Decision Model for Sustainable Electricity Procurement
Using Nationwide Demand Response

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Abstract—As part of the worldwide effort towards achieving sustainable energy generation, an increasing share of renewable energy sources are connected to the electricity networks. This intermittent electricity output from renewable energy resources causes changes in prices and feed-in volumes. One approach to compensate for the supply side fluctuations is the active management of the demand side via so-called Demand Response (DR). Demand Response is defined as providing incentives to electricity consumers to shift electricity consumption to the economically most favorable time. Analyzing such load shifts economically is challenging, as prices depend on the quantity requested. We analyze this interdependency by explicitly modeling the load dependence of electricity prices and thus develop a decision model for nationwide electricity expenses in the form of a quadratic optimization. Using real market data, we show a decrease in average electricity prices and price volatility.

1. Introduction

Electricity demand varies strongly throughout the day. These variations are driven by consumers who usually start using electricity in the morning with two peaks peak during the day and then reduce demand again over night. This is true for most private households, as well as many industrial and commercial consumers. As electricity is traded on a market, times of high demand – especially during the day – often correlate with high prices. On the other hand, at night, demand and prices are generally low. This is shown in Figure 1 in which long-term averages of the electricity prices and their 5% and 95% quantiles are plotted for each hour throughout the day.

Because of the price differences during day and night, electricity retailers who are purchasing energy on day-to-day auctions on the spot market can achieve significant cost savings if volume and timing of their electricity purchases were optimized to the economically most feasible solution [1], [2]. Often a shift of a few hours is enough to realize savings and for many applications does not impair the customer [3], e.g., a freezer’s compressor is running at night instead of during the day. Hence, such shifts usually occur in times of high demand and high prices, where consumption is shifted to hours of lower demand and also lower prices. It is also possible that electricity supply may be high, e.g., due to favorable weather for renewable generation, which could make it beneficial to consume more energy at such a time even if overall demand is also high. Such shifts in consumer electricity usage can be achieved, for example, by providing incentives in programs or tariffs. In the following, we refer to any lever which influences the electricity consumption as Demand Response (DR) [2], [4].

As a result of their central role in purchasing and distributing energy, electricity retailers are often considered as innovators in establishing DR [5]–[7]. DR entails several advantages, such as reduced procurement costs and improvement of the grid stability; many of which benefit electricity retailers. In addition, consumers capable of shifting demand

Figure 1. Plot shows the fluctuations in average electricity prices for each hour of the day, including 5% and 95% quantiles (EPEX spot market between 2009 and 2012).
can only be rewarded for their flexibility if retailers provide appropriate contracts. However, governments and policy makers also have stakes in DR and should seek opportunities to drive a nationwide adoption [8].

For governments and policy makers, DR is especially important in its function as an enabler for sustainable energy generation from intermittent renewable sources. Renewable energy sources are promoted by many countries [9], [10]. However, due to specific properties of renewable generation, such as their intermittency, this also poses a challenge to electricity networks from the supply side [1], [11]. Active management of the demand side can help to compensate [1], [8], [12] for an increase in electricity prices and volatility of power generation. Furthermore, this allows to shut down environmentally unfriendly generation plants (because of the decrease in peak demand due to DR) and one can also reduce transmission infrastructure.

Previous literature has covered multiple individual assessments of the benefits of DR on household level [13], [14]. However, we are not aware of any nationwide analytics or decision models to evaluate the optimal re-distribution of demand. Furthermore, no holistic evaluation of the impact of DR on cost savings, prices and price volatility has been undertaken. Evaluation of these parameters is particularly challenging since prices are affected by load shifts.

In order to analyze the nationwide cost savings of Demand Response, we propose a novel decision model for electricity expense optimization. Using a quadratic optimization problem, we minimize the electricity expenses and identify the optimal timing for load shifts.

