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ESTIMATING ECONOMIC BENEFITS OF ELECTRICITY STORAGE AT THE END CONSUMER LEVEL

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Abstract

The underlying question of this research work is whether small, distributed storage devices on the electricity grid can help to lower the average electricity cost and foster the integration of renewable energy sources. This article addresses the question whether it is economically beneficial to install such storage capacity.

The article presents two models that estimate the economic benefits from using electrical storage devices for arbitrage accommodation at an end consumer level and assumes flexible electricity tariffs.

The models reveal a saving potential between 9% and 15% on total cost, based on technical specifications of storage devices in a developmental stage.

1. Introduction

The most recent developments and issues on the EU energy market show that the utilities industry as well as most energy consumers are facing significant changes in the future. Examples for decisions and targets behind these changes are the intended increase of energy generation from renewable and distributed energy sources, the significant CO_2 reduction in the EU until 2020, and a continuation of the ongoing liberalization and unbundling movements in the market [23] [25].

The significant increase of power generation from distributed and renewable energy sources is a central target, which would positively contribute to an increase in energy autonomy and a reduction of CO_2 emissions. Depending on the ownership and market structure in the power generation sector, it could also contribute to further liberalization of the energy markets. A shift from today's centralized market structure towards a decentralized model would cause problems in terms of keeping or improving quality and reliability of energy supply and would require major investments in the electricity grid.

One of the key characteristics of electrical energy is that supply and demand need to be in balance at each point in time to make the energy grid run stable. Therefore, Transmission System Operators (TSO) are obliged to reserve a certain amount of capacity (Primary, Secondary, and Tertiary Control) in order to react appropriately to deviations from the forecasted demand. An increasing

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amount of distributed energy production from renewable sources like wind and solar energy complicates the process of balancing demand and supply. In comparison to coal or nuclear power plants, the output of these energy sources is more volatile and less predictable since it strongly depends on environmental (weather) conditions. The increasing need for (expensive) control capacity may lead to rising energy prices for the end consumer.

Up to now, energy suppliers and large industrial customers have planned and adjusted their supply and demand volumes in order to balance the model. Commercial customers, public institutions and private households are not actively involved in matching demand and supply of the electricity markets, although their share is about 50% of the total consumption [19]. The main reason is that commercial customers and private households do not have a direct economic incentive to change their load profiles yet, since energy tariffs are flat, i.e., do not depend on the current demand and supply levels. In Germany, this will change from beginning of 2011 onwards when load-dependent tariffs must be offered [24]. Additionally, these consumer groups do not have access to market information that would allow them to shift parts of the demand (load) appropriately.

The aim of this article is to estimate the economic benefits of installing small, distributed electricity storage at the end consumer level. The hypothesis is that storage applications could help to improve the flexibility[3] of the demand side and, thus, to integrate supply from renewable energy sources more efficiently. In all cases, adequate (market) information at the consumer level is required to decide on the load shifts. Thus, information and communication technology (ICT) is a fundamental basis for the implementation of storage applications. Especially the application of distributed storage devices makes modern ICT essential.

Section 2 gives a brief overview of the related literature. In Section 3, we introduce a basic model that estimates the economic benefits of using small storage devices on the end consumer level for arbitrage accommodation. As a benchmark for the first model, Section 4 presents a linear optimization model. Section 5 gives a conclusion and an outlook on further research in this area.

2. Related Work

Whereas large, centralized storages of more than 1 MWh capacity exist since the beginning of the 1980s and have been discussed and analyzed in the scientific literature (an overview is given in [4]), distributed storage is a more recent and less researched field. The focus of this article will be on small, distributed storage devices. Technical and economic literature on storage for electrical energy describes various, partly overlapping storage applications. In [3], storage devices are used as emergency power supply during transmission & distribution (T&D) or generation interruptions. The improvement of power quality by correcting load voltage profiles, regulating frequency, or stabilizing long transmission lines is in the focus of [8] and [12]. A set of deeply researched storage application areas is shaping the load curve through peak shaving, load leveling or providing spinning reserves, e.g., in [1], [2], [6], [15] and [17]. [11] and [14] focus on the economic impact of storage by analyzing investment deferrals in generation and transmission capacity through either stationary or mobile storage devices. Arbitrage accommodation, i.e., charging at low and discharging at high market prices, is a storage application with an economic objective, e.g., analyzed in [5], [9], [10] and [16].
The focus of this article is on arbitrage accommodation as the primary objective of the storage application. As a side effect, this can also lead to load profile modifications as through peak shaving or providing spinning reserves. A prerequisite for arbitrage accommodation are flexible, time-

