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Measuring the financial impact of demand response for electricity retailers

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Abstract

Due to the integration of intermittent resources of power generation such as wind and solar, the amount of supplied electricity will exhibit unprecedented fluctuations. Electricity retailers can partially meet the challenge of matching demand and volatile supply by shifting power demand according to the fluctuating supply side. The necessary technology infrastructure such as Advanced Metering Infrastructures for this so-called Demand Response (DR) has advanced. However, little is known about the economic dimension and further effort is strongly needed to realistically quantify the financial impact. To succeed in this goal, we derive an optimization problem that minimizes procurement costs of an electricity retailer in order to control Demand Response usage. The evaluation with historic data shows that cost volatility can be reduced by 7.74 %; peak costs drop by 14.35 %; and expenditures of retailers can be significantly decreased by 3.52 %.

Keywords: Demand Response, Load shifting, Economic potential

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1. Introduction

The integration of intermittent sources of electricity generation, such as wind and solar power, comes at the cost of unprecedented fluctuations in electricity supply. Although their intermittent nature poses a challenge from the grid operation perspective, many states aim at increasing the share of renewable energies extensively. For example, the European Union strives to have renewable sources make up 20 % of the energy consumption by the year 2020. Germany, the largest member state, even passed a law in 2011 mandating 35 % of renewables by 2020 and 80 % by 2050. Since renewable electricity sources are volatile in nature – in contrast to the so-called baseload power sources such as coal or nuclear, which are independent of weather conditions – the integration of 20 % and more of renewables into the electricity markets will lead to considerable discrepancies between power supply and demand.

One possible path to match power supply and demand is given by the concept of Demand Response. Demand Response (DR) is defined by the U.S. Department of Energy and the FERC (2009) as: *"Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized."* Even though Demand Response implies shifting load to when supply exceeds demand, the general idea of managing the demand-side of electricity markets is referred to as Demand Side Management. This umbrella term thus refers not only to Demand Response, but also to similar approaches such as the general increase of energy efficiency and time-based electricity pricing for end-consumers (Sui et al., 2011).

In many studies related to Demand Response (cf. EU-DEEP, 2009; SEDC, 2011; Faruqui et al., 2010a, and EU funded project ADDRESS), it is frequently assumed that Demand Response will be driven by electricity retailers. Consequently, we focus on a setup where Demand Response activities are being integrated on the distribution network level. In this way (cp. Mohagheghi et al., 2010), we implicitly incorporate requirements imposed by the power grid structure (e. g. congestion and node voltage limitations) into the proposed model.

Hence, this paper focuses on a retailer level to derive optimal Demand Response decisions. Based on these decisions, we can estimate and quantify the economic effects of Demand Response.

The remainder of this paper is organized as follows. Section 2 gives a literature overview how consumers react to price changes. In Section 3, publications related to the financial benefits from Demand Response are reviewed. Afterwards, Section 4 identifies parameters that govern decisions in Demand Response programs to pioneer a mathematical problem such that Demand Response decisions of retailers are optimized. Finally, Section 5 evaluates the decisions derived by the model in a simulation based on historic data and analyzes their financial benefits.

2. Pricing Effects

The integration of Demand Response is closely linked with the reaction of consumers to price changes. In this section, we review related work on price elasticities (Section 2.1) as this gives evidence how price changes control demand. Understanding price elasticities is the key to designing suitable pricing strategies (Section 2.2).

2.1. Price Elasticities

Several studies estimate price elasticities in the residential sector (Faruqui and Sergici, 2010; Filippini, 1995; Hirst, 1994; Hunt et al., 2003; Torriti, 2012). For example, Filippini (1995) calculates and compares the short-run as well as long-run own-price elasticities in the Swiss residential electricity market. The author finds long-run values to be higher and his results also show a high responsiveness of electricity consumption to changes in price. Furthermore, positive values of cross-price elasticities indicate that peak and off-peak electricity demand are substitutes. Altogether, these affirmative results suggest that pricing policies can be an effective instrument for achieving electricity conservation. Gyamfi et al. (2013) provide a detailed survey on references estimating the elasticity of demand as a result of time-of-use (TOU) pricing. According to the authors, own-price elasticities range from -0.29 to -0.79 (-0.049 to -0.79 with dynamic pricing), while elasticities of substitution range from 0.04 to 0.21 with significant differences across seasons. Finally, Espey and Espey (2004) perform a meta-analysis to determine factors that affect estimated elasticities systematically.

Masiello et al. (2013) argue that it might not be sufficient in the future for balancing authorities to simply calculate the volume of load shifting. Effectively, it may become important to also estimate the reaction to prices.

2.2. Time-Based Pricing

Price-based programs that control the demand side are alternatives to flat tariffs. Examples include critical peak pricing, extreme day pricing, real-time pricing and time-of-use (TOU) tariffs (Albadi and El-Saadany, 2008). Understanding how consumers react to various pricing strategies is crucial to control electricity demand effectively. Several studies investigate the relationship between time-of-use tariffs and energy consumption (Bernard et al., 2011; Garcia-Cerrutti, 2000; Kamerschen and Porter, 2004; Olmos et al., 2011; Walawalkar et al., 2010). Pilot studies have reported significant demand reductions in the industrial and commercial sectors for some time-based pricing experiments (Barbose et al., 2004).

Furthermore, other publications deal with the effects of time-based pricing. Time-based pricing is an instrument enabling Demand Response that has recently drawn significant attention. For example, Cappers et al. (2010) provide empirical evidence on price-based Demand Response in the U. S. electricity markets. A positive price responsiveness has been reported for some programs that have been implemented recently, while the majority of them remained in pilot phase (Faruqui and Sergici, 2010). Torriti (2012) assesses the impacts of time-of-use tariffs from residential users in Northern Italy. Apparently, a significant level of load shifting occurs during morning peaks, while there is only a marginal effect during evening peaks.

Finally, Gyamfi et al. (2013) present an economic model in the Demand Response context that links price elasticities and pricing strategies with human behavior. The authors recommend incorporating social psychology in order to realize changes in electricity consumption.

3. Financial Benefits from Demand Response

To understand the financial dimension of Demand Response, we look at previous publications that estimate financial savings at household level (Section 3.1) and at an aggregate level (Section 3.2).

