Sensitivity Analysis of the Economic Benefits from Electricity Storage at the End Consumer Level

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***Abstract*--The article presents the results of simulations based on a linear optimization model of a storage system that calculates the economic benefits of distributed storage devices at the end consumer level by determining the cost optimal charge-discharge-schedule. The primary objective of the storage application is arbitrage accommodation.**

Particularly, parameters for a li-ion-based and a lead-acid-based storage system are simulated. All parameters of the model are varied and analyzed regarding their impact on the economic benefits. The simulation results quantify these impacts and show that the costs per storage capacity unit (EUR/kWh) and the efficiency degrees of the storage system have the highest impact. Additionally, the price spreads as well as the distribution of the market price curve in relation with the distribution of the consumer's load curve (demand) influence the achievable benefits significantly. Overall, the model reveals a saving potential of 17% on total cost for the reference case.

***Index Terms*--Batteries, demand-side management, economic sensitivity analysis, energy storage**

I. 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 announced CO_2 reduction in the EU until 2020, and a continuation of the ongoing liberalization and unbundling movements in the market [1], [2].

The significant increase of power generation from distributed and renewable energy sources is a central target, which can 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.

Clearly, a shift from today's centralized market structure towards a decentralized model would cause problems in terms of keeping or improving the level of quality and reliability of energy supply and would require major investments and technological innovations in the electricity grid infrastructure.

Assuming an infrastructure that allows providing time-dependent electricity tariffs to the end consumer level, consumers would have an economic incentive to reduce energy consumption in peak hours and shift it to off-peak hours – if appropriate price signals are provided. A storage application could help to maximize demand-side flexibility, i.e., having the option to shift portions of demand to different times than those where they actually occur.

This article defines and analyzes a detailed storage model that links technical, economic, market, and consumer parameters. The model calculates the economic benefits of a distributed storage device at the end consumer level by determining its optimal charge-discharge-schedule. All parameters of the model are analyzed with respect to their impact on the resulting total cost.

The motivation behind this research is that distributed storage devices might help to lower the average electricity cost, increase the demand-side flexibility and, hence, foster the integration of intermittent energy sources.

The remainder of this article is structured as follows: Section II gives an overview of related scientific literature. In Section III, the linear optimization model and its parameters are defined. Section IV presents the results of the sensitivity analyses. Section V gives a conclusion of the findings.

II. 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 [3]), distributed storage is a more recent and less researched field. The focus of this article is on distributed storage devices. Technical and economic literature on storage for electrical energy describes various, partly overlapping storage applications. In [4], storage devices are used as emergency power supply during interruptions in transmission and distribution or generation. Power quality improvements through correcting load voltage profiles, regulating frequency, or stabilizing long transmission lines are in the focus of [5] and [6]. A set of deeply researched storage application areas aims at shaping the load curve through peak shaving, load leveling or providing spinning reserves, e.g., in [7], [8], [9] and [10]. A

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storage application with a primarily economic objective is arbitrage accommodation. Arbitrage accommodation, i.e., charging at low and discharging at high market prices, is the focus of this article. It is also analyzed in, e.g., [11], [12] and [13].

III. Model Definition

A. Parameters and Data Sources

Analyzing and assessing the economic benefits of a storage system at the consumer level requires a detailed description of the storage system's technical specification and of the external parameters of the environment where the storage system is located. The storage system consists of the storage device and peripherals, e.g., power converters. The external parameters contain information about the context of the consumer and the energy market where the consumer obtains its energy from. Fig. 1 depicts an overview of the basic parameters and their interdependencies.

1) Storage System Parameters: The key parameters of a storage system are its dimensions *capacity*, *power*, *efficiency*, and *estimated system life time*, as well as their corresponding cost components. Table I contains an overview of all storage system parameters.

The estimated life time of the system can be distinguished into the expected life time of the peripherals τ (years) and the number of expected nominal (full) charge cycles of the storage device γ (#), according to a defined limit for the maximal depth of discharge (DOD) $\hat{\delta}$ (%).

2) Market and Consumer Parameters: The parameter p_t models the price curve by indicating the energy price (EUR/kWh) per timeslot t and, thus, determines the price curve's granularity and distribution.

Another market parameter - that is not directly related to the energy market - is the interest rate i (%). In this paper, the interest rate is the key parameter for the capital cost of the investment into the storage system.

The customer parameter ℓ_t models the load curve by indicating the load (kWh) per timeslot t. Its distribution and aggregated height (annual load) differ depending on the household's size, consumer habits, and electrical devices used. Table II contains the market and consumer parameters.