[3] I.e., having the option to shift portions of demand to different timeslots than those where they were planned to occur respectively actually occur (load shifting potential).

dependent energy prices for the end consumer. The spectrum of such tariffs reaches from a single day vs. night tariff differentiation, over various fixed block tariffs for defined time periods during the day, to hourly or real-time pricing. This work assumes flexible hourly tariffs at the end consumer level.

3. Basic Estimation Model

The main goal of the basic model is to determine the impact of a simple charge and discharge decision heuristic for the storage device. The basic approach is to charge the device at low prices and to discharge at peak prices. The decision heuristic indicates the system when to charge and discharge the storage device in order to maximize the average arbitrage accommodation per day in a given time period. The time period consists of T timeslots and D days. The index for timeslots is $t = 1...T$, for days it is $d = 1...D$. Each day has $T^D = T \cdot D^{-1}$ timeslots. The results of the model will allow to estimate the impact of the storage device on the total cost for the given time period.

3.1. Parameter Definition and Data Sources

The parameters of the model describe the technical characteristics of the storage device, the energy demand for each timeslot [kWh], the market price per energy unit in each timeslot [EUR/kWh] and the decision variables.

Storage parameters

- C is the maximal capacity of the storage device [kWh]
- η is the efficiency degree[4] of the storage device [%], with $0 \le \eta \le 100$
- v is the number of timeslots needed to fully charge the storage device at the maximal charging speed [#timeslots]
- ψ is the storage cost per nominal (full) charge cycle [EUR/nominal cycle], defined as the quotient $\psi = \alpha \cdot \beta^{-1}$, where α is the total investment and operational cost over life time and β the expected number of full charge cycles over life time of the storage

Energy demand and market price parameters

- ℓ_t is the energy demand (load) in timeslot t [kWh]
- p_t is the market price per energy unit in timeslot t [EUR/kWh]

Auxiliary parameters

- $t_d := rank(p_t, d)$ indicates the rank of a market price p_t within a the day d from $t_d = 1$ for the lowest price (timeslot with the lowest price) during the day d to $t_d = T^D$ for the highest price

Decision variables

- i is the limit for a ranked market price for "off-peak timeslots" in which the system charges the storage device, i.e., the system should charge the storage if the rank t_d of the current market price p_t is less or equal i, thus $t_d \le i$ with $1 \le i < T^D$
- j is the according limit for "peak timeslots" in which the storage is discharged, i.e., if the rank t_d of the current market price p_t is greater or equal j, thus $t_d \ge j$ with $1 < j \le T^D$

Thus, the limits i and j define the lower bound of the "peak timeslots" for discharging respectively the upper bound of the "off-peak timeslots" for charging the storage device. Since the limit pa-

[4] Self-discharge of the storage devices is not modeled due to its negligible impact when charging and discharging the device at least one time per day (see also [7]).

rameters i and j apply for the entire time period (365 days of the year 2007) with different weekdays and seasons, they are defined as index values instead of absolute prices [EUR/kWh].[5]

The input for the technical storage parameters is derived from systems in a developmental stage [13] of which Table 1 contains selected details. We varied the data input within four scenarios as presented in Table 2. Data for market prices accord to the price curve distribution of the published hourly prices in 2007 on the European Energy Exchange [22] and is normalized to an annual average price of 0.18 EUR/kWh [21]. The data for the energy demand (load) reflect the standard "H0 profile" (profile of a private household) published by the BDEW (Association of the German Energy and Water Industry) [20]. The standard "H0 profile" is normalized to an annual consumption of 1,000 kWh and multiplied with a random vector (± 15% for each value).
The granularity of the load data corresponds to 15-minute-timeslots. The hourly market price data has therefore been transformed into 15-minute-timeslots as well. Thus, each day contains 96 timeslots for 365 days in 2007, resulting in 35,040 timeslots for the following analyses.

