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The Impact of Control Strategies on the Performance and Profitability of Li-Ion Home Storage Systems

Nina Munzke[a]*, Bernhard Schwarz[a], James Barry[a]

[a]*Karlsruhe Institute of Technology (KIT), INT-PCE*
Hermann-von-Helmholtz-Platz 1,
76344 Eggenstein-Leopoldshafen, Germany

Abstract

An increase in electricity prices along with a decrease in the price of storage systems has led to rapid expansion of the PV-battery home storage system market in Germany. In order to be economically viable PV-storage systems must fulfill certain performance criteria, and in this context the system control strategy has a large impact on the overall system performance. In a nutshell, the control software should regulate the system in such a way as to maximize the self-supply ratio as well as the battery lifetime. An intelligent control strategy also has added benefits for the grid operator.

At KIT 20 commercially available PV-battery systems have been analyzed with respect to specific performance criteria: of those the following were used to quantify the level of intelligence of the storage system control software: (a) whether the software contains a predictive module at all, and if so whether it depends on external weather data; (b) the success of delayed charging in reducing the time spent at high stage of charge (SOC) levels and (c) whether prediction errors lead to the battery not being fully charged so that the user's self-sufficiency is unnecessarily reduced. Since the different effects are not independent the goal is to quantify the effects on system performance and profitability in each case. This shows the effect of software on the overall economics of energy storage systems and complements other studies based on simulation or those that look at different aspects like cell aging in an isolated context.

Roughly one quarter of the systems tested have an intelligent algorithm that controls the battery charging in such a way as to minimize calendar aging. In addition, differences of up to two years in battery lifetime are shown using voltage measurements with realistic household profiles and measured PV data. In this way, the present work outlines how control software can influence the performance and in particular the calendar aging of PV storage systems.

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* Corresponding author. Tel.: +49721 608 28283; fax: +49721 608 28284.
E-mail address: nina.munzke@kit.edu

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1. Introduction

Efficient and economic energy storage technologies are key elements for a sustainable future energy supply, indeed, attractive and economical applications can be established if persistent and cost-efficient storage systems for electrical energy can be provided.

Since electricity prices in Germany have increased over the last few years [1] and storage prices are starting to decline, the economics will soon become attractive for small German household applications. It can already be seen that more and more PV home storage systems have been installed during the last years [2].

There are several critically important aspects affecting the performance and as a consequence the commercial viability: the system design and dimensioning, the level of development of the system control software and the calendar and cycle life of the battery and electronic components.

The system control strategies as well as the efficiency of different components have a large impact on the overall system performance. For this reason, 20 commercially available PV-battery systems with a usable storage capacity of between 2 and 8 kWh are currently being analyzed with respect to different performance criteria. The present work focuses on the system control strategy and its effect on system performance.

The control software should regulate the system in such a way as to maximize the self-supply ratio. The underlying algorithms must also ensure the longest possible operational lifespan of the battery; in particular the various electrochemical processes that take place during the normal operation of a lithium-ion battery must be taken into account. For this reason a vital component of the software is its ability to predict both the energy needs of the customer as well as the energy supplied by the PV-array, throughout the day. In essence one needs to be able to predict the load as well as the available power, to deduce how the system should best be regulated in order to increase profitability.

One concrete example of this is that excess energy should not be stored in the battery right at the start of the day, but rather only after midday, since lithium-ion batteries age faster when their state of charge (SOC) is high [3].This requires serious brainpower in the control system, since one has to decide in advance when and with what power the battery should be charged or discharged in order to simultaneously maximize self-supply and ensure a long battery life.

The main aim of this work was to find out how well-developed the system control software is, how good the performance of commercially available systems already are and which future developments are still necessary in this area.

2. Methodology

2.1. Input data

To find out whether the commercial home storage systems possess any sort of intelligent and/or predictive charging/discharging algorithm, they are tested within a hardware-in-the-loop environment similar to that described in [4]. The test setup, including all points of measurement is described in [5]. The measurements are done for typical reference days with measured solar PV data from KIT with a time resolution of one second and load curves for single-family households that can be generated based on the VDI 4655 reference profiles [6]. The tests were performed with an annual electricity demand of between 3500 and 4200 kWh, which corresponds to between 2 and 5 inhabitants per household. The resulting household load profiles have a time resolution of one minute. The PV data comes from the 1 MW PV plant at KIT north campus, located at 49.1° N, 8.44° E, which corresponds to climate zone TRY12 in the VDI 4655 classification system.

