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IS MORE INFORMATION BETTER THAN LESS? UNDERSTANDING THE IMPACT OF DEMAND RESPONSE MECHANISMS IN ENERGY MARKETS

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Abstract

Due to the integration of intermittent resources of power generation such as wind and solar, the amount of supplied energy will show 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. This so-called Demand Response mechanism requires innovations in Information Systems such as Advanced Metering Infrastructures. Whereas the technology side of these infrastructures is relatively well understood, further effort, to quantify the economic dimension of Demand Response, is strongly needed. Therefore, we present the foundation of a Demand Response system to model both costs and revenues based on-real world data. Although our model suggests that an average energy retailer faces initial setup costs for the infrastructure of up to € 24 million, we provide evidence that savings from load shifting exceed the running costs of the Information System significantly – by more than € 250k per year. With higher information granularities, revenues from Demand Response increase further. However, this effect is countervailed by disproportionately growing communication costs and opposes the common expectation that more information is better than less.

Keywords: Green IT/IS, business value of IS/value of IS, demand-side, information systems, decision making/makers.

1 Introduction

The integration of intermittent sources of energy generation, such as wind and solar power, comes at the cost of unprecedented fluctuations in energy supply. Although their intermittent nature poses a challenge from the grid operation perspective, many states aim at increasing the share of renewable energies rapidly. For example, the European Union set the target share of renewables to 20 percent. Germany, the largest member state, even passed a law in 2011 mandating 35 percent of renewables by 2020 and 80 % by 2050. Since renewable energy sources are volatile in nature – in contrast to 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 (see Figure 1) between power demand and supply.

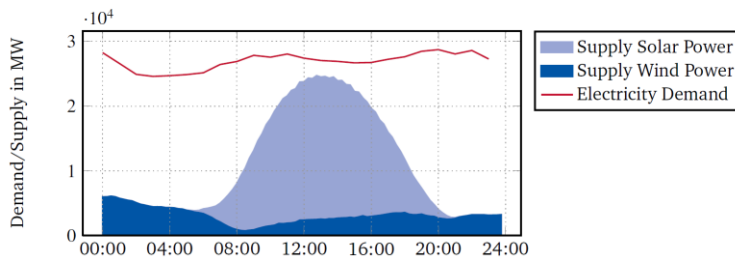


Figure 1. *Discrepancy between power demand and supply in Germany on May 26th, 2012 traded at the European Energy Exchange (EEX, 2012).*

One possible path to match power demand and supply is given by the concept of Demand Response. Demand Response (DR) is defined by the U.S. Department of Energy (2006) and the FEDC (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.”* While 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 (c.f. EU-DEEP, 2009, SEDC, 2011 and EU funded project ADDRESS), it is frequently assumed that Demand Response will be driven by energy retailers. Consequently, we focus on a setup where DR 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 our modeling efforts. We restrict our publication to Demand Response based on an Advanced Metering Infrastructure (U.S. Department of Energy, 2008). Having in mind the intricate information flows and huge amount of data, Demand Response unveils to be inherently daunting for Information Systems (IS) research. Hence, the inevitable need for Information Systems to match supply and demand in the power grid was stressed by Detrick (2010).

As a main contribution to IS research, this paper not only designs an Information System for Demand Response, but, based on this design, provides a rigorous derivation of a comprehensive model to gauge both costs and corresponding savings. Using real-world data, the value of information in a DR system is quantified. In addition, we investigate whether a positive pay-off can be gained from more fine-grained usage data. Interestingly, we show that more data on the customers’ energy profile are not necessarily accruing a positive pay-off for the retailer. If the data is too fine-grained (10 minutes), the associated communication costs outweigh the savings potentials. This finding contradicts e.g. Wicker and Thomas (2011), whose adverse recommendations rests on the assumption that an increase in information granularity incurs no costs.

2 Related Work

To fully capture the notion of DR systems, it is necessary to view the underlying Information Systems from two angles. On one hand, we identify related publications that contributed to the design of a DR system and, on the other hand, explore literature related to costs and benefits of a DR system. Based on this literature review, we conclude this section by deriving our research questions and providing evidence that these questions are relevant and important to the IS community.