3.1. Household Level

To simulate and evaluate the economic effects of Demand Response at household level, related research studies how Demand Response can be controlled by real-time pricing. More precisely, Gottwalt et al. (2011) propose an optimization procedure for load shifting based on real-time pricing. They also analyze the effect at household level, but neglect the financial benefits. Similarly, Lujano-Rojas et al. (2012) present an optimal load management strategy that considers predicted electricity prices, electricity demand and renewable power production. In their fictitious scenario, users can reduce electricity bills by 8 % to 22 % during a typical summer day.

Other authors pursue approaches that optimize the deployment of each household appliance individually. As a result, a household may save up to € 18 per months in winter and up to € 26 per month in summer (Vasirani and Ossowski, 2012, 2013). Gudi et al. (2012) show that their heuristic optimization leads to cost savings of up to 21 %. However, both findings rely upon a fictitious setting without being calibrated by real data.

Prüggler (2013) analyzes the economic potential of Demand Response using different standardized load profiles. Additionally, the author compares break-even investment costs across various lifetimes of infrastructure. According to the study, annual cost savings reach around € 6.5. However, this result relies on the assumption that load shifting accounts for 15 % during 12 hours per day.

While the literature gives insights into Demand Response programs, none of them are based on real data and, to sum up, the conclusions drawn are just estimates.

3.2. Aggregate Level

Various references (e. g. Ridder et al., 2009) suggest that, due to the usage of Demand Response, profits of electricity retailers will increase. Demand Response activities do not actually decrease the amount of electricity consumed, but merely shift it to when it is more convenient from the grid operation perspective (Shaw et al., 2009; Strbac, 2008; Denholm and Margolis, 2007). Recent references such as (Dena, 2010; Faruqui et al., 2010b; van Horn, 2012; Austria, 2010; NERA Economic Consulting, 2008) provide an overview of the economic costs and benefits of Demand Response through Advanced Metering Infrastructures.

Demand Response can reduce both peak load as well as the marginal costs at peak time. In general, Demand Response programs reduce electricity costs significantly, but raise electricity prices slightly (Hirst, 1992). Simultaneously, Demand Response can reduce electrical distribution losses (Shaw et al., 2009). According to Bergaentzlé and Clastres (2013), Germany can achieve a 4.57 % reduction in peak demand by managing active demand. However, the authors define a static peak time at 19 p. m. (where marginal costs are roughly 41 €/MWh), while we follow a dynamic approach. Aalami et al. (2010) carry out a study to simulate and compare the effects of Demand Response programs. However, the authors lack real-world data on the available load shifting potential and, consequently, the results are susceptible to missing external validity. Dave et al. (2013) perform an agent-based simulation. As a result, the authors find that (when assuming that 30 % of the U. K. population participates) it is possible to guarantee a 20 % peak load reduction. Furthermore, an average household in the U. K. contributes savings of £1800 over a 20 year period by avoiding peak generation costs. Hirst (1994) quantifies the incremental benefits and costs of Demand Response programs in the context of external uncertainties (namely, economic growth, fuel prices, costs of building power plants and costs to operate Demand Response programs). Here, Demand Response reduces the net present value of revenue requirements by $490 million plus an additional $30 million (i. e. additional 6 %) from the reduced uncertainties.

Demand Response potential can also be used for operating reserves. Paulus and Borggrefe (2011) perform a cost-benefit-study for electricity-intensive industries in Germany that sell their load shifting potential at an exchange for spinning reserve, but the authors do not consider additional financial savings from more beneficial electricity purchases.

In summary, little is known about the economic potential of Demand Response in liberalized markets (Aghaei and Alizadeh, 2013). All listed publications lack both (1) a simulation of the shifted loads and its financial savings and (2) coherent real-world data on the available load shifting potential. Consequently, quantifying the economic benefits still seems to be an open research question.

4. Mathematical Model

This section identifies parameters that impact decisions in Demand Response programs. We derive – based on earlier work (Feuerriegel et al., 2012, 2013) – a mathematical problem to optimize revenues for electricity retailers.

4.1. Parameters

How the retailer controls and operates Demand Response is affected by several parameters. These parameters are presented in Figure 1 where we group them into supply and demand side factors. Factors governing the supply side are as follows:

- The *Demand Response potential* varies across both industries and time of day. Furthermore, each individual DR-capable device (e. g. washing machine, A/C) or industry is subject to the extent its electricity consumption can be moved in time and, thus, the Demand Response potential is specified by a set of time-dependent variables.

- The monetary expenditures are largely influenced by *electricity prices*. In today's electricity markets, retailers can participate in trading future options and in hourly spot auctions (Stoft, 2001). The former, so-called future options, can be traded to guarantee – ahead of time – electricity delivery for long-term periods. Frequent examples comprise futures options that (contractually) fix delivery durations ranging from years to single days. In order to reduce the complexity of our model, we aggregate all future options into a single derivative. Let p_F denote the future option's price per watt-hour. In addition to future derivatives, a spot market provides electricity at price $p_A(t)$ per watt-hour for a specific time t

of the day. Most notably, these derivatives are sold at day-ahead auctions. As a third option, an intraday market can satisfy short-term needs of electricity, but can be neglected due to insufficient market liquidity (EPEX, 2012; Weber, 2010).

According to Figure 1, the demand side is affected by the following parameters:

- The amount of electricity that a retailer has to purchase is determined by the *electricity load*. It consists of the overall electricity demand minus the electricity that is produced by the retailer.
- When an adequate financial incentive is offered, some industries can reduce their electricity demand for short periods. This is named *peak clipping*. In practice, peak clipping is controlled by an activation decision.

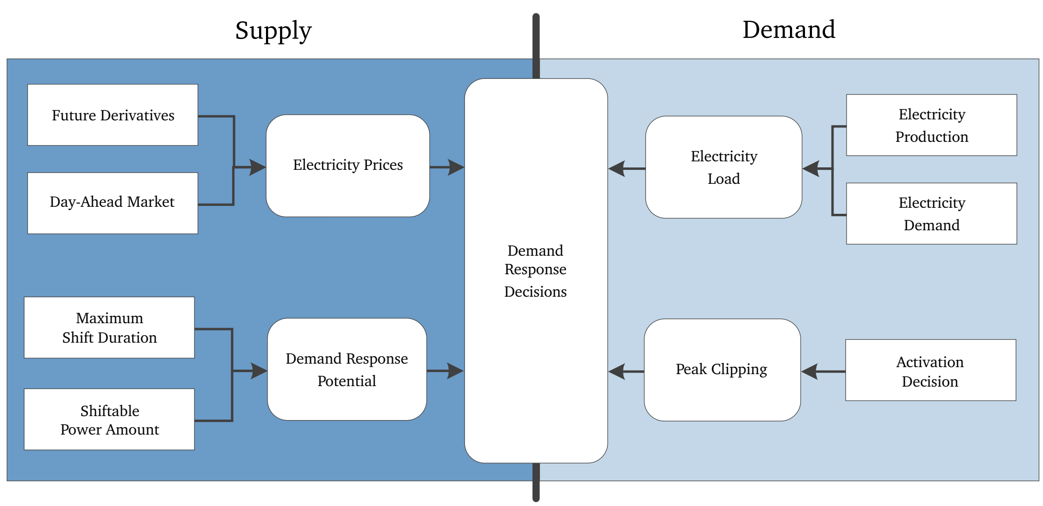

Figure 1: Parameters affecting Demand Response decisions to optimize load shifting.