By testing all 10 different reference days of the VDI 4655 and using the corresponding frequency of each day within climate zone TRY12, the results can be extrapolated to the whole year.

In addition, tests were performed using the same PV data from summer and load data of one household from one summer week of measurements at 1 Hz, from the project “ADRES-CONCEPT” [7].

Table 1: Test configurations

Criteria	Test 1	Test 2
Load data	VDI 4655 - TRY 12 [6]	Two households of one week in summer, from the project "ADRES-CONCEPT" (HH14) [7]
Annual electricity demand - inhabitants per household	4200 kWh - five inhabitants	~ 3500 kWh
PV data	Different days of the year according to the reference days	7 Summer day
PV-plant size	3.5 kWp	3.5 kWp

2.2. Test criteria

The following criteria were used to quantify the level of intelligence of the storage system control software of the systems under test: (a) whether the software contains a predictive module at all, and if so whether it depends on external weather data; (b) the success of delayed charging in reducing the time spent at high SOC levels and (c) whether prediction errors lead to the battery not being fully charged so that the user's self-sufficiency is unnecessarily reduced.

Throughout the test the power, current and voltage are recorded at different measurement points. To evaluate the success of delayed charging, especially on sunny days, the voltage of the batteries is measured. As the battery chemistry as well as the module topology of the batteries is known, the mean cell voltage can be calculated. For further evaluation the voltage range from the minimum to the maximum cell voltage is divided into 20 intervals. This is done separately for each of the cell chemistries. The battery voltage measured during operation can then be used to calculate how much time the battery spends in each interval.

In the present work only the measured battery voltage is used to determine the SOC of the systems. As the work focuses on high SOC stages where the current to and from the battery is rather small this simplification is realistic. The most common cell chemistries within the study are NMC and LFP. Due to the shapes of the respective OCV/SOC curves it is easier to determine the SOC via the voltage of NMC- than via that of LFP-based batteries. The evaluation that follows therefore focusses on 6 PV-storage systems (labelled A...F) with batteries based on NMC chemistries.

3. Results

The tests revealed that around 25 % of the systems tested possess an advanced control strategy with a predictive module. The strategy of most systems is just to increase the amount of self-consumption, represented by Figure 1. While 40 % of the advanced systems need online data the other 60 % use an offline prediction.

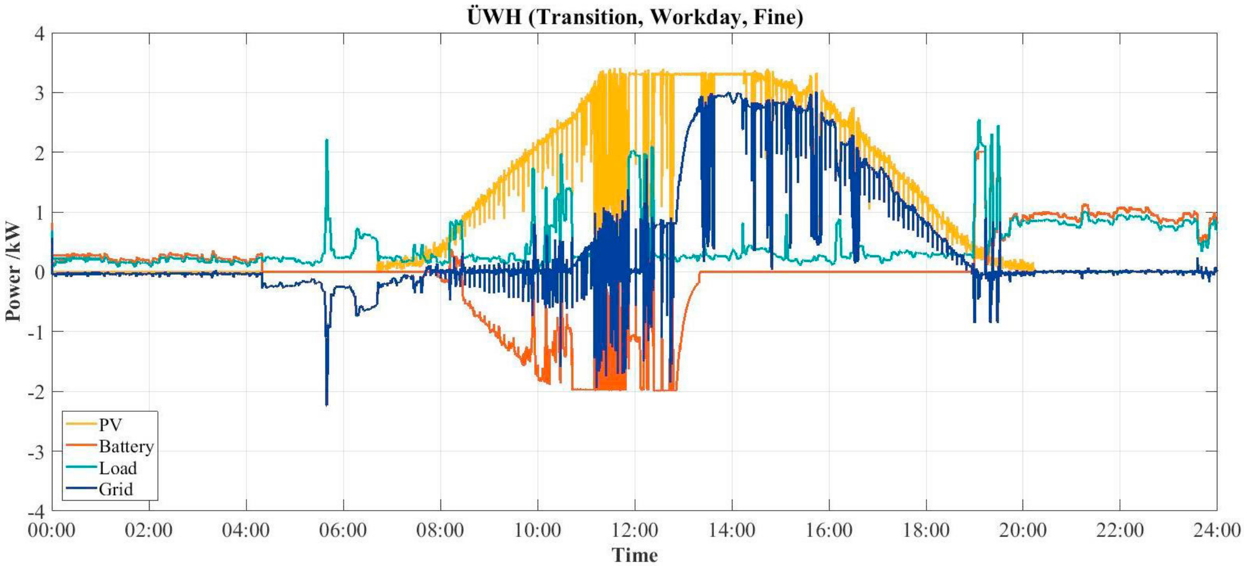

Figure 1: Measurement data for a transition day: example of a system (system A – 5.6 kWh usable storage capacity) that does not seem to have an intelligent charging algorithm