TABLE I
OVERVIEW OF STORAGE SYSTEM PARAMETERS

Parameter Description	Symbol	Unit
Maximal capacity of the storage device	C	(kWh)
Cost rate per storage capacity unit	κ	(EUR/kWh)
Maximal charging speed of the device (hours required for full charge cycle)	v^{store}	(h)
Power-in of the storage system (rectifier)	P^{in}	(kW)
Power-out of the storage system (inverter)	P^{out}	(kW)
Cost rate per power unit (in)	π^{in}	(EUR/kW)
Cost rate per power unit (out)	π^{out}	(EUR/kW)
Annual maintenance cost as percentage of the initial investment	m	(%)
Rectifier efficiency (in)	η^{in}	(%)
Storage efficiency	η^{store}	(%)
Inverter efficiency (out)	η^{out}	(%)
Self-discharge rate of the storage device	$\eta^{selfdch}$	(%/h)
Estimated life time of system peripherals	τ	(years)
Expected nominal cycles of the storage device	γ	(#)
Maximal depth of discharge allowed	$\hat{\delta}$	(%)

TABLE II
MARKET AND CONSUMER PARAMETERS

Parameter Description	Symbol	Unit
Price per energy unit in timeslot t	p_t	(EUR/kWh)
Interest rate on investment	i	(%)
Load (demand) in timeslot t	ℓ_t	(kWh)

3) Data Sources: The input values for the technical storage parameters reflect an average and a best case of a developmental stage of known technologies (see Table III), published in [14]. The best case of the lead-acid technology scenario is the reference case for all simulation results. Table IV depicts the reference values for the remaining storage and market parameters. Data for market prices accord to the price distribution of the published hourly prices in 2007 on the European Energy Exchange (EEX) [15] and are normalized to an annual average price of 0.18 EUR/kWh. The data for the load curve (electricity demand) reflect the standard "H0 profile" (profile of a private household) published by the Association

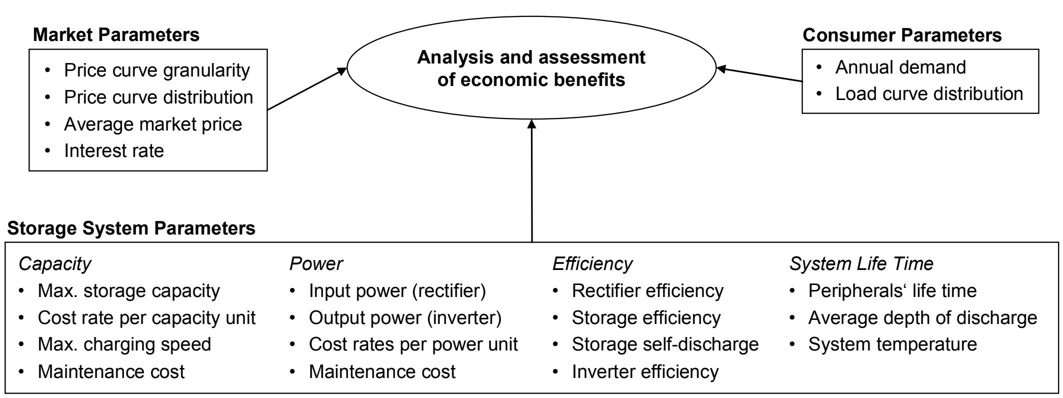

Fig. 1. Overview of model parameters (built on [14])

of the German Energy Industry (VDEW) [16]. This reference load profile is normalized to an annual consumption of 2,000 kWh and multiplied with a random vector (±15% for each timeslot).

The granularity of the load data corresponds to 15-minute-timeslots. The hourly market prices have therefore been transformed into 15-minute-timeslots as well. Thus, each day contains 96 timeslots (timeslots per hour $T^h = 4$) for 365 days, resulting in 35,040 timeslots for the following analyses.

TABLE III
TECHNOLOGY SCENARIOS [a]

	Technology	γ [b]	κ	π^{in}, π^{out}	η^{store}
Best case	Lead-acid (*ref. scenario*)[c]	3000	100	120	85
	Nickel-cadmium	10000	400	120	70
	Li-ion	10000	300	130	95
Average case	Lead-acid	2100	175	175	82
	Nickel-cadmium	7500	550	177	65
	Li-ion	7000	650	315	92

[a] Published in [14]
[b] Maximum DOD: 80%.
[c] The best case of the lead-acid technology is the reference scenario for all later simulation results, unless differently stated.