	Storage technology	**Efficiency** η [%]	**Capacity** C [kWh]	**Charging speed** v [#timeslots]	**Storage cost** ψ [EUR/cycle][6]	**Life time** [full cycles]	**Storage investment** [EUR/kWh]	**Other investment** [EUR][7]
Best case	Lead-acid	85	1	4	0.073	3,000	100	120
	NiCd	70	1	4	0.052	10,000	400	120
	Li-Ion	95	1	4	0.086	5,000	300	130
Average case	Lead-acid	83	1	4	0.167	2,100	175	175
	NiCd	65	1	4	0.0971	7,500	550	178
	Li-Ion	93	1	4	0.138	7,000	650	315
Worst case	Lead-acid	80	1	4	0.400	1,200	250	230
	NiCd	60	1	4	0.187	5,000	700	235
	Li-Ion	90	1	4	0.375	4,000	1,000	500

Table 1: Selected parameters of storage technologies in developmental stage [13]

	Capacity C [kWh]	**Charging speed** v [#timeslots]	**Efficiency** η [%]	**Storage cost** ψ [EUR/cycle]
Scenario 1	0.5	2	80	0.10
Scenario 2	0.5	2	90	0.10
Scenario 3	1.0	4	80	0.10
Scenario 4	1.0	4	90	0.10

Table 2: Parameter values for basic estimation model

3.2. Definition of the Basic Estimation Model

The model estimates the economic impact of varying the limits for "off-peak timeslots" and "peak timeslots" in which the system will charge respectively discharge the storage device in order to maximize the arbitrage accommodation. The model will therefore calculate the savings through storage usage for different charge and discharge limits. The savings are calculated against the cost baseline K [EUR] of a system without storage usage, based on the given vectors p_t for the market price and ℓ_t for the demand per timeslot:

$$K = \sum_{t=1}^{T} \ell_t \cdot p_t \tag{1}$$

[5] Price profiles vary significantly between different weekdays and seasons, as exemplary shown in [18].
[6] (Storage investment * Capacity + Other investment) / Life time.
[7] Power Interface for 1kW, peripherals.

For each day d, $\bar{\ell}_d^j$ determines the volume of the demand within the "peak timeslots",

$$\bar{\ell}_d^j \quad = \quad \sum_{t \in \bar{t}_d^j} \ell_t \text{ where } \bar{t}_d^j := \{t| \quad t_d \geq j\} \tag{2}$$

The average cost per energy unit in the "off-peak timeslots" of day d is

$$\underline{k}_d^i \quad = \quad \frac{\sum_{t \in \underline{t}_d^i} p_t}{i} \text{ where } \underline{t}_d^i := \{t| \quad t_d \leq i\} \tag{3}$$

The weighted average cost per energy unit in the "peak timeslots" is

$$\bar{k}_d^j \quad = \quad \frac{\sum_{t \in \bar{t}_d^j} \ell_t \cdot p_t}{\bar{\ell}_d^j} \text{ where } \bar{t}_d^j := \{t| \quad t_d \geq j\} \tag{4}$$

The model will determine the economic benefit of shifting load from "peak timeslots" (discharging) to "off-peak timeslots" (charging). The objective function of the model calculates the savings against the baseline cost K for each tuple (i, j) and takes storage cost into account:

$$\max \quad \rightarrow \quad \frac{1}{K} \cdot \sum_{d=1}^{D} \underbrace{\bar{\ell}_d^j \cdot \left(\bar{k}_d^j - \frac{\underline{k}_d^i}{\eta} \right)}_{A} - \underbrace{\frac{\bar{\ell}_d^j \cdot \psi}{C}}_{B} \tag{5}$$

