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**Author(s):**
Feuerriegel, Stefan; Bodenbenner, Philipp; Neumann, Dirk

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# Value and granularity of ICT and smart meter data in demand response systems

Stefan Feuerriegel[a,*], Philipp Bodenbenner[a], Dirk Neumann[a]

[a]*Chair for Information Systems Research, University of Freiburg, Platz der Alten Synagoge, 79098 Freiburg, Germany*

**Abstract**

The large-scale integration of intermittent resources of power generation leads to unprecedented fluctuations on the supply side. An electricity retailer can tackle these challenges by pursuing strategies of flexible load shifting – so-called demand response mechanisms. This work addresses the associated trade-off between ICT deployment and economic benefits. The ICT design of a demand response system serves as the basis of a cost-value model, which incorporates all relevant cost components and compares them to the expected savings of an electricity retailer. Our analysis is based on a typical German electricity retailer to determine the optimal read-out frequency of smart meters. For our set of parameters, a positive information value of smart meter read-outs is achieved within an interval of 21 to 57 minutes regarding variable costs. Electricity retailers can achieve a profitable setting by restricting smart meter roll-out to large customers.

*Corresponding author. Mail: stefan.feuerriegel@is.uni-freiburg.de; Tel: +49 761 203 2395; Fax: +49 761 203 2416.

*Email addresses:* `stefan.feuerriegel@is.uni-freiburg.de` (Stefan Feuerriegel), `philipp@bodenbenner.de` (Philipp Bodenbenner), `dirk.neumann@is.uni-freiburg.de` (Dirk Neumann)

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## 1. Introduction

Environmental sustainability has lately been identified as a prioritized societal goal. This evolving awareness has led to the fundamental transformation currently taking place in the energy sector; in particular, sustainability goals accelerate the introduction of renewable energy sources. For example, the European Union has set targets for renewables to make up 20 % of the total electricity generation by the year 2020 (EU-DEEP, 2009). The increasing share of renewable energy sources inevitably leads to unprecedented fluctuations in electricity supply. Hence, power grid operators face major challenges in stabilizing the grid and preventing imbalances between demand and supply (Lopes et al., 2007).

One remedy is to actively manage electricity demand so that it follows the shape of the fluctuating supply. This so-called *demand response* (DR) allows electricity providers, typically retailers, to flexibly shift load from peak times, associated with high costs, to off-peak time slots, where costs are much lower. Retailers can thus realize savings from optimizing their electricity procurement (Aalami et al., 2010; Aghaei and Alizadeh, 2013; Feuerriegel and Neumann, 2014).

The integration of demand response into electricity markets still remains an active area for research (Aghaei and Alizadeh, 2013; Strbac, 2008). For instance, Strbac (2008) claims that there is a lack of understanding of the benefits of demand response and, as such, *"there needs to be a comprehensive* *analysis of the costs and benefits of installing such a sophisticated infrastructure"*. Open questions are posed relating to, in particular, *information and communication technology* (ICT), such as the *"trade-off between ICT deployment and the achieved benefits in economic terms"* (Goebel et al., 2014). To close this research gap, this work contributes to the understanding of ICT costs within demand response systems as follows:

- **System design**. We formulate the underlying information flows and the architecture of an *information system* (IS).
- **Cost-value model**. Based on the IS architecture, we derive a comprehensive cost-value model for a DR system to determine its profitability.
- **Value of smart meter data**. Information on customers' usage patterns plays a key role in the smart grid, as more fine-grained data allows more precise demand management. We examine the monetary value of smart meter data across different read-out frequencies.

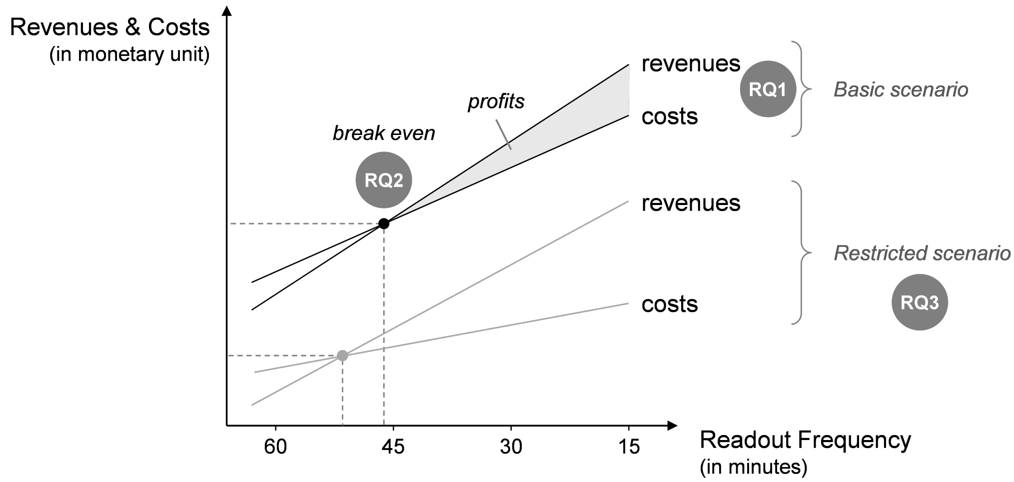


Figure 1: Research agenda with research questions labeled RQ1 to RQ3. Plot shows costs and revenues of demand response across different read-out frequencies of smart meters.

Our research agenda is illustrated in Figure 1. The plot shows curves indicating the costs and revenues from operating demand response with changing read-out frequencies. The intersection identifies the break-even point at which the operation becomes profitable. Individual research questions are as follows:

1. An advanced metering infrastructure comes with significant setup costs, IT-related run costs and potential savings. The analysis must address the question of whether the operation is profitable. Here, we utilize data for a typical Germany electricity retailer to compare different cost scenarios.

2. We then derive the optimal read-out interval for smart meters (indicated by the break-even point in Figure 1). Based on these results, we specifically address the open research questions that have been raised by Jagstaidt et al. (2011) regarding the optimum level of information granularity in a sensor network.

3. The setup of a comprehensive DR system requires substantial capital expenditures. It might be reasonable for an electricity retailer to restrict the roll-out of smart meters to certain groups of customers, since costs outrun benefits for small customers. We compare two scenarios, namely, a *basic* and a *restricted scenario* (see Figure 1). The basic scenario assumes all consumers operate smart meters for demand response, whereas, in the *restricted scenario*, smart meters are limited to the most valuable consumers.