4.2. Benchmark Model without Demand Response

With a few simplifying assumptions, the problem of optimally-harnessing Demand Response can be formulated as a linear optimization problem (Feuerriegel et al., 2012, 2013). However, we embark on the simpler problem where only the retailer's expenditure is minimized and continue to support Demand Response in the optimization problem at a later point. The resulting optimization problem is solved once for every day to derive optimal decisions for each of the $N = 24$ time slots per day.

Accumulating the retailer's spending across electricity derivatives, this yields the aggregated expenditures which constitute the target function. Accordingly, the retailer aims to reduce the estimated total expenditures as our target function c_Σ (during an optimization horizon of N time steps) denoted by

$$\min_{q_F, q_A(1), \ldots, q_A(N)} c_\Sigma = \min_{q_F, q_A(1), \ldots, q_A(N)} N p_F q_F + \sum_{t=1}^{N} p_A(t) q_A(t). \tag{1}$$

The first summand $N p_F q_F$ denotes the expenditures on future derivatives, while the second sums costs from on day-ahead auctions. The (time-dependent) parameters $q_A(t)$ and q_F indicate the demanded quantities in the day-ahead market and the future options respectively.

As a simplification, the electricity retailer is assumed to be only a purchaser of electricity at the energy exchange, but not a vendor selling to other market participants. As most German retailers do not produce electricity (Umweltbundesamt, 2013), this assumption is valid. Thus, the linear problem is bounded and a unique solution is assured to exist. Thus, we yield the following inequality constraints for our optimization problem,

$$q_A(t) \geq 0 \quad \text{and} \quad q_F \geq 0 \qquad \text{for } t = 1, \ldots, N. \tag{2}$$

Let $\mathrm{D}(t)$ denote for a given time t the amount of demanded electricity. As a further constraint, the purchased electricity must match the retailer's power demand at time t. This is stated by the following equality constraints,

$$q_A(t) + q_F = \mathrm{D}(t) \qquad \text{for } t = 1, \ldots, N, \tag{3}$$

where the left-hand side (accounts for the total energy purchased) is supposed to equal the right-hand side which accounting for the electricity demand.

Combining the target function and the above restrictions, we yield the complete optimization problem for a retailer given by

$$\min_{q_F, q_A(1), \ldots, q_A(N)} N p_F q_F + \sum_{t=1}^{N} p_A(t) q_A(t), \tag{4}$$

$$\text{subject to } q_A(t) + q_F = \mathrm{D}(t), \tag{5}$$

$$q_A(t) \geq 0 \quad \text{and} \quad q_F \geq 0 \quad \text{for } t = 1, \ldots, N. \tag{6}$$

$$\tag{7}$$

4.3. Demand Response Model with Load Optimization

In Figure 2, we classify Demand Response according to two types: When the total electricity demand remains inconstant and a financial incentive reduces peak load, this is named *peak clipping*. Contrarily, *load shifting* features a fixed total demand, but where demand can be shifted forward or backward in time to off-peak hours. In this section, the above optimization problem is extended to support decision-making for both types of Demand Response mechanisms.

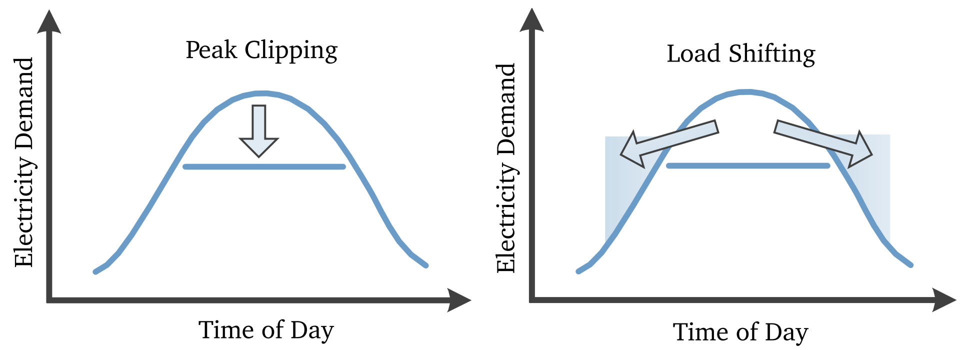

Figure 2: Comparing peak clipping versus load shifting.

4.3.1. Extension: Integrating Peak Clipping

By offering an adequate financial incentive, energy-intensive companies (e. g. in the chemical or metal-working industry) are encouraged to perform peak load reduction. This leads to a reduction of electricity demand of industrial processes for a short period of time. Depending on the actual industrial processes (Klobasa, 2007), the frequency of activating peak clipping can vary significantly[1], between daily activation or only up to a few days per year. This limited availability exerts pressure on the Demand Response model to use the offered number of activations wisely. Thus, we identify suitable occasions for peak load reduction with the following approach in order to maximize profits.

Our approach can be briefly sketched as follows. We control the usage of peak clipping by introducing a threshold. Then, peak clipping is activated only when the expected earnings exceed this threshold. Later, we determine *ex post* an appropriate value for this threshold from historic data.

[1]The actual frequency is limited by several factors, for example, quality reasons, maintenance, produced goods, underlying chemical process.