TABLE IV
REFERENCE PARAMETER VALUES

Symbol	Unit	Reference Value
p_t	(EUR/kWh)	EEX price data, 2007 [15]
ℓ_t	(kWh)	VDEW load profiles [16]
i	(%)	7
m	(%)	2
τ	(years)	10
C	(kWh)	5.0 [a]
P^{in}	(kW)	1.0 [a]
P^{out}	(kW)	0.5 [a]
η^{in}	(%)	95
η^{out}	(%)	98
$\eta^{selfdch}$	(%/h)	0 [b]
v^{store}	(h)	5.0
$\hat{\delta}$	(%)	80
T^h	(#/h)	4 [c]

[a] The optimal values for C, P^{in}, and P^{out} are adjusted depending on the simulated technology, consumer load curve, and market price curve. The reference values are the optimal values for the reference scenario.
[b] Self-discharge is neglected for the selected technology scenarios due to short time periods between charge and discharge cycles.
[c] Model parameter (no storage system parameter).

B. *Definition of a Linear Optimization Model*

The objective of the linear optimization model is to determine the minimal total costs for a given time period. For each timeslot t in the given period, the model can determine the amount of energy to charge into the storage device respectively to discharge from it. The time period consists of T timeslots t with $t = 1...T$. The decision variables are $\varphi_t \in [0;1]$ for charging and $\lambda_t \in [0;1]$ for discharging the storage device (see Table V). The decision variables indicate the percentage of time at which the storage is charged respectively discharged in timeslot t.

Hence, the possible modes for the storage device are charging ($\varphi_t > 0$), waiting/idle ($\varphi_t = 0 \quad \wedge \quad \lambda_t = 0$) and discharging ($\lambda_t > 0$).

TABLE V
DECISION VARIABLES

Parameter Description	Symbol	Unit
Charge parameter for timeslot t	φ_t	(%)
Discharge parameter for timeslot t	λ_t	(%)

The potential discharge volume q_t^{out} in timeslot t is limited by the power output P^{out} and the maximal capacity C of the storage system:

$$q_t^{out} = \min\left(\ell_t ; \min\left(C; \frac{P^{out}}{T^h}\right)\right) \tag{1}$$

The maximal charging speed of the storage system v (#) indicates the required timeslots for a nominal charge cycle. It depends on the slowest component (system's peripherals power limitation vs. charging speed of the storage device):

$$v = T^h \cdot \max\left(\frac{C}{P^{in}}; v^{store}\right) \tag{2}$$

The storable volume per timeslot is limited by the maximal charging speed v to $C \cdot v^{-1}$. The necessary charge volume q_t^{in} exceed the stored volume due to limited efficiency degrees of the power input component and the storage device itself.

$$q_t^{in} = \frac{C}{\eta^{in} \cdot \eta^{store} \cdot v} \tag{3}$$

The total costs of installing and operating the storage system consist of a fixed and a variable component:

$$K^{total} = K^{fixed} + \sum_{t=1}^{T} K_t^{variable} \tag{4}$$

The fixed costs are independent from the charge and discharge cycles of the storage system. They contain the annual depreciation rate for the peripheral components, the capital costs of the initial investment into the storage system, and the annual maintenance costs for the storage system, i.e., the storage device and the peripheral components:

$$K^{fixed} = \frac{P^{in}\pi^{in} + P^{out}\pi^{out}}{\tau} + (m+i) \cdot \left(P^{in}\pi^{in} + P^{out}\pi^{out} + C\kappa\right) \tag{5}$$

The variable costs depend on the scheduling and the volume of the charge and discharge cycles. They contain the energy cost components for (external) market supply, the savings due to supply from the (internal) storage system, the costs for charging the storage device, and the storage depreciation costs:

$$K_t^{variable} = K_t^{market\_supply} - K_t^{storage\_supply} + K_t^{storage\_charging} + K_t^{storage\_depreciation} \quad (6)$$

The costs for (external) market supply correspond to the costs the consumer would have without using a storage system, i.e., the product of the price per energy unit in timeslot t and the load (demand) volume in the same timeslot.

The savings due to supply from the (internal) storage system in timeslot t indicate the cost reduction respectively reduction of demand on the external market ($-\lambda_t \cdot q_t^{out}$), i.e., the demand is partly or fully served from the storage device.

The costs for charging the storage device in timeslot t are based on the price per energy unit in the current timeslot p_t and the charged volume ($q_t^{in} \cdot \varphi_t$).