The way in which read-out intervals of smart meters influence demand response has been studied in the literature (Feuerriegel et al., 2013; Bodenbenner and Feuerriegel, 2014). This research, however, is a major extension: we perform a rigorous study across the full spectrum of read-out intervals, compare different scenarios and, additionally, derive the optimal read-out interval mathematically.

The remainder of the paper is structured as follows: Section 2 reviews related works on the IS design and ICT dimension of DR systems. To close the research gap, Section 3 describes the design of an information system for demand response. Subsequently, Section 4 proposes a cost-value model, which Section 5 then evaluates using data from a typical electricity retailer. Finally, we discuss the results and outline managerial implications in Section 6.

## 2. Literature review

Demand side management today is still in its infancy: installations predominantly use rather simple mechanisms that exert *direct load control* for singular use cases. For example, the remote control of heating, ventilation and air conditioning systems allows grid operators to remotely switch on and off a number of electricity consuming devices according to the actual supply situation.

Using demand response in more comprehensive application scenarios, such as enabling an electricity retailer to perform load shifting for thousands of devices, requires the setup of large information networks in conjunction with sophisticated communication infrastructure. Taking the intricate information flows and huge volumes of data into account, ICT is regarded as a key enabler for the integration of load shifting into the electricity grid (Callaway and Hiskens, 2011). In particular, ICT is expected to unlock the full potential of flexible loads and allow effective demand side management for large numbers of such loads across multiple time scales (Callaway and Hiskens, 2011). Even if ICT *"is not a panacea to address all major challenges in a smart grid (...), it allows countries to manage growing volumes of electricity produced from renewable energies and supports structural shifts in supply and demand"* (Reynolds and Mickoleit, 2011).

With the focus restricted to demand response as an instrument for achieving smart grids, the scope of relevant literature is considerably narrowed. Among them, Corbett (2011) hypothesizes that a DR system will lead to an increase in information processing requirements. As a consequence, the author argues that DR systems will incur massive volumes of data, an inherent IS problem.

Various authors work on the architecture and components of a DR system. For instance, Palensky and Dietrich (2011) construct a web-based energy information system and name its typical components. Tan et al. (2012) propose a high-level design of a decision support system for demand side management. Sui et al. (2011) provide a high-level overview on how to utilize smart metering to set up a DR system. Furthermore, Mohagheghi et al. (2010) discuss the integration of DR architectures into a network control center on the distribution network level and present the underlying communication flow. Finally, Law et al. (2012) focus on tethering the end-consumer.

In addition to these aforementioned publications on DR systems, there are a number of publications dealing with different aspects of smart grids in general. For our purpose, the topics of smart metering and advance metering infrastructures are particularly interesting (e. g. Galli et al., 2011; Gungor et al., 2011).

## 3. System model for demand response

This section provides a technical perspective on DR systems by presenting the flow of information and deriving the corresponding architecture. In many studies related to demand response (see e. g. EU-DEEP, 2009; Smart Energy Demand Coalition, 2011, and EU funded project ADDRESS), it is usually assumed that demand response adoption will be driven by electricity retailers. Consequently, we focus on a setup where DR activities are integrated on the distribution network level.[1]

For the sake of simplicity, but without loss of generalization, we assume an incentive-based demand response program, which is based on a priori commitments of consumers to shift electricity demand (Mohagheghi et al., 2010). Consumers thus communicate their maximal shift duration and shiftable power volume to the retailer. Based on this information, the retailer calculates the optimal load-shifting scheme for each consumer and remotely controls the con-

[1] In this way, we implicitly incorporate requirements imposed by the power grid structure into our modeling efforts (Mohagheghi et al., 2010).

sumers' devices accordingly. With direct load control, this would likely happen automatically across different (household) appliances, such as washing machines and heating. Finally, the consumers receive compensation according to the defined incentive scheme. This approach ensures full efficiency, i. e. all adjustments on the consumer side are executed as demanded – there is no need to take into consideration individual consumer behavior.

### *3.1. Protocols for data exchange*

Even though a number of different data packages have to be exchanged between the retailer and the consumer to use DR programs, there is currently no standard protocol or established message specification (Arnold, 2011).[2] In the following, we develop a generic exchange of data for operating a DR program that is extracted from the aforementioned protocols.

[2]The ongoing debate of researchers and professionals deems *Data Language Messaging Specification/Companion Specification for Energy Metering* (DLMS/COSEM), *Open Automated Demand Response* (OpenADR), and *Smart Energy Profile* (SEP) to be promising candidates for a future standard (McParland, 2012).

*3.2. Information flows*

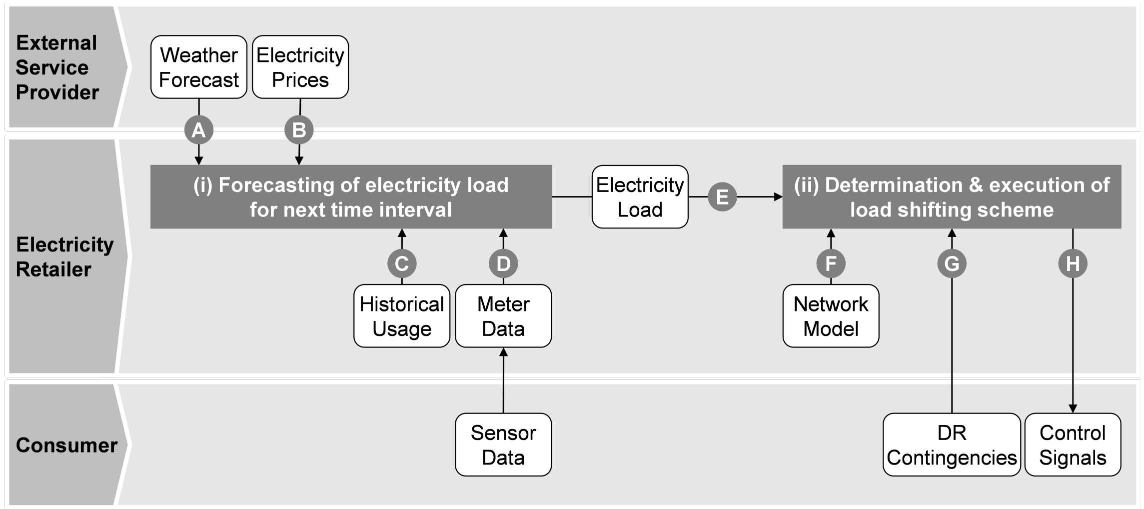


Figure 2: Information flow in an incentive-based demand response system.

