Integration scenarios of Demand Response into electricity markets: Load shifting, financial savings and policy implications

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Abstract

Demand Response allows for the management of demand side resources in real-time; i. e. shifting electricity demand according to fluctuating supply. When integrated into electricity markets, Demand Response can be used for load shifting and as a replacement for both control reserve and balancing energy. These three usage scenarios are compared based on historic German data from 2011 to determine that load shifting provides the highest benefit: its annual financial savings accumulate to €3.110 M for both households and the service sector. This equals to relative savings of 2.83 % compared to a scenario without load shifting. To improve Demand Response integration, the proposed model suggests policy implications: reducing bid sizes, delivery periods and the time-lag between market transactions and delivery dates in electricity markets.

Keywords: Demand Response, Load shifting, Economic potential, Policy

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implications, Optimization

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1. Introduction

In large parts of the world, renewable energies are the chosen resources to replace fossil fuels in the context of energy production. However, the associated integration of renewables has triggered fundamental changes in the organization of the energy sector. One of the these changes is the establishment of Demand Response facilities, which shift load away from the peaks to smoothen overall energy consumption.

Demand Response (DR) allows for the management of the demand side of electricity markets by shifting power demand according to the fluctuating supply side. It is defined by the U.S. Department of Energy (2006) and the Federal Energy Regulatory Commission (FERC) (2006) 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."* Active management of the demand side can help to compensate for an increase in the electricity price (Aghaei and Alizadeh, 2013; Bergaentzlé et al., 2014; Dyson et al., 2014; Klobasa, 2010) and volatility (Bierbrauer et al., 2007; Valenzuela et al., 2012). Consequently, integrating Demand Response into electricity markets can occur in several ways (e. g. Aghaei and Alizadeh, 2013; Madrigal and Porter, 2012).

Policy makers need to formulate a corresponding *policy design* that enables and appropriately encourages the use of Demand Response. As a result of recent efforts towards liberalization, such policies are most likely implemented in the form of an *efficient market design*. However, such markets and the roles of their participants need to be carefully designed to solve the complex underlying allocation problem (Cramton and Ockenfels, 2012; McAfee, 1998). For instance, Germany did not introduce limits to the in-feeds from renewable energies at first (in comparison with other countries, such as Switzerland); only the 2014 revision of the *Renewable Energy Sources Act* (EEG) established first forms. Therefore, the following characteristics of market designs need to be carefully chosen and the corresponding *policy implications* derived (Koliou et al., 2014):

1. **Contract duration.** One important aspect of markets is the contract duration (Bandiera, 2007; Just, 2010). While there are multiple theoretical propositions on contract duration, a small number of these have been tested econometrically (Saussier, 1999). For instance, costs of a long-term contract increase with transaction-uncertainty level (Saussier, 1999). Even though this statement was tested for the coal market, similar effects are likely to be present when looking at the delivery of electricity or contracts for load shifting.
2. **Contract volume.** Electricity markets usually require a minimum bid size. For instance, DR potential is often traded in blocks of 1 MW or 5 MW.
3. **Reliability.** Most sources of Demand Response originate from highly flexible sources. For instance, aggregations combine the demand flexibility of renewable energy sources or several households and sell this as load shifting capacities. However, a 100 % reliability may not be guar-

anteed and, instead, policy makers need to find alternative (or weaker) formulations for the reliability of offered DR (Paulus and Borggrefe, 2011).

4. **Time lag between trading and delivery.** Depending on the auction design, the minimal time span between trading and delivery varies significantly (Borggrefe and Neuhoff, 2011). For example, trades are often completed on an intra-day or day-ahead basis, while even longer scheduling horizons of up to several weeks in advance are not uncommon. This immediately poses a trade-off between long-term system stability as opposed to the possibility of optimally adjusting to the feed-ins from renewable energy sources (e., g. Koliou et al., 2014).

In order to provide insights into the above questions, this paper analyzes different scenarios in which DR is integrated into the German electricity market. We go beyond state-of-the-art and utilize real market data to quantify and compare the financials around the scenarios in order to derive dedicated policy implications. Depending on the actual market design, policy makers can considerably influence the efficiency and the way in which Demand Response is used. While some scenarios seem not profitable in the status quo, we perform a what-if analysis to see what makes them financially more rewarding.

The remainder of this paper is structured as follows. In Section 2, we discuss strategies to integrate Demand Response activities into existing electricity markets. Subsequently, we review related work on the financial dimension of Demand Response (Section 3). For each scenario, Section 4 models optimal decisions to gauge financial savings. In Section 5, we present the results by comparing Demand Response activities across different application scenarios. Finally, Section 6 summarizes the findings and discusses policy implications to improve the integration of Demand Response into electricity markets.

2. Integrating Demand Response into Electricity Markets

This section presents stakeholders in the electricity market (more precisely, we use the German market for the subsequent specifications and evaluations). This is followed by a description of the electricity market structure. Both then motivate different scenarios for the integration of Demand Response.

2.1. Stakeholders

One of the major challenges is to operate electricity markets successfully by guaranteeing grid stability. Due to highly volatile supply and demand, electricity grids may become unstable when large deviations from the desired power frequency occur. The maintenance of grid stability requires power frequency to be controlled continuously. Hence, grid operators (see Figure 1) have to immediately counteract any imbalances by means of short-term *control reserve*. While grid operators execute balancing activities in response to individual deviations in power frequency, the emerging costs are distributed across the associated electricity retailers. Whenever electricity retailers face unexpected deviations in demand or supply that might affect grid stability within their control area, they request the so-called *balancing energy*, which comes at varying penalty costs.

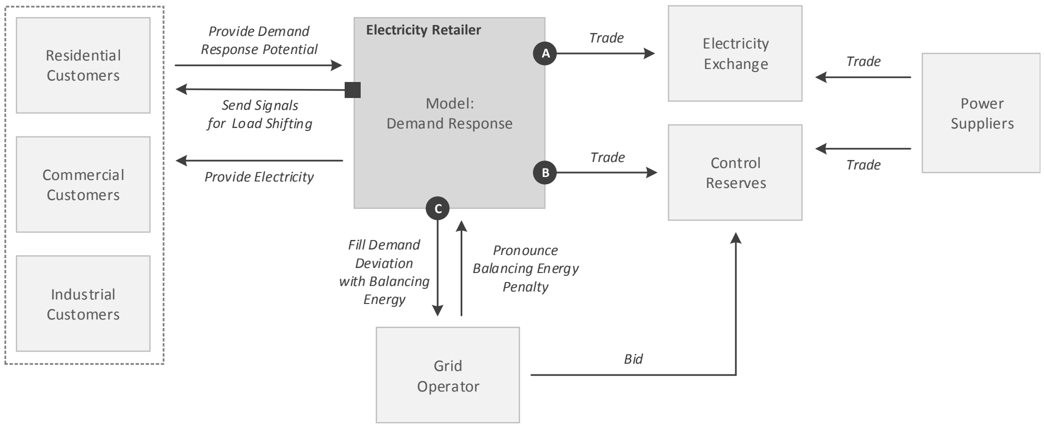

Figure 1: Overview of relevant stakeholders interacting with electricity retailers in the German electricity market, as well as the optimization model to manage Demand Response activities.

