$$price_t = \gamma_t + \beta_t \, vol_t \tag{1}$$

with coefficients γ_t and β_t. Here β_t encodes the price elasticity of demand, i.e. what the settled price changes with respect to demand. We can then replace vol_t in the above formula with $vol_t \pm shift_t$ in order to estimate how the settled price would have been in the case of shifting load $shift_t$.

We subsequently search for optimal load shifts by minimizing the total electricity expenditures $price_t \times (vol_t \pm shift_t)$ with total load shifting volume $shift_t$. The full derivation is consistent with related literature [32,37,27,44] and we thus briefly summarize it in A.

3.2. Electricity price and volume

We use actual market data from EPEX Spot[1] for the combined German and Austrian electricity market in order to achieve realistic results. All prices and demand volumes originate from hourly day-ahead auctions for the year 2014. In this year, 1.04 million GWh were traded on this market with an hourly peak of 49 GW.

We model electricity prices as a function of trading volume based on actual supply curves from EPEX Spot. These curves feature all bids for an electricity auction in a given hour and include the merit-order of electricity generation. Hence, we can infer the intercept γ_t and the price elasticity of demand, β_t, from them by calculating the corresponding gradient around the price settlement point.

3.3. Potential load for shifting

In order to evaluate the impact of load shifting, one first needs an estimation of the electricity volume that is available for shifting. Several publications aim at quantifying the available load shift potential: one approach evaluates smart meter data to identify the actually available load shifting potentials in Northern California [45]. An alternative strategy is a bottom-up estimation of the theoretically available load potential [46,47]. In Germany, this yields a potential 14 GW reduction from shedding or postponing load, as well as a 32 GW increase from shifting load to an earlier point in time. These studies assume 39.8 million households and an annual tertiary sector electricity demand of 136.17 TWh/a. The estimate in [48] suggests a similar magnitude, also resembling the estimates in [49,50]. The latter works identify a shiftable potential of 3 GW in the German industrial sector, 8 GW in the commercial sector and more than 20 GW from private households.

In this paper, we draw upon the previous expert estimates and aggregate them in order to identify the shiftable load volumes for our analysis. Fig. 1 thus shows the theoretically available volume for load shifting for each maximum shift duration, while the colors indicate the type of appliance. Here we exclude season-specific air-conditioning and heating applications, which would occur only in summer or winter, respectively. In addition, our load shifting potential is scaled such that it represents the combined loads from Germany and Austria. Furthermore, we omit load shedding or peak shaving, which are common in the industrial sector. Instead, we consider foremost the residential and commercial sectors by focusing on shiftable load. The resulting shifting potential ranges in the middle of the spectrum as compared to the previous publications.

Fig. 1 specifies theoretically available potential, though current technology enables only portion of it to be controlled, as methods such as time-based pricing or remote switching are not yet widely established [46]. For this reason, we perform an extensive sensitivity analysis and compare different scenarios as described in Section 4.1.

4. Results

This section presents the results of our optimization. More precisely, we study the impact of load shifting on trading volume, electricity spot price and nationwide expenses.

4.1. Specification of scenarios

Currently, only a limited volume of load can be shifted, as there is a lack of both incentives and the necessary technology. We thus introduce different scenarios to evaluate the impact of increasing adoption of load shifting in the future. These scenarios are as follows: a potential of 0%, i.e. no load shifting, serves as a base-case where expenses and electricity price reflect the status quo. In the other scenarios, we investigate a 1%, 10% and 25% utilization of the available load for shifting. We calculate these volumes by proportionally down-scaling the theoretically available volume. These scenarios are studied in an hourly simulation for a time span ranging from January 1 to December 31, 2014.

[1] EPEX Spot. URL: http://www.epexspot.com/. Retrieved on May 15, 2015.