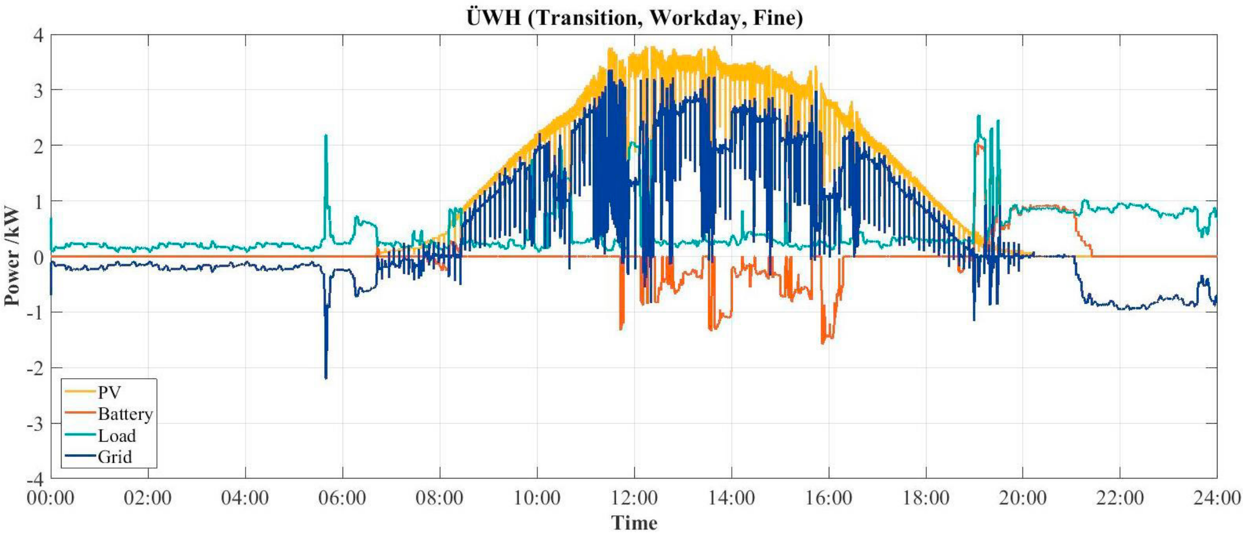

Figure 2: Measurement data for a transition day: example of a system (system D – 2.0 kWh usable storage capacity) that displays intelligent behavior regarding its battery charging algorithm

Figure 1 and 2 show two different control strategies for a stationary energy storage system: In both cases the battery is not big enough to store all of the surplus energy supplied by the installed PV panels. In the case shown in Figure 1 the batteries are charged much faster than in the one shown in Figure 2. Even though the useable storage capacity of system D (Figure 2) is only 36 % of system A (Figure 1) it is fully charged 2.9 hours after system A stops charging. The test was done with the test configuration Test 1 described in Table 1. As a consequence system D only spends 3 hours instead of 5.8 hours at an SOC level of up to nearly 100 %.