As visualized in Figure 2, an incentive-based DR program runs in two phases: (i) forecasting the load for a future time slot and (ii) determining load curtailments if necessary. In more detail, thesea are as follows:[3]

- **Load forecasting**. Initially, the retailer forecasts the electricity demand and supply for a future time window based on the historic and current electricity consumption. Information concerning the consumption is extracted from the usage data records D, which the retailer collects from the connected

[3]The illustrated communication exchange between retailer and consumer – intentionally – includes some simplifications, i. e. an executable design of a communication protocol, additional notification and status messages are presumably required. Certain security requirements might induce additional message transfers. Furthermore, all status and monitoring data (e. g. regarding the power quality) transmitted across the network is not included our considerations.

smart meters. In case the load forecasting algorithm detects a shortage in supply, a suitable load curtailment scheme has to be calculated.

- **Load curtailment**. The projected load forecast E serves as input for determining the load curtailment scheme for all consumers that are connected to the distribution network. First, the retailer requests the consumers to transmit their available DR contingencies (i. e. their maximal shift duration and shiftable power volume) for the next optimization interval G. In the second step, the retailer uses the projected electricity demand along with the network model F and contingencies to determine an optimal load shifting schedule. The retailer then sends a set of control signals H to the smart meters or load control devices in order to induce the required load shifts.

### *3.3. IS architecture of the demand response system*

The previously described information flows of a DR program can be translated into a corresponding system design, as shown in Figure 3 (see online appendix for details).

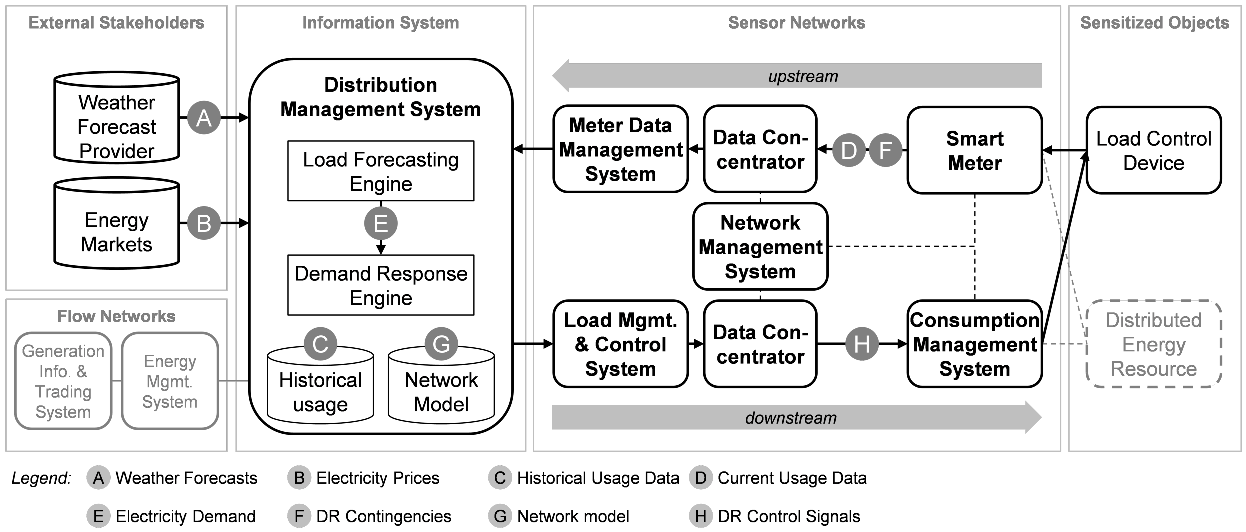


Figure 3: System view on demand response with advanced metering infrastructure based on Mohagheghi et al. (2010), Lo and Ansari (2011), Simmhan et al. (2011), Sui et al. (2011), as well as Fan et al. (2013).

### *3.4. Communication technology for demand response systems*

Demand response systems are often based on an advanced metering infrastructure (AMI). This type of DR system is endorsed by McDonald (2008) since it assumes *"a critical role in the discussion of finding least-cost alternatives to new build or expensive power purchases"*. An AMI establishes two-way communication and consequently higher control and accuracy when compared to other infrastructures used for direct load control programs.

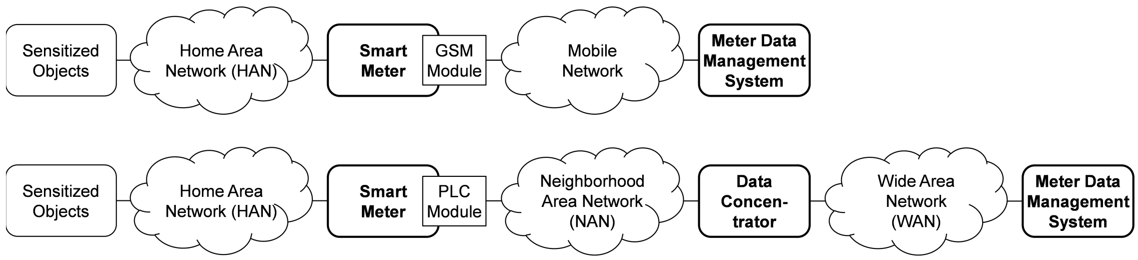


Figure 4: Differences in required communication infrastructures based on GSM (top) and PLC (bottom).

We denote smart meters as electronic meters that collect electricity consumption data from the consumer, so-called usage data records, at defined time intervals and optionally features a unit for two-way communication (Brophy Haney et al., 2009). Data within an AMI can be transferred through various types of communication technology (see e. g. Fan et al., 2013; Khalifa et al., 2011; Lo and Ansari, 2011). However, mobile phone networks (GSM and its successors) and *power line carriers* (PLC) are regarded as the most suitable technologies for smart grid applications (see e. g. Galli et al., 2011; Gungor et al., 2011; Llaria et al., 2013). They combine cost-effectiveness and bandwidth, while not requiring the installation of additional cables. Their characteristics are as follows (see Figure 4):

- GSM-enabled meters establish direct point-to-point connections with the AMI backend by making use of the widely available wireless GSM network.

- The communication stream from PLC-enabled meters is sent through data concentrators that are directly connected to the backend. PLC has traditionally been used by electricity retailers for remote metering and (low bandwidth) load control applications.

## 4. Cost-value model for smart meter data in demand response systems

In this section, we present the cost-value model to gauge both the cost and saving potentials of implementing a DR program. The online appendix investigates the costs, which the components of the previously described DR infrastructure generate. Moreover, we use an optimization problem (see online appendix) to model optimal load shifts and, consequently, allow the retailer to procure cheaper electricity. Finally, we integrate the cost and saving perspectives in a combined metric named the *information value for demand response*.

### *4.1. Model assumptions*

Our model is based on the following assumptions.

