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Article

Model Predictive Control for Residential Battery Storage System: Profitability Analysis

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Abstract: For increased penetration of energy production from renewable energy sources at a utility scale, battery storage systems (BSSs) are a must. Their levelized cost of electricity (LCOE) has drastically decreased over the last decade. Residential battery storage, mostly combined with photovoltaic (PV) panels, also follow this falling prices trend. The combined effect of the COVID-19 pandemic and the war in Ukraine has caused such a dramatic increase in electricity prices that many consumers have adjusted their strategies to become prosumers and self-sufficient as feed-in subsidies continue to drop. In this study, an investigation is conducted to determine how profitable it is to install BSSs in homes with regards to battery health and the levelized cost of total managed energy. This is performed using mixed-integer linear programming (MILP) in MATLAB, along with its embedded solver Intlinprog. The results show that a reasonable optimized yearly cycling rate of the BSS can be reached by simply considering a non-zero cost for energy cycling through the batteries. This cost is simply added to the electricity cost equation of standard optimization problems and ensures a very good usage rate of the batteries. The proposed control does not overreact to small electricity price variations until it is financially worth it. The trio composed of feed-in tariffs (FITs), electricity costs, and the LCOE of BSSs represents the most significant factors. Ancillary grid service provision can represent a substantial source of revenue for BSSs, besides FITs and avoided costs.

Keywords: battery storage system; economics; optimization; profitability

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1. Introduction

Over the past 10 years, from 2011 to 2021, total electricity production from photovoltaic (PV) plants has multiplied by 25 [1]. Boosted by the hugely reduced cost of PV modules, whose price has decreased by more than 90% since 2009 [2], the worldwide total of installed power in residential PV plants reached 145.4 GW in 2021, which is about nine times the installed capacity 10 years prior [1,3]. This trend has emphasized the energy management challenges faced by grid operators, especially when power is generated from intermittent sources. Battery storage systems (BSSs) are becoming more and more useful as their prices have considerably decreased [4]. A widely adopted strategy to alleviate this power management issue is to prioritize PV power self-consumption [5–8]. In all major world regions, especially in developed countries, feed-in tariffs (FIT) for residential solar power are reduced, on average, to a quarter of their value 10 years ago [9–12]. The shortest path to achieving electrical self-consumption of PV power requires an intermediate BSS to match the home electricity demand and power supply.

There has been a prolific number of research works that have presented different methods and techniques to maximize the energy self-sufficiency rate [13–17]. Some have reviewed the different ranges of services BSSs can offer in a power system [18]. Others have studied the potential revenue achievable by BSSs or home energy management systems [19,20]. On the battery's hardware side, there are continuous studies focusing on improving the reliability and, more intensively, the robustness of rechargeable batteries [21,22]. However, the battery-charging power profile, its health degradation, limited lifetime expressed as number of cycles, and the self-consumption of the battery management system are somehow overseen, especially in advanced predictive models of BSS power control strategies that exploit the volatility of electricity prices to generate profit [23–25].

In this paper, a simplified analysis of the profitability of residential BSSs coupled with PV power is presented. The method relies on a model predictive control approach to estimate yearly potential income, considering the cost of storing and using energy from the batteries. The levelized cost of this energy flow through the battery is the determining key indicator. The revenues are composed of the FITs and the avoided costs from the energy sold to the grid and the avoided energy consumption provided by the PV unit. The consumed energy costs are derived from the historical day-ahead market prices from the previous 12 months (from November 2021 to October 2022).

2. Previous Related Works

The authors of [18] presented a very detailed analysis of the profitability of a combined plant of PV power and battery storage, including the provision of negative reserve service to the grid. They found that battery costs are still high and have a higher impact on system profitability for homeowners. It is also stated that discovering the precise break-even battery price is a multivariable problem specific to the local weather and economy. The major missing point is that the analysis was conducted using average electricity prices. Considering the volatile prices experienced recently can double the projected BSS cycling rate.

In [13–17], which are mainly studies on commercial size power systems, the focus is on the self-sufficiency rate with little regard for BSS usage cost. In [13], for example, the BSS was so oversized that the state of charge (SOC) remained quite low (below 30%) for up to three days despite the power cycling. The study carried out in [23] considered a too-ideal battery unit. BSS self-consumption, as well as self-discharge, are not included.