Term A determines the arbitrage benefit. In total, $\bar{\ell}_d^j$ energy units [kWh] will be shifted from "peak timeslots" to "off-peak timeslots". The arbitrage benefit for each shifted energy unit corresponds to the difference between the weighted average cost per energy unit in the "peak timeslots" $\bar{k}_d^j$ and the average cost per energy unit in the "off-peak timeslots" $\underline{k}_d^i$. Due to the limited efficiency degree η of the storage device, the amount of energy charged into the storage device (respectively the price paid) must be higher than the amount that is actually discharged, therefore $\underline{k}_d^i \cdot \eta^{-1}$. The arbitrage benefits from Term A must be reduced by the cost for storage usage in Term B. Given the amount of load shifted $\bar{\ell}_d^j$ and the maximal capacity of the storage device C, $\bar{\ell}_d^j \cdot C^{-1}$ charge cycles are required with costs of ψ per nominal charge cycle.

To obtain a valid solution, the input parameters for the objective function must comply with two constraints. The tuple (i, j) must not lead to overlapping "off-peak" and "peak timeslots":

$$i \quad < \quad j \tag{6}$$

The second constraint reflects the maximal charging speed of the storage device. Since the required number of timeslots to fully charge the storage device is v and $\bar{\ell}_d^j \cdot C^{-1}$ energy units need to be shifted, the charging limit i must fulfill

$$i \quad \geq \quad v \cdot \frac{\underline{\ell}_d^i}{C} \qquad \forall d \tag{7}$$

3.3. Result Analysis

The basic model estimated the saving potential on total cost for different charge and discharge limits for an algorithm that controls the storage device. The limits define the lower bound of the "peak timeslots" in which the storage device is discharged respectively the upper bound of the "off-peak timeslots" in which the storage device is charged. The length of a timeslots was 15 minutes and the analyzed time period was the year 2007 with 365 days, i.e., 35,040 timeslots in total. The parameter values used for the simulations are listed in Table 2. Results from the simulation runs using these parameters are presented in Figure 1.