- We do not consider any cross-effects of the DR programs, such as the impact on electricity prices or a fundamental reduction in electricity demand.
- In order to determine the savings, we only consider load shifting. Additional DR mechanisms, such as peak clipping, are not part of the model. Furthermore, we focus on day-ahead electricity markets, while neglecting other markets, e. g. for reserve energy.
- The model assumes that the retailer owns the distribution management system and the sensor network. In reality, the ownership and operations of the infrastructure are split between several parties, especially in liberalized electricity markets. This may require additional efforts to secure data transfer between the parties.
- The model considers the IS and communication infrastructure attributed to the retailer. The components and communication networks of the end user,

namely, the sensitized objects and home area networks (HAN), are not integrated. Other studies concentrate on this aspect of smart grid infrastructure (Gottwalt et al., 2011). We presume the availability of remotely controllable devices on the premises of all end users, as this is a necessary condition for the efficient use of DR programs in our setup.

### 4.2. *Value of smart meter data for demand response*

In the following, we conduct a value of information analysis (Keisler et al., 2014), which compares the associated revenues and costs. Therefore, we introduce an expedient metric that measures the value of usage data from smart meters; we name this *information value of demand response*.

The overall run costs $C_{\text{VAR}}(f,t)$ for a DR system in a year $t$ are computed by adding up operation and communication costs. Let $R(f,t)$ denote the retailer's savings given a read-out frequency $f$ at a time step $t$. Consequently, we define the information value of demand response of a single usage data record in year $t$ as

$$IV_{\text{VAR}}(f,t) = \frac{R(f,t) - C_{\text{VAR}}(f,t)}{F(t)} \tag{1}$$

with $F(t) = Mf$ as the total number of read-out operations in year $t$, where $M$ gives the number of minutes per year. We supplement $IV_{\text{VAR}}(f,t)$ with a second metric

$$IV_{\text{TOT}}(f,t) = \frac{R(f,t) - C_{\text{VAR}}(f,t) - C_{\text{FIX}}(f)}{F(t)}. \tag{2}$$

that incorporates the annual fix costs $C_{\text{FIX}}(f)$.

### 4.3. *Setup and data for computational analysis*

For our evaluation, we assume scenarios and data as follows:

- **Electricity consumption.** We evaluate our model with data that resembles a typical German electricity retailer responsible for 2000 GWh. We exclude 50 % of the electricity consumption since this portion is consumed by large industries, which often have special contracts. The remaining 1000 GWh is equally divided between residential households and commercial customers. We further assume that average annual electricity consumption totals to 3500 kWh per residential household and 6500 kWh per commercial customer. This is equal to a customer base for the retailer of 143,000 households (i. e. 290,000 residents) and 77,000 commercial customers.

- **Smart meters.** Consequently, this setup requires a total of 220,000 smart meters. Not all smart meters need to be equipped with their own communication module; they can be bundled in larger apartment buildings. With the distribution of household and building sizes in Germany taken into consideration, the required communication modules total 130,000.

- **Electricity demand.** To determine electricity usage per hour, we use the aggregated average daily load profiles for household and commercial customers in Germany (E.ON, 2012); these standard load patterns are usually applied by retailers in practice. The capabilities of shifting load vary considerably between both commercial consumers and residential households (see Table 1).

- **Electricity prices.** To calculate potential savings, we use historic hourly data from the EEX to configure the cost-value model (EEX, 2012). The price for future options is based on the index prices, named ELIX Day Base. All additional configuration parameters of the cost model are summarized in

Table 2.

- **Revenue function.** The given optimization model is very complex and extensive; computing continuous values for the revenue function is not feasible. This is particularly true for very small values of $f$. Hence, we approximate the revenue function by a quadratic polynomial for a given optimization model configuration.

- **Scenarios.** We evaluate our model in the two previously defined scenarios, namely, the basic scenario and the restricted scenario. In both scenarios, the smart meters are rolled out stepwise to the consumers; full coverage is reached after a period of six years. We have chosen a total observation period of 15 years, since this resembles the typical lifetime of a DR infrastructure (PWC, 2010). After 15 years, new investments are likely to be made to upgrade the infrastructure.

| | | | | | |
|---|---|---|---|---|---|
| Commercial Consumers | Max. Shift Duration (in h) | 1 | 2 | 12 | 16 |
| | Average Power Shift (in kW) | 16,164 | 8850 | 4650 | 5129 |
| Residential Households | Max. Shift Duration (in h) | 1 | 2 | 12 | 16 |
| | Average Power Shift (in kW) | 7353 | 6750 | 35,068 | 3616 |

Table 1: DR potential through load shifting scaled for the electricity retailer in our evaluation setting, based on Klobasa (2007).

| Parameter | Variable | Value |
|---|---|---|
| Share of GSM-enabled smart meters | $\beta_{\text{GSM}}$ | 20 % |
| Volume-based communication costs for GSM | $c_{\text{GSM}}$ | Logarithmic cost function |
| Hardware costs per meter (incl. GSM-/PLC-module) | $c_{\text{SM}}$ | € 95 / € 80 |
| Number of PLC-enabled meters per concentrator | $\omega_{\text{C}}$ | 200 |
| Number of meters per MDMS server | $\omega_{\text{M}}$ | 30,000 for $f = 15$ minutes |
| Number of meters per NMS | $\omega_{\text{N}}$ | 1, i. e. NMS is continuously scalable |
| Size of messages per iteration of DR program | $\gamma$ | 300 Byte |

Table 2: Parameters of demand response system based on expert estimations (NERA Economic Consulting, 2008; PWC, 2010).

## 5. Value and granularity of ICT data in demand response systems

This section analyzes the financial value of collecting smart meter data within a DR system. Based on the findings, we derive managerial and policy implications.

### *5.1. Influence of read-out intervals on ICT costs*

We now evaluate the cost-value model across two scenarios: (i) the prices for GSM communication stay constant throughout the observation period, denoted as $\Omega_{\text{CON}}$ or (ii) prices decrease annually with an annual price decline by $\Omega_{\text{MIN}} = 5\,\%$ and $\Omega_{\text{MAX}} = 15\,\%$. With the increasing efficiency and prevalence it is expected that GSM communication follows the past trend of decreasing prices. Figure 5 plots IT-related run costs $IV_{\text{VAR}}$ of smart meter data over time. Here, the electricity retailer achieves a profitable value after a few years only for scenarios $\Omega_{\text{MIN}}$ and $\Omega_{\text{MAX}}$. In the fifteenth year, the DR program generates an information value $IV_{\text{VAR}}$ per 1000 meter read-outs between € −0.013 for $\Omega_{\text{CON}}$ and € 0.103 for $\Omega_{\text{MAX}}$.