2.2. Electricity Market Structure

Most electricity markets in developed countries (e. g. Kirby, 2004) can be divided into three categories, namely, a product market, a control reserve exchange and balancing energy (cp. Fig. 2). As all three categories are suitable for Demand Response, this section elaborates on the possible strategies (based on the above scenarios) for Demand Response integration.

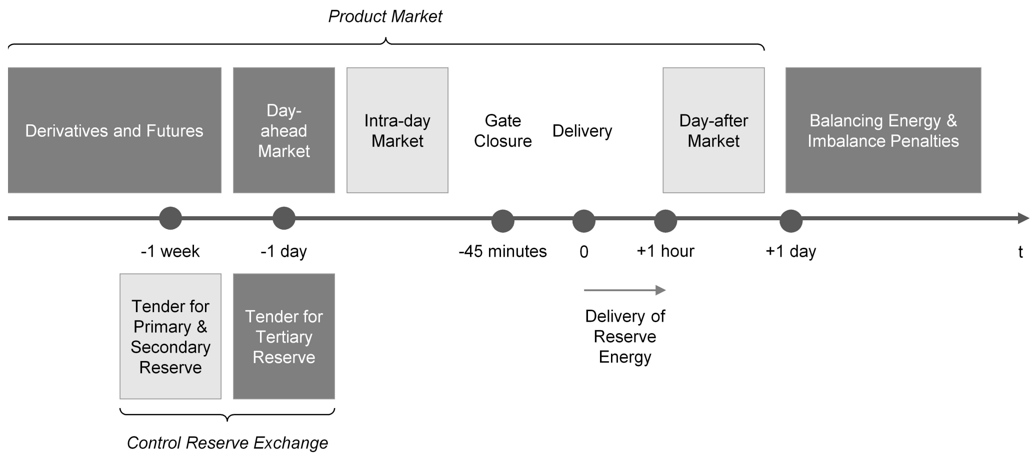

Figure 2: Overview of electricity market structure (with time spans valid for Germany) based on Kirby (2004) and Liebau (2012). Market components marked in dark gray are assessed in terms of Demand Response integration. Note that we account for intra-day load shifting via balancing energy, since the load curves must be fixed day-ahead, which makes intra-day spot markets infeasible given the current regulatory framework in Germany.

2.3. Integration Scenarios for Demand Response

Consequently, integrating Demand Response into the German electricity market can occur in several ways (e. g. Aghaei and Alizadeh, 2013; Koliou et al., 2014; Madrigal and Porter, 2012):

- *Scenario A: Using load shifting to optimize electricity procurement.* The electricity retailer employs Demand Response to optimize electricity procurement at the regular electricity exchanges. Here, the retailer merely shifts load from peak to off-peak hours in order to purchase electricity at lower prices.

- *Scenario B: Trading DR potential at the exchange for reserve energy.* When large deviations from the desired power frequency occur in electricity grids, grid operators counteract any imbalances by means of short-term reserve energy, named *control reserve*. As an alternative, activating control reserve can be (partially) replaced by shifting electricity load. Therefore, in practice, electricity retailers can offer their available Demand Response potential from the customer end at the exchange for reserve energy.

- *Scenario C: Using DR to avoid balancing energy.*

  While grid operators execute balancing activities in response to individual deviations in power frequency, the emerging costs are distributed across the associated electricity retailers. Thus, whenever electricity retailers face unexpected deviations in demand or supply that might affect grid stability within their control area, they request the so-called *balancing energy* which comes at varying penalty costs. As a remedy to these costs, balancing energy can be (partially) replaced by Demand Response mechanisms. In practice, retailers forecast their electricity demand in advance. When deviations occur, the electricity retailer employs Demand Response to avoid penalties by shifting load.

We note that scenarios B and C are essentially different sides of the same coin: both payments originate from the discrepancy between predicted and actual load. While scenario B bills the effort to eliminate the deviation, scenario C charges the stakeholder responsible for the prediction error. As such, the electricity retailer can avoid the costs the first place. As an alternative, scenario B might me a more viable business opportunity as it accounts for the deviations of all grid operators. In addition, scenario A expects all decisions on load shifting to be fixed day-ahead, while scenarios B and C allow for adjustments occurring intra-day.

The German regulations establishes a framework which only allow the previous cases (e. g. Aghaei and Alizadeh, 2013; Madrigal and Porter, 2012). For instance, the roles of electricity retailers and transmission grid operators are disentangled to a large degree. This is e. g. why we do not expect the grid operator to participate in load shifting. In addition, it is frequently assumed that Demand Response will be driven by electricity retailers (cf. EU-DEEP, 2009; SEDC, 2011; Faruqui et al., 2010a, and EU funded project ADDRESS). That is also the reasoning why not individual end-consumers trade at the exchange for control reserve, but it is handled by the electricity retailer. Our model follows the German regulatory framework with the exception of minimum bid sizes. We relax this constraint on purpose to derive policy implications.

For each of the three scenarios, this paper derives optimal Demand Response decisions to quantify the economic effects of Demand Response. Hence, we estimate to what extent the electricity retailer can achieve financial savings. Furthermore, we deduce policy changes in market design that improve the integration of Demand Response resources and increase market efficiency.

2.3.1. Scenario A: Electricity Procurement at the Product Market

Most developed countries allocate electricity through a product market where standardized contracts, as well as over-the-counter (OTC) deals, are traded. For example, German derivatives are traded at the European Energy Exchange, short EEX, and EPEX spot market (EEX, 2012; EPEX, 2012). In order to reduce procurement costs, electricity retailers can use Demand Response to match electricity demand and supply, as well as to reduce electricity procurement during peak times. Hence, Demand Response does not serve as market product itself, but as a mechanism for load shifting to reduce procurement costs.

While Demand Response is frequently studied in the context of load shifting, various references (e. g. Ridder et al., 2009) suggest that, due to the usage of Demand Response, profits for electricity retailers will increase. Demand Response activities do not actually decrease the amount of energy consumed, but merely shift it to when it is more convenient from the grid operation perspective (Denholm and Margolis, 2007; Shaw et al., 2009; Strbac, 2008). Thus, it can reduce both peak load, as well as marginal costs at peak time (Bergaentzlé and Clastres, 2013; Dave et al., 2013).