The storage depreciation costs in timeslot t are the product of the discharged volume relative to the storage system's capacity ($\lambda_t \cdot q_t^{out} \cdot C^{-1}$) and the costs for a nominal discharge cycle ψ (EUR):

$$\psi = \frac{C \cdot \kappa}{\gamma} \quad (7)$$

Thus, the variable costs are defined as follows:

$$K_t^{variable} = p_t \ell_t - p_t q_t^{out} \lambda_t + p_t q_t^{in} \varphi_t + \frac{\kappa}{\gamma} q_t^{out} \lambda_t \quad (8)$$

For the formulation of the linear optimization model, $K^{variable}$ can be transformed into (9) with a_x as ex ante given vectors. Accordingly, (5) can be represented by an ex ante given value a_0.

$$K_t^{variable} = \lambda_t \underbrace{\left(q_t^{out} \left(\frac{\kappa}{\gamma} - p_t \right) \right)}_{a_1} + \varphi_t \underbrace{\left(q_t^{in} p_t \right)}_{a_2} + \underbrace{p_t \ell_t}_{a_3} \quad (9)$$

C. Model Formulation

Based on the definitions and equations of the preceding paragraphs, we can now formulate the optimization problem. The objectives of the optimization model are to determine the optimal timeslots for charging and discharging the storage device in order to minimize the total cost for the given time period ($t = 1 \ldots T$). For each timeslot t, the model must determine the amount of energy to charge into the storage device respectively to discharge from it. The costs resulting by using an optimally dispatched storage system are calculated against the annual baseline cost $K^{baseline}$ (EUR) for an identical consumer scenario without a storage system.

$$K^{baseline} = \sum_{t=1}^{T} p_t \cdot \ell_t \quad (10)$$

Hence, the objective function of the linear optimization model is

$$\max \quad \rightarrow \quad 1 - \frac{1}{K^{baseline}} \cdot \left(K^{fixed} + \sum_{t=1}^{T} K_t^{variable} \right) \quad (11)$$

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 $[0;1]$ (12). Charging and discharging within the same timeslot t is allowed, but must not overlap (13). At each point in time, the system's state of charge (SOC) ξ_t must be positive, but not exceeding the maximal capacity of the storage device (14). After a start-up phase (initial charging), the SOC ξ_t must not fall below the maximal DOD $\hat{\delta}$ (%) (15). The SOC ξ_t in timeslot t must take the intended charge and discharge actions into account (17):

$$0 \le \varphi_t, \lambda_t \le 1 \quad \forall t \quad (12)$$

$$\varphi_t + \lambda_t \le 1 \quad \forall t \quad (13)$$

$$0 \le \xi_t \le C \quad \forall t \quad (14)$$

$$\left(1 - \hat{\delta}\right) \cdot C \le \xi_t \quad \forall t > t' \quad (15)$$

The start-up phase until t' can be set arbitrary, but must be in the following range to ensure a sufficiently long initial charging phase with respect to the system's charging speed v.

$$\left\lceil 1 - \hat{\delta} \right\rceil \cdot v \le t' \le T \quad (16)$$

$$\xi_t = \sum_{t'=1}^{t} \frac{C}{v} \cdot \varphi_{t'} - \frac{q_{t'}^{out}}{\eta^{out}} \cdot \lambda_{t'} \quad (17)$$

As (9) expresses, the usage of a storage system with the objective of arbitrage accommodation is beneficial, if the avoided cost for external supply in the moment of discharge are higher than the previously required cost for charging and using (depreciating) the storage device. In the standard case the costs for using (depreciating) the storage device are greater zero, i.e., the cost per unit for charging the device must be less than the cost for external supply (per unit) in the moment of discharge. Thus, time-dependent electricity tariffs are required.

IV. Simulation Results

The linear optimization model calculated the annual savings that a consumer could ideally realize when using a storage system in comparison to the baseline case of a scenario without a storage system. The reference case for the storage system parameters is given in Tables III and IV. The load curve data (electricity demand) for the reference case are taken from the standard household profile of the VDEW. The distribution of the reference case's electricity tariff corresponds to the price curve of the EEX from 2007 (all defined in Section III.A).

The following paragraphs present the results of varying the input parameters of the reference case, namely the impact of sizing the storage system's capacity, changing technical and economic parameters, and modifying the characteristics of price and load curves.