2.1 Demand Response in IS research

A recent literature review (Strüker and van Dinther, 2012) shows that there is a small but growing number of IS-related research papers on Demand Response. Corbett (2011), Palensky and Dietrich (2011), Tan et al. (2012) have contributed to IS research by deriving requirements and researching necessary components for the design of Demand Response systems. However, these references lack a design of the underlying strategy that controls load shifting. Feuerriegel et al. (2012) derived a mathematical formulation for optimal control of load shifting and load reduction, but the authors considered neither the costs nor different data granularities.

Little is known about the economic potential of Demand Response in deregulated markets. Various references (e.g. Ridder et al., 2009) suggest that, due to the usage of Demand Response, profits of retailers will decrease. 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 (Strbac, 2008). To quantify the retailer's profits, Feuerriegel et al. (2012) and Aalami et al. (2010) performed a study with real-world data. However, these authors neglected both investment and running costs for using available load shifting potential. Paulus and Borggreffe (2011) performed a cost-benefit-study for energy-intensive industries in Germany that sell their load shifting potential at an exchange for spinning reserve, but did not consider efficiency gains from more convenient energy purchases. Recent references such as (NERA Economic Consulting, 2008, Faruqui et al., 2010, PWC Austria, 2010, Gottwalt et al., 2011) provide an overview of the economic costs and benefits of Demand Response through Advanced Metering Infrastructures; however, all listed publications lacked (1) a simulation of the shifted loads and its financial savings and (2) an in-depth analysis of operational costs of smart meters. Consequently, quantifying the economic benefits still seems to be an open research question.

Since the above research papers have concentrated on partial examinations of either revenues or costs of the required infrastructure, many questions have been left unanswered.

2.2 Research framework

Recently, Strüker and van Dinther (2012) asked *“how large is the economic value of demand response”*. Likewise, Strbac (2008) claims that there is a *“lack of understanding of the benefits of Demand Side Management solutions”* and, thus, *“there needs to be a comprehensive analysis of the costs and benefits of installing such a sophisticated infrastructure”*. As part of our evaluation, we will integrate both the cost as well as the revenue perspective in a combined cost-value-model. This model will help to understand the value of information in Demand Response.

Research Question 1 (RQ1): (a) What are the costs when implementing Demand Response based on an Advanced Metering Infrastructure? (b) Which savings can be realized in such a setup?

As both costs and revenues in the above research questions are dependent on the information granularity, we will evaluate the behavior of our model across multiple information granularities. Therefore, we vary the frequency of meter readout between intervals of 60, 30, 15 and 10 minutes as input for our model. We especially address the research questions of Watson et al. (2010) and Jagstaidt et al. (2011) on the optimum level of information granularity in a sensor network for optimizing a given distribution network. As we are not aware of any publications examining Demand Response across varying information granularities, we will address the following research question.

Research Question 2 (RQ2): (a) How do the saving potentials change across multiple information granularities and (b) how does this affect the costs? (c) What is the optimal amount of information?

3 The Model

In this section, we analyze the IS architecture of a Demand Response system and depict the relevant information flows of Demand Response, in order to rigorously derive the costs structure and the savings from Demand Response afterwards. An integrated view on both perspectives allows us to realistically assess the profitability of DR solutions and answer the research questions.

3.1 Designing the Demand Response system

The benefits of Demand Response unfortunately do not come for free, since it requires a sophisticated IS infrastructure. For leveraging the advantages, the retailer needs a lot more information than is available in today's power networks. Hence, we lay out the design for an appropriate DR system and structure it according to the energy informatics framework of Watson et al. (2010), which partitions an energy system into the following building blocks: a central information system, sensor networks, sensitized objects, flow networks and related external stakeholders (cp. Figure 2).