Let us define the threshold by θ and the expected hourly profit by θ_c. For the moment, we assume w. l. o. g. that the threshold θ is fixed and given. The model recognizes appropriate time slots for activation, which is the expected profit θ_c originating from peak clipping exceeds the threshold θ. Mathematically speaking, this occurs when the inequality $\theta_c > \theta$ holds. Let M denote the maximum duration of peak load reduction. Then, we derive the expected hourly profit θ_c via

$$\theta_c = \max_{t \in \{1,\ldots,N-M\}} \frac{1}{M} \sum_{\tau=t}^{t+M-1} p_A(\tau), \tag{8}$$

where we choose the arrangement out of all constellations of peak load reduction that maximizes the financial spendings on electricity. Having estimated the hourly profit θ_c, we need to derive the time step θ_t within the day when peak clipping is activated. The according optimization problem resolves to[2]

$$\theta_t = \operatorname*{arg\,max}_{t \in \{1,\ldots,N-M\}} \frac{1}{M} \sum_{\tau=t}^{t+M-1} p_A(\tau). \tag{9}$$

Altogether, the electricity demand $\mathrm{D}'(t)$ after peak clipping is given by

$$\mathrm{D}'(t) = \begin{cases} \mathrm{D}(t) - \partial, & t \in \{\theta_t, \ldots, \theta_t + M - 1\} \text{ and } \theta_c > \theta, \\ \mathrm{D}(t), & \text{otherwise,} \end{cases} \tag{10}$$

where, depending on the activation of peak clipping, the previous demand $\mathrm{D}(t)$ is reduced by a certain load ∂. This load reductions is performed every day when potential for load reduction is available. To sum up, peak clipping is activated in a first come, first served principle, i. e. it is possible that the

[2] Here, arg max stands for the argument of the maximum, i. e. $f(x_{\max}) = \max f(x) \Leftrightarrow x_{\max} = \arg\max f(x)$.

peak clipping potential is depleted during the simulation. Finally, we point out that knowledge from experts might further improve profits. Irregular events of extreme weathers and possible errors in the forecasting methodology can only be treated by human expertise.

Having assumed that the threshold to be given, we are now in the position to deduce a threshold for activating peak clipping. Based on our dataset (see Section 5.1 and Table 2), we are informed that all relevant industrial processes can perform peak clipping up to 40 times a year. Thus, we need to calculate the 40 highest savings from peak clipping in each year (i. e. the 40 highest values of θ_c) and use the lowest ex post value as our threshold. Figure 3 shows the highest hourly savings from peak clipping per day sorted in descending order. We see that hourly savings range from 14.51 €/MWh to as high as 166.95 €/MWh. An additional vertical line shows the cut off value for the 40 highest values. This vertical line represents the optimal threshold in each year. Thus, peak clipping should be activated whenever expected savings exceed this threshold. The corresponding savings at the vertical cut off line are 76.27 €/MWh in 2009, 70.87 €/MWh in 2010, 72.86 €/MWh in 2011 and 67.78 €/MWh in 2012. Evidently, the optimal thresholds in the years 2009 till 2012 show almost no variance. We set the final threshold for activating peak clipping to the average of the optimal thresholds from the previous two years. Then, we get $\theta = 73.57$ €/MWh in 2011 and $\theta = 71.87$ €/MWh in 2012.

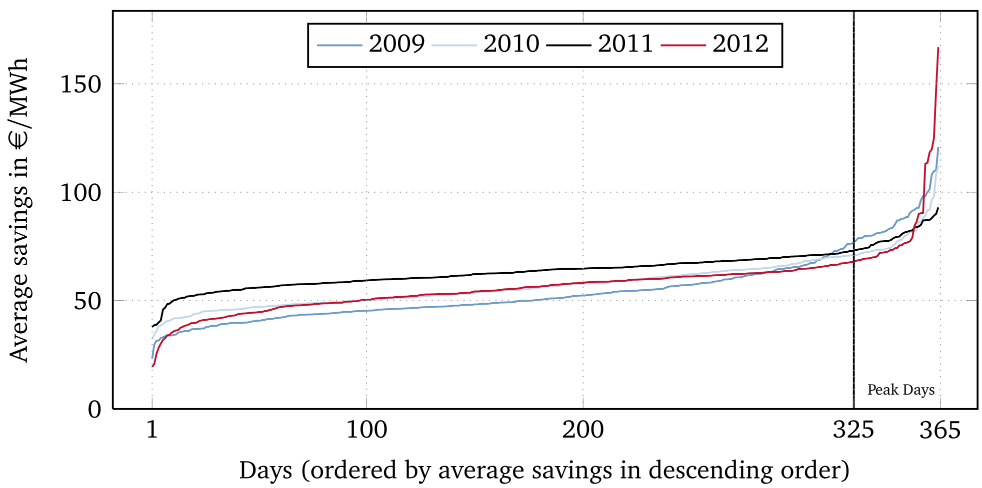

Figure 3: The hourly savings θ_c from peak clipping in each year sorted in descending order. As peak clipping can be activated up to 40 times a year, the cut off values to identify 40 highest savings are given by the vertical line.

4.3.2. Extension: Integrating Load Shifting

Let us assume that we are granted a certain Demand Response potential for each time interval (Feuerriegel et al., 2012, 2013). This potential can now be shifted forward or backward in time. However, each type of load can only be moved up to a certain maximum duration j (e. g. 1 h, 2 h, etc.). For each of these shifts j, the variables $\Delta_j(t)$ denote the available potential. Let $\text{DR}_j(t, t' - t)$ specify the shifted load between hours t and t' where j indicates the maximum possible length of the shift. The value of $\text{DR}_j(t, t' - t)$ denotes the amount of power that is less consumed at time step t, but that is additionally required at time step t'. For instance, $\text{DR}_2(t, -1)$ accounts for load shifting potential (with maximum shift of two hours) that is moved from time step t by one hour to the previous interval $t - 1$.

Figure 4 shows schematically how Demand Response changes the load by shifting it to off-peak hours. The total demand at time t is increased by the sum of $\mathrm{DR}_1(t+1,-1)$, $\mathrm{DR}_1(t-1,+1)$, $\mathrm{DR}_2(t+2,-2)$, $\mathrm{DR}_2(t+1,-1)$, $\mathrm{DR}_2(t-1,+1)$, $\mathrm{DR}_1(t-2,+2)$, etc. However, the demand at time t is simultaneously decreased by $\mathrm{DR}_1(t,0)$, $\mathrm{DR}_2(t,0)$, etc. In order to guarantee that demand matches the purchased electricity, we derive the following constraint,

$$
\begin{aligned}
q_A(t) + q_F = \mathrm{D}(t) - \mathrm{DR}_1(t,0) - \mathrm{DR}_2(t,0) + \ldots \quad && (11)\\
+ \mathrm{DR}_1(t+1,-1) + \mathrm{DR}_1(t-1,+1) \quad && (12)\\
+ \mathrm{DR}_2(t+2,-2) + \mathrm{DR}_2(t+1,-1) \quad && (13)\\
+ \mathrm{DR}_2(t-1,+1) + \mathrm{DR}_2(t-2,+2) \quad && (14)\\
+ \ldots \qquad \text{for } t = 1,\ldots,N. \quad && (15)
\end{aligned}
$$

This constraint is only fulfilled when the purchased quantities on the left-hand side equal the right-hand side which itself consists of the demand and possible alterations due to Demand Response. Whenever $t < 1$ or $t > N$, we define $\mathrm{DR}_j(t,i) \stackrel{\text{def}}{=} 0$.