The authors of [24] presented a very advanced control strategy, like this work, based on model predictive control (MPC). The considered time-of-use (TOU) electricity prices were constant values during three periods of the day. With such low volatility, the presented controlled BSS depicted up to two cycles per day, which is considerably high for lead–acid batteries. This would be much more frequent with the highly volatile prices nowadays. The BSS charging power is constant throughout the whole charging period. Such ideal behavior does not reflect the reality of available industrial battery management systems. The authors of [26] had to constrain the discharge of the battery only after the SOC reached a given threshold. This is a clear limitation of any financial optimization trial.

This paper is a combination of the strengths of previous studies and a trial to overcome their weaknesses. The present work used mixed-integer linear programming (MILP) optimization and the MPC strategy. The considered electricity prices are the 15 min day-ahead electricity spot prices, instead of the averaged daily prices of the TOU prices' profile. Most importantly, a financial cost for storing power into the BSS was directly integrated into the optimization problem. This aims to avoid non-profitable cycling of the BSS, especially with volatile electricity prices.

3. MPC Models and Constraints Definition

The profitability optimization problem is solved using the MILP technique as detailed in [27]. The mathematical formulation of the problem and the objective function are defined in the next lines. (The abbreviations in the following equations are defined in Abbreviations part.)

3.1. Electrical Power Balance

The electrical power balance at the point of connection of the BSS, the PV plant, the loads, and the grid must be respected and is represented by Equation (1) as follows:

$$\boldsymbol{P}_{buy} + \boldsymbol{P}_{BSS-} + \boldsymbol{P}_{pv} = \boldsymbol{P}_{sell} + \boldsymbol{P}_{BSS+} + \boldsymbol{P}_{load} \quad (1)$$

In this studied case, there is a single bi-directional power counter. Thus, the possibility to buy and sell power simultaneously is excluded, and the sum of both simultaneous values are limited to a maximum value. It is expressed as follows:

$$0 \leq \boldsymbol{P}_{buy} \leq \boldsymbol{P}_{buy,max}.\boldsymbol{BIN}_{buy} \quad (2)$$

$$0 \leq \boldsymbol{P}_{sell} \leq \boldsymbol{P}_{sell,max}.\boldsymbol{BIN}_{sell} \quad (3)$$

$$\boldsymbol{BIN}_{buy} + \boldsymbol{BIN}_{sell} \leq 1 \quad (4)$$

3.2. Battery Storage System

The BSS is the most sensitive and complex unit to model. Without investigating every single electrochemical and thermal interaction, the model employed considers the observable electrical behavior. The self-discharge rate of batteries themselves is very low. When kept in a proper environment with a constant 20 °C ambient temperature, lead–acid batteries lose as little as 4% of the stored energy in one month. Lithium-ion batteries perform better and lose about 2%/month. With a non-linear self-discharge rate, they lose 4% in 3 months [28,29]. However, the inverters belonging to the BSS require minimum power to supply the electricity and ensure the proper and safe use of the batteries. This leads to a self-discharge rate of the BSS that is much higher than that of the batteries themselves. Several small-scale BSS manufacturers (not all) indicate zero-load, standby, overnight, idle state, or nighttime consumption or power ranging from 3 to 18 W, depending on the state of the inverter. The smaller the installed battery capacity, the bigger the impact of the inverter standby consumption on the SOC. For a 5 kWh lead–acid BSS capacity, an idle consumption as low as 3 W by the BSS inverter leads to 2.16 kWh energy being consumed in one month. This is 43% of the total battery capacity being used. The apparent self-discharge rate (43% in a month) is then ten times the intrinsic self-discharge rate of the battery bank. The same inverter, handling 20 kWh storage, would use 11% of the total energy stored.

The state of charge of the BSS can then be expressed as follows (5):

$$d\boldsymbol{SOC}_t = \frac{1}{\boldsymbol{E}_{BSS,max}}\left(\boldsymbol{\eta}_{BSS+}\boldsymbol{P}_{BSS+,t} - \frac{1}{\boldsymbol{\eta}_{BSS-}}\boldsymbol{P}_{BSS-,t} - \boldsymbol{P}_{BSS,loss,t}\right) dt \quad (5)$$

To achieve a defined usage time with proper usage of the BSS, especially the battery bank of the BSS, the SOC is constrained to clear the lower and upper SOC values, i.e., $\boldsymbol{SOC}_{min}$ and $\boldsymbol{SOC}_{max}$.

$$\boldsymbol{SOC}_{min} \leq \boldsymbol{SOC}_t \leq \boldsymbol{SOC}_{max} \quad (6)$$

BSS manufacturers, as well as battery manufacturers, indicate the maximum charging current permitted for the battery bank. However, based on up-to-date battery-charging techniques, the charging power does not remain constant during a complete charging cycle. As depicted in Figure 1 [30], the charging cycle can be divided into two steps. The first is the constant current phase, where the battery is charged by a controlled constant current. The battery voltage increases to a specific threshold along with the charging power. This phase is followed by the constant voltage (CV) charging phase. The voltage is held constant; the current continues to flow, although at a decreasing rate until it reaches 0; and the battery is then fully charged. The power during the CV phase decreases and is therefore proportional to the inverse on the SOC of the battery bank.