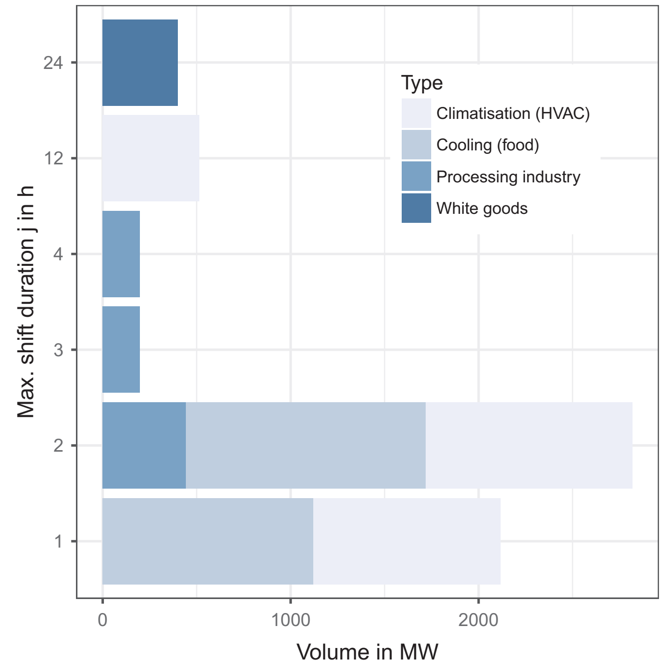

Fig. 1. Magnitude and type of load shift potentials for every hour for the combined markets of Germany and Austria (all-season appliances only).

4.2. Impact on load

4.2.1. Net-effects of simulated load shifts

Based on our model, we calculate the resulting load shifts. Fig. 2 presents these shifts averaged across each hour of the simulation horizon. Its horizontal axis shows the hour of the day and the vertical axis the shifted volumes. Bars oriented in a positive direction indicate that electricity was shifted from a different time to this hour, whereas negative bars represent shifts away. The colors of the bars denote the duration of the shifts. Overall, we observe a pattern of load shifted from day to night. The resulting net-effect is given by the solid line in black. Peaks in this line during night time imply that the electricity demand is increased by load shifting at these times. In contrast, a strong drop at noon and a weaker one in the afternoon highlight the times at which average demand decreases due to load shifting. The overall pattern remains the same for all scenarios, i.e. 1%, 10% and 25%, but with values of smaller magnitude.

Throughout the day, all shifts contribute to a reduction in overall electricity expenses of different magnitude. Short shifts, such as a 1 and 2 h displacement, allow for the movement of to move a relatively large part of the demand away from peak times. Medium shifts of 3 and 4 h appear almost negligible due to the relatively small volume. In contrast, the long shifts of 12 and 24 h play a substantial role in moving demand from day to night and thereby benefit from the large difference in price.

Load shifting consequently alters electricity demand and the total grid load as measured by the total trading volume. Hence, Fig. 3 demonstrates how load shifting increases demand during the night time in comparison to the base scenario. As a benefit, we observe a decrease in the average peak demand around noon. In the 25% scenario, this corresponds to an average reduction of 1.4 GW from the peak level of