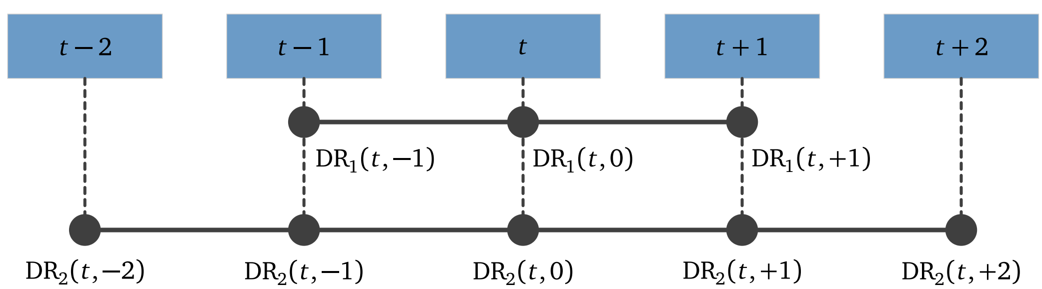

Figure 4: Potential of Demand Response at time t.

Next, we derive additional constraints for the potential of Demand Response. Recall that the variables $\Delta_1(t)$, $\Delta_2(t)$, $\Delta_3(t)$, etc. limit the maximum amount of energy that can be displaced. Thus, we deduce

$$\mathrm{DR}_1(t,0) \leq \Delta_1(t), \mathrm{DR}_2(t,0) \leq \Delta_2(t), \ldots \tag{16}$$

Additionally, we need constraints that limit the flow direction (i.e. that demand is moved solely away from time interval t). When we shift electricity demand from time interval t by j hours in either direction, this value must not be negative,

$$\mathrm{DR}_j(t+i,-i), \mathrm{DR}_j(t-i,+i) \geq 0 \quad \text{for all } j \quad \text{and} \quad i = 1, \ldots, j. \tag{17}$$

Furthermore, we need to guarantee the energy conservation of used load shifting potential, i.e. all reductions in demand finally added at some other interval, thus

$$\sum_{i=-j}^{+j} \mathrm{DR}_j(t+i,-i) = 0 \quad \text{for all } j. \tag{18}$$

Both, the number of equality constraints and the number of lower bounds grow linearly. For example, with $N = 24$ and Demand Response potentials $j \in \{1,2,3,4,12,16,24\}$, we get 2125 unknown parameters, a total of 192 linear equality constraints, whilst the number of lower bounds accounts for a total of 2125.

5. Evaluation

In this section, we test our mathematical model in a simulation using historic data. Before presenting the results, we provide an overview on the applied parameters and datasets. Ultimately, we evaluate the financial benefits of Demand Response.

5.1. Datasets

In the following scenario, we assume a German retailer delivering electricity to both residents and industries. The retailer's overall annual energy demand accounts for 2000 GWh, out of which 1500 GWh are delivered to industries while 500 GWh are delivered to a total of 300 000 residents (E-Control, 2012; E.ON, 2011; Werlen, 2007). Here, the electricity demand is given by load profiles of a real electricity retailer (NGS, 2013).

All prices for electricity derivatives and spot auctions are based on the hourly data from the years 2011 and 2012 of the European Power Exchange, EPEX for short (EPEX, 2012). The price for future options q_F originates from the Phelix Day Base index.

5.2. Demand Response Potential

The capabilities of Demand Response vary strongly among both industry and households. Later, our scenario studies the economic effects of Demand Response in Germany and, accordingly, we need data that quantifies the Demand Response potential. Various publications such as (Dena, 2010; Klobasa, 2007; Paulus and Borggrefe, 2011; Styczynski, 2011; Werlen, 2007) aim at quantifying the magnitude of load shifting potential in Germany. A comparison of these references is given in Table 1. Even though Table 1 reveals differences across sectors, the magnitude of the overall Demand Response potential seems rather similar and robust. Among these references, Klobasa (2007) provides estimates with the highest granularity as the author also gives the duration that each appliance can be moved in time. Thus, we will use the Demand Response potential quantified by Klobasa (2007) in our analysis.

Source	Industries	Service Sector	Households	Nationwide
Dena (2010)	pos: 2143 MW neg: 485 MW	pos: 2420 MW neg: 14.28 GW	pos: 6732 MW neg: 35.28 MW	*pos: 6732 MW* *neg: 35.28 MW*
Paulus and Borggrefe (2011)	2610 MW			
Styczynski (2011)		4800 MW	24.5 GW	29.9 GW
Werlen (2007)			2 GW to 16 GW	
Klobasa (2007)	*2800 MW*	*938 MW*	*20.59 GW*	

Table 1: Demand Response potential at peak in Germany (in italics: own calculations that aggregate values).

Klobasa (2007) derives the nationwide Demand Response potential for both German industries and residents. We must scale these values to comply with our scenario, i. e. to fit a retailer supplying electricity to both industries (1500 GWh) and 300 000 residents (500 GWh). Thus, we multiply Demand Response potentials from (Klobasa, 2007) by the ratio of 300 000 residents and the German population of 83 million. Accordingly, the maximum possible shift of the retailer can reach up to 41.8 MW. Table 2 shows the retailer's potential of Demand Response through peak clipping. Table 3 contains aggregated results specifying the maximum displacement in time and the average possible amount available for load shifting. While average power demand of the retailer accounts for 228.31 MW, the average power shift accounts for 32.14 MW. More precisely, the proportion of shiftable power totals approximately 14.08 %.

Sector	Initiations in Days/Year	Max. Duration/h	Average Power Reduction/kW
Chemistry & Metal Processing	40	4	5892
Nonmetallic Mineral Processing	365	3	651
Others	365	2	3578

Table 2: Retailer's potential of Demand Response through peak clipping (own scaling; based on (Klobasa, 2007)).