The remainder of this paper is structured as follows. We define the required terminology in Section 2 before presenting related work on the benefits of Demand Response, as well as decision models in Section 3. Next, Section 4 presents the quadratic optimization problem, which we use to identify the optimal amount of load shifting throughout a single day. This is followed by an evaluation of our decision model based on real-world data in Section 5. Finally, we present policy implications in Section 6 and Section 7 summarizes the most important findings.

2. Terminology

A general term describing any activities within the demand side of the electricity network is given by Demand Side Management (DSM). Three types of Demand Side Management can be identified, which differ in their objectives [1]:

1) Economic/market-driven DSM aims to reduce the overall cost of electricity by various means. For example, this may be achieved through a shift of demand to times with lower prices.

2) Environmental-driven DSM focuses on improving the environmental aspects of energy production and consumption, such as the general reduction of demand and avoidance of generation technologies that are particularly polluting.

3) Network-driven DSM focuses on enhancing network stability and reducing the need for additional capacities in generation and transmission.

In addition to the above terminology, market-driven (and partly network-driven) Demand Side Management ties to so-called Demand Response (DR). Demand Response is a term which has been used traditionally to describe peak clipping – a measure to actively cut down demand in times of very high electricity usage. Recently, however, institutions such as the U.S. Department of Energy and the Federal Energy Regulatory Commission have used the term more generally as a name for “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” [4]. This includes the use of incentive- or price-based programs to steer demand [2]. In this paper, we use the term Demand Response to describe the shifting of load by customers in response to appropriate incentives, whereas DSM could include any measure that influences the demand side, such as an awareness campaign for energy efficient lighting.

3. Related Work

In this section, we present literature which evaluates the benefits of Demand Response and decision models for DR.

3.1. Benefits of Demand Response

It is generally agreed that Demand Response entails a large variety of benefits for almost all stakeholders [2], [15]–[18]. Multiple studies point out how sustainable electricity generation based on renewable energy resources can be supported by the active management of the demand side through DR [1], [8], [12], [19]. For example, one study specifically mentions the intermittent properties of renewable energy generation which prohibit their use as “dispatchable resources” [1]. Hence, Demand Response is regarded as a very suitable instrument [20], [21] for intermittency mitigation, in addition to other measures such as energy storage systems [22]. Furthermore, Demand Response and environmental goals are called an “optimal complementary approach” [8].

In addition, cost savings are expected for customers capable of shifting their load; as shifts flatten the overall load curve and hence reduce the general cost of electricity production. Customers without Demand Response capability benefit from lower overall electricity prices [18]. This comes at the cost of reduced profits for electricity retailers offering expensive peak reserve generation capacities [23], [24].

While many studies evaluate the available load potential (e.g. [8], [12], [19], [25], [26]), the results strongly depend on the underlying assumptions. Klobasa [19], [25] provides a very detailed bottom-up analysis for Germany calculating a potential of 3 GW in the industrial sector, 8 GW in the
commercial sector and above 20 GW from private households.

In terms of financial savings, it is estimated that establishing smart meters in Europe could provide savings of up to EUR 67 bn if optimal adoption is achieved and only EUR 14 bn for the less optimistic scenario [27]. Also, the cost of smart meters would have to be covered first. Average household savings in the UK are estimated at around GBP 1,800 present value over a 20 year period if at least 30\% of the population participate and also accept 1 h of reduced consumption per day [28].

Altogether, knowledge of the nationwide economic potential of Demand Response in liberalized markets is still limited [1], [13] and we are not aware of any analysis that includes a simulation of load shifting whilst using actual real-world data.

3.2. Decision Models for Demand Response

Using models and methods from Operations Research (OR) to solve questions regarding the energy market is widely established [29]–[32]. In this context, decision models are used to provide recommendations on how to achieve the optimal outcome for a given problem [33], [34].

Multiple studies related to Demand Response aim to create decision models for households [35], [36], consumer groups [13], [37], [38] or even individual appliances [39]. However, decision models on an aggregate level are scarce.