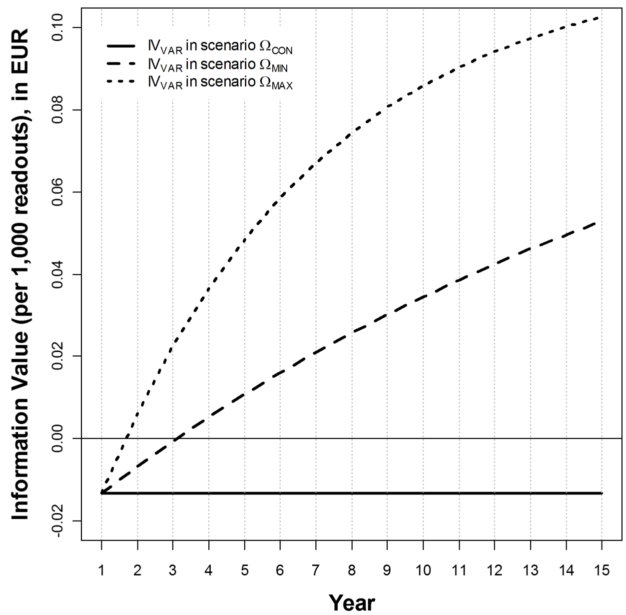


Figure 5: Information value $IV_{\text{VAR}}$ of the demand response system compared across different price declines for GSM-transactions. The figure shows the accumulated information value for 1000 meter read-outs and a meter read-out interval of 60 minutes.

The picture further deteriorates when including capital expenditures, since the roll-out requires immense investment. In our setting, the infrastructure exhibits a negative overall net present value (NPV) of €−22.37 M for scenario $\Omega_{\text{CON}}$ over a runtime of 15 years and a prevalent discount rate of 5 %. A marginally better result can be achieved when assuming a scenario $\Omega_{\text{MAX}}$; the NPV is still negative and accounts for €−20.91 M.

In the following, we assess which parameters need to be adjusted to obtain a profitable system configuration. We first analyze the communication technology, followed by the price of smart meters.

#### 5.1.1. *Sensitivity analysis: share of GSM-based smart meters*

As data transfer is at the core of a DR program, it is obvious that these components have a substantial impact on the cost of the DR infrastructure. In the case of communication via GSM networks, usage-based charges have to be paid in addition to base fees. In contrast, PLC communication only generates base fees without any usage-based premiums. Hence, the number of smart meters with GSM communication modules considerably determines the annual costs. To assess the exact impact, we conduct a sensitivity analysis by varying the share of smart meters with GSM modules.

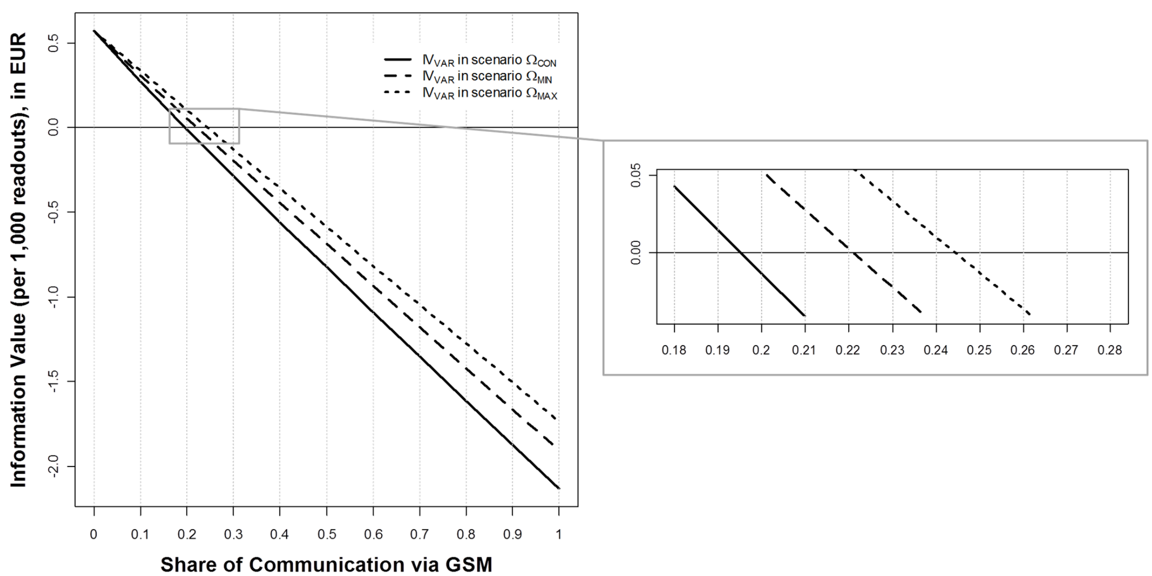


Figure 6: Results of sensitivity analysis reveal how the share GSM communication affects the information value $IV_{\text{VAR}}$. The figures are based on a meter read-out interval of 60 minutes and show values in year $t = 15$.

In order to determine the maximum share of GSM communication, we set the information value to zero and solve the equation for the GSM share $\beta_{\text{GSM}}$.

Figure 6 illustrates the results of the sensitivity analysis. When considering only the run costs, the share of GSM-based communication has to be below 19.60 % in the constant scenario $\Omega_{\text{CON}}$ and 24.50 % in scenario $\Omega_{\text{MAX}}$ to achieve a profitable system configuration.

When also taking the capital expenditures into account, the information value is negative for any given GSM share in the chosen system configuration; even when all communication is carried out via PLC, a positive surplus cannot be achieved. The share $\beta_{\text{GSM}}$ of GSM transactions substantially determines the profitability of a DR system, as formulated in Proposition 5.1 (the proof is given in the online appendix).

**Proposition 5.1** *The information value $IV_{\text{VAR}}$ is positive for all shares of GSM communication that satisfy*

$$\beta_{\text{GSM}} \geq 0 \text{ and } \beta_{\text{GSM}} < \frac{T\ [R(f) - c_{\text{OPS}}(f)]}{x_{\text{SM}}\, \varepsilon\, v(f) \sum_{t=1}^{T} c_{\text{GSM}}^{t}(v(f))} \tag{3}$$

*with the total number of smart meters $x_{\text{SM}}$, the ratio $\varepsilon$ of of smart meters including communication modules and an annual data volume $v(f)$.*

As shown, a positive information value cannot be achieved in full cost calculation (i. e. taking fixed costs into consideration, as well as run costs) when only the share of GSM communication is taken as the basis for a sensitivity analysis.