Application	Max. Shift Duration/h	Average Power Shift/kW
Cooling	1	1012
	2	3199
Air Conditioning	1	1577
Ventilation	1	3253
Heating	12	1681
	16	1854
Laundry*	24	517
Drying*	24	374
Washer*	24	416
Thermal Energy Storage*	1	2658
	2	2440
	12	12 675

Table 3: Retailer's Potential of Demand Response through Load Shifting (own scaling; based on (Klobasa, 2007)). Marked items (*) are time-dependent and scaled according to Figure 5.

The Demand Response potential in households varies strongly throughout the day, and, hence, the household values in Table 3 must be weighted accordingly. Figure 5 depicts the used normalization coefficients derived by Groiß (2008); Groiß and Brauner (2009). One can clearly notice a higher Demand Response potential in the afternoon compared to a significantly lower potential at night time.

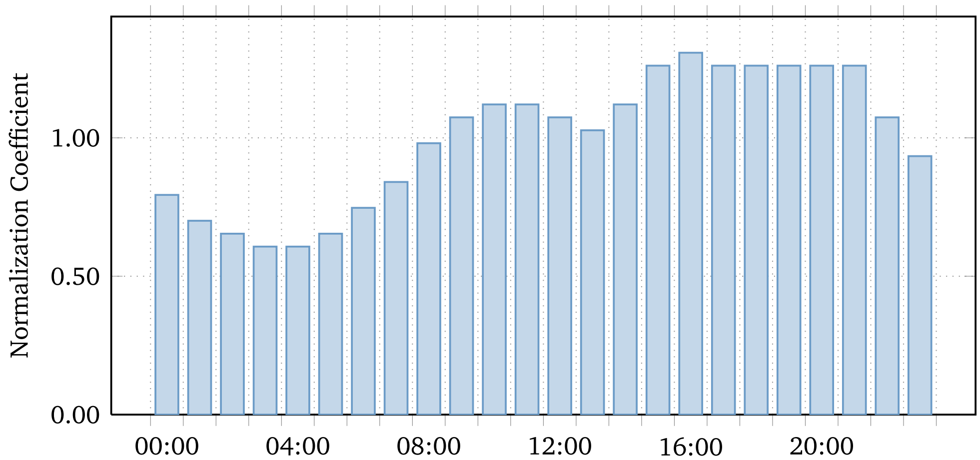

Figure 5: Normalization coefficients used to express time-dependency of Demand Response potential (Groiß, 2008; Groiß and Brauner, 2009).

5.3. Results

In this section, we evaluate our scenario using the above datasets for the years 2011 as well as 2012. The computational analysis requires solving more than 1450 single optimization problems. In order to demonstrate and quantify the efficiency of our rather simple Demand Response model, we will use the notation $c_H(t)$, defined by $c_H(t) = p_F q_F + p_A(t) q_A(t)$, to denote the retailer's hourly expenditures. We can state three striking results (see Table 4 for details).

- **Finding 1.** In general, electricity demand is almost inelastic; though, Demand Response shows that the retailer's expenditures for electricity can be reduced. This decrease in expenditures will be attained by both shifting the load from peak to off-peak periods and activating peak clipping. In our scenario, the retailer's expenditures plummet by 3.18 % in 2011 and 3.93 % in 2012 respectively. The fact of decreasing expenditures is not novel in itself; however, our study allows the financial benefits to be quantified.

- **Finding 2.** Active Demand Response shows a possible path to flatten peaks in expenditures. Peak load reduction as an inherent feature of Demand Response is well known (cf. Aghaei and Alizadeh, 2013), but by facilitating the Demand Response model, we are able to estimate the magnitude of peak clipping. In fact, peak clipping reduces the maximum hourly expenditures given by $\max c_H(t)$ in the year 2011 by 14.63 %, while the cut in 2012 accounts for 14.17 %.

- **Finding 3.** Utilizing our Demand Response reduces fluctuations in expenditures significantly. We measure the magnitude of these fluctuations by $\text{Var}(c_H(t))$, which represents the variance of hourly expenditures. In the year 2011, this variance indicates the uncertainty of expenditures is reduced by 10.12 %. The variance in 2012 is cut by 5.88 %.

		Year 2011	**Year 2012**	**Annual Average**
Financial return	Using DR	€ 103.4×10^6	€ 87.3×10^6	€ 95.3×10^6
	Without DR	€ 106.8×10^6	€ 90.9×10^6	€ 98.8×10^6
	Absolute benefit	€ 3.39×10^6	€ 3.57×10^6	€ 3.48×10^6
	Relative change	−3.18 %	−3.93 %	−3.52 %
Hourly peak costs	Using DR	€ 31.4×10^3	€ 48.6×10^3	€ 40.0×10^3
	Without DR	€ 36.8×10^3	€ 56.6×10^3	€ 46.7×10^3
	Absolute benefit	€ 5.38×10^3	€ 8.03×10^3	€ 6.70×10^3
	Relative change	−14.63 %	−14.17 %	−14.35 %
Variance of hourly costs	Using DR	20.1×10^6	27.0×10^6	23.6×10^6
	Without DR	22.4×10^6	28.7×10^6	25.5×10^6
	Absolute benefit	2.26×10^6	1.69×10^6	1.98×10^6
	Relative change	−10.12 %	−5.88 %	−7.74 %

Table 4: Benefits from the Demand Response (DR).

Although the model is limited to measuring the financial costs of electricity retailers, the above results reveal several interesting implications:

- Employing the Demand Response model for decision-making, Figure 6 visualizes the average achieved financial benefits arising from load shifting. The length of the possible time shift strongly affects the monetary return. With longer forward and backward shifts (e. g. 16 and 24 hours), the optimization problem benefits from higher differences in electricity price and can relocate demand to hours with the highest financial gain. By employing load shifting, the retailer gains an average return of 12.3 €/MWh as a financial advantage. Although activations of peak clipping are rare, Figure 7 shows that peak clipping yields higher financial returns – financial benefits above 60 €/MWh. Electricity retailers are advised to facilitate peak clipping before load shifting to maximize their financial advantage.

- Even though peak clipping features a higher marginal utility, load shifting is responsible for the majority of savings. The ratio of benefits due to load shifting out of all savings from Demand Response account for 91.8 % in 2011 and 92.8 % in 2012. In other words, most savings originate from load shifting.

- Although the electricity retailer gains an immense financial advantage by implementing Demand Response, the average savings per person are relatively small (e. g. Gottwalt et al., 2011; Vasirani and Ossowski, 2012, 2013) and account for only € 11.6 per annum. However, as electricity prices are likely to rise in the future, revenues due to Demand Response will also increase.