A. Capacity Variation

The larger the storage system capacity, the more load can be shifted from peak to off-peak hours. Such load shifting is beneficial, if the spread between off-peak and peak tariffs is greater than the costs for using the storage device. The costs for using the device are determined by the technology used, namely its costs per storage capacity unit and the expected number of nominal (dis-)charge cycles (see (7) and (8)). Disadvantageously, extending the capacity leads to higher fixed costs due to higher capital costs of the system (see (5)). Fig. 2 shows the impact of capacity extensions for the technology cases presented in Table III.

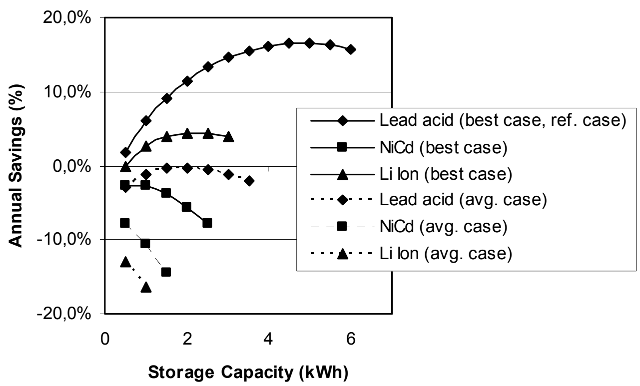

Fig. 2. Impact of capacity variations for different technology cases

The results of the capacity variation reveal that the parameter "cost per storage capacity unit" κ (EUR/kWh) has the largest impact on the overall result. Although the li-ion technology (best case) has a by factor 3.3 higher number of expected life cycles and a higher storage efficiency than the lead-acid technology (best case), the lead-acid technology with its by factor 3.3 lower costs per capacity unit leads to significantly better results of ~17% vs. ~5% annual savings.

For the reference scenario[1], the system based on lead-acid technology has an optimal storage capacity of 5 kWh, while this is 2.5 kWh for the li-ion-based system. For larger capacity values, both cases result in lower percentage of annual savings.

For all other technologies, the analysis reveals negative annual savings. Thus, in these cases the use of a storage system is not beneficial in the given scenario.

For the following simulation results, the lead-acid technology scenario (best case) is the reference, unless a different scenario is explicitly named.

B. Sensitivity Analysis of System Parameters

Besides the storage system's capacity, technical and economic parameters of the storage system determine the annual savings. In order to assess their impact on the savings, each parameter is varied separately in 4 levels (±1%, ±10%) from the reference value in Table III respectively IV (all parameters are varied separately from each other). The results in Fig. 3 reveal that variations of the efficiency parameters[2] and the cost rate per storage unit show the highest sensitivity on the annual savings. These results are in line with the findings of a sensitivity analysis in [10].

Although the variation of the cost rate per storage capacity unit shows a lower sensitivity than the efficiency degrees, it still has the highest absolute impact on the savings (see previous paragraph) due to the larger absolute differences between the parameter values (100 [EUR/kWh] (lead-acid) vs. 300 [EUR/kWh] (li-ion)). Variations of the remaining parameters have a minor influence on the savings.

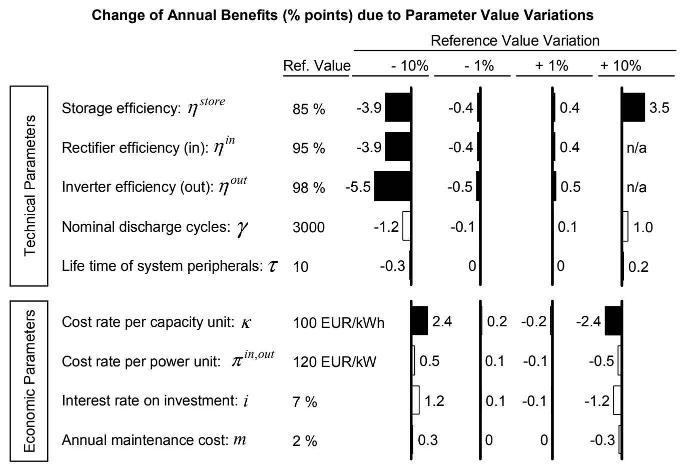

Fig. 3. Sensitivity analysis for technical and economic storage parameters

C. Price Curve Variation

The fluctuations of the market price determine the off-peak and peak periods when the storage system can be charged respectively discharged. Additionally, the price level and the spread between peak and off-peak periods determine the charge and discharge volumes.