2.3.2. Scenario B: Market Design of Control Reserve Exchanges

In case of major load fluctuations, such as power outages, *reserve energy* is activated. Reserve energy appears as both positive and negative reserves: *positive reserves* are used to offset a lack of energy, whereas *negative reserves* withdraw power from the network and, thus, address energy excesses. Depending on response time and duration, reserve energy is grouped into primary, secondary and tertiary reserves. The only control reserve suited for Demand Response is the *tertiary* reserve (e. g. Ma et al., 2013; Paulus and Borggrefe, 2011). The tertiary reserve has to be fully available within 15 minutes after activation. Today, tertiary reserve is used only in approx. 3 % of the cases (Riedel and Weigt, 2007). However, in the future, it is likely that the demand for tertiary reserve will increase (Paulus and Borggrefe, 2011).

With liberalization of the energy markets, markets for trading control reserve have been established in many European countries (e. g. Denmark, Switzerland and Germany) and numerous regions in the U. S. (e. g. New England, Texas and California) (Kirby, 2004). In Germany, the system operators procure reserve energy in a control power market where bidding is done through an Internet-based marketplace (Regelleistung, 2012).

For example, German tertiary reserve is tendered in day-ahead combinatorial reverse auctions, whereby positive and negative reserve is tendered separately in time slices of four hours that divide the day into six even intervals (Riedel and Weigt, 2007). The auction bids consist of three values, namely, the *amount*, the *capacity price* and the *working price*. As the amount of required reserve power cannot be determined precisely in advance, each tenderer specifies the amount of (positive resp. negative) reserve energy capacity that the tender is able to provide for a specific time slot. Moreover, the tenderer communicates the capacity price (per MW) for provisioning the offered capacity. The capacity price has the character of an option fee. Finally, the working price (per MWh) defines the tenderer's desired price for actual use of the capacity.

We focus on the marketplace for trading tertiary reserve energy as it provides an opportunity for integrating Demand Response potentials. Demand Response holds the potential to be activated and provided within the required time frame of 15 minutes. By shifting load, electricity retailers can generate both positive and negative reserve potentials that could be offered at the control reserve exchange. For instance, participation in Germany is limited to providers that are able to deliver energy blocks larger than 5 MW over a duration of 4 hours. Due to the strict requirements, the marketplace for tertiary reserve energy is today only populated with larger power plants and aggregators that pool smaller providers. Rosen and Madlener (2012) propose an auction design for local energy reserves that allows for integrating smaller, decentralized generation capacities (e. g. capacities that are available in households).

In the future, a major increase in control reserve capacities is required (Madrigal and Porter, 2012; Paulus and Borggrefe, 2011). While today's electricity markets already bear control reserve as a major cost driver, the situation will worsen further since demand and the related costs are assumed to rise significantly. This development is triggered particularly by the growing share of renewable energy supply. First, its unpredictability leads to greater fluctuation in the reserve requirements (Jacobsen and Zvingilaite, 2010) and, in addition to that, additional balancing reserves will be needed (Gross et al., 2006). Second, prices will also increase sharply (Kladnik et al., 2012).

2.3.3. Scenario C: Penalties from Balancing Energy Usage

While control reserves actually stabilize the grid, their induced costs are distributed by an ex-most metric named *balancing energy*. Its price equals the expenditures for grid stabilization, which is paid by electricity retailers. The amount of required balancing energy coincides with the deviations between actual electricity demand and demand forecasted by an electricity retailer.

Similar to control reserves, balancing energy is a major cost driver in electricity markets. For example, wind power increases balancing power requirements due to its variability and limited predictability (Vandezande et al., 2010). Hence, Demand Response mechanisms can help to reduce expenditures for balancing energy. Whenever the retailer perceives that an imminent deviation of the actual demand from their projected forecast will occur, the retailer can shift load to prevent imbalances in the grid.

3. Related Work on Financial Benefits from Demand Response

Little is known about the financial benefits from Demand Response in liberalized markets (Aghaei and Alizadeh, 2013). Recent references, such as (Faruqui et al., 2010b; NERA Economic Consulting, 2008; Prüggler, 2013; PWC, 2010; van Horn, 2012), provide an overview of the economic costs and benefits of Demand Response through Advanced Metering Infrastructures. 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 (Gottwalt et al., 2011; Lujano-Rojas et al., 2012). A different approach optimizes the deployment of each household appliance individually (Gudi et al., 2012; Vasirani and Ossowski, 2012, 2013). However, none of the financial benefits are validated by real data.

To study Demand Response at an aggregate level, Aalami et al. (2010) carry out a study to simulate the effects of Demand Response programs. However, the authors lack real data on the available load shifting potential and, accordingly, the results are susceptible to missing external validity. Feuerriegel and Neumann (2014) model DR decisions mathematically to estimate financial effects, but use cases other than load shifting are neglected.

Demand Response potential can also be used as control reserve. Paulus and Borggrefe (2011) perform a cost-benefit-study to compare different energy-intensive industries in Germany by their ability to use their DR potential at a reserve energy market. However, the authors do not consider load shifting and, thus, cannot compare which usage scenario for Demand Response achieves the highest financial benefit. Similarly, Ma et al. (2013) present a methodology to assess the economic value of Demand Response for control reserve services. While their scenarios provide insights into what extent Demand Response can meet regulatory requirements, neither the findings on the resulting Demand Response usage nor on financial numbers are presented. Shayesteh et al. (2010) analyze the effects of an incentivized program to participate in reserve markets by formulating an optimization problem. However, the model is not calibrated using real-world data and the financial impacts are not evaluated.

4. Modeling Demand Response Usage

This section presents – across each scenario – mathematical models to gauge the financial benefits from Demand Response activities. To estimate savings, we follow the frequently-used approach (Doostizadeh and Ghasemi, 2012; Feuerriegel and Neumann, 2014; Meng and Zeng, 2012) that assumes a single electricity retailer to measure the financial impact. Based on the previous literature, we take the electricity retailer in all our models as the player which optimizes DR and thus the objective function.[1] We now briefly distinguish between the current regulations in Germany and our specific as-

[1]The retailer can also work as a producer of electricity; though this does not directly change the decisions on load shifting in the given model. Similar findings and additional reasoning is given in (Feuerriegel and Neumann, 2014).

sumptions.[2] In fact, our analysis is based on the German regulatory framework; however, we ignore the minimum bid sizes in order to study what the potential effects are.

The following model is evaluated for a the period of a full year, though it can be freely extended to any time span of interest. We split the time horizon into smaller decision problems that optimize Demand Response for a single year. This is due to the regulatory framework in Germany, which requires electricity retailers to transmit the expected load on a day-to-day basis. In addition, we focus on households and the service sectors, as industrial customers usually have a different tariff scheme and load shifting mechanism (Paulus and Borggrefe, 2011). While we conduct our analysis based on the German regulations, the model itself can be adapted to other countries with similar markets (Kirby, 2004). We refer to related references for further information on international context (e. g. Bergaentzlé et al., 2014; Boßmann and Eser, 2016; O'Connell et al., 2014).