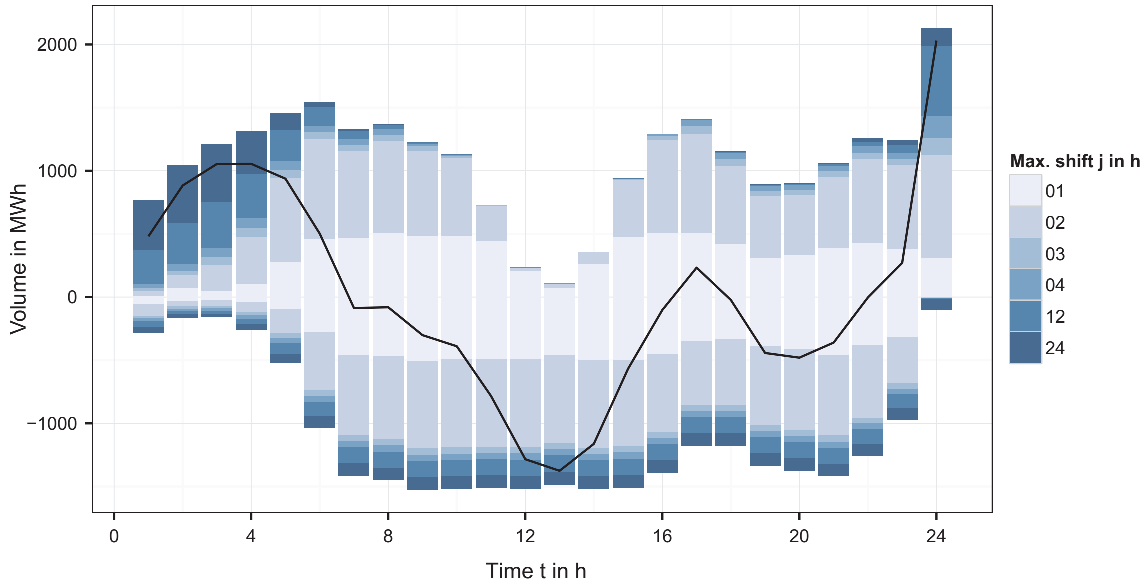

Fig. 2. Bar chart shows average load shifts. For each hour, the received volume is shown as a bar extending in the positive direction on the vertical axis; load shifted away appears as a negative bar. The color indicates the maximum possible shift duration in hours. The solid line represents the net-effect between power received and shifted away (25% scenario). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

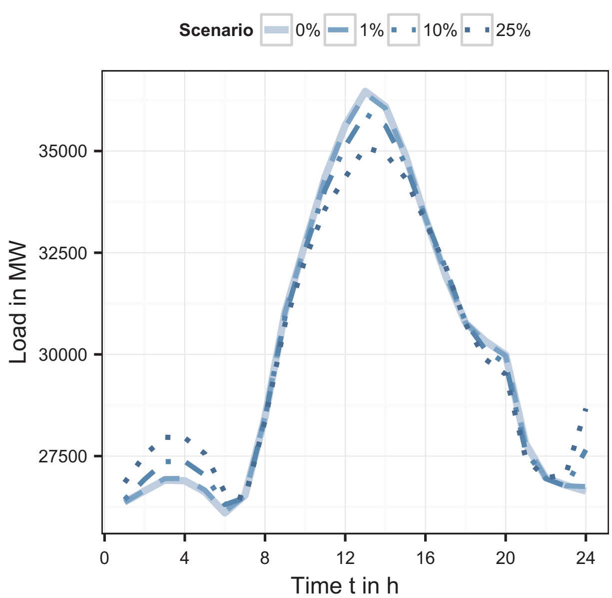

Fig. 3. Total trading volume of the auction spot market across different scenarios. Volumes are averaged over one year.

36.5 GW in the base scenario.

4.2.2. Net-load shifts

In addition, we provide a breakdown of changes in demand throughout the course of the year. As such, Fig. 4 shows all calculated load shifts on each day and each hour in 2014 for the 25% scenario. The outcome for the other scenarios evince similar patters but with shifts of smaller magnitude. Colors indicate the magnitude of the net-load shift, i.e. the sum of electricity received in this hour minus the sum of all electricity shifted away for this hour. Night hours are mostly blue, which indicates that more load is received during these times than is shifted away, while red colors indicate that load is shifted away, which happens especially at noon and in the evening. The load shifts at noon are mostly independent of the season, whereas those in the evenings and afternoons exhibit a stronger seasonal pattern. Furthermore, significant loads are often shifted to the hour before midnight due to particularly low prices at this time of the day.

4.2.3. Changes in demand volatility

Load shifting changes the point in time of electricity consumption and can potentially flatten the demand curve. Therefore, it is of interest to study the volatility of electricity demand as this is relevant for grid stability. Here we measure demand volatility by the standard deviation across all hourly volumes.

Table 1 provides an overview of the impact of load shifting on several observed metrics. In the first row, the load volatility is shown, for which we observe a decrease by up to 7% in the 25% scenario. Hence, a optimization of electricity expenses also results in a less volatile and thus more stable demand curve. Such an outcome can be beneficial for the electricity market as this could be an indicator of higher demand predictability. Even more important, this also can reduce the need for short-term balancing capacities, such as ancillary reserves [34].

4.2.4. Changes in peak demand

Demand peaks represent a crucial aspect for operators of electricity grids as these define the maximum capacity of generation and transmission. In the following analysis, we calculate the average across all peak demands of each day, as well as their standard deviation. As shown in Table 1, we observe a decrease in both the average of daily peak demand and the standard deviation of peak volumes. Consequently, load shifting flattens the demand curve and removes peaks.