#### *5.1.2. Sensitivity analysis: cost of smart meters*

The installation and operation costs of smart meters are critical cost drivers as well. Due to their high value, smart meters have a significant influence on the total cost of a DR system. Hence, we broaden our analysis by incorporating the costs of smart meters into the sensitivity analysis. The parameter set contains the share of GSM communication and the cost of smart meters. Even for this extended sensitivity analysis, noticeable reductions of parameter values are required to obtain a profitable system configuration.

Compared to the initial system configuration, the parameters under consideration (i. e. GSM share and costs for smart meters) have to be decreased by 30.84 % in the constant scenario $\Omega_{\mathrm{CON}}$, by 29.64 % for $\Omega_{\mathrm{MIN}}$ and by 28.30 % for $\Omega_{\mathrm{MAX}}$ to achieve a positive total information value.

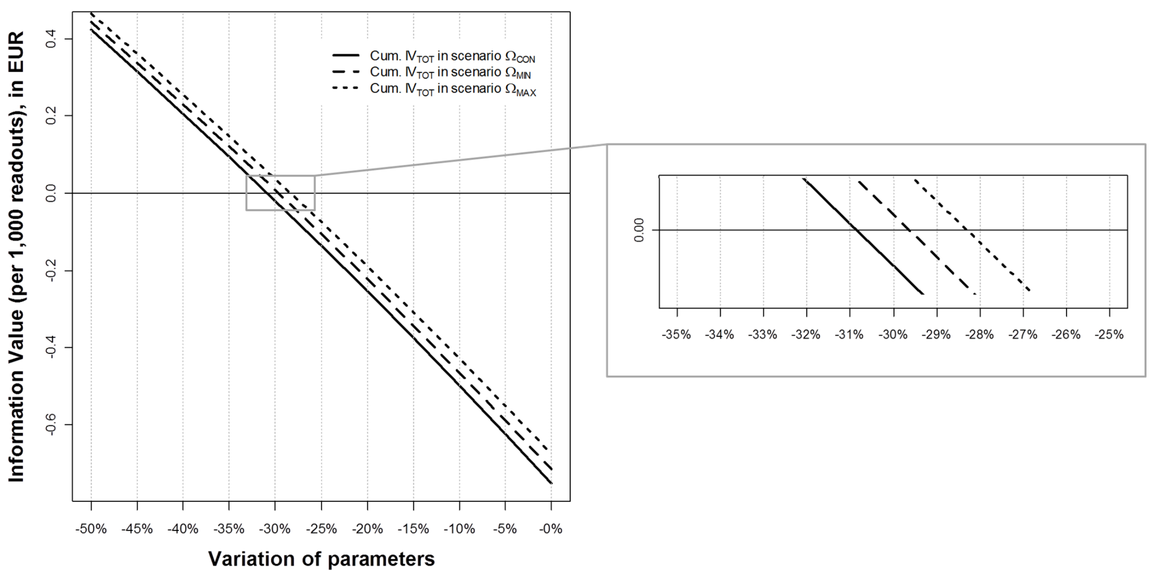


Figure 7: Results of sensitivity analysis combining variations of GSM share and costs of smart meters. The curves show the accumulated information value of $IV_{\mathrm{TOT}}$ based on a meter readout interval of 60 minutes.

Figure 7 presents the results of the extended sensitivity analysis. Further details are presented in Table 3. The initial hardware prices of smart meters need to be as low as € 65.70 (GSM-enabled) and € 55.39 (PLC-enabled) in the constant scenario $\Omega_{\text{CON}}$ to become profitable. These prices are far below current market prices; they could only be achievable by the purchasing power of a very large electricity retailer.

| **Scenario** | Percentage decrease of parameters | GSM share | Cost of GSM-enabled smart meter | Cost of PLC-enabled smart meter |
| --- | --- | --- | --- | --- |
| **Initial system configuration** | | | | |
| | — | 20.00 % | 95.00€ | 80.00€ |
| **Target values of parameters** | | | | |
| $\Omega_{\text{CON}}$ | −30.84 % | 13.83 % | 65.70€ | 55.39€ |
| $\Omega_{\text{MIN}}$ | −29.64 % | 14.07 % | 66.84€ | 56.29€ |
| $\Omega_{\text{MAX}}$ | −28.30 % | 14.34 % | 68.12€ | 57.36€ |

Table 3: Results of sensitivity analysis for two scenarios of price decline. Target values of parameters are chosen to obtain profitable system.

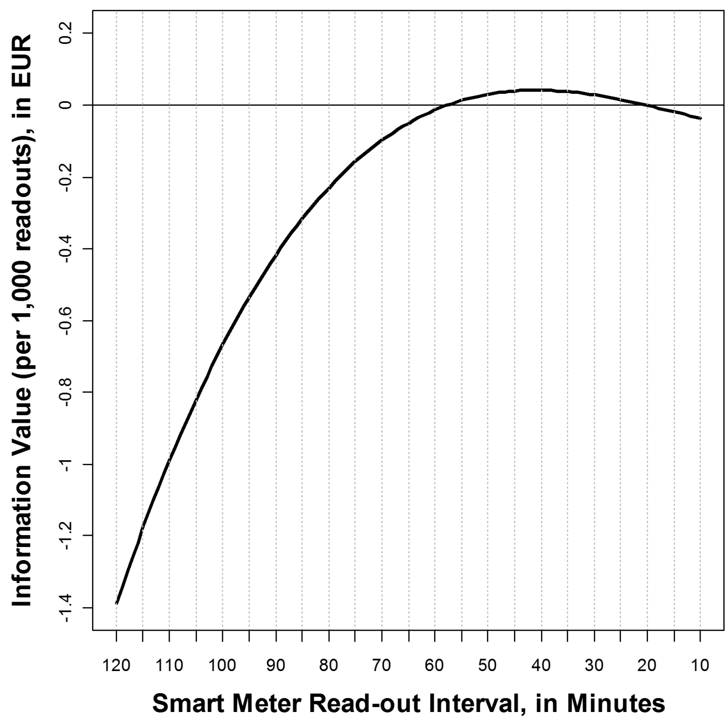


Figure 8: Information value $IV_{\text{VAR}}$ per 1000 smart meter read-outs across various read-out intervals in year $t = 15$.