Central information system. As stated earlier, we are focusing on a setup, where Demand Response is realized on the distribution network level. In such a setup, the Distribution Management System (DMS) is the core information system. It features functions allowing for network monitoring and dynamic decisions for optimizing resources and managing demands for the entire distribution network (Simmhan et al., 2011). Within the DMS, two modules are of special interest for executing DR programs: the load forecasting engine, for predicting shortages of supply, and the Demand Response engine, for determining an optimal load curtailment scheme.

Sensor networks. We are looking at a DR system based on an Advanced Metering Infrastructure (AMI). Hence, the AMI constitutes the sensor network closing the gap between the retailers' DMS and the distributed customer premises. The smart meter exhibits the interface towards the customer. We denote "smart meters" as electronic meters that collect energy consumption data, so-called usage data records, at user-defined time intervals and optionally feature a unit for two-way communication. The transfer of usage data records within the AMI happens across various types of communication networks. We restrict our focus to the two most popular (cp. Gungor et al., 2011), namely wireless networks (GSM), and power line carrier (PLC). Whereas GSM-enabled meters establish direct point-to-point connections with the backend, the communication stream from PLC-enabled meters is sent through concentrators. In any case, the central Meter Data Management System (MDMS) receives the collected usage data records, processes them and shapes the information into a useful asset for the retailer. These components build the "upstream" channel of an AMI. The "downstream" channel is composed by the central load management and control system, which distributes signals from the backend towards the consuming management system. The consuming management system represents the downstream's counterpart of the smart meter, forwarding the transmitted signals towards the sensitized objects at the customers' premises. The data volume that is produced within an AMI can easily overload a "traditional" DMS. Thus, upgrades for boosting its performance are required.

Sensitized objects. Both energy consuming (i.e. load control devices) and producing (i.e. distributed energy resources) devices can be connected to and controlled by the DR system. In doing so, the only pre-requirement for connecting any device is that it is capable of being remotely controlled.

Flow networks. Interfaces to the energy management system at the transmission network level secure information exchange with neighboring and overlying levels of the power network.

External stakeholders. The DR system is rounded off by interfaces to various service providers for acquisition of external data sources, such as energy prices and weather forecasts.

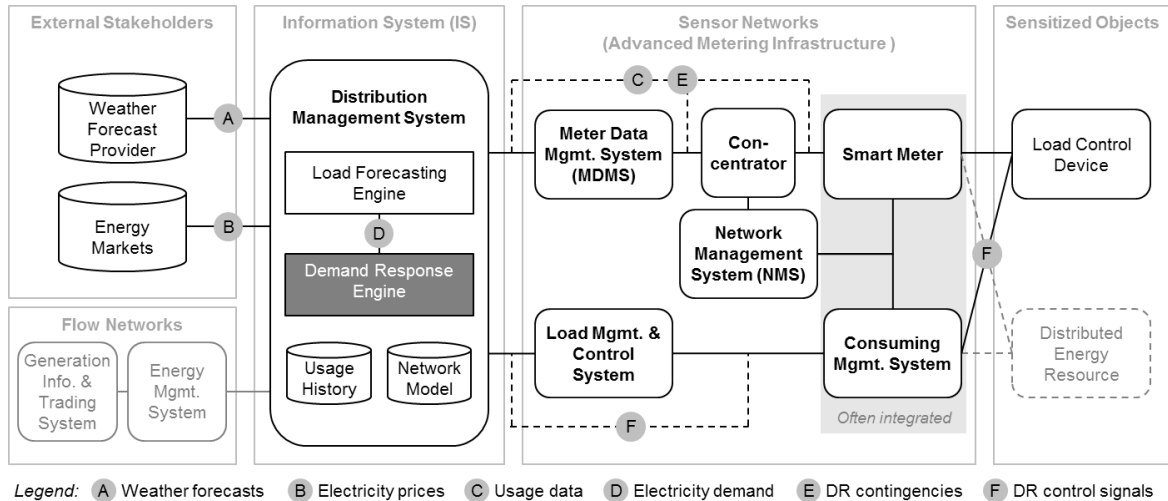


Figure 2. System view on a Demand Response system with Advanced Metering Infrastructures based on Mohagheghi et al. (2010), Watson et al. (2010), Simmhan et al. (2011), Sui et al. (2011).