Furthermore, we focus on the peak demand of the full year, which accounts for 49 GW. Here load shifting achieves a reduction of 205 MW or 0.4%. These findings suggest positive implications for grid operators, since grids are designed to accommodate the peak load and any reduction thereof can save costs by permitting the construction of electricity networks with lower capacity.

4.3. Impact on electricity spot price

As the load shifts are of relatively large magnitude, a shift in demand also alters the corresponding price of electricity. Hence, this section studies the impact of a change in demand on electricity spot prices.

Fig. 5 compares the average hourly electricity price across different

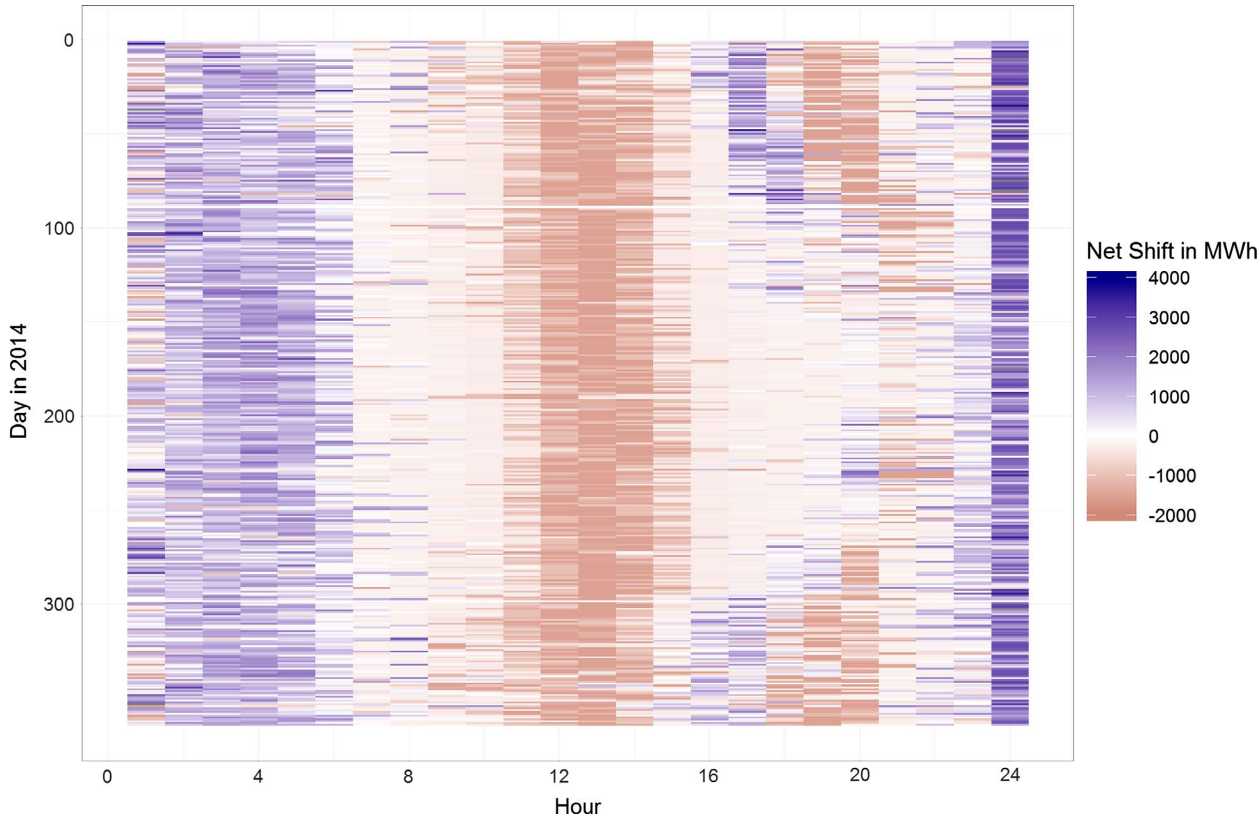

Fig. 4. Net-load shifts by hour and day during the time horizon of our study. Blue indicates that load is shifted to this hour and red indicates load shifted away (25% scenario). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

scenarios. The solid line represents the base-case, without load shifting, as given by the historic market price. This price features two peaks, one in the morning and one in the early evening. Load shifting results in a lower average price but with higher fluctuation. For instance, the simulated price in the 10% scenario is higher than the original price during night hours and lower during the daytime. We thus observe an increase in the volatility of electricity prices. In Fig. 5, the curve prior to load shifting follows a reverse U-shape, while it features two peaks in the 25% scenario. This pattern arises because the price elasticity is especially high at noon where, on average, even expensive forms of power generation are activated due to the overall high demand. The price is fairly inelastic during morning and afternoon hours, thus resulting in a lower price reduction.