Faruqui et al. [27] use direct calculation of savings based on a fixed reduction of peak cost by a given percentage. While such estimates are possible, they do not take into account the electricity market dynamics and also provide no insight into the required load shifts and how to use different appliances with different maximum shift durations.

Nguyen and Nguyen [40] optimize electricity expenses with a dynamic programming backward algorithm. Using stochastic optimization uncertainties are taken into account. Yet, the problem is solved only for individual appliances such as ventilation and electric vehicles. As prices can be assumed fixed for such solitary problems, this is not very accurate. Furthermore, the DP problem has exponential dimensionality and is computationally inefficient.

Another approach [28] simulates the behavior of three types of stakeholders: the utility, an aggregator and households. However, here the usage of Demand Response in form of net curtailment and load shifting is presented as a binary on-or-off decision depending on static thresholds.

In summary, none of the above decision models provides full insights in how to optimally shift loads depending on actual market data and demand curves for a given time period.

4. Methodology

In this section, we describe how nationwide usage of Demand Response can be modeled by methods from Operations Research. In a first step, we describe the underlying model that aggregates expenses from electricity auctions. In a second step, we extend the decision model to include Demand Response usage. Here, we formulate a quadratic optimization problem which allows us to simulate the price dependency on the traded volumes of the (multi-)national electricity exchange.

Electricity can be purchased via different products on the markets. Usually, there is a baseload product, which is traded in options and futures to ensure the long-term supply of electricity. To further differentiate these long-term needs, the baseload package which usually covers all 24 h of a day, may be complemented by various peak and off-peak products, which allow a differentiation of the time of the day. The remaining energy is traded on a spot market, which is particularly important to balance day-to-day variations in electricity demand. In this paper, we focus on the expenses for electricity on the spot market.

4.1. Optimization of Volume-Dependent Electricity Expenses

Let us calculate the nationwide costs $C_{\text{nation}}$ (in EUR/MWh) spent on daily electricity auctions on the spot market. Furthermore, let us introduce the hourly prices for electricity auction contracts $p_A(t,q_A(t))$ and their corresponding traded volumes $q_A(t)$ at hour $t$. Here, the expression $p_A(t,q_A(t))$ denotes that prices at the exchange depend on the corresponding hours, as well as the nationwide quantities. Then, the expenses for electricity traded as auctions on a day-to-day basis may be written as

$$C_{\text{nation}} = \sum_{t=1}^{24} p_A(t,q_A(t)) q_A(t)$$

(1)

where we sum over all hours $t = 1,\ldots,24$ of a single day.

Within a reasonable neighborhood, we can assume a linear relationship between volume and day-to-day prices [41]. This is justified when looking into the bid-ask curves of the electricity exchange. Thus, we model prices with the linear model

$$p_A(t,q_A(t)) = \alpha(t) + \beta(t) q_A(t)$$

(2)

with suitable coefficients $\alpha(t)$ and $\beta(t)$. These coefficients can, for example, be estimated via ordinary least squares or other regression techniques. We show later how we derive this linear model from actual demand curves (Section 5.2).

Combining the previous ideas from Equations (1) and (2), we yield a formulation in which prices are dependent on volumes via

$$C_{\text{nation}} = \sum_{t=1}^{24} \alpha(t) q_A(t) + \sum_{t=1}^{24} \beta(t) q_A^2(t).$$

(3)

While the above equation for $C_{\text{nation}}$ states how to calculate nationwide costs, the actual computation of $q_A(t)$ is not yet specified; this is addressed in the following section where we formulate a corresponding optimization problem.
4.2. Electricity Expense Optimization

The previous section has outlined how to model nationwide spending on electricity, while the actual calculation of \( q_{A}(t) \) in Equation (3) is left unclear. As a remedy, we pursue the following approach: we first rewrite the above model as an optimization problem and then transform it into matrix notation. The matrix formulation simplifies notation and serves as a default input for most solvers.