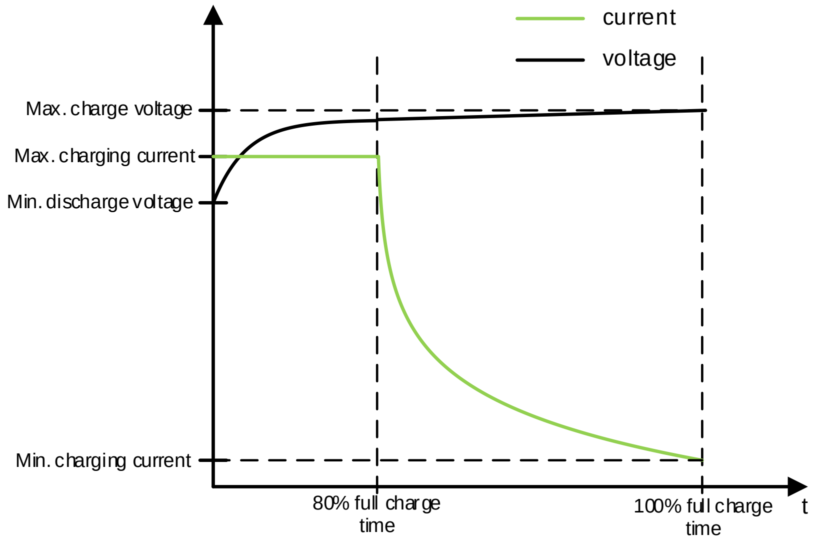
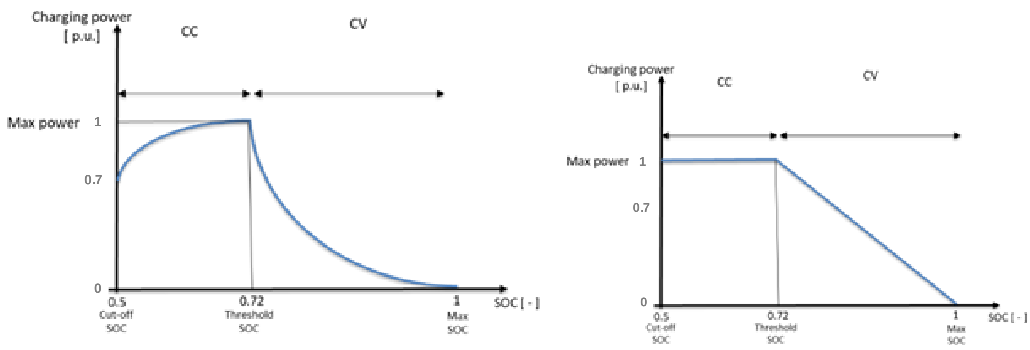


Figure 1. Typical charging voltage and current profile of a battery and operation modes of a battery charger.

This maximum charging power profile of the BSS can be modeled as depicted in Figure 2a and expressed as follows:

$$\boldsymbol{P}_{BSS+,max} = f(\boldsymbol{SOC}_t) \tag{7}$$

Depending on the targeted accuracy, the function f can be a polynomial function of high order. In this work, the following simplification was made: during the CC phase, the charging power is constant and then decreases linearly with the SOC after the SOC threshold is reached (see Figure 2b).



(**a**) (**b**)

Figure 2. (**a**) Typical charging power profile of a battery; (**b**) Simplified charging profile of a battery.

The computing $\boldsymbol{P}_{BSS+,max}$ within the optimization process would add another unnecessary complexity to the problem. Hence, to keep the problem linear, the maximum charging power is recalculated once between each optimization step. This creates a small bias in the model but with little impact because only the charging power is limited to that contact value during one optimization step.