In addition, the 25% scenario exhibits another interesting pattern as some price points during the day are actually lower than during the night. This effect is due to the relatively large volume shifts in this scenario combined with cheap electricity from solar power during the day.

Fig. 6 studies the relationship between demand and settlement price in our simulation. At noon, load is mainly shifted away and we thus observe that a higher share of load shifting reduces the price of electricity. The opposite happens at 11:00 p.m., where prices actually increase with increasing load shifting usage. Altogether, we see that the absolute change in price appears fairly independent of ex post load.

4.4. Nationwide electricity spending

Nationwide costs for electricity procurement accounted for €8.53 billion in 2014. The overall electricity expense decreases as the mean electricity price drops. The total costs amounted to €8.50 billion in the 1% scenario, €8.30 billion in the 10% scenario and €8.01 billion in the 25% scenario. This results in savings of up to €500 million in the 25% scenario, as shown in Table 1.

The above findings confirm the positive financial impact of load shifting on electricity expenses. Significant savings are possible even in the very conservative scenario (which uses only 1% of the theoretically available load shifting potential). We also note that further savings can originate from second-order effects, such as the reduction of transmission infrastructure and reduced expenses for load balancing.

Table 1
Impact of load shifting on key metrics (absolute value and relative change) categorized by trading volume and electricity price for each scenario.

			Impact for each scenario					
Category	Metric	Base-case	1% scenario		10% scenario		25% scenario	
Trading volume	Grid load standard deviation in MW	5373.49	−18.89	0%	−170.02	−3%	−393.02	−7%
	Average daily peak demand in MW	36739.46	−50.04	0%	−461.86	−1%	−1013.49	−3%
	Standard deviation of daily peak demand in MW	4132.34	−2.98	0%	−32.57	−1%	−73.25	−2%
Price	Average electricity price in €/MWh	32.8	−0.06	0%	−0.59	−2%	−1.39	−4%
	Electricity price standard deviation in €/MWh	12.79	−0.10	−1%	−0.47	−4%	0.14	1%
	Total electricity expenses in € million	8529.27	−24.73	0%	−226.67	−3%	−516.30	−6%

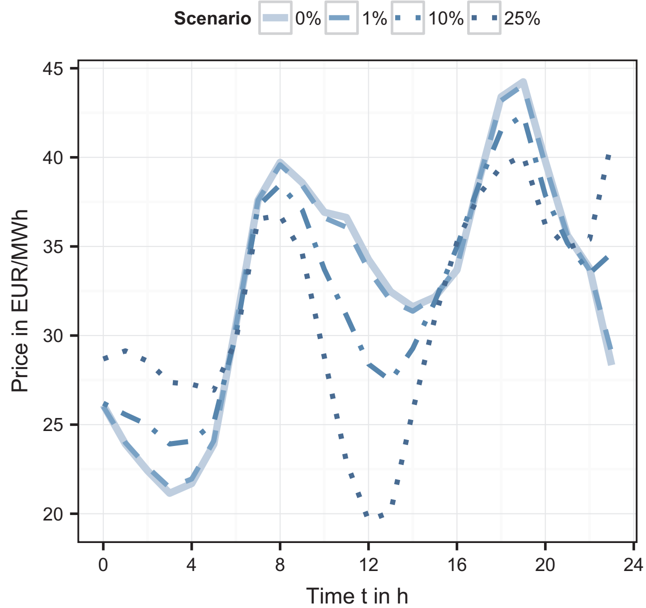

Fig. 5. Plot shows simulated electricity spot price for each hour across different scenarios. The low prices at noon are achieved due to the availability of large amounts of cheap solar power during this time of the day.