The optimization problem in order to determine the quantities \( q_{A}(t) \) is given by

\[
\min_{q_{A}(1),\ldots,q_{A}(24)} C_{\text{nation}} = \min_{q_{A}(1),\ldots,q_{A}(24)} \sum_{t=1}^{24} \alpha(t) q_{A}(t) + \sum_{t=1}^{24} \beta(t) q_{A}^{2}(t) \tag{4}
\]

with an additional constraint as follows. Let us introduce a new variable \( D(t) \) which denotes the nationwide electricity demand in hour \( t \). Then, the quantities bought at the electricity exchange need to equal the nationwide demand for electricity from auctions, e.g., excluding any demand that is fulfilled with other products, such as options and futures.

Mathematically speaking, we obtain the following constraint

\[
q_{A}(t) = D(t) \quad \text{for all } t = 1, \ldots, 24. \tag{5}
\]

This states that the purchased electricity power from auctions must meet total demand \( D(t) \) in every hour \( t = 1, \ldots, N \).

To make notation easier, we now rewrite the above equations in matrix form. Hence, we define \( x \in \mathbb{R}^{24} \) as the quantities of electricity purchased at every hour \( t \). Using this, we write the nationwide electricity expense in quadratic form as

\[
\min_{x} -a^{T}x + \frac{1}{2}x^{T}Gx. \tag{6}
\]

Transforming the minimization problem into quadratic form can be achieved by defining the vectors and matrices of Equation (6) and Equation (10) as

\[
a = \begin{bmatrix} -\alpha(1) \\ -\alpha(2) \\ \vdots \\ -\alpha(24) \end{bmatrix} \in \mathbb{R}^{24}, \tag{7}
\]

\[
x = \begin{bmatrix} q_{A}(1) \\ q_{A}(2) \\ \vdots \\ q_{A}(24) \end{bmatrix} \in \mathbb{R}^{24}. \tag{8}
\]

Here, \( G \) is a diagonal matrix \( G \in \mathbb{R}^{24 \times 24} \), where the diagonal entries are \( 2\beta(t) \). Then, our constraints need to be rearranged in the form

\[
\begin{bmatrix} 1 & 0 & \ldots & 0 \\ 0 & 1 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & 1 \end{bmatrix} \in \mathbb{R}^{24 \times 24}. \tag{11}
\]

The demand on the right-hand side is written as a vector

\[
b = \begin{bmatrix} D(1) \\ D(2) \\ \vdots \\ D(24) \end{bmatrix} \in \mathbb{R}^{24}. \tag{12}
\]

Using general information about the electricity market we have shown how the total expenses can be derived and represented in quadratic form. We can easily add further constraints to Equation (10) by appending more rows to \( C \).

In the next section, we show how Demand Response can be included in our model.

Now, it becomes obvious that our optimization problem is quadratic with linear equality constraints. This can be easily solved with a large variety of solvers from quadratic programming [42, 43] in polynomial time [44] if the matrix \( G \) is positive-definite.

4.3. Modeling Demand Response

In order to extend the above quadratic optimization to include DR, we need to introduce the following notation (see Figure 2). It is important to note that not all energy can be shifted by the same maximum duration \( j \). For example, heating the flat may be delayed by an hour or two, whilst washing the laundry could be delayed by \( j = 12 \) h or more. Hence, we define \( LS_{j}(t,d) \) as the load shift from \( t \) to \( d \) hours with a maximum shift by \( j \) hours according to the given appliance. In other words, we denote a shift from \( t \) to \( t' \) via \( LS_{j}(t,t' - t) \). For example, let \( LS_{2}(t,-1) \) be the potential (i.e. all appliances with maximum shift of \( 2 \) h) which is shifted by \( -1 \) h from \( t \) to \( t - 1 \). By definition, we set all \( LS_{j}(t,d) \equiv 0 \) where \( t + d < 1 \) or \( t + d > 24 \) (out of range). In addition, a shift \( LS_{j}(t,0) \) by \( 0 \) hours is not defined.