For execution of a DR program (i.e. the algorithm), various information exchanges need to be established between components of the above DR system. The standardization process for respective communication protocols and interfaces for this purpose is still under way (cp. Arnold, 2011). Envisioning the information flow in a DR system and the arising data traffic is essential for deducing the related communication costs later on. In the following, we provide a brief overview of generic informational exchanges that need to be performed before and during execution of a DR program.

At first, the load forecasting engine projects the energy demand and supply for a future time window based on externally acquired weather forecasts [A] and electricity prices [B] and the usage data records [C], which are being collected from the connected smart meters.

In case the load forecasting engine detects a shortage in supply, it passes the respective shortfall value to the DR engine [D]. Subsequently, the DR engine determines the optimal load curtailment and reduction scheme for all consumers connected to the distribution network. The type of DR program determines the subsequent communication procedure that is being conducted between the Demand Response engine and the smart meters. As a matter of fact, there are three major variants of how the detailed process flow for a DR program can be organized (Mohagheghi et al., 2010): (1) incentive-based, (2) rate-based and (3) consumer-induced. We restrict our focus to incentive-based programs.

The execution of an incentive-based DR program follows a three-stepped approach. First, the consumer transmits his DR contingencies, i.e. his maximal shift duration and shiftable power amount, for the next optimization interval to the retailer [E]. Second, the retailers uses the collected DR contingencies in conjunction with the projected energy demand [D] and the electricity prices [B] to calculate the optimal load shifting scheme. Third, the retailer reports back a set of control signals to the consumer [F]. The control signals contain the commands, which specify when to curtail resp. shift certain loads at given future time windows. We assume that the control signals are designed to be mandatory, i.e. the consumer is bound to execute these commands.

The incentive-based DR program is an a-priori commitment by the consumers to reduce energy. Thus, the consumer receives a (monetary) compensation according to the prior defined incentive scheme after the load shifting took place. It should be noted, that all status and monitoring data (e.g. regarding the power quality), which is being transmitted across the network is not part of our considerations.

3.2 Cost structure of the Demand Response system

Based on the above architecture of a DR system we develop a cost model that incorporates both initial capital expenditures as well as the running costs for the system.

Sizing of the DR system is accomplished bottom-up – from the consumer interface towards the backend. Let x_{SM} be the number of smart meters of both residential and industrial customers, which are connected to the given distribution network. Going “upstream” the DR system, the number of concentrators x_C and MDMS servers x_M can be derived from x_{SM} . Let c_{SM} , c_C , c_M and c_N denote the running costs for the prior mentioned components. We assume the load management and control system’s functionality to be integrated with the MDMS. Similarly, the consuming management is assumed to be integrated into the smart meters. Furthermore, the NMS needs to be sized according to x_{SM} , which is reflected by the running cost c_N of the NMS. The DMS is assumed to be in place even without an AMI. But as stated earlier, the boosted information load in an AMI requires performance tweaks for the DMS. Thus, additional running costs for the DMS, denoted by c_D , are inevitable. Given these assumptions, we define the following cost pools.

Capital expenditures. The costs of procuring and installing the above mentioned components constitute the total capital expenditures for the DR system.

Communication costs. Two major communication streams need to be evaluated for depicting the communication costs: (1) executing the DR program and (2) reading out usage data records. Let β_{GSM} be the share of deployed meters with GSM-modules and c_{GSM} be the related price function for data transfer via GSM. Communication via PLC-enabled meters does not produce any volume-based costs. For executing the assumed incentive-based DR program, two messages need to be exchanged between retailer and consumer (cp. section 3.1). For simplicity’s sake and w.l.o.g. the frequencies of reading, meter values and for execution of DR control signals are assumed to be equal and denoted by f . Hence, the total daily data volume can be calculated as $v = 1440 \cdot f \cdot \gamma$, with γ being the total message size and 1440 the number of minutes per day. All in all, the communication costs per meter for executing the DR program result as

$$c_{COM,DR} = \underbrace{\beta_{GSM}}_{\text{Share of GSM meters}} \cdot \underbrace{v}_{\text{Data volume DR program}} \cdot \underbrace{c_{GSM}(v)}_{\text{Comm. cost GSM (per MByte)}} \cdot \underbrace{365}_{\text{days p.a.}}$$

The annual communication costs per meter for reading out usage data records are derived analogously and are denoted by $c_{COM,UD}$.