4.5. Model limitations

We now discuss the underlying assumptions of our model, as well as two practical limitations: first, we have conducted an ex post simulation of load shifting with theoretical values. In order to achieve financial gains in practice, electricity retailers and end-consumers need to expend considerable effort in order to actually implement demand response beyond the current level. This necessitates advances in terms of incentive schemes and technology. Second, we assume a linear relationship between price and demand which is only valid in a certain neighborhood. For larger load shifts, our model might reach non-linear areas of the supply curve, causing a model imprecision for which one must propose an alternative formulation in order to simulate the electricity price for a given demand. This also represents a potential option for coping with scenarios that postulate a load shifting utilization beyond 25%. Third, we have not dealt with regulatory hurdles, such as the Renewable Energy Law in Germany, that might impede the effective exploitation of load shifting. We have also not investigated the case of load shedding, which is common in industrial processes and offers further opportunities for managing the demand side.

Our model specifically focuses on the status quo and further research is necessary to make extrapolations in anticipation of future developments. For instance, technological advances, such as better energy storage, are likely to improve appliances for load shifting and thus enable load shifts by more hours than is possible today. Decreasing electricity costs for households and businesses might lead to further interaction effects, as their total electricity consumption may increase as a result.

Our model does not explicitly simulate how load shifting helps to compensate for fluctuating feed-ins from intermittent energy sources. However, it implicitly takes this circumstance into account through the underlying supply curves. These curves (as reflected by their slope) already incorporate different prices for different forms of renewable energy, as well as situations of scarce or excess supply. If desired by policy-makers, load shifting can be used to immediately compensate for fluctuations from renewables, e.g. by appropriate policies. For that, one would need to update the objective function, as well as constraints, of our optimization problem accordingly.

Altogether, we demonstrate a method of estimating the financial benefits of load shifting. We compare different scenarios in order to overcome previous limitations and show the impact of demand response at different maturity levels.

5. Discussion

In previous literature, there is a general agreement that demand response entails a large variety of benefits for most stakeholders. Our paper contributes to the existing body of research by studying the financial dimension of load shifting on a macro level. We find a wealth of positive effects on the electricity price and the corresponding trading volume:

- **Price characteristics**. Economic- and market-driven benefits predominantly originate from a lower average electricity price. This, in turn, also cuts total electricity expenses on a national level. Fig. 5 reveals that an increase in price volatility becomes evident when

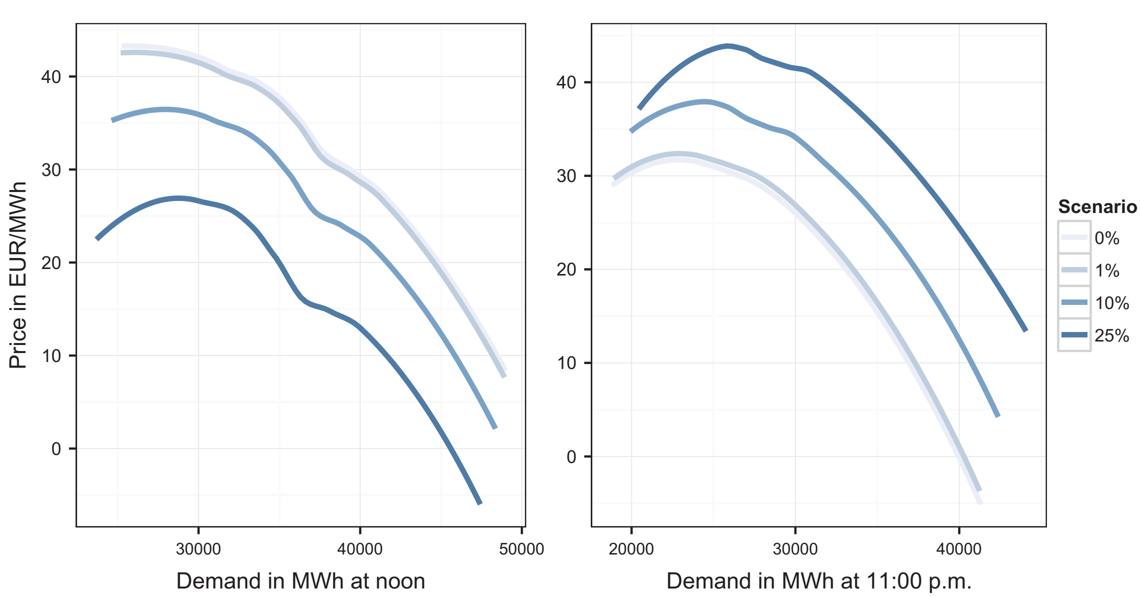

Fig. 6. This plot shows the relationship between demand and settlement price after load shifting at noon and 11:00 p.m. Here the 365 daily values from our simulation are used as an input for a local polynomial regression which is then plotted as a line.