The following paragraphs analyze the relative impact of price spreads, the average price level, and the granularity on the annual savings. The point in time of peak and off-peak periods does not shift.[3]

1) Variation of the Average Market Price: The variation of the average market price analyzes a linear decrease respectively increase of the average (annual) market price. The market price vector contains a price p_t for each timeslot t. Each price is increased respectively decreased with the same constant value. Price vectors with average market prices of 90%, 99%, 101%, and 110% of the reference vector's average price are compared in the analysis. For each price vector, Fig. 4 depicts the relative savings in the context of the reference scenario.

As shown in Fig. 4, the relative savings decrease in case of an increasing market price. Since all market prices for the analyzed time period are varied by the same constant factor, the realizable spreads remain the same. Thus, the absolute savings also remain equal. Since a decrease in market prices also leads to lower baseline cost (see (10)), the relative savings decrease.

[1] Variations from the reference scenario, e.g., a variation of the load curve distribution or the annual load volume, lead to different optimal capacity values.

[2] Storage efficiency and rectifier efficiency have the same impact due to the model formulation, see (2). An increase of the rectifier and inverter efficiency by 10% from the reference value is not applicable, since this would lead to efficiency values >100%.

[3] The effect of shifting peak and off-peak hours is indirectly analyzed in Paragraph IV.D, where the load curve distribution is varied.

Additionally, limited efficiency degrees even decrease the absolute savings in case of higher average market prices (see (2) and (9)).

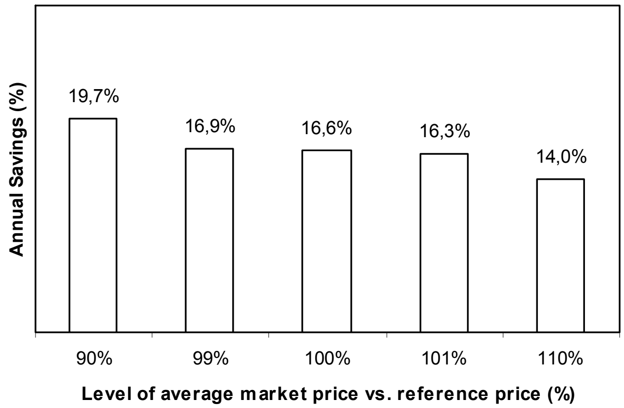

Fig. 4. Impact of market price level variations

2) Variation of Price Spreads: The variation of price spreads analyzes a linear increase respectively decrease of the average spread between peak and off-peak timeslots. The average (annual) market price is constant in all compared cases in Fig. 5.

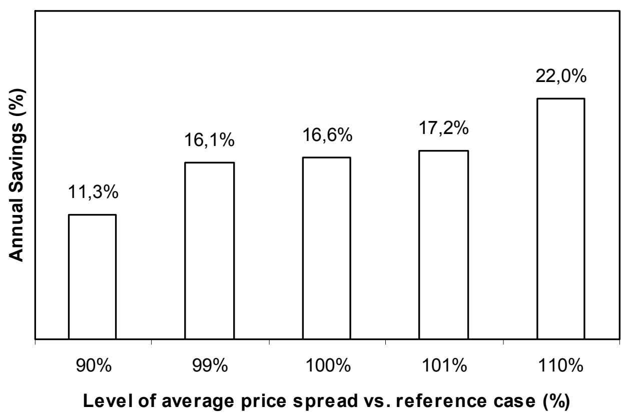

Fig. 5. Impact of price spread variations

For the reference scenario, an increase of the average price spread by 1% leads to 0.6%-point higher annual savings. An increase by 10% raises the annual benefits through the storage system to 22.0% (+5.4%-points). In the context of increasing shares of intermittent energy sources that are likely to cause more volatility on future electricity prices, the significant influence of the spread supports the benefits of the storage model.

3) Variation of the Price Curve Granularity: The price curve granularity determines the number of (potentially) different price blocks per day. The assumption is that all price blocks are of equal size, i.e., account for the same number of timeslots. The market price within a price block is constant. All market price variations base on the reference price vector, which has 24 different price blocks per day. Fig. 6 depicts the relative savings in dependency from the price curves granularity.

The analysis shows that an increasing number of market price blocks per day increases the benefits from a storage system. A larger number of price blocks allow the storage system to charge in particularly low-price timeslots and to avoid external market supply in timeslots with extremely high prices. A decreasing number of price blocks flattens the extreme values of a price curve and impedes the arbitrage accommodation strategy of the storage system.