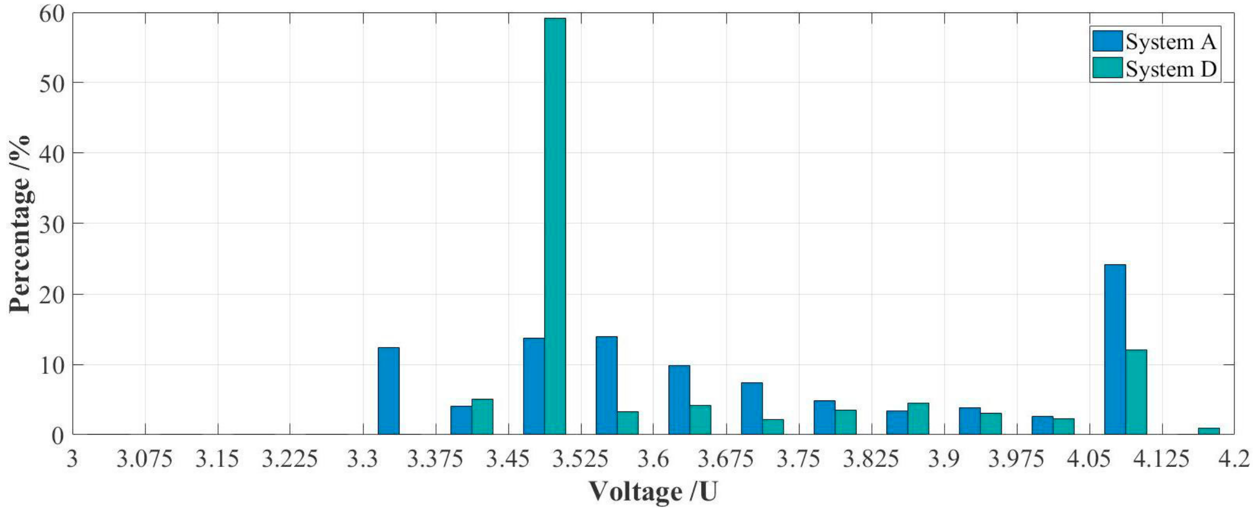

Figure 3: Distribution of the measured battery voltage during the reference day (ÜWH) for System A and D (Test 1)

The distribution of the measured voltage during the reference day (ÜWH) can be seen in Figure 3. Due to the fact that system A does not possess an intelligent charging algorithm 33.9 % of the voltage values are higher than 3.825 V. In comparison, system D remains at a voltage higher than 3.825 V for only 22.7 % of the time.

In addition, systems A…F were tested using the test criteria Test 2 (see Table 1). While Figure 5 shows the results of measurements of one summer week, Figure 4 represents the extrapolated results for a whole year. Both tests show a similar trend: even though system D is the smallest within the evaluation, it spends the least amount of time at voltage levels higher than 3.825 V during summer days (see Table 2), i.e., it spends the least amount of time at a high SOC level in summer (31.1 %). However this is not the case when comparing the values for the whole year – due to its lower capacity it spends the highest percentage of time at high SOC levels in winter.

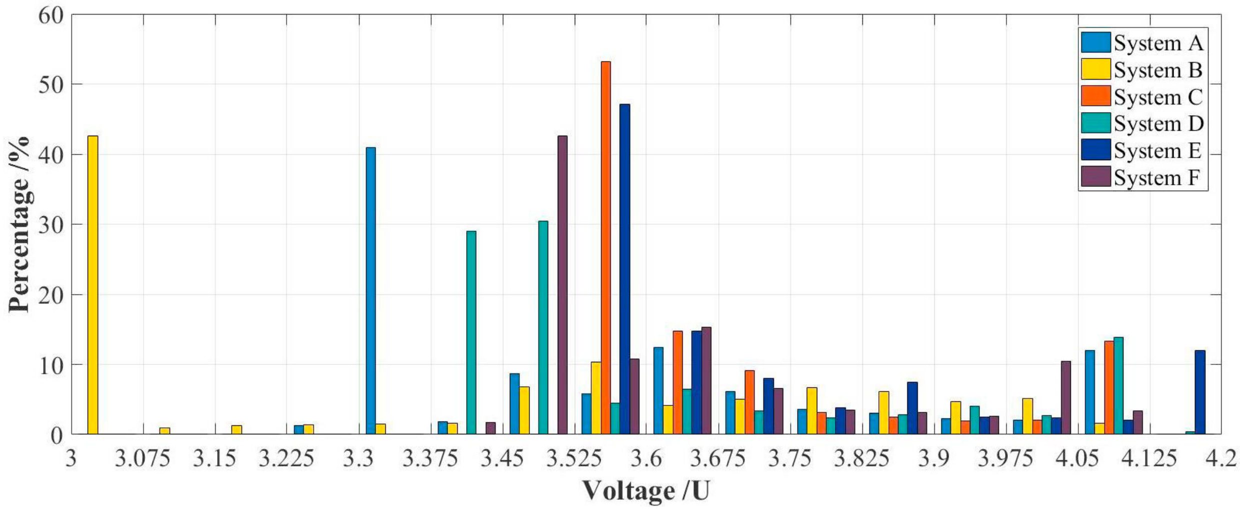

Figure 4: Distribution of the battery voltage extrapolated for a whole year for System A…F (Test 1)

System B, whose storage capacity is higher than that of system D but less than all the others, spends the least amount of time at voltage levels higher than 3.825 V during the whole year. Note that the summer week (Test 2) could not be evaluated for system B so far due to missing data. A qualitative analysis of the measurement results shows that only two of the six systems (B and D) show an intelligent charging strategy.