Operating costs. The operating costs cover the annual expenditures for e.g. maintenance, personnel, energy, etc. for all components of the DR system. The operating costs for the DR system are

$$c_{OP} = \underbrace{c_{SM} \cdot x_{SM}}_{\text{Smart meters}} + \underbrace{c_C \cdot x_C}_{\text{Concentrators}} + \underbrace{c_N}_{\text{NMS}} + \underbrace{c_M \cdot x_M}_{\text{MDMS}} + \underbrace{c_D}_{\text{DMS}}$$

Total running costs. The total annual costs for the DR system include the operating costs as well as the communication costs:

$$c = c_{OP} + c_{COM,DR} + c_{COM,UD}$$

For determination of the cost components we do not consider support costs (e.g. setup of a customer call center), related process costs (e.g. registration of new meters) and additional effort for integrating the DR system into the existing IS landscape. Further investments into the communication infrastructure, beside the deployed communication units, are not incorporated into the model.

3.3 Modeling the savings realized through Demand Response programs

Having assessed the cost perspective in the previous section, we now put the attention to the savings potentials of Demand Response. Therefore, we derive a mathematical model to optimize DR decisions. As shown in section 3.1, we design a DR engine that is affected by the following parameters: energy demand, DR contingencies and electricity prices. We restrict our model to support two of the most common energy derivatives: future options and day-ahead auctions. The former can be traded to guarantee – ahead of time – energy for long-term delivery periods ranging from years to single days. In order to reduce the complexity of our model, we aggregate all future options into a single derivative with price p_F per watt-hour. In addition, a day-ahead spot market provides energy at price $p_A(t)$ per

watt-hour for a specific time t of the day. As a third option, the intraday market can satisfy short-term energy needs, but can be neglected due to insufficient market liquidity.

The problem of optimally harnessing Demand Response can be formulated as a linear optimization problem (Feuerriegel et al., 2012). Accumulating the retailer's expenditures on energy derivatives yields the aggregated expenditures which embody the target function r_Σ (during an optimization horizon of N time steps) denoted by

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

The first summand accounts for the expenditures on future derivatives, while the second sums costs from 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 energy retailer is assumed to be only a purchaser of energy. As most German retailers do not produce electricity (Umweltbundesamt, 2013), this assumption is valid. Thus, the linear problem is bounded and a unique solution exists. We yield

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

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

$$q_A(t) + q_F/N = D(t) \quad \text{for } t = 1, \dots, N,$$

where the left-hand side accounts for the total energy purchased that is supposed to equal the right-hand side, which accounts for the energy demand.

Let us assume that we will be granted for each time interval a certain DR potential. This potential can now be shifted forward or backward in time. Here, we distinguish load shifting potential according to the maximum duration j (e.g. one, two, etc. hours) that it can be displaced. For each of these shifts j , the variables $\Delta_j(t)$ denote the available potential. When we shift DR potential between two hours t and t' , this is indicated, with j being the maximum length of the shift, by the parameter $DR_j(t, t' - t)$. The value of $DR_j(t, t' - t)$ denotes the amount of power that is consumed less at time step t , but that is additionally required at time step t' . In order to guarantee that demand matches the purchased energy amounts, we derive the following constraint,

$$q_A(t) + q_F/N = D(t) - DR_1(t, 0) - DR_2(t, 0) + \dots + DR_1(t + 1, -1) + DR_1(t - 1, +1) + DR_2(t + 2, -2) + DR_2(t + 1, -1) + DR_2(t - 1, +1) + DR_2(t - 2, +2) + \dots$$

This new 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 with some arbitrary i for reasons of readability $DR_j(t, i) \stackrel{\text{def}}{=} 0$.