load shifting aims at minimizing the overall expenditures for electricity.

- **Load**. Reducing fluctuations in the grid load is especially beneficial as it reduces the effort necessary to stabilize the electricity network, e.g. by providing additional flexibility on the generation side. Similarly, a decrease in peak load is desirable for generation and transmission as it requires less reserve capacity. This also entails additional environmental benefits, since it simultaneously reduces the need for fossil fuel power plants. The decrease in the standard deviation of daily peak volume mainly supports network/generation and environmental goals.

Altogether, these findings confirm that multiple benefits could be achieved by using DR.

Our model suggests that DR entails cost savings, which can be the source for various business opportunities. Current battery technology[2] can generate savings that would pay back the investment in less than three years. In future, amortization could be achieved in even less than two years, as prices of roughly €0.3 million per MW battery storage are likely, according to current research.

Multiple sources suggest that governments should actively support DR, considering its manifold advantages. Examples include the U.S. [20], the U.K. [51], and China [52,53]. This paper not only confirms these advantages, but also provides a research framework for quantifying them. Similar financial savings from load shifting are to be expected in other liberalized electricity markets. This is also confirmed by related literature [e.g. 52,22,31]. However, the magnitude of financial savings might vary depending on the characteristics of the market. In general, we expect higher savings when the volume of shiftable load or the flexibility of load shifting increase. In addition, one can assume further savings when there is less correspondence between power demand and power generation from non-flexible electricity sources (e.g. nuclear power plants or intermittent energy sources), since non-flexible power sources are commonly linked to an inelastic electricity price. This is where load shifting promises financial savings by increasing the flexibility to match electricity demand and supply.

Similar to [54], we thus propose that governments and policy-makers support the rapid and widespread adoption of demand response. However, nations will bear high costs for the development of regulations, standards and control systems. It is possible that these can be covered by the expected savings, but this may require a re-distribution of savings. We refer to [55], which discusses enablers of DR.

On the whole, even stakeholders who do not actively participate in DR programs benefit from lower average prices for electricity. However, consumers with non-conventional demand patterns and limited flexibility may be forced to purchase electricity at a higher cost than previously. Electricity prices increase slightly during the night and, for instance, operators of street lighting will thus face higher costs. This reveals an inherent and significant trade-off in terms of policy design: policy-makers need to be aware of this side effect in order to align different policy goals. In the most extreme case, this could drive certain types of (heavy) industries out of the market or prompt them to relocate to other countries. If governments and policy-makers prefer to avoid such losses, they need to come up with adaptations for inflexible customers, such as special pricing schemes.

To further promote DR, markets which allow for the trading of load shifts are required. There is currently a program for shiftable load[3] in Germany. However, participants need to offer a minimum load of 50 MW and must be connected to the high-voltage transmission system. These requirements are impossible to meet for individual households and even most companies [56]. In addition, this program is only designed for load decreases at critical moments and not for day-to-day balancing. Nonetheless, [57] identifies significant improvements in the European Union as it moves towards increasing demand response usage. Existing markets, such as the analyzed day-ahead auctions, require guaranteed delivery of traded loads, which prohibits the application of DR where customer participation might not be guaranteed. Hence, removing or adjusting such barriers, or even introducing a separate market for shiftable loads, could be viable steps by which to achieve greater DR utilization.