Like the power balance at the main supply point of the house, the power balance of the BSS is also bi-directional but not simultaneous. The power can flow in one direction at a time and is limited by the maximum charging and discharging power of the batteries. The BSS inverters are considered optimally sized for the battery pack.

$$0 \leq \boldsymbol{P}_{BSS+} \leq \boldsymbol{P}_{BSS+,max}.\boldsymbol{BIN}_{BSS+} \tag{8}$$

$$0 \leq \boldsymbol{P}_{BSS-} \leq \boldsymbol{P}_{BSS-,max}.\boldsymbol{BIN}_{BSS-} \tag{9}$$

$$\boldsymbol{BIN}_{BSS+} + \boldsymbol{BIN}_{BSS-} \leq 1 \tag{10}$$

3.3. Objective Function

Some studies that focused on a similar optimization problem in the past considered that FITs are equal to the price of electricity bought. In this case, the objective function is simplified as shown in (11). Minimizing the energy consumption from the grid directly automatically leads to the cost minimization.

$$Min.\left(\sum_i^n \left(\boldsymbol{P}_{buy,i} - \boldsymbol{P}_{sell,i}\right)\boldsymbol{p}_{buy,i}.\Delta T\right) \tag{11}$$

However, incentives for supplying the grid with solar power are now drastically reduced and are far below that of electricity prices. Taking that into consideration, the objective function in (12) can be changed and expressed as follows:

$$Min.\left(\sum_i^n \left(\boldsymbol{P}_{buy,i}.\boldsymbol{p}_{buy,i} - \boldsymbol{P}_{sell,i}.\boldsymbol{FIT}_i\right)\Delta T\right) \tag{12}$$

To integrate the LCOE of the BSS, it is assumed that the energy generated by PV power is given because the investigation focuses on the profitability of the BSS and not that of the system PV-BSS. The final objective function is therefore given in (13). It minimizes the total cost of the consumed electrical power, taking into consideration that the power flow through the battery to be charged is not 100% efficient.

$$Min.\left(\sum_i^n \left(\boldsymbol{P}_{buy,i}.\boldsymbol{p}_{buy,i} - \boldsymbol{P}_{sell,i}.\boldsymbol{FIT}_i + \left(\boldsymbol{\eta}_{BSS+}\boldsymbol{P}_{BSS+} + \frac{1}{\boldsymbol{\eta}_{BSS-}}\boldsymbol{P}_{BSS-}\right)\boldsymbol{p}_{BSS}\right)\Delta T\right) \tag{13}$$

Basically, this means that the power saved into the battery should be used at periods where electricity prices are so high that they compensate the total cost of storage (primary energy cost + cost for storing).

4. Lab Experiment

Some tests on the BSS's self-discharge could be performed at the University of Luxembourg. In a three-phase power system, SMA Sunny Island battery inverters, working as full batteries management systems, manage the charge and discharge rate of the installed 21.6 kWh lead–acid batteries from Hoppecke (see Table 1). The minimum SOC is set at 50% with a max discharge power of 4 kW. The inverters remain in the "no-load" state and need up to 55 W when the SOC value is between 100% and 55%. Below this low threshold, the inverters jump into the idle state and minimize consumption to a total of 18 W. The inverters automatically monitor and keep the batteries' SOC in the range of 50–53% with very short charging phases once the SOC reaches 50%. In this state, the inverters are fully decoupled from the grid. The typical profile of the apparent self-discharge of the BSS is depicted in Figure 3. The batteries are charged with constant power until the SOC reaches about 80%, then the constant voltage phase starts, and the charging power decreases with the increase in SOC. Once fully charged, the BSS stays in the "no load" state and uses up to 56 W to power the electronics and remain coupled to the grid. In about 5 days, the SOC reaches 55%, and the battery inverters reduce their consumption to 20 W as they switch to the standby state. The SOC drops from 55% to 52% in 12 h. This power consumption by the BSS itself causes an apparent self-discharge rate of about 8% a day. This apparent self-discharge rate is extremely high compared to the intrinsic self-discharge rate of the batteries only (estimated 4% in a month for lead–acid batteries).

Table 1. Main characteristics of the test bench equipment.