Next, we derive additional constraints on 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. Therefore, we deduce

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

Additionally, we need additional constraints that limit the flow direction (i.e. that demand is moved solely away from time interval t). Therefore, when we shift energy from time interval t by j hours in either direction, this value cannot be negative,

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

Furthermore, we need to guarantee the conservation of used load shifting potential such that all demand that is shifted away is finally added somewhere else, thus

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

3.4 The value of information in Demand Response

In order to combine the two previously discussed views – namely costs and savings potentials of a DR system –, we introduce an expedient metric named *information value of Demand Response*. In the Smart Grid realm, the core information piece is given by usage data records. Their value is determined by multiple components, which can be derived from the numerous areas of application for which these records can be applied, such as process optimization through automated meter reading and optimization of energy demand and supply. Here, we focus on the contribution of Demand Response to the overall value of usage data records. Hence, we define the information value of a single record as

$$IV(f) = \frac{(\sum r_{\Sigma} - c)}{T}, \text{ with } T \text{ being the number of meter readouts per year.}$$

4 Evaluation – Computational Analysis

In the following section, we test our mathematical model in a setting using real-world data. The gained results are used for evaluating the above research questions.

4.1 Datasets

For our evaluation setting, we assume a fictitious German retailer delivering electricity to 290,000 residents. The retailer’s overall annual energy demand accounts for 2,000 GWh (E-Control, 2012). As a next step, we aggregate the average daily demand curves for residential households, commercial and industrial customers in Germany (E.ON, 2012) with ratio 25 %:/ 25 % / 50 % (Styczynski, 2011) to derive the hourly amounts of energy demand. To achieve an annual demand accounting for 2,000 GWh in total, the demanded power is normalized accordingly. Industrial customers are excluded from calculation of the DR saving potentials.

Commercial Customers	Max. Shift Duration/h	1	2	12	16
	Average Power Shift/kW	16 164	8850	4650	5129
Residential Households	Max. Shift Duration/h	1	2	12	24
	Average Power Shift/kW	7353	6750	35 068	3616

Table 3. DR Potential through load shifting scaled for retailer (Klobasa, 2007).

All prices for energy derivatives and spot auctions are based on the historic hourly data of the European Energy Exchange, EEX for short (EEX, 2012). Here, the price for future options q_F is based on the index prices named ELIX Day Base. The data granularity of electricity prices and energy demand is increased by linear interpolation to gain the desired granularity.

The capabilities of Demand Response vary strongly among both industry and households. Klobasa (2007) analyzed the market penetration of Demand Side Management and its overall potential for Germany (see Table 3). To utilize this potential, we assume a DR system characterized by the parameters in Table 5. The number of smart meters is computed as 220 k based on an assumed annual energy consumption of 3,500 kWh per residential household and 6,500 kWh per commercial customer. We assume that all meters are rolled out and put into operation at the same time.

By varying the frequency of collecting usage data from the meters, we have designed four scenarios to evaluate our model across different information granularities. Scenario 1 assumes an information granularity of 60 minutes. In this base scenario, the usage data is recorded once every 60 minutes or 24 times per day respectively. In fact, 60-minute-intervals are a frequent delivery period when trading at energy exchanges (EEX, 2012). In the case of Germany, 60-minute-intervals are further enforced by regulatory issues (Bundesnetzagentur, 2012). Scenario 2 assumes an information granularity of 30 minutes, while scenario 3 is based on an information granularity of 15 minutes. In related literature (cp. PWC Austria, 2010), a 15-minute-interval is often used as standard for collection of usage data records. In scenario 4, the information granularity is increased further and set to 10 minutes. Calculating the

results for this scenario already required more than 24 hours of computation and, therefore, we restricted our evaluation to these four scenarios.