While the previous analysis is based on a read-out interval of 60 minutes, we now vary the frequency in a range of 1 to 120 minutes. We plot the corresponding information value in Figure 8. Within the set $f \in \{21\,\text{min}, \ldots, 57\,\text{min}\}$, the information value takes positive values and thus the DR system generates a surplus for the retailer. The optimal information value $IV_{\text{VAR}}$ is located at a read-out interval of 41 minutes. We formulate these findings mathematically in the following propositions (cf. the online appendix for proofs).

**Proposition 5.2** *The information value for smart meter read-outs features an optimal interval given by the linear optimization problem*

$$\max_{f \in \mathbb{N}} \sum_{t=1}^{T} IV_{\text{VAR}}(f,t) = \max_{f \in \mathbb{N}} \sum_{t=1}^{T} \frac{R(f,t) - C_{\text{VAR}}(f,t)}{TF(t)}. \tag{4}$$

*with constraints*

$$R(f,t) \geq 0, \quad C_{\text{VAR}}(f,t) \geq 0 \quad \textit{for } t \in [1,T] \textit{ and } \forall f. \tag{5}$$

*The objective function is accumulated over an optimization horizon of $T$ steps to achieve the accumulated information value. The optimization model for $IV_{\text{FIX}}$ is set up analogously.*

When observing $IV_{\text{VAR}}$ in our setting, its shape suggests that – for cases when the optimal information value is positive – only a certain range of read-out intervals yield a positive information value.

**Proposition 5.3** *Both $IV_{\text{VAR}}$ and $IV_{\text{TOT}}$ are second degree polynomial functions. The information value is positive read-out frequencies in the range that is determined by computing the two real roots of $IV_{\text{VAR}}$ and $IV_{\text{TOT}}$ respectively.*

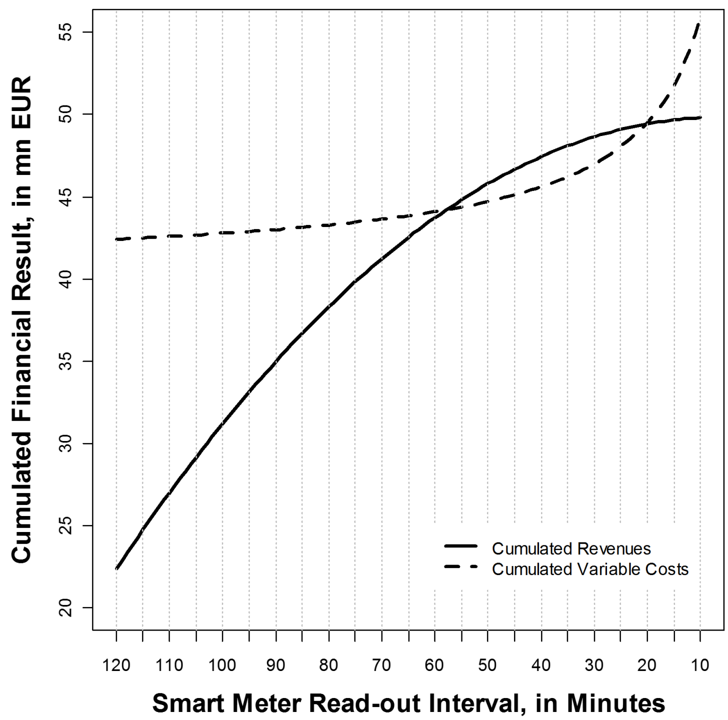


Figure 9: Revenue and variable cost curve across various read-out intervals (accumulated value over observation period of 15 years).

Contrary to expectations (and current literature), there is no *break-even* point for information granularity that serves as a starting point for continuously increasing profits. For the defined configuration of the DR system, the retailer only exhibits a positive information value for a limited range of read-out intervals. Figure 9 illustrates the corresponding revenue and cost curves, which obviously deviate from the revenue and cost curves showing the expected characteristics, as sketched in Figure 1.

*5.3. Optimal roll-out strategy for smart meters*

We have previously assumed that retailers operate smart meters for all customers connected to the distribution network. We now examine at which extent retailers can maximize their profit by reducing the number of deployed smart meters. In fact, smart meters could thus only be distributed to financially lucrative consumers. For this purpose, we first determine the marginal costs[4] of a single smart meter. We compute the marginal run costs per smart meter for two read-out intervals of 15 and 60 minutes that are common in today's electricity markets.

As a result, the value of the marginal volume of electricity increases with a larger read-out interval, consistent with the marginal costs per smart meter. This is self-evident since the run costs – as shown in the findings of the previous sections – rise with increased read-out frequency. The electricity retailer should thus aim at only those customers whose power consumption exceed a certain threshold. Such a threshold ensures that the customer's annual consumption yields enough load shifting potential to amortize the run costs and communication effort. We formulate this in the following proposition (cf. the proof in the online appendix).

**Proposition 5.4** *The revenues of an electricity retailers are maximized in a setup with a limited smart meter roll-out. The roll-out scheme is determined by thresh-*

[4]The revenue is assumed to be linearly related to the addressed electricity consumption and can therefore be converted simply to a value per MWh to determine the marginal volume of electricity. The marginal volume of electricity represents the minimal annual volume of electricity a customer needs to consume in order to become profitable to the retailer when employing a DR program.

*old $\Delta_{\text{kWh}}(f)$ for the annual consumption of consumers. It depends on the marginal variable costs $C'_{\text{VAR}}(f,t)$ per smart meter and the revenue per kWh of the annual consumption $r_{\text{kWh}}(f)$, i. e.*

$$\Delta_{\text{kWh}}(f) = \frac{\sum_t C'_{\text{VAR}}(f,t)}{T\, r_{\text{kWh}}(f)}. \tag{6}$$

Next, we select those customers that exceed the threshold for annual electricity consumption. For a read-out interval of 60 minutes, a customer has to consume an annual electricity total of 8407 kWh to spawn a DR potential that can cover the system costs. The electricity consumption of around 0.98 % of all residential households exceeds this marginal electricity volume.[5] In addition, 31.66 % of the commercial consumers fit into the scheme.

This limitation on the number of customers leads to 25,758 smart meters that need to be deployed. The same number of communication modules are also required. In contrast to the basic scenario, we assume that each smart meter has to carry its own communication module. This is due to the fact that the overall number of residential smart meters is rather low; it can thus be assumed that the respective households are located at a substantial distance from one another. The overall number of smart meters corresponds to 11.72 %

[5]Residential households are clustered into households with 1, 2, 3, 4 and 5+ members according to the latest census in Germany (Federal Statistical Office of Germany, 2013). Within each cluster, the electricity consumption is assumed to be uniformly distributed. For example, for households with 1 member, the mean consumption is given as 2400 kWh per year – the consumption is assumed to be uniformly distributed within limits [1200 kWh; 3600 kWh]; the corresponding standard deviation is calculated as 692.82 kWh. Similarly, the electricity consumption of commercial customers is assumed to be arranged around a mean of 6500 kWh with uniformly distributed values within a range of [1300 kWh; 11,700 kWh] (E-Control, 2012).

when compared to the basic scenario, whereas the total electricity consumption of 258 GWh corresponds to 25.81 %.