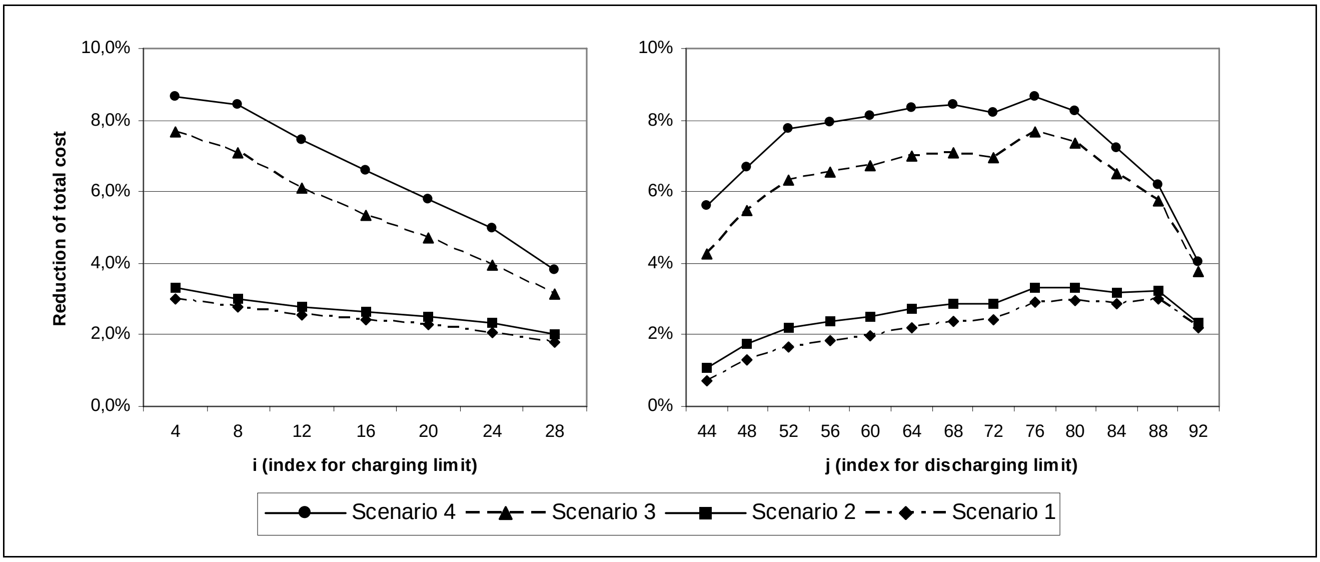

Figure 1: Results of the basic estimation model – Variation of the charging limit i and discharging limit j

The left side of Figure 1 shows the result for variations of the charging limit i. In this case, the optimal (i.e., resulting in maximal reduction of total cost) value for the discharging limit j has been chosen automatically. Accordingly, the right side of Figure 1 shows the result for variations of the discharging limit j with optimal values for the charging limit i. The maximal reduction of total cost with the basic model is estimated at ~ 9%.
The results reveal that the underlying cost per capacity unit (which links the parameters capacity and storage cost) is the most important factor to reduce the total cost. Scenario 4 and 3 with a storage capacity of 1,000 Wh and storage cost of 0.10 EUR per full charge cycle result in a maximal reduction of total cost of ~ 9%, while scenarios 1 and 2 with a 500Wh-capacity-storage device and the same storage cost (i.e., relatively twice as high as in scenarios 3 and 4) achieve ~ 3% total cost reduction only. Clearly, these results must be interpreted in the context of the given load profile with a normalized annual load of 1,000 kWh, which is below the consumption volume of an average household in Europe or the US.

Regarding the definition of the limit values, the results reveal that setting the charging limit has a significant impact on the overall results. A too largely defined period of "off-peak timeslots" will result in significantly lower reduction of total cost. In contrast, the limit for defining the "peak timeslots" has little influence on the reduction, if the limit is in the range of $j = 56$ to $j = 80$. In case of the charging limit, the realized reduction of total cost decreased significantly for limit values of $i > 8$. For a heuristic decision algorithm without (precise) ex-ante knowledge of the price curve's distribution this implies a greater risk when setting the absolute charging limit for a day (depending on the expected price distribution for the day): if the limit is set too high, the realized arbitrage accommodation will be significantly lower than the best (with this algorithm) achievable value. If set too low, no arbitrage accommodation will be realized on that day. In case of setting the discharging limit, this risk is lower due to the larger range of discharge limits that lead to a solution close to the best (with this algorithm) achievable result.

For a heuristic decision algorithm including a forecast function, this implies that the quality of price forecasting for "off-peak timeslots" (i.e., lowest market prices for a day) has greater importance than price forecasting for "peak timeslots" (i.e., highest market prices of a day).
As described, the presented model estimates the total cost reduction achieved by a simple heuristic decision algorithm; it does not calculate the maximal reduction of total cost for the described scenarios. In order to benchmark the results of this model and to evaluate the improvement potential of

the presented model, we present a simple linear optimization model in Section 4. The results of the linear optimization model will outline the maximal reduction of total cost.

4. Simple Linear Optimization Model

The main objective of the linear optimization model is to determine the optimal timeslots for charging and discharging the storage device in order to minimize the total cost for the given time period. For each timeslot t in the given period, the algorithm will determine the amount of energy to charge into the storage device respectively to discharge from it. As defined in Section 3, the time period consists of T timeslots t with $t = 1...T$. The linear optimization model neglects the distinction of the time period into days. Instead, the optimization algorithm considers the time period as a continuous data stream.

4.1. Parameter Definition and Data Sources

The parameter definition for the linear optimization model builds on the parameters defined in Paragraph 3.1, particularly the storage parameters (C, v, η, ψ) and the demand and market price parameters (ℓ_t, p_t). However, the decision variables are different from Section 3.

Decision Variables

- φ_t [%] indicates the percentage of time at which the storage is charged in timeslot t ($\varphi_t \in [0;100]$)
- λ_t [%] indicates the same for discharging the storage device ($\lambda_t \in [0;100]$).