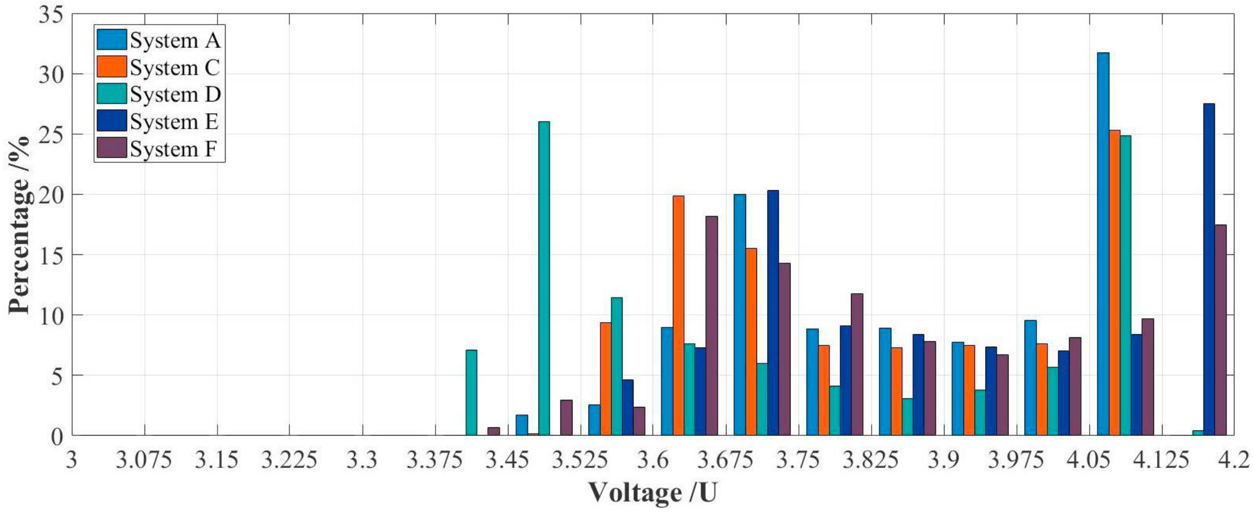

Figure 5: Distribution of the measured battery voltage for one summer week (Test 2) for System A and C…F

Table 2: Usable storage capacity and percentage of time spent at a measured voltage higher than 3.825 V for the systems A…F

		System A	System B	System C	System D	System E	System F
Usable storage capacity /kWh		5.6	4.4	5.0	2.0	5.0	5.0
Percentage of time spent at a voltage (extrapolation for a whole year – Test1)	> 3.825 V	19.3	17.6	19.8	23.8	26.3	19.6
	< 3.825 V	80.7	82.4	80.2	76.2	73.7	80.4
Percentage of time spent at a voltage (summer week – Test 2)	> 3.825 V	58.0	incomplete data	41.4	31.1	52.5	39.8
	< 3.825 V	42.0		58.6	68.9	47.5	60.2

In order to quantify the effect of charging strategies on cell aging it is useful to use existing results from the literature. Keil et al. [3] performed measurements of calendar aging for different cell chemistries, and their results show that the three cell chemistries NMC, LFP and NCA show a higher capacity fade (CF) at SOC levels greater than 60 % - 70 %. For NMC a capacity fade of 1 % - 3 % at SOC levels between 0 % and 60 % and 5 % to 6 % between 70 % and 100 % SOC is found, over a period of 10 months, where measurements were performed at 25 °C. By using these values and the extrapolated results (Table 2) for one year one can calculate the annual capacity fade due to calendar aging, i.e.,

$$CF_{per\ year} = \frac{t_{V>3.825}}{t_{total}} * CF_{SOC\ 70\,\% - 100\,\%} + \frac{t_{V<3.825}}{t_{total}} * CF_{SOC\ 0\,\% - 70\,\%}\ , \qquad (1)$$

as well as the time until the system reaches a relative capacity of 80 %, assuming only calendar aging takes place. A relative capacity of 80 % is defined as the end-of-life (EOL) criterion. For NMC, an SOC higher than 70 % corresponds to an open circuit voltage (OCV) of around 3.8 V (see Figure 6). Using the simplification described under Section 2.2, all voltage levels higher than 3.825 V represent an SOC higher than 70 %. The results can be seen in Table 3.