This notation is now used to integrate Demand Response usage into the above model. We append further constraints and include additional components in the parameter \( x \). Then, we obtain a new optimization problem in the following high-level formulation

\[
\min_{q_{A}(t),LS_{j}(t,d)} C_{\text{nation}} \pm \text{Demand Response usage.} \tag{13}
\]
When using Demand Response, we actively modify the demand at certain hours. Furthermore, according to our definition any load shift must be positive, such that
\[ LS_j(t + i, -i) \geq 0 \quad \text{and} \quad LS_j(t - i, +i) \geq 0 \quad \text{for all } t, j, i. \] (14)

In addition, the load shifted away is limited by a maximum available capacity \( \Delta_j(t) \). For example, the sum of all \( LS_2(t, d) \) is thus bounded, i.e. \( LS_2(t, t - 1) + LS_2(t, t + 1) + LS_2(t, t + 2) \) must be smaller or equal than \( \Delta_2(t) \). We formalize this in a second constraint
\[
\sum_{i=-j}^{-1} LS_j(t, i) + \sum_{i=1}^{j} LS_j(t, i) \leq \Delta_j(t) \quad \text{for all } j, t. \] (15)

Finally, our model requires a new constraint that validates if electricity demand is satisfied by traded quantities and Demand Response usage. This is given by
\[
q_A(t) = D(t) - \text{load shifted away} + \text{load shifted here} \] (16)
for \( t = 1, \ldots, 24 \)

This expression can then be extended to
\[
q_A(t) = D(t) - \sum_j \left[ \sum_{i=-j}^{-1} LS_j(t, i) - \sum_{i=1}^{j} LS_j(t, i) ight. \\
\left. + \sum_{i=-j}^{-1} LS_j(t - i, i) + \sum_{i=1}^{j} LS_j(t - i, i) \right] \] (17)
for \( t = 1, \ldots, 24 \) and with the original demand \( D(t) \). Then, the variable \( q_A(t) \) gives the quantity of electricity that needs to be purchased at a time \( t \) to fulfill the original demand after load shifting for the given time slot.

The previously proposed additions require multiple changes to the quadratic implementation of this minimization problem. The solution vector \( x \) denoting the demand is now extended to comprise of one value for each possible demand shift in addition to the 24 values for each hour, while the cost function remains the same.

5. Evaluation

This section describe how we solve the quadratic optimization problem to determine optimal load shifting. We first present our data sources and then outline how we model the relationship between traded electricity volume and corresponding price. Finally, we present our simulation results which are based on real-world data.

5.1. Data Sources

Several publications aim at quantifying the available load shifting potential in Germany (e.g. [12], [25], [26]). In this paper, we use the estimated DR potential from Klobasa [25] as these values feature the highest granularity. In addition, this DR potential ranges in the middle of the spectrum when compared to other publications. These potentials are based on a bottom up assessment of available capacities in households, commercial and industrial applications. We calculate the average daily shift potential in Germany and include only appliances which are applicable to a winter day. As such, we exclude, for instance, air conditioning but include heating applications. In addition, we scale the data to also include Austria.\(^\text{1,2}\)

The previous description addresses the theoretically possible Demand Response potential, based on which we derive the following three scenarios. These scenarios vary in terms of the penetration of Demand Response that is assumed: accordingly, we set the ratio of Demand Response utilization to 1 %, 10 % and 25 %. The corresponding volumes available for load shifting are given in Table 3.

In order to achieve realistic estimates of the savings possible through Demand Response, we use actual market data from EPEX spot\(^3\) for the combined German and Austrian electricity market. Here, we use hourly auction prices and volumes for December 19, 2012 as an exemplary simulation horizon. In our calculations, we determine the electricity demand based on data from EEX transparency\(^4\).