Let us assume that we are granted a certain DR potential for each time interval. This potential can now be shifted forward or backward in time. However, each type of load can only be moved up to a certain. For instance, washing machines are commonly assumed to be more flexible than heating. Hence, we group different types of load by its maximum possible time shift j, e. g. 1 h, 2 h, etc. For each of these shifts j, the variable $\Delta_j(t)$ denote

[2] Due to regulatory requirements and the timing of different markets (Koliou et al., 2014), we treat each scenario individually and do not consider a case where the retailer makes a trade-off between bids on the reserve energy side or on the electricity exchange. This allows us also to separately assess the value of each scenario.

the available potential. Furthermore, let $DR_j(t, \sigma)$ denote the load that is shifted from hour t by an offset of σ hours, where j specifies a certain type of load (with a corresponding maximum duration). For example, the expression $DR_j(12, 2)$ means that load type j shifts its consumption from noon to 2:00 p. m. Hence, the electricity demand is lowered by $DR_j(t, \sigma)$ at hour t, while it increases by the same value in hour $t + \sigma$.

4.1. Scenario A: Modeling Load Shifting to Optimize Electricity Procurement

This load shifting model is based on a linear optimization problem that minimizes the retailer's accumulated expenditures over the course of arbitrary time horizon (e. g. one year as in our evaluation). We split the time span into disjunct decision problems, where each optimization determines the daily load shifting activities across 24 hours. Furthermore, the model supports two common energy derivatives, namely, futures and day-ahead auctions. Their prices at day d and hour t are given by $q_{\mathrm{F}}(d)$ and $q_{\mathrm{A}}(t)$ respectively. Further, let $q_{\mathrm{F}}(d)$ denote the procured electricity quantities as future derivatives and let $q_{\mathrm{A}}(t)$ specify procurement at the day-ahead market at day d and hour t respectively. Whenever $t < 1$ or $t > 24$, we define $DR_j(t, i) \overset{\text{def}}{=} 0$. Given the relatively small size of a retailer compared to the overall electricity market, we assume that a load shifting leaves the price of electricity unchanged (Märkle-Huß et al., 2016).

Although originally proposed in (Feuerriegel and Neumann, 2014), we briefly repeat the optimization problem, given by

$$\min_{q_{\mathrm{F}}(d), q_{\mathrm{A}}(1), \ldots, q_{\mathrm{A}}(24)} 24\, p_{\mathrm{F}}(d) q_{\mathrm{F}}(d) + \sum_{t=1}^{24} p_{\mathrm{A}}(t) q_{\mathrm{A}}(t), \tag{1}$$

$$\text{s. t. } q_{\mathrm{A}}(t) + q_{\mathrm{F}}(d) = \mathrm{D}(t) - \sum_{j} \left[DR_j(t,0) - \sum_{i=1}^{j} DR_j(t \pm i, \mp i) \right], \tag{2}$$

$$q_{\mathrm{A}}(t) \geq 0, \quad q_{\mathrm{F}}(d) \geq 0, \tag{3}$$

$$DR_1(t,0) \leq \Delta_1(t), \quad DR_2(t,0) \leq \Delta_2(t), \quad \ldots, \tag{4}$$

$$DR_j(t+i,-i), \quad DR_j(t-i,+i) \geq 0, \quad \text{for } i = 1, \ldots, j, \tag{5}$$

$$\sum_{i=-j}^{+j} DR_j(t+i,-i) = 0 \tag{6}$$

$$\text{for all } j \quad \text{and for } t = 1, \ldots, 24.$$

Eq. 1 defines the target function that minimizes the retailer's overall expenditures on electricity. Eq. 2 and Eq. 3 state that electricity is procured and quantities must equal demand minus Demand Response activities. Furthermore, Eq. 4 limits the maximum load shifted, while Eq. 5 guarantees that shifted load is always positive. Finally, Eq. 6 enforces that shifted demand is added somewhere else; thus, ensuring the conservation of Demand Response potential.

4.2. Scenario B: Modeling Demand Response Usage as Tertiary Control Reserve

Electricity retailers can use their Demand Response potential for tertiary control reserve. Here, we distinguish between two optimization problems for both negative (Section 4.2.1) and positive control reserve (Section 4.2.2).

Figure 3 shows schematically how Demand Response changes the load by shifting it according to the needs for control reserve.

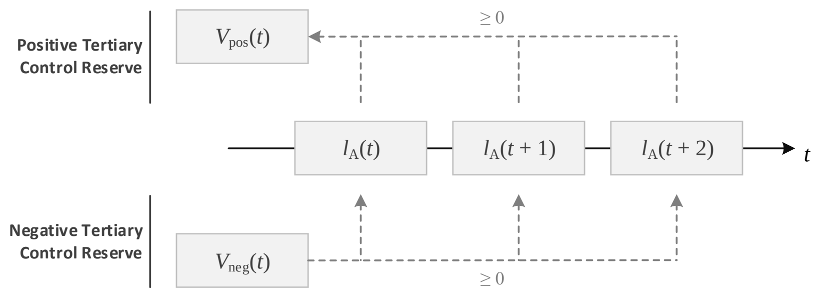

Figure 3: Schematic visualization how load changes $l_\mathrm{A}(t)$, $l_\mathrm{A}(t+1)$, ... are determined according to needed positive control reserve $\mathrm{V}_\mathrm{pos}(t)$ (or negative control reserve $\mathrm{V}_\mathrm{neg}(t)$ respectively) due to Demand Response activities.

4.2.1. Modeling Demand Response as Negative Control Reserve

Negative control reserve, if requested, implies that demand must be shifted away. Let $\mathrm{V}_\mathrm{neg}(t)$ denote the energy level that needs to be decreased. As regulatory issues force electricity demand to be fixed day-ahead, this additional volume $\mathrm{V}_\mathrm{neg}(t)$ can only be shifted to the following day. Let the price for electricity at the day-ahead market be given by $p_\mathrm{A}(t)$ and let $l_\mathrm{A}(t)$ denote the delta by changing the load on the day-ahead market. Then, we can split our volume $\mathrm{V}_\mathrm{neg}(t)$ across the quantities $l_\mathrm{A}(t)$ of the next day. The optimal time slots are those that give the highest savings and result from the following optimization problem. Here, the electricity retailer maximizes its earnings for the next day; the target function is given by

$$\max_{l_\mathrm{A}(1),\ldots,l_\mathrm{A}(24)} \sum_{t=1}^{24} p_\mathrm{A}(t) l_\mathrm{A}(t). \tag{7}$$

The necessary constraints are as follows. According to Eq. 8, the volume of positive reserve energy must equal the additional energy moved here. Eq. 9 specifies the changes $l_{\mathrm{A}}(t)$ for the day-ahead market. Furthermore, Eq. 10 guarantees the conservation of used load shifting potential such that all demand that is shifted away is added somewhere else, i. e.