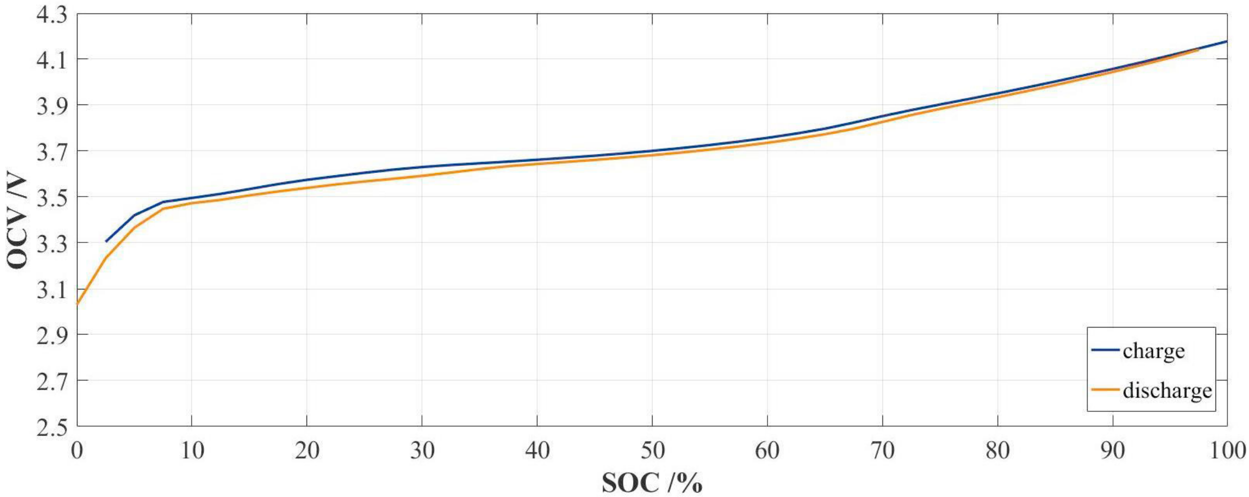

Figure 6: Example of an SOC/OCV curve with graphite anode and a NMC cathode

Table 3: Calculated annual capacity fade and the time until the system reaches a relative capacity of 80 % assuming only calendar aging for the Systems A…F

	System A	System B	System C	System D	System E	System F
Capacity fade per year (%)	2.580	2.528	2.594	2.715	2.788	2.588
End of life (EOL) in years	7.753	7.911	7.711	7.366	7.175	7.729

The results shown in Table 3 are rather high for batteries used within PV-storage systems. Since the cells used within the systems under test may have a longer calendar life and less sensitivity to higher SOC levels than the cells used in the tests by Keil et al., a sensitivity analysis was done for these two factors. Figure 7 to 9 show the effect of a different capacity fade at the different SOC levels. The results were calculated using the assumptions of Table 4 and Equation 1. The calculated lifetime of the systems under test differ from each other as a function of the percentage of time spent at a measured voltage higher than 3.825 V and as a consequence an SOC higher than 70 %. The higher the capacity fade at an SOC higher than 70 % is, the more important it is to reduce the time spent at high SOC. It can be seen that system B shows the least capacity fade per year in all three scenarios (see Figure 7 to 9). As a consequence the battery lasts the longest until it reaches a relative capacity of 80 %, i.e., its end-of-life. If the capacity fade per year at an SOC higher than 70 % reaches 5.5 % per year, the difference in lifetime caused by calendar aging varies between 0.79 and 1.99 years depending on the capacity fade per year at an SOC lower than 70 %.

Table 4: Input parameters for the sensitivity analysis

		Figure 7	Figure 8	Figure 9
Capacity fade per year (%)	> 3.825 V / > 70 % SOC	2.0 – 6.0	1.3 – 6.0	1.00 – 6.0
	< 3.825 V / < 70 % SOC	2.0	1.3	1.0