Hence, the three possible states for the storage device are *Charging* ($\varphi_t > 0$), *Waiting* ($\varphi_t = 0 \quad \wedge \quad \lambda_t = 0$) and *Discharging* ($\lambda_t > 0$). As for the presented model in Section 3, the values for the technical storage parameters will base on published storage specifications (see Table 3). Furthermore, all load values ℓ_t and all market price values p_t are given for the entire time period. The data sources for the values are equal to those described in Paragraph 3.1.

	Capacity C [kWh]	**Charging speed** v [#timeslots]	**Efficiency** η [%]	**Storage cost** ψ [EUR/cycle]
Scenario 1	0.5	2	80	0.10 – 0.30
Scenario 2	0.5	2	90	0.10 – 0.30
Scenario 3	1.0	4	80	0.10 – 0.30
Scenario 4	1.0	4	90	0.10 – 0.30

Table 3: Parameter values for linear optimization model

4.2. Definition of the Linear Optimization Model

The linear optimization model calculates the minimal costs of a time period with given demand and market price data. Therefore, it calculates the optimal charge and discharge vectors φ_t and λ_t. Using the notation defined in Paragraph 4.1, we formulate the linear optimization problem as

$$\min \quad \rightarrow \quad \sum_{t=1}^{T} \underbrace{p_t \cdot \ell_t}_{A} - \underbrace{p_t \cdot \min(\ell_t; C) \cdot \lambda_t}_{B} + \underbrace{p_t \cdot \frac{C}{v \cdot \eta} \cdot \varphi_t}_{C} + \underbrace{\frac{\psi}{v} \cdot \varphi_t}_{D} \tag{8}$$

Term A determines cost for ℓ_t energy units purchased at market price p_t in timeslot t. Term B indicates the cost reduction respectively reduction of demand on the external market due to storage discharge, i.e., the demand is partly or fully served from the storage device. Term C calculates the cost for energy charged into the storage device. The maximal charging speed v limits the amount of charged energy to $C \cdot v^{-1}$ energy units per timeslot. Furthermore, the model takes the efficiency degree of the storage system into account so that the amount of energy charged into the storage device is by a factor η^{-1} greater than the actually used amount of energy. Term D additionally takes cost for the storage usage into account.

Since all parameters except for φ_t and λ_t are constants respectively given values, equation (8) represents a linear optimization problem. The constraints for the optimization problem are as follows: A solution is valid only if the decision variables φ_t and λ_t are kept within their range $[0;1]$ (9). At each point in time, the amount of discharged energy must not exceed the amount of energy previously charged into the storage and the storage device must not be overload (10).

$$0 \le \varphi_t, \lambda_t \le 1 \quad \forall t \tag{9}$$

$$0 \le \sum_{t'=1}^{t} \frac{C}{v} \cdot \varphi_{t'} - \min(\ell_{t'}; C) \cdot \lambda_{t'} \le C \quad \forall t \tag{10}$$

4.3. Result Analysis

The first simulations with the linear optimization model have been carried out in order to study the impact of a storage device on the total electricity cost for a small end consumer. The length of a timeslots was 15 minutes and the analyzed time period was the year 2007 with 365 day, i.e. 35,040 timeslots in total. The parameter values used for the simulations are listed in Table 3. Results from the simulation runs using these parameters are presented in Figure 2.

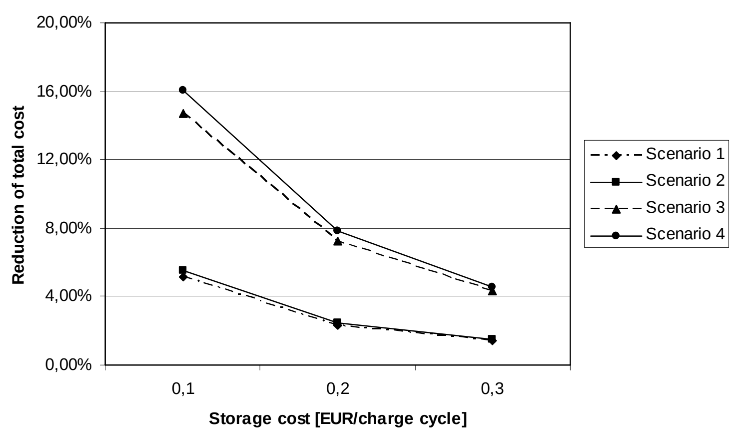

Figure 2: Results of the linear optimization model – Reduction of total cost through storage usage