Since only profitable, large-scale consumers are equipped with smart meters, the accumulated revenues exceed the total costs significantly. The surplus is even large enough to cover the initial capital expenditures. Within the restricted scenario, the DR system yields a positive net present value, namely, €0.89 M. The results of the restricted scenario for intervals of 15 and 60 minutes are summarized in Table 4.

| | Share of HH/CC | Total annual consumption | Number of smart meters | Net present value |
|---|---|---|---|---|
| **Read-out interval: 15 minutes** | | | | |
| Marginal costs per smart meter: € 30.14 / Marginal annual consumption $\Delta_{\text{kWh}} = 9100\,\text{kWh}$ | | | | |
| **Base scenario** | 100 % / 100 % | 1000 GWh | 219,781 | € −25.45 M |
| **Restricted scenario** | 0.66 % / 25.00 % | 209 GWh (20.90 %) | 20,172 (9.18 %) | € 0.98 M |
| **Read-out interval: 60 minutes** | | | | |
| Marginal costs per smart meter: € 24.51 / Marginal annual consumption : $\Delta_{\text{kWh}} = 8408\,\text{kWh}$ | | | | |
| **Base scenario** | 100 % / 100 % | 1000 GWh | 219,781 | € −22.37 M |
| **Restricted scenario** | 0.98 % / 31.66 % | 258 GWh (25.80 %) | 25,758 (11.72 %) | |

Table 4: Comparison of scenarios across various read-out intervals ("HH" are households, "CC" commercial customers).

### 5.4. Discussion

In summary, the retailer achieves a comparative advantage by operating a DR system. Superior knowledge of the current demand enables the retailer to decrease peak demands and optimize electricity purchases accordingly. As a result, the DR mechanism generates a positive information value – when considering operational costs only – and the retailer thus has a financial benefit. For our set of parameters, a positive information value of smart meter read-outs is achieved within an interval of 21 to 57 minutes regarding variable costs. In total, a retailer can achieve a net present value of €0.89 M. Since it assumed that both the mean and the volatility of electricity prices is likely to rise in the future, this also impacts our analysis where we assume an observation period of 15 years – most likely with an increase in the net present value.

Moreover, this work contributes to the discussion on the optimal information granularity. While electricity markets usually operate in contracts with lengths of 15 or 60 minutes, the optimal value is located somewhere in between. Although contrasts of 60 minutes are still most common, a recent European legislation also leans towards a minimum read-out interval of 15 minutes (European Commission, 2012) and the EEX now also offers 15-minute contracts. Nevertheless, this research is not only restricted to demand response but also relates to other applications in the smart grid.

Not all of the above scenarios are profitable. If we keep in mind that Germany targets the large-scale integration of smart meters, alternative solutions are required. This can be either governmental subsidies, a substantial decrease of installation costs of smart meters, or the use of a different communication technology (esp. beyond GSM). Alternatively, and this seems to be the most compelling method of resolution, economies of scale or scope can be leveraged. To apply these, information intermediaries are required. They could profit from the setup of an infrastructure when offering their services to multiple retailers.

### *5.5. Managerial and policy implications*

Based on the above evaluation, we derive implications regarding smart grids and demand response as follows:

- Demand response programs can only achieve their full potential when fully-fledged home area networks (HAN) are in place at consumers' premises to control devices remotely. Currently, this is far from reality and thus the retailer cannot fully tap the potential of load shifting. In addition to the substantial investments necessary for the consumers' premises, their consent is also required. Concerns relating to data privacy and security could be veritable roadblocks here (McKenna et al., 2012).

- Our analysis is based on an incentive-based DR program. The consumers thus need to be incentivized to take part in the program. Presumably, this can only be achieved by paying a financial compensation to the consumer.

- The basic DR scenario requires substantial investments, whereas the restricted scenario seems financially more intriguing. Accordingly, limiting the deployment to large consumers ensures a cost-effective setup while still offering a substantial electricity volume for load shifting.

All in all, these implications catalyze the questions of who sets up and operates a DR infrastructure. This is especially important in liberalized electricity markets, such as in Germany and other European countries, where market roles are separated.

Although investments and operating costs are immense, a veritable business might arise for new service providers, such as intermediaries. They can profit from synergies when offering the infrastructure to more than one electricity retailer. In addition, they can also reuse both infrastructure and meter data for additional applications and services, e. g. monthly billing, electricity theft prevention. As a result, telecommunication providers are positioned at the forefront for taking up the role of the intermediary (Mind Commerce, 2012). This reasoning is based on the fact that they are experienced in operating communication networks and that they could even reuse parts of their existing networks for meter data collection and aggregation.

## 6. Conclusion

In the near future, electricity generation will show unprecedented fluctuations due to an increasing share of renewable energy resources. Electricity retailers can address this challenge by leveraging demand response to actively manage the demand side. However, this requires a comprehensive ICT infrastructure to handle the vast volumes of smart meter data.

This work shows that savings from a DR system significantly exceed its running costs. As a result, electricity retailers face an interesting business opportunity in order to achieve a competitive advantage through the optimization of electricity procurement. Our analysis reveals that collecting more granular smart meter data does not necessarily result in higher profits due to a disproportionate increase in ICT costs. In our scenario, an electricity retailer can expect a positive return when the meter read-out occurs every 21 to 57 minutes, with an optimum timing every 41 minutes. Furthermore, huge upfront investments do not amortize for a single retailer over the expected lifetime of 15 years for a DR infrastructure. Therefore, we consider an alternative scenario in which the roll-out of smart meters is restricted to large-scale consumers. Such a scenario is most profitable with a net present value of €0.89 M when one equips 12 % of the largest customers with a smart meter. These customers exhibit a level of electricity consumption which is high enough to ensure the payback of investment costs.

Our study still leaves room for future research. First of all, profitability is strongly affected by the technical configuration of a DR system. Since (technical) standards have not yet gained wide acceptance, regulatory efforts can have a large impact. For example, the Federal Office for Information Security in Germany is currently preparing a directive (3/31/2014) to establish the mandatory usage of certain protection profiles for smart meters, which could considerably increase data volume as a side effect. In addition, further research is needed to understand the business case of intermediaries in demand response systems.


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