This paper focuses on the benefits of demand response, while neglecting the question of changing consumer behavior. A wide range of studies explores suitable pricing mechanisms as an incentive to control load shifts. An overview of such pricing schemes can be found, for instance, in [11,9]. Other publications study the relationship between demand and price, with a focus on response times [58] or smart meters [59]. For instance, demand shifts can be the result of time-based pricing [e.g. 13,60,16]. In addition, time-based pricing is an intriguing tool as it encourages consumers to actively adjust their demand [51]. Based on the previous studies, we conclude that it is indeed possible to steer demand with appropriate pricing schemes. Related literature forecasts a reduction in demand due solely to the introduction of time-based prices without any further technological modifications [20]. Finally, new technologies in the form of home electricity storage, and especially plug-in electric vehicles, a natural source for demand response. Hence, incentives and control mechanisms should be designed to allow for the smooth integration of such storage systems into the electricity network.

6. Conclusion

Demand response promises financial benefits, yet little is known about its exact impact in terms of quantitative numbers. As a remedy, this paper analyzes how load shifting serves as an effective instrument to reduce nationwide spending on electricity. We identify cost savings of up to €500 million in the 25% scenario for the German and Austrian markets. This amounts to approximately 6% of the overall spending on electricity. Furthermore, we find evidence that the stability and capacity of the transmission networks would be bolstered due to a reduction in demand volatility and peak demand.

Further quantitative analysis of the potential benefits of DR promises to be intriguing: first, with regard to financial savings, quantitative assessments of other financial advantages could help to further support demand response. Among these, benefits relating to transmission and generation, as well as environmental areas, seem possible. Second, a more expansive knowledge of investment costs is needed to evaluate the net benefits of DR. Establishing DR may require investments in smart metering, electricity storage technologies, new infrastructure and other such technical upgrades. It would be very interesting to gauge the magnitude of necessary investments. Third, researchers and policy-makers could benefit from a quantitative assessment that simultaneously incorporates price and supply elasticity.

Appendix A. Derivation of the optimization problem

The following equation minimizes the total electricity expenses (in €) via

$$\min_{\{vol_t\}} cost = \min_{\{vol_t\}} \sum_t price_t \, vol_t. \tag{A.1}$$

[2] Tesla Power Wall, investment cost approx. €0.5 million per MW (14 kWh at €6770). URL:https://www.tesla.com/de_DE/powerwall. Accessed on July 24, 2017.

[3] Transmission system operators invite tenders for load which can be turned off at their request.

Here we incorporate the electricity price $price_t$, which also depends on trading volume vol_t in hour t. Eq. (A.1) thus represents the total cost across all hours under study. Then, the volume vol_t in hour t must equal the demand $demand_t$ with additional load shifting.

In order to integrate load shifting, we introduce the following notation. Each type of consumption can shift the demand by a certain maximum duration j. For instance, heating may be delayed by an hour or two, whilst washing the laundry could be delayed by $j = 12$ h or more. Thus, we define $shift_j(t,d)$ as the load shift from hour t by d hours for a given appliance j. For example, we express a shift from t to t' by $shift_j(t,t'-t)$. Furthermore, we set all $shift_j(t,d) = 0$ where $t + d < 1$ or $t + d > 24$ due to regulations.

We now adapt the constraints from [32,37,27] given by

$$vol_t = demand_t + \sum_j \Big[\underbrace{-\textstyle\sum_{i=-j}^{j} shift_j(t,i)}_{\text{load shifted away}} + \underbrace{\textstyle\sum_{i=-j}^{j} shift_j(t-i,i)}_{\text{load received}}\Big], \tag{A.2}$$

$$shift_j(t \pm -i, \mp i) \geqslant 0 \quad \text{for all } t,j,i, \tag{A.3}$$

$$\sum_{i=-j}^{-1} shift_j(t,i) + \sum_{i=1}^{j} shift_j(t,i) \leqslant \overline{shift_j}(t) \quad \text{for all } j,t. \tag{A.4}$$

According to Eq. (A.2), electricity demand at every hour equals the original demand plus load received minus load shifted away. Eq. (A.3) requires that load shifts always be positive in order to guarantee a unique solution. Furthermore, Eq. (A.4) limits the maximum shift volume by an upper boundary $\overline{shift_j}(t)$. Overall, no energy is gained or lost and thus the model is energy neutral for every individual day.

We perform this optimization based on the data described in Section 3. For this purpose, we utilize the software "R" together with the package "quadprog", which ships a solver for quadratic programming. The solver implements the dual method from [61,62].

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