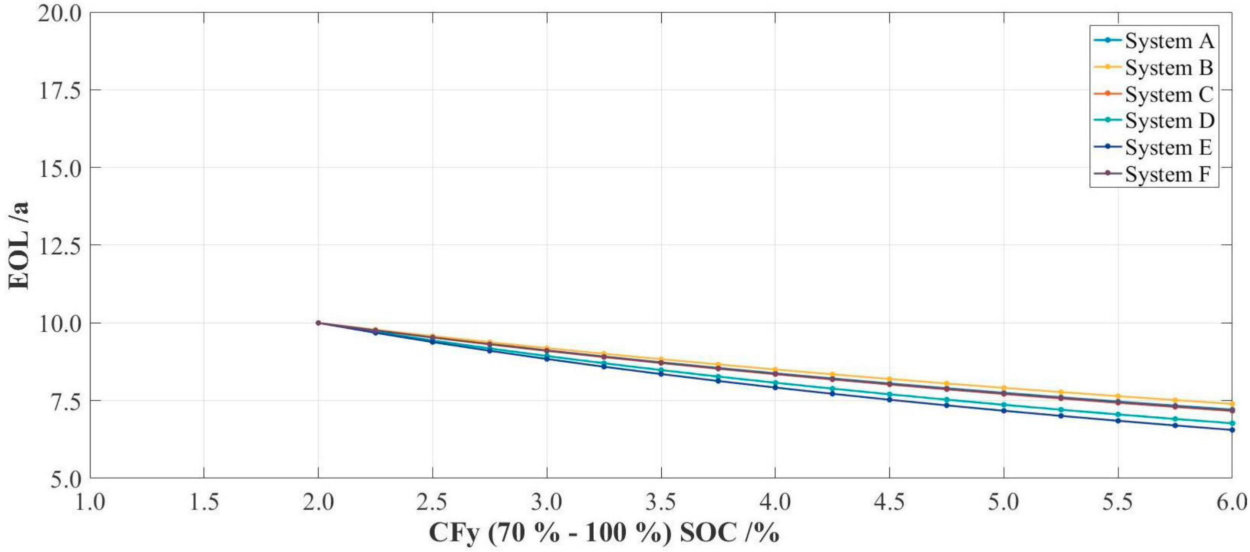

Figure 7: Lifetime of the PV-storage systems due to calendar aging calculated with a capacity fade per year of 2.0 % for SOC levels between 0 % and 70 % and a variation of 2.0 % - 6.0 % for SOC levels between 70 % and 100 %

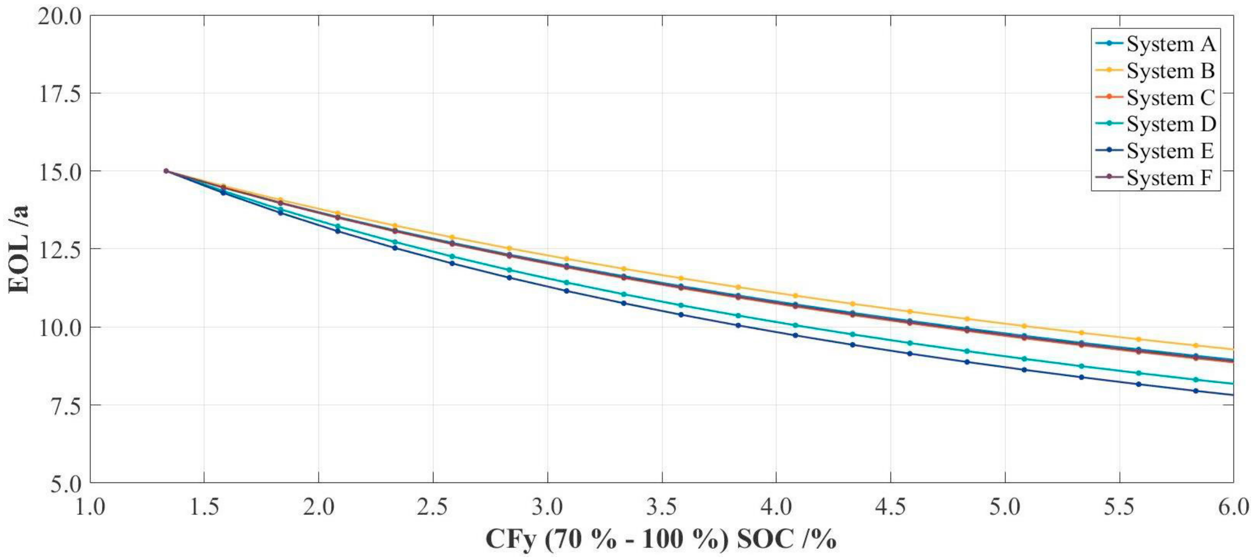

Figure 8: Lifetime of the PV-storage systems due to calendar aging calculated with a capacity fade per year of 1.3 % for SOC levels between 0 % and 70 % and a variation of 1.3 % - 6.0 % for SOC levels between 70 % and 100 %