$$\mathrm{V}_{\mathrm{neg}}(t) = \sum_j DR_j(t,0), \tag{8}$$

$$l_{\mathrm{A}}(\tau) = \sum_j DR_j(t,\tau - t), \tag{9}$$

$$-DR_j(t,0) + \sum_{i=24-t+1}^{+j} DR_j(t,+i) = 0 \quad \text{for all } j. \tag{10}$$

Next, we derive constraints on the DR potential. Thus, we constrain the maximum DR potential that is shifted away by

$$DR_1(t,0) \leq \Delta_1(t), \quad DR_2(t,0) \leq \Delta_2(t), \quad \text{etc.} \tag{11}$$

Additionally, we need constraints to guarantee that shifted demand is not negative. Thus,

$$DR_j(t,+i) \geq 0 \quad \text{for all } j \text{ and } i = 1,\ldots,j. \tag{12}$$

4.2.2. Modeling Demand Response as Positive Control Reserve

Positive control reserve, if requested, implies that further energy is needed and Demand Response potential must be shifted here. This additional electricity demand given by $\mathrm{V}_{\mathrm{pos}}(t)$ must be filled with energy from the next day. The reason is that regulatory issues preventing load shifting within the day to satisfy short-term needs. Let the price for electricity at the day-ahead market be given by $p_{\mathrm{A}}(t)$ and the amount we can sell there by $l_{\mathrm{A}}(t)$. Then, we can distribute the energy $\mathrm{V}_{\mathrm{pos}}(t)$ among the quantities $l_{\mathrm{A}}(t)$ of the next day. By reducing the associated costs, the target function is

$$\min_{l_{\mathrm{A}}(1),\ldots,l_{\mathrm{A}}(24)} \sum_{t=1}^{24} p_{\mathrm{A}}(t) l_{\mathrm{A}}(t). \tag{13}$$

The necessary constraints are as follows. According to Eq. 14, the volume of positive reserve energy must equal the additional energy moved here. In addition to that, Eq. 15 specifies the quantities $l_{\mathrm{A}}(t)$ from the day-ahead market, i. e.

$$\mathrm{V}_{\mathrm{pos}}(t) = \sum_{\tau=1}^{24} \sum_{j} DR_j(\tau, t-\tau), \tag{14}$$

$$l_{\mathrm{A}}(\tau) = \sum_{j} DR_j(\tau, t-\tau). \tag{15}$$

Next, we derive constraints on the Demand Response potential. 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 constrain the maximum DR potential that is shifted away by

$$DR_1(t,-i) \leq \Delta_1(t), \quad DR_2(t,-i) \leq \Delta_2(t), \quad \text{etc.} \tag{16}$$

As an additional constraint, shifted demand is non-negative,

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

As all of the above constraints are either equality constraints or bounds. Both optimization problems are linear and can be solved using e. g. a simplex algorithm, since a unique solution exists.

4.3. Scenario C: Modeling Demand Response Usage to Avoid Balancing Energy

Electricity retailers must pay a penalty whenever their actual electricity demand differs from the expected demand. Let $BE(t)$ denote the gap in watt-hour at time t. This imbalance can be either positive or negative; however, the penalty costs rise linearly with the deviation $|BE(t)|$. At the same time, each time slot t is associated with a penalty price $p_{\mathrm{BE}}(t)$. Similar to Vasirani and Ossowski (2012, 2013), an electricity retailer pays

$$c_{\mathrm{BE}}(d) = \sum_{t=1}^{24} p_{\mathrm{BE}}(t)\,|BE(t)|. \tag{18}$$

during 24 hours of day d. To reduce these expenditures $c_{\mathrm{BE}}(d)$ for balancing energy, the retailer can harness Demand Response as a remedy. Now, we introduce the notation for Demand Response usage and we derive the corresponding optimization problem. Its target function $c_{\mathrm{BE,DR}}(d)$ minimizes the retailer's expenditures at day d and, thus, sums the penalty costs over a time horizon. Let $q_{\mathrm{BE}}(t)$ denote the amount of balancing energy that must still be requested after DR usage. Then,

$$c_{\mathrm{BE,DR}}(d) = \min_{q_{\mathrm{BE}}(1),\ldots,q_{\mathrm{BE}}(24)} \sum_{t=1}^{24} p_{\mathrm{BE}}(t)\,|q_{\mathrm{BE}}(t)|. \tag{19}$$

In addition to that, we introduce a set of constraints:

- **Demand equality.** With $BE(t)$ indicating the demand of balancing energy, this energy must be replaced by the sum of Demand Response activities and the residual balancing energy, i. e.

$$BE(t) = q_{\mathrm{BE}}(t) - \sum_{j} \left[DR_j(t,0) - \sum_{i=1}^{j} DR_j(t \pm i, \mp i) \right]. \tag{20}$$

- **Conservation of DR potential.** We need to guarantee the conservation of used DR potential; thus

$$\sum_{i=-j}^{+j} DR_j(t+i,-i) = 0 \quad \text{for all } j. \tag{21}$$

- **Bounds.** We limit the maximum amount of energy that can be displaced via

$$DR_1(t,0) \le \Delta_1(t), \quad DR_2(t,0) \le \Delta_2(t), \quad \text{etc.} \tag{22}$$

Additionally, we need constraints that limit the flow direction, i. e.

$$DR_j(t+i,-i), \quad DR_j(t-i,+i) \ge 0 \quad \text{for all } j \text{ and } i = 1,\ldots,j. \tag{23}$$

The above optimization can be easily turned into a linear problem. Depending on the sign of $BE(t)$, we use a different price that always yields the desired outcome. Thus, we replace the price $p_{\mathrm{BE}}(t)$ for balancing energy by a new price $p'_{\mathrm{BE}}(t)$, which is defined by

$$p'_{\mathrm{BE}}(t) \stackrel{\mathrm{def}}{=} \begin{cases} -p_{\mathrm{BE}}(t), & BE(t) < 0, \\ p_{\mathrm{BE}}(t), & \text{otherwise.} \end{cases} \tag{24}$$

As all of the above constraints are either equality constraints or bounds. The optimization problem is also linear and can be solved using e. g. a simplex algorithm, since a unique solution exists.

5. Evaluation

In the following section, we test our mathematical model in a setting using historic German data from 2011. Before presenting the results, we provide an overview on the applied parameters and datasets. Ultimately, we evaluate the financial benefits of Demand Response and compare these across each scenario.

5.1. Datasets

In our evaluation, we assume a German retailer that delivers electricity to both residents and the service sector. The retailer's overall annual energy demand accounts for 2000 GWh, out of which 500 GWh are delivered to a total of 290 000 residents and an additional 500 GWh to the service sector (E-Control, 2012; E.ON, 2011; Werlen, 2007). The electricity demand is given load profiles of a real electricity retailer (NGS, 2013).