Finally, we need to specify how we determine electricity prices when simulating traded electricity volumes that differ from the historic data. For this, we employ actual demand

\(^{1}\)Here, we choose a scaling factor of 1.11. This factor is based on Eurostat data of gross inland consumption of energy for 2012 in Germany and Austria.


TABLE 3. AVAILABLE ELECTRICITY VOLUME AVAILABLE FOR LOAD SHIFTING WITH A BREAK DOWN BY THE MAXIMUM SHIFT DURATION FOR THREE SCENARIOS WITH 100%, 25%, AND 1% DR UTILIZATION (DATA BASED ON [25]; SCALED FOR THE COMBINED MARKET OF GERMANY AND AUSTRIA; APPLIANCES FILTERED FOR A WINTER DAY).

<table>
<thead>
<tr>
<th>Maximum Shift Duration $j$ in h</th>
<th>Maximum Load Shift $\Delta_j$ in MW</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>100%</td>
</tr>
<tr>
<td>1</td>
<td>2,117</td>
</tr>
<tr>
<td>2</td>
<td>2,819</td>
</tr>
<tr>
<td>3</td>
<td>199</td>
</tr>
<tr>
<td>4</td>
<td>197</td>
</tr>
<tr>
<td>12</td>
<td>4,391</td>
</tr>
<tr>
<td>16</td>
<td>567</td>
</tr>
<tr>
<td>24</td>
<td>400</td>
</tr>
</tbody>
</table>

curves from EPEX spot. These curves feature all bids for an electricity auction in a given hour. On average, an auction consists of 691 bids.

5.2. Dependency of Electricity Prices on Trading Volumes

In economics, relationships between variables are frequently assumed to be linear for a given neighborhood of observed data [45]. Accordingly, we adopt this approach and also assume a linear relationship between electricity price and traded volume [41]. We validate this procedure visually by depicted all bids for an exemplary electricity auction in Figure 4. Here, the red dot indicates the actual market price and we see that a linear relationship is valid in its neighborhood.

In order to calculate the gradient, we first filter the data and then perform a linear regression. For the former, we choose the 0.5% and 99.5% quantiles of all electricity prices between 2009 and 2012. These represent a set of feasible prices which we can expect during normal operations on the electricity exchange. Hence, our regression is thus based on prices between 0.04 EUR/MWh and 93.81 EUR/MWh in order to compute the gradient. This range is highlighted by an shaded area in Figure 4. Interestingly, the intercept from the linear model is not needed for further evaluations, instead we only use the slope from the regression and then calculate the simulated price based on gradient and the historic price.

5.3. Results

We now evaluate the effects from Demand Response usage on electricity prices and their volatility. Thereby, we compare three different scenarios that vary in the utilization (1%, 10% and 25%) of the theoretically available DR potential. In our analysis of shifted volumes, we predominantly focus on the 25% simulation to provide insights on how the shifts work. In addition, we compare and discuss the economic effects across all three scenarios, finding a similar pattern for the expected savings.

Figure 5 illustrates how electricity demand is shifted to minimize costs. Here, the $x$-axis shows the hour of the day and the $y$-axis the volumes shifted. Bars in positive direction indicate that electricity was shifted from some time to this hour, whereas negative bars reveal that electricity was shifted to other hours. The colors of the bar denote the duration of the shift. Overall, we see the following pattern: electricity is mostly shifted to night hours from 0 to 5 am and from 9 pm to midnight. During the day, electricity is mostly shifted away, except for a peak at 3 pm when relatively low electricity prices promote higher usage. Furthermore, these shift mainly originate from appliances that are highly flexible in terms of scheduling. More precisely, all shift durations $j$ are used to relocate the electricity demand. One and two hour shift potentials are activated to shift peak demand to times of lower electricity usage at the boundaries and the potentials with longer shifts, such as 12 h, 16 h and 24 h, are used in the morning and evening to shift electricity towards midnight.