Parameter	Variable	Value
Share of GSM-enabled smart meters	β_{GSM}	20%
Communication costs for GSM per kByte	c_{GSM}	Logarithmic cost function
Hardware costs per meter GSM / PLC	c_{SM}	€ 95 / € 80
Number of PLC-enabled meters per concentrator	x_{SM}/x_C	200
Number of meters per MDMS server	x_{SM}/x_M	30,000, for $f = 1/15$
Size of messages per iteration of DR program	γ	300 byte

Table 4. Parameters of Demand Response system based on expert estimations and PWC Austria (2010) and NERA Economic Consulting (2008).

4.2 Results

This section addresses each research question (cp. section 2.2) individually to present our findings.

Findings to Research Question 1. When evaluating the costs and revenues of a DR system, we recall scenario 1 with a granularity of 60 minutes. The initial investments for the system add up to a total sum of € 24.217 M and the annual running costs amount to € 3.381 M (RQ1a). The corresponding annual savings account for € 3.10 M (RQ1b) – resulting in a positive annual surplus. The DR case has the potential to financially sustain itself, when only running costs, without investments being considered. Following this assumption, Demand Response even contributes a substantial share to the overall business case of introducing AMI.

Findings to Research Question 2. Next, we assess the DR system’s financial performance across varying information granularities. The results of potential savings and costs are listed in Table 5.

Load shifting decreases the retailer’s expenditures for procuring electricity from € 109.9 M down to € 106.8 M – a significant cut of € 3.10 M. An increase in information granularity allows the retailer to allocate energy even more efficiently. By increasing data granularity to 15 minute intervals, earnings rise to € 3.360 M. Compared to the 60 minute case, this is a considerable increase of 8.04 %. Scenario 4 shows a lower efficiency gain compared to the other granularities which might be a drawback of using a polynomial interpolation of first order in our model. When comparing the savings with and without DR, the results turn out to be more striking. The benefit from a higher granularity is several times higher than in the case without DR – purely by shifting load more efficiently.

	Scenario 1: 60 minutes	Scenario 2: 60 vs. 30 min	Scenario 3: 60 vs. 15 min	Scenario 4: 60 vs. 10 min
Savings from higher granularity only	–	€ 80 k	€ 90 k	€ 90 k
Savings from DR & higher granularity	€ 3.10 M	€ 3.230 M	€ 3.360 M	€ 3.270 M
Efficiency gains	–	+3.86 %	+8.04 %	+5.14 %
Total running costs	€ 2.852 M	€ 3.080 M	€ 3.471 M	€ 3.788 M
... thereof: DR communication costs	€ 124 k	€ 213 k	€ 357 k	€ 477 k
Total cost increase	–	+7.99 %	+21.70 %	+32.79 %
Information value per 1000 meter readouts	€ 0.20	€ 0.06	€ -0.02	€ -0.07

Table 5. Comparison of efficiency gains in 2011 across different information granularities.

Looking at the costs, we observe an increase as well. In particular, the communication costs grow severely; doubling the information granularity exhibits the double amount of data that needs to be transferred and processed. Hence, the communication costs almost quadruple when comparing scenario 1 and 4, whereas the remaining operating costs only increase by around 8 %.

The information value links costs and saving potentials. An information value that grows with an increasing information granularity is equivalent to an improved overall profit of the retailer. In such a case, more information would result in higher profits. However, counter-intuitively, our results draw a different picture (see Figure 6): the information value decreases heavily with increasing information density. Based on our four scenarios we reckon that the information value even decreases more than linear, leaving the retailer with a shrinking overall annual profit. In addition to that, Figure 6 shows the information value for data granularities of 90 and 120 minute intervals where hourly blocks are traded at the day-ahead market. As the meter readout granularity exceeds the market resolution, the load cannot be shifted to the optimal time interval and, matter-of-factly, the information value turns negative.