The storage costs per nominal charge cycle have been varied between 0.10 and 0.30 EUR per charge cycle for each of the scenarios. In scenarios 1 and 2, the storage device has a capacity of 500 Wh, while it has 1,000 Wh in scenarios 3 and 4. Overall, doubling the storage capacity from 500 to 1,000 Wh lead to a ~ 3 times higher reduction of total cost for the given demand data with an annual consumption of 1,000 kWh. Similarly, a decrease of storage cost from 0.30 to 0.10 EUR per charge cycle lead to a ~ 3 times higher reduction of total cost. In case of low storage cost and larger storage capacity, an increase of the storage cycle efficiency from 80% to 90% lead to ~ 10% increase in total cost reduction, while the same cycle efficiency variation for small storage capacity and high storage cost increased total cost reduction by ~ 3% only.

Our first simulation runs of the linear optimization model support the findings of the previous model in Section 3. The most important factor is the cost per capacity unit of the storage device, which links the storage cost and the capacity parameter (the investment cost will increase with the capacity of the storage, while the expected life time respectively number of full charge cycles will not). In the simulation environment with ex-ante known load and price curves, total cost for an end consumer in 2007 could be reduced by ~ 15% when assuming values of a best-case scenario for future Lithium-Ion batteries as depicted in Table 1.

5. Conclusions

This article addressed the question whether it is economically beneficial to install small, distributed storage devices on the electricity grid. Therefore, two models were presented. Both models address the decision problem when to charge and discharge the storage devices in order to maximize arbitrage accommodation. The first model estimates the benefits that could be achieved using heuristic decision algorithms that base on a lower limit for charging and an upper limit for discharging the storage. The second model is a linear optimization model that determines the optimal charge-discharge-strategy for a given time period and a given set of input parameters; it served also as a benchmark for the results of the first model. For technical parameters of storage devices that are currently in a developmental stage, the linear optimization model resulted in a ~ 15% reduction of total cost, while the basic model estimated a ~ 9% reduction for a simple heuristic algorithm.

The main reason for the lower cost reduction of the heuristic algorithm in comparison with the optimal solution is the rough granularity of the charge and discharge limits. The basic estimation model sets only one, even though relative, value for the discharge and charge limits within the given time period. Thus, it calculates the limits that result in the highest average cost reduction per day, but not the highest absolute cost reduction for each day, as the linear optimization model does. Therefore, one possible refinement would be individual limits for each day. Additionally, the basic estimation model calculates the cost of charging the storage device on the average market price within the "off-peak timeslots", whereas the linear optimization model calculates on the precise cost per timeslot. Although the heuristic decision algorithm is obviously simple and offers a lot of room for improvement, it results in a saving potential on total cost of 9% (vs. 15% optimal solution). Thus, more sophisticated heuristic algorithms in realistic settings are likely to achieve more than 10% savings on total cost.

In further research, we plan to refine and extent the presented models. Potential refinements are a more detailed design of the cycle efficiency[8] and, as explained before, a more sophisticated and detailed approach to determine the charge-discharge-limits. Part of an extended heuristic model would be a forecast function using a pool of historic data. Regarding the linear optimization model, we will conduct in-depths analyses of the interdependencies of the model parameters, in particular between the demand data and the optimal storage size. In order to address the basic research question whether small, distributed storage devices on the electricity grid can help to lower the average electricity cost and foster the integration of renewable energy sources, a model respectively simulation that aggregates the individual storage effect is needed. Potentially, this could be addressed with a multi-agent system.

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