Hence, this market parameter is an important decision and steering (incentive) variable for consumers, providers, and regulators.[4]

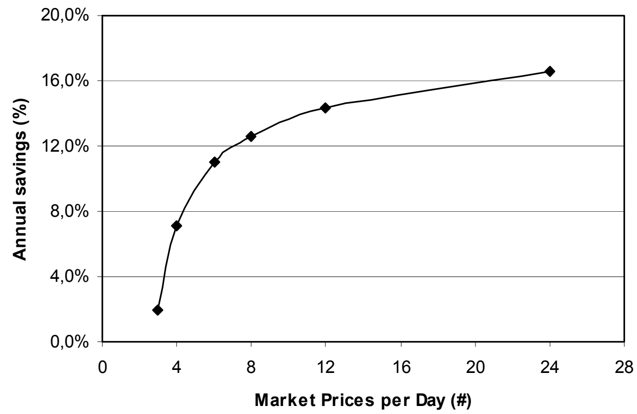

Fig. 6. Impact of price curve granularity on annual savings

D. Load Curve Variation

The load curve represents the electricity demand of the analyzed consumer case for each timeslot. It is assumed that the load data are ex-ante given. The main characteristics of the load curve are its distribution and its aggregated height, i.e., the annual load (electricity demand) of the consumer.

The following paragraphs analyze the influence of these components on the relative savings.

1) Annual Load Variation: The variation of the annual load is a linear modification of the consumer's annual consumption. Each load value ℓ_t of the load curve vector is multiplied with a constant variation factor. The analysis compares annual loads from 1000 kWh to 8000 kWh for a lead-acid-based storage system and a li-ion-based storage system.

Due to the higher annual load, the load shift volumes also increase. Therefore, each data point in Fig. 7 is based on the optimally sized storage system for the corresponding situation.[5]

The simulation results in Fig. 7 reveal that higher annual loads do not necessarily lead to higher relative savings. Besides the optimization of the storage system capacity, an optimization of the power converter dimensions is required. Nevertheless, size variations for the power and storage capacity can not always achieve positive annual savings. Both, the charging speed limit and the increasing power converter costs are bottlenecks in case of larger annual loads (see (2) and (5)).

[4] E.g., the offering of flexible tariffs is legally required in Germany from beginning of 2011 onwards [17].

[5] The optimal storage capacity has been determined separately for each annual load variation and technology scenario.

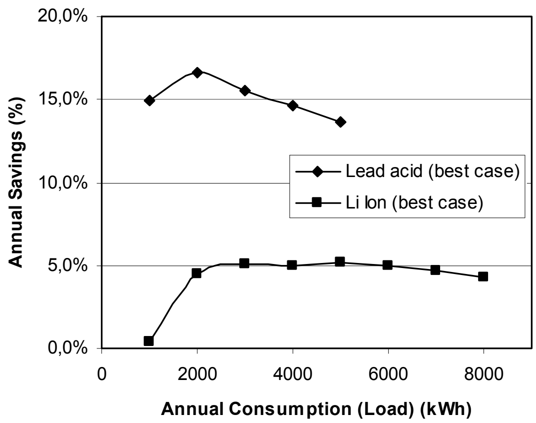

Fig. 7. Influence of the annual consumer demand on relative savings

2) Variation of the load curve distribution: Load distribution variations, i.e., shifting the time of occurrence and level of load peaks, change the characteristic of the load curve. As a consequence, the optimal charge-discharge-schedule differs for each load distribution (assuming the same price curve). The saving potential of a storage system depends on the distribution of the load curve in comparison with the price curve's distribution. Load distribution variations do not change the annual load.

Besides the reference load curve, two additional load curves were generated: a load curve with an approximately equably distribution as the price curve and a generated load curve of a single working household. The reference load profile and the generated load profile differ only in their intra-day load distribution. The seasonal and weekday-specific load distributions are equal. As Fig. 8 shows, the variation of the load curve's distribution has a significant impact on the relative savings that can be achieved by operating a storage system.

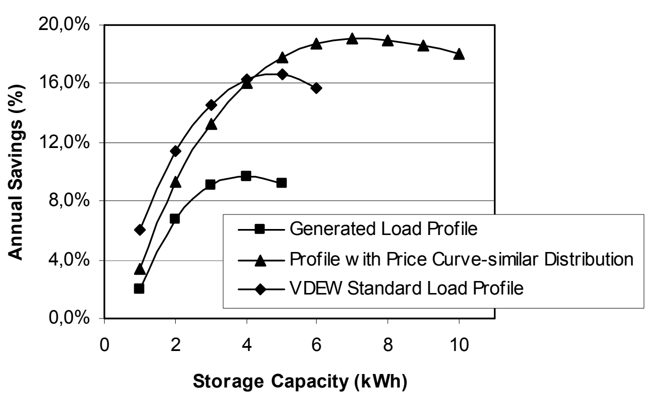

Fig. 8. Impact of the load profile shape on relative savings

The more the load curve distribution differs from the given price curve distribution, the more the relative savings decrease. The indicator χ^{shape} measures the similarity of the load curve distribution to the price curve distribution.