The previous findings are confirmed by Table 6 in more detail: the net effect from Demand Response remains positive for a given hour if this hour receives more energy than is shifted away. Night hours, especially in the early morning, receive up to 4.1 GW electricity, whereas our decision model shifts electricity most away during day time. The maximum Demand Response potential for each individual hour accounts for 2.7 GW, which is equivalent to using the full 25% potential. This happens at 7 pm, which is also one of the hours with highest electricity prices (cf. the original
electricity prices in Table 6). In contrast, receiving electricity is not limited by this volume, since electricity can be shifted from multiple hours to another.

Figure 7 compares visually the simulated electricity prices across all three Demand Response scenarios. The solid line represents the benchmark without Demand Response. These prices are equivalent to the originally observed ones. Based on the simulated prices, we observe two peaks in the late morning and early evening, which both mirror the previous load shifting. In the scenarios with Demand Response potential, load is shifted, resulting into prices that are more balanced. Interestingly, we find evidence of considerably more stable and less volatile prices in scenarios with higher Demand Response utilization. For instance, the simulated prices in the 25% scenario (dashed line) is above the original prices during night hours and below during daytime.

Furthermore, we observe one interesting pattern in simulation using 25% of the theoretically available shift potentials. In this case, some prices during the night are higher than during the day. These effects are driven by the large volumes of shifted load. As a consequence, it is not realistic to study DR utilization of above 25% with the given decision model as this might violate the assumption of a linear relationship between electricity price and traded volume. For such evaluations, one needs to either develop a different decision model or validate the outcomes with results from practical experiments.

Finally, we compare the effects on electricity prices across all Demand Response scenarios. As such, we provide descriptive statistics of simulated electricity prices from Demand Response usage in Table 8. When using Demand Response, the mean electricity price decreases for
**TABLE 6. OVERVIEW OF HOURLY NET EFFECT INDUCED BY DEMAND RESPONSE USAGE ACROSS EACH HOUR OF THE DAY FROM VOLUME SHIFTS (SCENARIO WITH 25 % DR PENETRATION).**

<table>
<thead>
<tr>
<th>Time Slot $t$ (in h)</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original Volume (in GW)</td>
<td>23.8</td>
<td>24.4</td>
<td>23.8</td>
<td>23.5</td>
<td>23.0</td>
<td>23.3</td>
<td>25.0</td>
<td>24.3</td>
<td>27.8</td>
<td>28.4</td>
<td>28.4</td>
<td>29.4</td>
</tr>
<tr>
<td>Volume After DR (in GW)</td>
<td>27.8</td>
<td>28.2</td>
<td>27.8</td>
<td>26.5</td>
<td>25.2</td>
<td>25.1</td>
<td>24.3</td>
<td>23.0</td>
<td>25.5</td>
<td>25.9</td>
<td>26.5</td>
<td>26.9</td>
</tr>
<tr>
<td>Net Effect (in GW)</td>
<td>4.0</td>
<td>3.7</td>
<td>4.1</td>
<td>2.9</td>
<td>2.3</td>
<td>1.8</td>
<td>0.7</td>
<td>1.3</td>
<td>1.5</td>
<td>1.4</td>
<td>1.5</td>
<td>1.5</td>
</tr>
<tr>
<td>Original Price (in EUR/MWh)</td>
<td>36.07</td>
<td>35.32</td>
<td>35.21</td>
<td>34.22</td>
<td>34.20</td>
<td>36.99</td>
<td>44.28</td>
<td>60.45</td>
<td>66.35</td>
<td>66.22</td>
<td>65.10</td>
<td>63.91</td>
</tr>
<tr>
<td>Price After DR (in EUR/MWh)</td>
<td>55.60</td>
<td>53.50</td>
<td>55.09</td>
<td>49.97</td>
<td>47.28</td>
<td>47.38</td>
<td>40.16</td>
<td>50.77</td>
<td>42.67</td>
<td>40.65</td>
<td>41.71</td>
<td>39.10</td>
</tr>
</tbody>
</table>