All prices for energy derivatives and spot auctions are based on the historic hourly data from the year 2011[3] of the European Energy Exchange, EEX for short (EEX, 2012). The price for futures $q_{\mathrm{F}}(d)$ originates from the Phelix Day Base index (daily delivery horizon), while the time series $q_{\mathrm{A}}(t)$ originates from the hourly day-ahead market covering the combined market of Austria and Germany. We use the amount of balancing energy provided by E.ON Mitte[4] for the year 2011. The original values account for 1.5 million inhabitants, so we scale it down to 290 000. The penalty price of balancing energy is provided by Transnet BW[5] for the year 2011. All volumes

[3] Due to data availability.

[4] E.ON Mitte AG (2013). Differenzbilanzierung. Web: `http://www.eon-mitte.com/de/netz/veroeffentlichungen/strom_/veroeffentlichungen_nach_12_abs_3_stromnzv`. Accessed April 5, 2013.

[5] Transnet BW GmbH (2013). Bilanzkreisabrechnung. Web: `http://www.transnetbw.de/strommarkt/bilanzkreismanagement-und-bilanzkoordination/`

and prices for tertiary control reserve are published on an Internet platform (Regelleistung, 2012).

Commercial Customers	Max. Shift Duration/h	1	2	12	16
	Average Power Shift/kW	5648	3092	1625	1792
Residential Households	Max. Shift Duration/h	1	2	12	24
	Average Power Shift/kW	2569	2358	12 253	1264

Table 1: Demand Response potential through load shifting in Germany (Klobasa, 2007); scaled according to retailer's electricity demand.

The capabilities of Demand Response vary considerably between both industry and households. Industrial customers are excluded from the calculation of DR saving potentials as industrial customers hardly participate in load shifting, but rather reduce their energy consumption when granted financial incentives. Klobasa (2007) analyzes the nationwide market penetration of Demand Side Management and its overall potential for Germany. To comply with our scenarios, we scale the nationwide potential (i. e. 83 million) to 290 000 residents – see Table 1. Across each time of day, the Demand Response potential for households varies significantly and, hence, the household values in Table 1 are weighted by time-dependent coefficients (Groiß, 2008; Groiß and Brauner, 2009).

5.2. Scenario A: Use Load Shifting to Optimize Electricity Procurement

Scenario A analyzes potential financial savings from utilizing Demand Response in order to optimize electricity procurement. This is achieved by

`bilanzkreisabrechnung/`. Accessed April 5, 2013.

shifting load from time slots with high prices to ones with significantly lower costs. As a benchmark, the electricity retailer spends €109.93 M on producing electricity in the year 2011. When integrating Demand Response in the above optimization, this spending drops to €106.70 M. Thus, the overall savings (cp. Figure 5) for the retailer are computed to €3.110 M or 2.83 % respectively.

5.3. Scenario B: Trading Demand Response Potential at the Exchange for Reserve Energy

In our setting, reserve energy has to be activated 6895 times within the observation period (i. e. one year). Of this total, 5612 activations are attributed to negative reserve energy and the remaining 1283 activations to positive reserve energy. Within the 6895 activations of reserve energy, our retailer is able to trade a mean volume of 0.0849 MW of negative and 0.0332 MW of positive reserve energy per activation (cp. Table 2). The mean volume of traded energy is substantially higher for positive reserve energy. Nevertheless, the actually served volume of negative reserve energy exceeds the volume of positive reserve energy. The potential savings from traded and served reserve energy accumulate to €125 k per year. This corresponds to an average earning of € 18.09 per activation.

Dimension	**Negative Reserve Energy**	**Positive Reserve Energy**	**Total**
Activations	5612	1283	6895
Mean traded volume	0.0849 MW	0.0332 MW	–
Max traded volume	0.3598 MW	0.1877 MW	–
Earnings	€ 92 930	€ 31 800	**€ 124 720**
... from service price†	€ 41 704	€ 18 210	€ 43 525
... from working price†	€ 50 494	€ 32 408	€ 82 901
... from adjusted demand (based on $l_A(t)$)	€ 728	€ −2433	€ −1705
Avg. earnings per activation	€ 16.56	€ 24.78	€ 18.09

† Prices are settled *ex post* based on the actual activations (see Section 2.3.2) and are thus not part of allocating optimal load shifts.

Table 2: Overview on trading volumes and financial impact of trading DR potential at the exchange for reserve energy for given evaluation setup (own calculations).

5.4. Scenario C: Use Demand Response to Avoid Balancing Energy

Scenario C aims to avoid penalty costs associated with requested balancing energy. Our fictional retailer faces total costs of around €798 k. These costs account for all the deviations in forecasted and actual electricity demand occurring in the year 2011. As shown in Table 3, Demand Response provides a possible path as to how these costs can be significantly decreased. By using Demand Response programs, penalties are reduced, as almost all balancing energy can be avoided, down to €1.7 k.

However, the additional potential savings of using DR instead of balancing energy outweigh the costs. Hence, setting up the DR infrastructure and employing it for multiple use cases, including scenario C, could be a viable approach.

	Without DR	Using DR	Relative Change	Difference
Total expenditures	€798.4 k	€1.7 k	−99.8 %	**€−796.7 k**
Required balancing energy	95.28 MWh	1.92 MWh	−98.0 %	−93.37 MWh
Max. daily costs c_{BE}	€17.266 k	€ 858.76	−95.0 %	€−16.4 k
Std. dev. c_{BE}	2720.8	83.1	−96.9 %	−2637.7

Table 3: Comparison of expenditures for penalties for balancing energy (own calculations).

5.5. Comparison

This section provides insights how each of the above Demand Response models performs in practice. We focus on households and the service sectors, as industrial customers usually have a different tariff scheme and load shifting mechanism. For industrial customers, we refer to related works, such as by Paulus and Borggrefe (2011).

As a starting point, Figure 4 shows how Demand Response potential is utilized across all three scenarios on January 1, 2011 as a show case. When looking in depth, we observe the following pattern: scenario A performs pure load shifting and thus reveals several spikes as result of the hourly blocks that are shifted. Furthermore, we see a clear peak at 6:00 a. m. when electricity prices reach the daily plateau. Most of the total demand is shifted to this time frame in order to reduce electricity procurement costs. Scenario B trades the Demand Response potential at the exchange for reserve energy. Activations of reserve energy occur only rarely, as we can see in Figure 4 where Demand Response is mobilized between 9:30 a. m. until 12:00 p. m. On this sample day, the shifted demand is only negative as demand is shifted from January 2 to January 1, 2011 in order to supply reserve energy. Finally, scenario C avoids penalties from balancing energy and shows the most wavy curvature. The usage of Demand Response is bounded in this scenario by the relatively low need for balancing energy. Overall, we identify shifting patterns across all Demand Response models that are completely different from each other. While Figure 4 visualizes only a single exemplary day, additional graphics can be found in the appendix. In addition, we present the overall performance comparison in the following.