$$\chi^{shape} = \frac{1}{T} \cdot \sum_{t=1}^{T} abs\left(\frac{\ell_t}{\tilde{\ell}_t} - 1 \right) \tag{18}$$

The vector $\tilde{\ell}_t$ represents a load curve with the same annual load as ℓ_t and the similar distribution as the reference price curve p_t:

$$\tilde{\ell}_t = p_t \cdot \left(\sum_{t'=1}^{T} \ell_{t'} \right) \cdot \left(\sum_{t'=1}^{T} p_{t'} \right)^{-1} \tag{19}$$

$$\sum_{t=1}^{T} \ell_t = \sum_{t=1}^{T} \tilde{\ell}_t \tag{20}$$

TABLE VI
LOAD CURVE DISTRIBUTION INDICATOR VALUES

Load Curve	χ^{shape}	Annual Savings (%)
VDEW Standard Load Profile (reference)	0.51	16.6
Profile with Price Curve-similar Distribution	0.29	19.1
Generated Load Profile of a single working household	1.57	9.6

A series of simulations with 60 randomly generated load profiles of 1- and 2-person households (30 households each, includes 67% working and 33% not working households) confirms the correlation of χ^{shape} and the relative annual savings (see Fig. 9), which is not intuitive regarding the number of possible load distributions and their effects on the savings through the storage system. Thus, the indicator χ^{shape} can be seen as an indicator for investment decisions that allows an ex-ante estimation of potential benefits from a storage system for a given consumer profile.

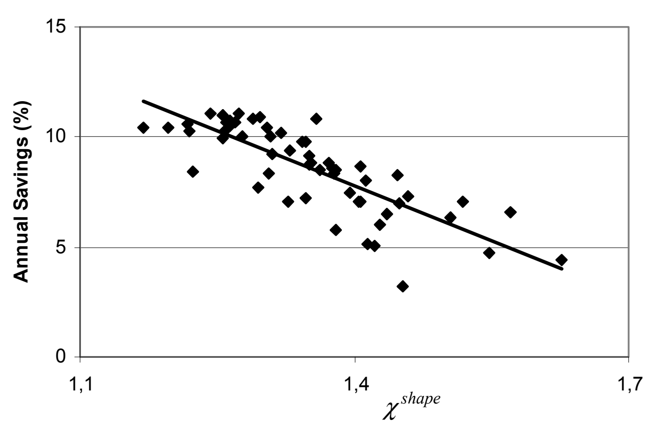

Fig. 9. Impact of the load profile shape on relative savings

Furthermore, the optimal system capacity varies depending on the load curve distribution. If the consumer's load is high in low-price timeslots and low in peak price timeslots, the baseline cost and the saving potential are low due to low load shifting volumes, which again results in a lower optimal storage capacity value. If the load curve distribution is pro-cyclic with the price curve (highest electricity demand occurs in price peak timeslots), the annual savings potential, the load shifting volumes and the corresponding optimal storage capacity value are high.

V. Conclusions

The presented model reveals a cost reduction potential through a storage system of up to 17% on total annual costs with a lead-acid-based storage system, whereas a li-ion-based system achieves only ~5% savings. The sensitivity analyses underline the outstanding impact of the costs per storage unit (EUR/kWh) and the high sensitivity of the efficiency degrees on the achievable benefits.

In the context of increasing shares for intermittent energy sources with their potential impact on the resulting market price, the analysis of price curve variations reveals further benefit potentials for the presented storage application in case of increasing gaps between peak and off-peak prices. The market price granularity results as an important incentive parameter regarding investments into storage systems for consumers, regulators and electricity providers. Additionally, the developed indicator χ^{shape} may serve as an indicator for investment decisions. It allows an ex-ante estimation of potential benefits from a storage system for a given consumer profile.

The next research step will deepen the assessment of potential benefits from distributed storage. Analyzing the impact of available forecasts regarding the consumer load and the market prices will address a weakness of the presented model that assumes ex ante known values of price and load data.

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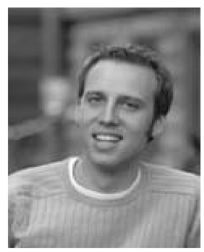

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