- In order to investigate which time frames are affected by load shifting, we calculated the load shifts between different time slots across each day. The changes in electricity consumption outline the following pattern as shown in Figure 8. The more the load is exchanged between time slots, the darker is the corresponding rectangle. Similar to the findings by Gottwalt et al. (2011), a large proportion of the savings arise at night time. In fact, most load is shifted to the time interval from 1 a. m. to 6 a. m.. The reason is that electricity is significantly cheaper at night. A second time interval that gains load reaches from 2 p. m. to 6 p. m.. In addition to that, the load that can only be shifted by 1 h is visualized by the gray diagonal pattern.

- There is a subtle difference in returns between summer and winter. While the average return due to load shifting accounts for 10.3 €/MWh from April to September 2011 (i. e. summer), this return rises to 12.2 €/MWh in the winter period of 2011. In contrast to that, the difference in earnings between weekdays and weekends is negligible.

- Europe faced an extreme winter from February 1, 2012 to February 14, 2012 with temperatures as cold −45 °C and resulting peaks in electricity prices. During that period, the average return from peak clipping almost doubles from an average 64.4 €/MWh to 110.1 €/MWh. Similarly, the return from load shifting jumped from an average 11.9 €/MWh to 19.8 €/MWh. This immense increase shows how the implementation of Demand Response can account for significant financial benefits.

- Out of 80 days available for peak clipping, more than half (43 days) were used in the month November, followed by February (12 days) and May (6 days). The overall picture indicates that peak clipping has the highest potential in spring and fall.

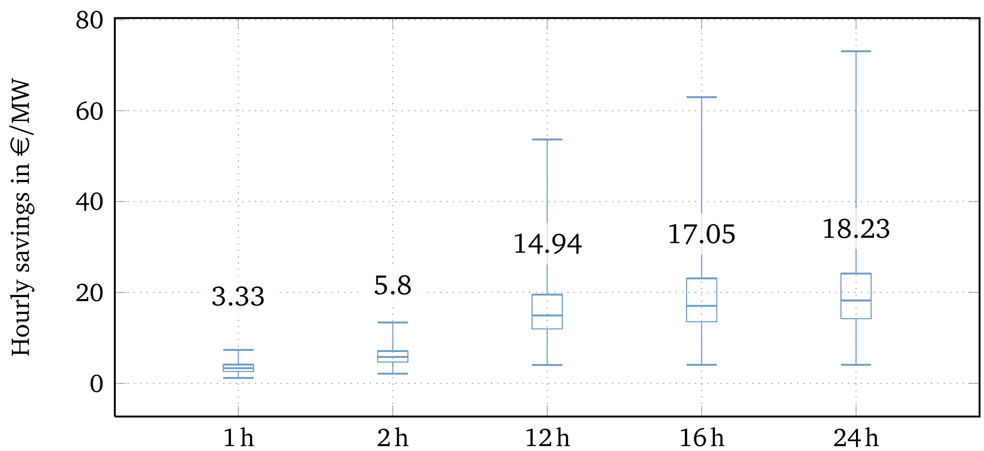

Figure 6: Box plot of financial benefits from load shifting in 2011 across varying maximum shift durations (values denote the median).

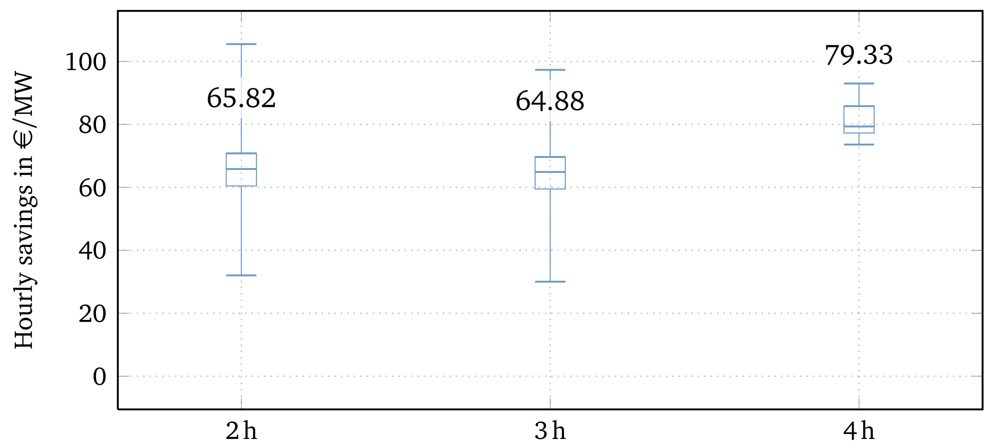

Figure 7: Box plot financial benefit from peak clipping in 2011 across varying maximum time shifts (values denote median).

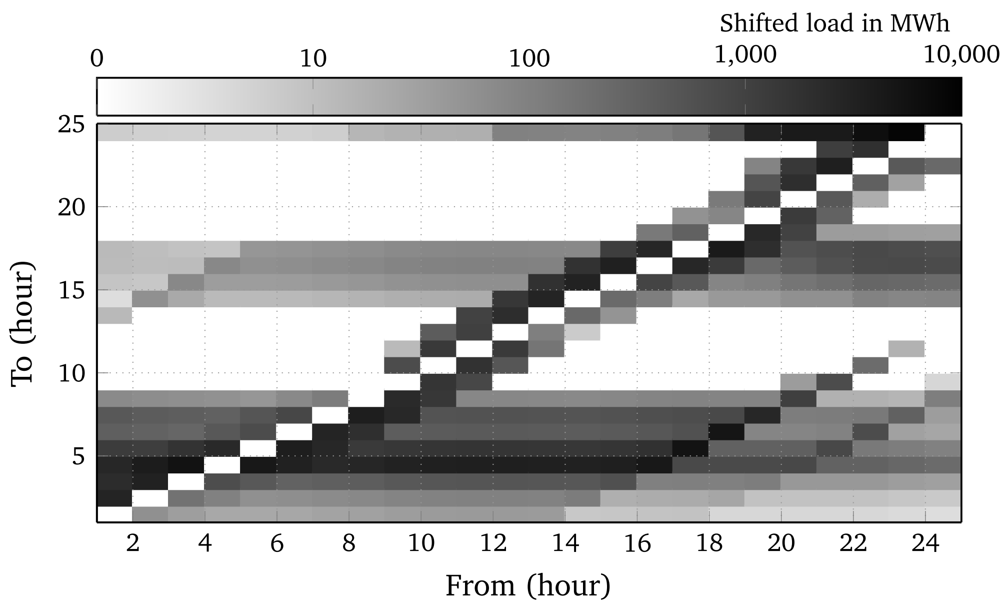

Figure 8: Load (in MWh) shifted throughout 2011 due to Demand Response activities (simulation results from the above model).