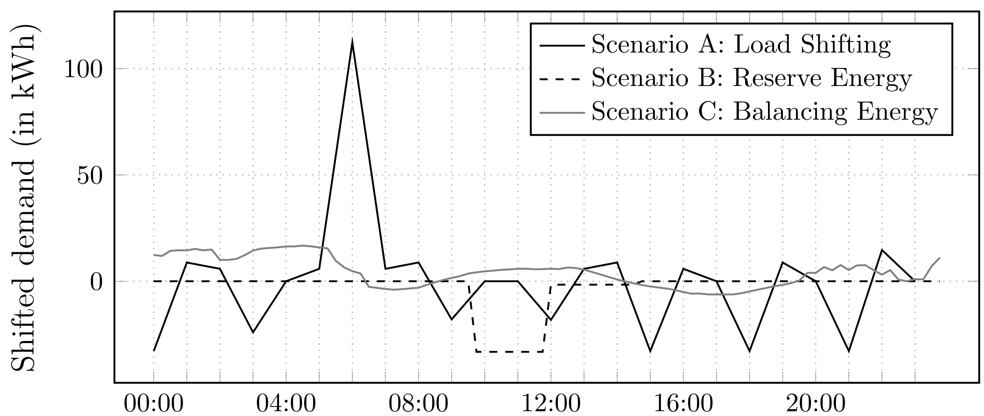

Figure 4: Demand Response usage on January 1, 2011 as a show case day reveals completely different shifting patterns for each of the three Demand Response scenarios (own calculations).

Combining the prior evaluation results (see Figure 5), a clear answer concerning our research question can be formulated: scenario A, i. e. using load shifts to optimize electricity procurement, provides the largest benefit for the electricity retailer. For instance, the service price for tertiary reserves and the costs for balancing energy must increase by 72.61 and 3.90 times respectively in order to give the same revenue as purely optimizing electricity procurement.

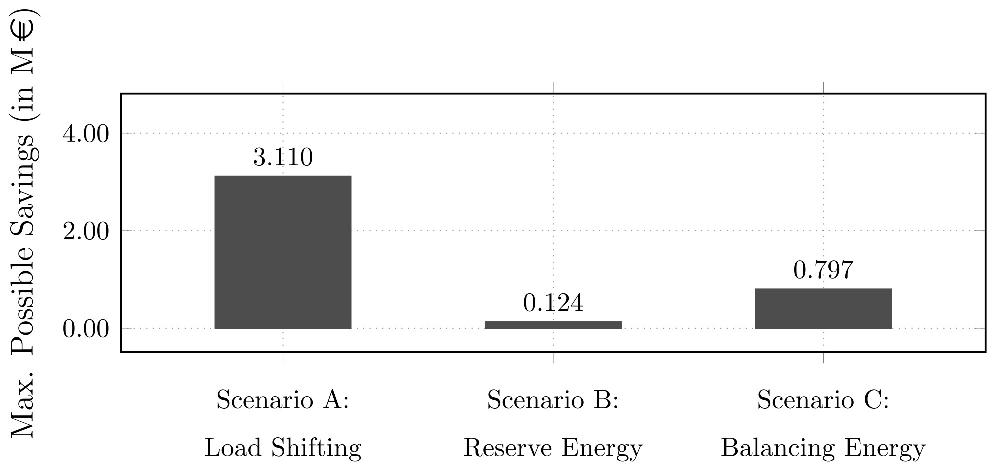

Figure 5: Summary of maximum potential savings for an electricity retailer across scenarios A, B and C (own calculations).

6. Conclusion and Policy Implications

This section presents policy implications derived from our model, followed by a brief summary and an outlook.

6.1. Policy Implications

Demand Response can shift power demand according to the fluctuating supply side and, consequently, integrating Demand Response into electricity markets. As we have shown in this paper, a scenario where an electricity retailer leverages Demand Response for optimizing the energy procurement strategies is most profitable compared with application scenarios using DR resources as tertiary reserve or to avoid balancing energy penalties. However, this only represents a snapshot. Prices for reserve and balancing energy are assumed to be rising significantly in the near future (Kladnik et al., 2012;

Madrigal and Porter, 2012), which consequently leads to increased financial benefits for the retailer and could hence make these scenarios financially rewarding.

It is generally agreed that Demand Response entails a large variety of benefits for almost all stakeholders (Albadi and El-Saadany, 2008; Erdinc et al., 2015; Safdarian et al., 2014; Siano, 2014). As also noted by Ma et al. (2013), the integration of DR resources into current electricity markets requires various changes, in particular, to the market design of reserve exchanges. In the following, we discuss, in detail, the required key adjustments:

- Regulations in Germany and the U. S. obliges retailers to offer a minimum amount of 5 MW of tertiary reserve energy capacity.[6] However, a retailer of average-size is hardly able to meet this prerequisite. In fact, our evaluation reveals volumes that on average are less than 1 MW. According to Table 2, our simulation shows average of 0.0849 MW for negative and 0.1877 MW positive reserve energy.

- We observe relatively low savings of €0.124 M and €0.797 M from scenario B and C. In other words, it is more profitable for retailers to use DR for optimizing their load shifting (corresponding to savings of €3.110 M) than trading at the control reserve or avoiding balancing energy. According to our evaluation, the service price for tertiary reserves and the costs for balancing energy must increase by 72.61 and

[6] Source: BK6-10-099 in Germany; e. g. PJM (`http://www.pjm.com/~/media/documents/manuals/m11.ashx`) as a Regional Transmission Organization which belongs to the Eastern Interconnection in the United States.

3.90 times respectively in order to give the same revenue as purely optimizing electricity procurement. In addition, scenario A is the only scenario that generates a substantial surplus at all. However, it should be noted that for scenario A the situation similarly changes as soon as the required capital expenditures from literature are taken into account as well. Then the potential savings implied by the DR system can hardly cover the overall costs (cp. results in Feuerriegel et al., 2013, 2016). However, even if the DR system is not profitable today, the assumed cost increases for control reserves and balancing energy can potentially lead to a positive financial case in the medium term.

- As a potential remedy, policy makers can e. g. decrease these constraints. As an alternative, several electricity retailers bundle their DR resources to offer virtual forms thereof. However, this might need to be encouraged further as the tertiary control itself is not providing sufficient financial benefits and such bundling of DR resources across different retailers is not yet common.

In addition, we can draw further implications from discussing the restrictions and assumptions of our model. We thus expect the following regulatory changes to have a positive influence on the benefits from DR usage. They reflect regulatory constraints and revealed itself as limiting factors during our modeling process in Section 4. If relaxed, they might increase the effectiveness of load shifting as follows:

- The tertiary reserve energy exchanges underlie strong restrictions. For example, reserves must be activated and available within 15 minutes with extremely high certainty. It is not clear if DR resources are able to comply with the previous requirements.

- While costs for balancing energy and control reserve are charged for 15-minute intervals, contracts offered at many energy exchanges – such as the EEX (2012) – comprise delivery periods of at least one hour. As a result, the retailer has no chance to procure missing electricity for any imbalances of 15-minutes. Hence, our model suggests the consideration of electricity contracts with shorter delivery periods.