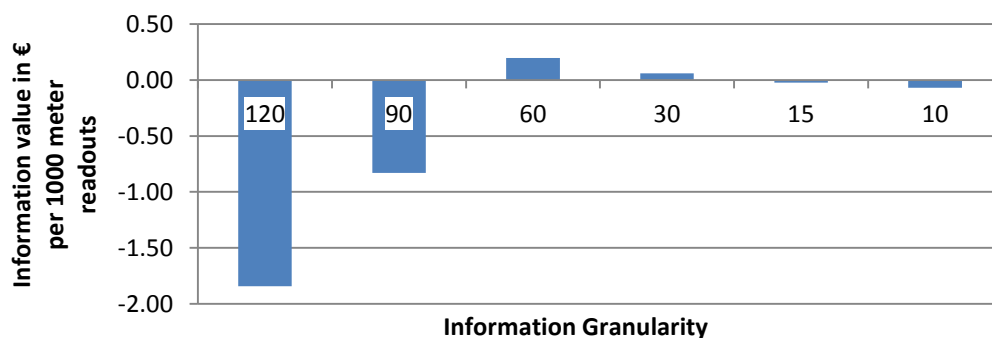


Figure 6. The diagram shows the information value for granularities across 120 to 10 minutes. We assume spot auctions with delivery periods that match the granularity, except for the 90 and 120 minute cases where hourly blocks are traded at the day-ahead market.

In a nutshell, we have shown that – for our setting – an augmented information granularity boosts the savings potentials significantly (RQ2a). However, the savings are eaten up by disproportionately increasing costs (RQ2b). Summing up, these findings lead to a surprising conclusion regarding the optimal information granularity (RQ2c): more information is not better, but even leads to shrinking financial profits. However, based on our set of four discrete scenarios, a universal proposition on the optimal amount of information cannot be provided.

4.3 Managerial and policy implications

In the previous evaluation section, we have illustrated the potential profits of a DR system. Beyond costs for setup and operations of the system, the implementation as well as the success is also determined by additional cost components. In particular, financial compensation to the participating consumers must be considered due to the assumed incentive-based DR program. Klobasa (2007) proposes an average payment of roughly € 2 per MWh.

As shown, if only Demand Response is being considered as a use case for installation of an AMI, more information does not necessarily entail more profit. However, it should be taken into account that for other application scenarios, such as not-yet-defined value-added services, a higher information granularity is essential or leading to a considerably better service quality and, thus, an increased profit.

Furthermore, when looking at the financial benefits of implementing an AMI, one cannot disregard the potential cross-effects, such as reduction of consumed energy due to an increased transparency on the consumer side, which would lead to reduced revenues of the retailer. Analogously, additional positive effects could occur. For example, process costs would be reduced as a result of billing process automation and improvement. In addition, further synergy effects can potentially be realized when implementing gas and water meters as well.

The regulator inherits a very important role in the context of smart meter rollouts. First, the regulator designs the market roles involved in operations of a DR system. In major energy markets (e.g. Germany), the concept of segregated market roles has been implemented. The variety of players, such as metering point operators, distribution network operators and energy suppliers, significantly increases the complexity of a DR system. The increased number of interfaces leads to more demanding security requirements and a higher data volume. Second, the regulator decides upon subsidization for an AMI rollout. Our results contribute to this policy discussion as they support the argument of providing substantial subsidy for implementing such an infrastructure. The use case of Demand Response is not capable of fully funding the required infrastructure, but it can contribute a substantial value share to its operations.

5 Conclusion and Outlook

Due to the integration of intermittent resources of power generation, the amount of supplied energy 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 we have shown in this paper, savings from load shifting exceed the running costs for a respective information system significantly. However, an average energy retailer faces huge initial costs for setting up an appropriate infrastructure. As these costs cannot be covered by the annual surplus, governmental subsidies might be necessary to install the DR system. Moreover, we have shown that collecting more information does not necessarily yield a higher profit for the retailer; increasing revenues are devoured by a disproportionate increase in costs. We have shown the financial impact of a DR system for a retailer in Germany. The results can be easily transferred to other European countries that rely on a similar energy market design.

In future work, we will apply a multi-year perspective as, especially, communication costs are likely to become significantly cheaper over the next year. Moreover, the communication protocols probably get further optimized and, thus, induce less communication efforts. In addition, changing the DR system's topology (e.g. deployment of aggregators or different communication media) might alter the cost effects. Additional positive cost effects might originate from using Demand Response for grid stabilization instead of load shifting. These questions must be addressed in future work.

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