**TABLE 8. DESCRIPTIVE STATISTICS OF SIMULATED PRICES ACROSS DIFFERENT DR SCENARIOS.**

<table>
<thead>
<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0 %</td>
<td>52.97</td>
<td>58.11</td>
<td>13.58</td>
<td>77.4</td>
<td>-0.13</td>
<td>-1.49</td>
</tr>
<tr>
<td>10 %</td>
<td>52.78</td>
<td>58.36</td>
<td>12.95</td>
<td>76.52</td>
<td>-0.13</td>
<td>-1.46</td>
</tr>
<tr>
<td>25 %</td>
<td>48.61</td>
<td>48.07</td>
<td>9.49</td>
<td>62.62</td>
<td>-0.14</td>
<td>-0.68</td>
</tr>
</tbody>
</table>

Demand Response can also compensate for fluctuations in the power generation of renewable energies [1], [11]. In addition, this paper provides evidence that load shifting reduces average electricity prices and their volatility. Hence, it is desirable to advance smart metering and generally any technology which allows load shifting [27], [46], [47]. Consequently, governments should consider supporting this trend with appropriate policies [48].

Challenges in the nationwide adoption of Demand Response have been clustered into four groups in a recent study for the Federal Energy Regulatory Commission [49]: regulatory, technical, economic and other. These are as follows: (1) regulatory challenges refer to any barriers created through policies. (2) Technical obstacles denote the need for new types of appliances, communication protocols and advances in metering technology. (3) Economic challenges include all cases in which the financial benefits are not clear. (4) Finally, the category “other” comprises the remaining difficulties. Examples include customer perception of DR and their willingness to enroll. Clearly, governments should tackle these challenges in the pursuit of increasing Demand Response adoption [27], [48], [50]. Also, any initiative in support of DR should be carefully designed to provide an effective measure [51].

In future, additional Demand Response potentials can be unlocked as technology improves, for instance, from smart cars [16] and home electricity storage systems [15], [36]. These technologies entail the advantage of providing highly flexible load shifting, which fosters their use in stabilizing the electricity grid. Hence, it should be a key goal of policy makers to bolster the introduction of such technologies from an early point onwards.

### 6. Policy Implications

The manifold benefits of Demand Response make it an intriguing lever for any sustainability strategy. Individual advantages are as follows: Demand Response usage can result in cost and infrastructure savings [16]–[18]. Demand Response serves as an effective instrument to mitigate the intermittency of renewable energy resources, whilst also providing very promising financial savings to electricity retailers and consumers. While previous research...
has predominantly addressed the financial savings on household or retailer level, little is known on the economic consequences on a nationwide dimension. Hence, this paper proposes a decision model in order to simulate implications of Demand Response usage for financial savings and electricity prices. Since price and volume are dependent on each other, we need to implement a corresponding price model in form of a quadratic optimization problem.

Based on our decision model, we infer optimal load shifts for a simulation scenario based on the German and Austrian spot market. When assuming a 25% penetration of the theoretic Demand Response potential, our simulation reveals nationwide savings for a single day of up to EUR 3.12 mn. This result should make the adoption of Demand Response an obvious choice for electricity retailers wherever feasible. In addition, governments and policy makers should evaluate the benefits of Demand Response especially with regards to enabling sustainable electricity generation and cost savings.

While we have chosen a sample day for all evaluations in this paper, future work will focus on making the results more reliable by studying longer time horizons. Furthermore, policy makers would also benefit from detailed assessments of the cost structure for all Demand Response scenarios in order to evaluate the total net benefit of Demand Response.

References