- Due to current market design, we had to exclude primary and secondary reserve in the beginning as part of our assumptions. We now discuss potential changes in order to integrate them into our model and utilize them for load shifting. Auctions for secondary reserve take place 1 month before delivery and, for primary reserves, even 6 months beforehand. According to Paulus and Borggrefe (2011), *"the requirements for secondary and primary reserve markets are too restrictive"* for the integration of DR resources. Borggrefe and Neuhoff (2011) adds to this and states that day-ahead auctions are required.

  This is particularly true when looking at our setting due to uncertainty and risk management for the retailer. Here, we assume that a DR mechanism is used to address increasing volatility on the supply side that is induced by renewables (Koliou et al., 2014). The electricity retailer is not able to generate reasonable estimates and offer respective resources that far in advance. Even intra-day auctions might become necessary to leverage the full potential of Demand Response – this would also require changes to the current exchanges for tertiary reserve that execute day-ahead auctions only.

6.2. Summary

When integrated into electricity markets, Demand Response can be used for load shifting and as a remedy for both control reserve and balancing energy. These three usage scenarios are formulated as optimization problems and compared based on historic German data from 2011 to determine that load shifting provides the highest revenue: annual financial savings accumulate to €3.110 M for both households and the service sector. This equals to relative savings of 2.83 % compared to a scenario without load shifting.

Based on our evaluation for Germany, we present policy implications that are beneficial when incorporated into electricity market design. In short, market transactions have to be conducted in the short-term (at least day-ahead) and allow for smaller volumes to be traded.

6.3. Outlook

In future work, we plan to extend the financial perspective. First, we have restricted the optimization problem to study direct savings for the electricity retailer. Hence, it would be intriguing to design a novel optimization model and study the related research question of how DR affects load and electricity prices on a macro-level, i. e. for a full nation. Similarly, one can think of analyzing the expected effects of DR in capacity markets. Furthermore, we intend to further enhance the model by allowing intra-day allocation and shifting of load. This would better reflect the effects of integrating renewables into the power grid. Hitherto, all market transactions are fixed day-ahead.

Acknowledgment

The valuable contributions of Philipp Bodenbenner and Laura Cuthbertson are gratefully acknowledged.

Appendix A. Additional Visualizations of Load Shifting Patterns

Figures A.6 to A.8 show the load shifting on April 1, July 1 and October 1 respectively.

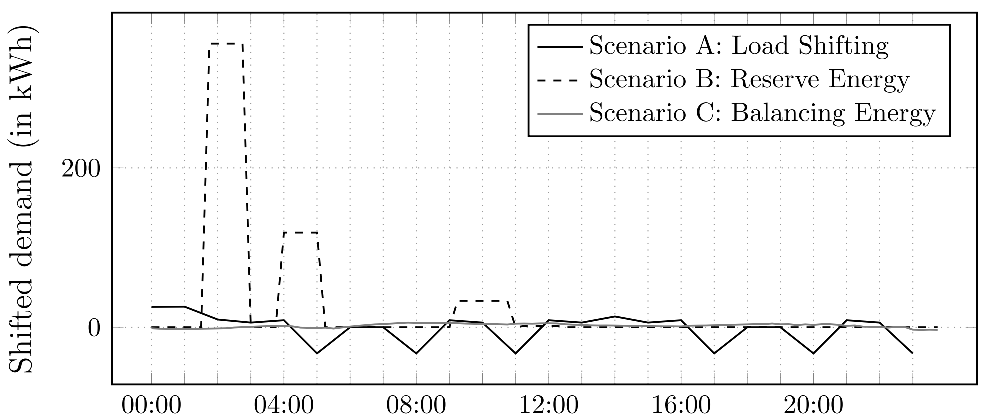

Figure A.6: Demand Response usage on April 1, 2011 as a show case day reveals completely different shifting patterns for each of the three Demand Response scenarios (own calculations).

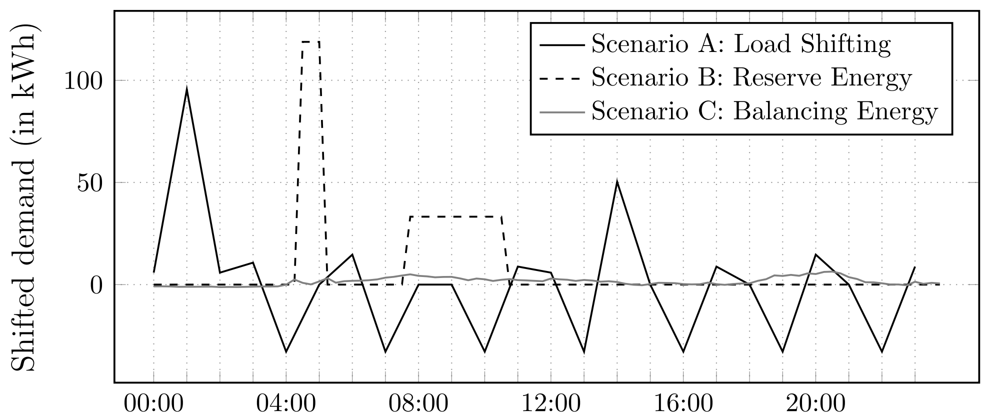

Figure A.7: Demand Response usage on July 1, 2011 as a show case day reveals completely different shifting patterns for each of the three Demand Response scenarios (own calculations).

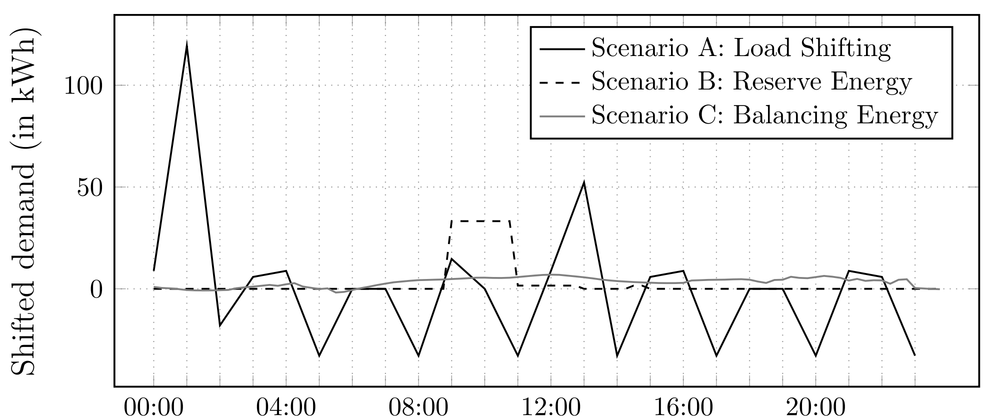

Figure A.8: Demand Response usage on October 1, 2011 as a show case day reveals completely different shifting patterns for each of the three Demand Response scenarios (own calculations).

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