5.4. Sensitivity Analysis

This section analyzes how results change when parameters of the models are varied (see Table 5).

Benchmark. Changing the overall electricity demand of the retailer affects the absolute financial benefits, but this has no effect on the results from Table 4 given as relative benefits. In fact, when changing the overall demand, costs continue to drop by 3.52 %. Likewise, the reductions in volatility (7.74 %) and peak costs (14.35 %) remain constant.

Standardized Load Profiles. Switching from real to standardized load profiles affects outcomes only slightly. When using standardized[3] load profiles instead, the evaluation based on historic data from 2011–2012 yields that cost volatility can be reduced by 12.22 %; peak costs drop by 12.14 %; and expenditures of retailers can be significantly decreased by 3.42 %. Altogether, values remain at a similar magnitude.

Selling Electricity Produced by the Retailer. In addition, we examine a model where the retailer produces and sells electricity. Let $P(t)$ denote the retailer's electricity production. We assume a constant electricity production of $P(t) = 3000\,\text{kW}$. Then, the new model affects the constraints in

[3] We aggregate the demand curves for households and industries in Germany from the years 2011 and 2012 (E.ON, 2012) with ratio 25 % to 75 % (Styczynski, 2011) to derive the hourly electricity demand. To achieve an annual demand accounting for 2000 GWh in total, the demanded electricity is normalized accordingly.

Equations (2) and (3) which are replaced by

$$q_A(t) \geq -P(t) \quad \text{and} \quad q_F \geq \max_{\tau\in\{1,\ldots,N\}} -P(\tau) \qquad \text{for } t = 1,\ldots,N, \tag{19}$$

$$q_A(t) + q_F = \mathrm{D}(t) - P(t) \qquad \text{for } t = 1,\ldots,N. \tag{20}$$

In Equation (19), we change the upper bound such that the retailer can sell electricity; whereas Equation (20) enforces that demand equals procured electricity minus a new term denoting the production. The average results from 2011–2012 show that expenditures drop by 3.57 %, cost volatility by 7.73 % and peak costs by 14.41 %. Overall, the financial effect of Demand Response seems to be robust even when the retailer acts as a producer of electricity.

Time-Invariant Potential. The above simulation relies on normalization coefficients used to express the time-dependency of Demand Response coefficients (i. e. there is a larger Demand Response potential available during afternoons than during nights). We investigate the sensitivity of time-varying factors by studying a model without time-dependency. Thus, we set all normalization coefficients to 1. As a result, cost volatility is cut by 7.74 %; peak costs drop by 14.35 %; and expenditures decrease by 3.52 %. Once again, only marginal changes can be observed.

Overall, the sensitivity analysis (see Table 5) reveals that varying model parameters hardly changes the outcome.

Scenario	Expenditures Without DR	Using DR	Change	Cost Volatility	Peak Costs
Benchmark	€ 98.8×10^6	€ 95.3×10^6	−3.52 %	−7.74 %	−14.35 %
Standardized Load Profiles	€ 101.9×10^6	€ 98.5×10^6	−3.42 %	−12.22 %	−12.14 %
Selling (Produced) Electricity	€ 97.6×10^6	€ 94.1×10^6	−3.57 %	−7.73 %	−14.41 %
Time-Invariant Potential	€ 98.8×10^6	€ 95.3×10^6	−3.52 %	−7.74 %	−14.35 %

Table 5: Sensitivity analysis comparing proportional reductions in total expenditures, cost volatility and peak costs from Demand Response (DR) usage in years 2011–2012 across different scenarios.

5.5. Policy Implications

In the future, financial benefits from Demand Response activities are likely to increase due to two reasons. First, rising electricity prices and increasing price volatility (Bierbrauer et al., 2007; Valenzuela et al., 2012) will encourage electricity retailers to implement and extend their Demand Response activities. The underlying reason is, as the literature on renewables suggests, that an increase in intermittent wind and solar generation comes at the cost of an increase in the spot-price variance (Chao, 2011; Green and Vasilakos, 2010; Jacobsen and Zvingilaite, 2010; Milstein and Tishler, 2011; Woo et al., 2011). Second, the penetration of Demand Response programs will also increase due to regulatory settings. As governments consider policy adjustments, the propagation of DR-capable devices and the DR-related profits can be augmented. Torriti et al. (2010) expect that large numbers of end-users (i. e. commercial customers and households) could be involved in future Demand Response programs. Several countries such as the member states of the European Union have already agreed to trigger the introduction of Demand Response programs. In fact, policy issues are broadly discussed by governments throughout the world (Cappers et al., 2010; Walawalkar et al., 2010; Ming et al., 2013). Greening (2010), for example, suggests that state regulators will need to regulate through the development of incentive mechanisms. Possible incentives consist of fiscal, tax and price policies according to Ming et al. (2013). However, governments must be careful when designing market structures and incentives for Demand Response in order to come up with effective market instruments (Grünewald and Torriti, 2013). Torriti et al. (2010) notice that governments put an emphasis on Demand Response activities in an industrial environment which agrees with our results that peak clipping, i. e. industrial Demand Response, yields the highest revenues. Overall, policy adjustments will give future activities in Demand Response a major boost and this paper helps to gauge the size of possible incentives.

6. Conclusion

Due to the integration of intermittent resources of power generation, the amount of supplied electricity will show unprecedented fluctuations. Electricity retailers can address this challenge by using Demand Response for shifting power demand according to the fluctuating supply side. As a contribution, this paper gives realistic insights into the financial impacts by Demand Response usage. More specifically, a full exploitation of Demand Response potential decreases cost volatility in our scenario by 7.74 %, whereas the overall expenditures can be reduced by 3.52 %. Consequently, electricity retailers that utilize Demand Response can gain considerable financial benefits.

However, we did not distinguish between different forms of shifting demand such as dynamic and real-time pricing or direct load control. Accordingly, we did not consider differences in cost and effectiveness of these instruments. Future research should take into account these costs and also the different price elasticities of residential, commercial and industrial customers. In the future, a detailed survey is necessary that compares both the financial benefits and related costs of Demand Response across different usages such as tendering control reserve and applications on a household level. In addition to that, financial impacts for a whole nation are also unknown. As changes in demand result in changes in price, further effort is required to calculate the cost-benefit ratio of Demand Response for an economy as a whole.

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