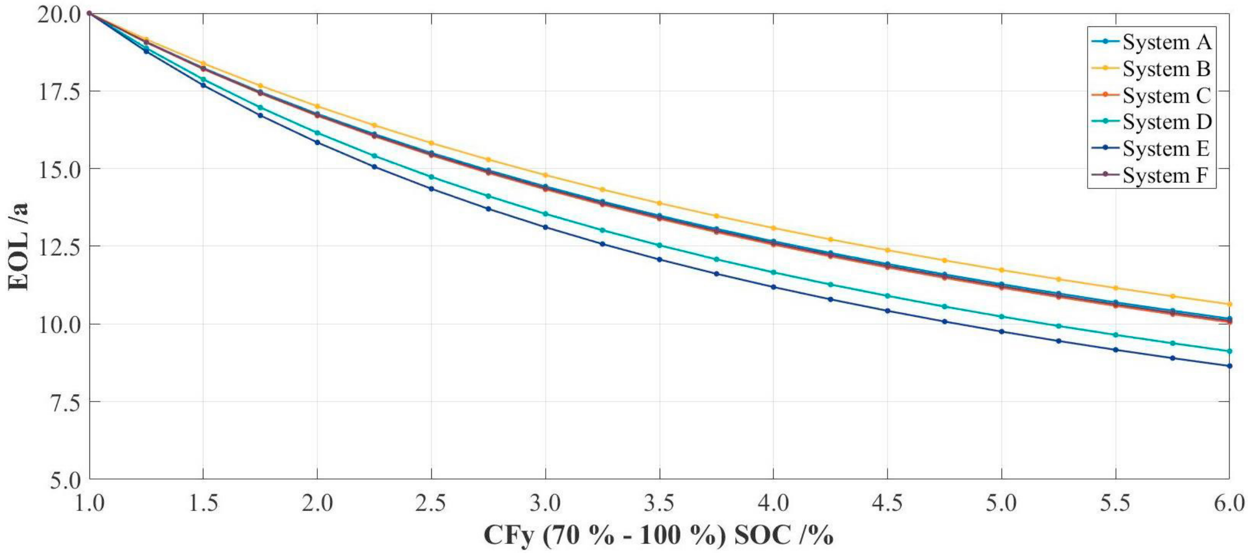

Figure 9: Lifetime of the PV-storage systems due to calendar aging calculated with a capacity fade per year of 1.0 % for SOC levels between 0 % and 70 % and a variation of 1.0 % - 6.0 % for SOC levels between 70 % and 100 %

4. Conclusion

It has been shown that an intelligent control strategy can prevent calendar aging. How large the effect is obviously depends on the dimensioning of the system and the sensitivity of capacity fade at different SOC levels. It has been observed that a difference in battery lifetime caused by calendar aging of up to nearly 2 years is possible. To determine the overall aging of the batteries, aging effects caused by cycling need to be taken into account as well. As the present work focuses on the effects of the software on system performance this still needs to be examined. How heavily the performance and as a consequence the profitability of the system is effected by an increased calendar aging depends on further factors such as the system's specific dimensions as well as its cycle lifetime. Nevertheless, as PV-storage systems are just starting to become economical, a longer battery lifetime could have quite a positive influence [8].

As mentioned, only 25 % of the systems tested possess an intelligent control strategy. A reduction of self-sufficiency caused by the control strategy could not be observed for system D and only in rare cases for system B. Further investigations are needed to quantify this effect.

An intelligent charge/discharge regime also benefits the grid operator: due to delayed charging the battery is not completely full around midday, enabling the system to perform peak-shaving of excess PV production that usually occurs around this time. A reduction of such peaks of up to 40 % of the installed PV power has been shown to be possible [9], but in each case this obviously depends on the system's specific dimensions.

Peak-shaving can also increase the overall system profitability in cases where the maximum power that can be fed into the grid is limited by law: during times of high PV production the predictive control system ensures that the excess energy is stored without having to throttle the PV generators. Nevertheless, an intelligent control strategy that minimizes calendar aging does not necessarily benefit the grid operator or minimize the time during which the PV generators need to be throttled (see Figure 2). Between 12:00 and 15:00 more than 2.6 kW out of a total of 3.5 kW of the generated PV power is fed into the grid. If the maximum power that is allowed to be fed into the grid were limited to 70 % or even 50 % of peak power (3.5 kWp), the PV generators would need to be throttled during that time.

Further investigations are needed to quantify the level of intelligence of the storage system control software in terms of the benefits for the grid operator as well as an increased profitability in cases where the maximum power that can be fed into the grid is limited by law.

In any case, the expected future increase in the amount of installations in the field makes the integration of an intelligent control algorithm that takes the above-mentioned aspects into account all the more important.

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