	3-phase DC–AC converters SMA, Sunny Island SI6.0H-11 3 × 4.6 kW No load consumption: 3 × 18 W Standby consumption: 3 × 6.8 W Efficiency: 95.5%		Lead–acid batteries' Hoppecke sun power VR L 2-520 1.80 V, 470 Ah C10 1.85 V, 574 Ah, C100 24 cells installed 21.6 kWh total capacity 2500 cycles at 50% DOD

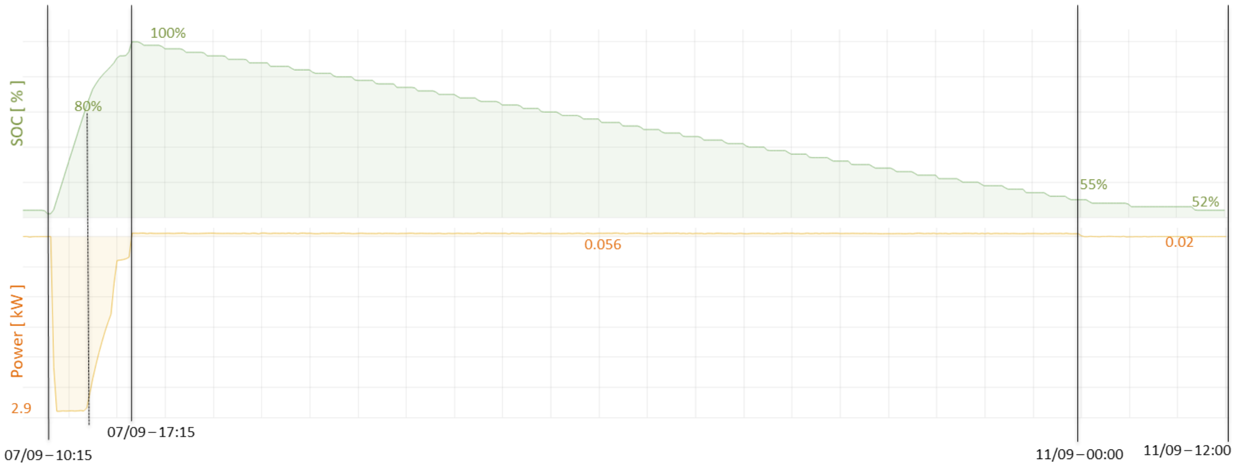


Figure 3. SOC and power profile during a cycle with no load.

5. Simulation and Results

5.1. System Configuration

The energy system considered in this work is a near-zero energy building as described in [31]. It is a residential building located in Luxembourg. The total electricity consumption is 6640 kWh a year. The following analysis discusses the optimal sizing of the BSS added to the given PV plant. The PV plant production of 7700 kWh a year is dimensioned based on yearly electricity consumption and system losses. The FITs for both the PV power and the BSS, are set at EUR 0.08/kWh. The reference system for profit comparison is the building with the grid-tied PV plant. The analysis focuses on the number of cycles undergone by the BSS. Then, calculation of the revenues the BSS can generate (including avoided expenses) is performed depending on battery capacity and its leverage cost. A comparison of these values is carried out between three cases:

Case 1: there is no MPC control, i.e., the simplest energy management strategy. The batteries are charged only by PV power and provide power back whenever demand exceeds the PV power (nighttime included).

Case 2: MPC used with a very small battery LCOE of EUR 0.01/kWh

Case 3: MPC applied with a low battery LCOE of EUR 0.04/kWh

Case 4: MPC applied with a high battery LCOE of EUR 0.10/kWh

Implementation

The data processing and simulation steps can be divided into three major phases.

First, the PV yield and house load demand profiles are generated from available data described in [31]. The PV yield is specific to Luxembourg's weather and is directly expressed in electric power. The installed surface, PV panels' efficiency, and plant orientation are not discussed in this work. The house demand profile is derived from the data of the main electricity provider CREOS. The published synthetic load profile is defined for a house with a 1000 kWh yearly demand. These values are then adjusted by a multiplication factor to meet the expected 6640 kWh house yearly demand as stated in [32].

Secondly, the electricity prices are obtained from the German market from October 2021 to November 2022. They stem from the most recent historical values of intraday continuous 15 min average prices [33]. It was an important update to include not only the recent high prices reached during the COVID-19 pandemic followed by the Ukraine–Russia conflict, but also the very high volatility experienced. The prices variations in Germany in 2019 and 2022 are shown in Figure 4. Not only did the average price over the year increase from EUR 0.024/kWh in 2019 to EUR 0.23/kWh in 2022, but the standard deviation in 2022 also increased by more than six times compared to the standard deviation in 2019.

Finally, seasonal reference profiles are generated to simplify the computational load. They are the average values of the daily profiles for each season. This is conducted for PV plant power, house electricity demand, and electricity prices. One simulation is run for each season and the yearly values are weighted values based on the number of days of each season.

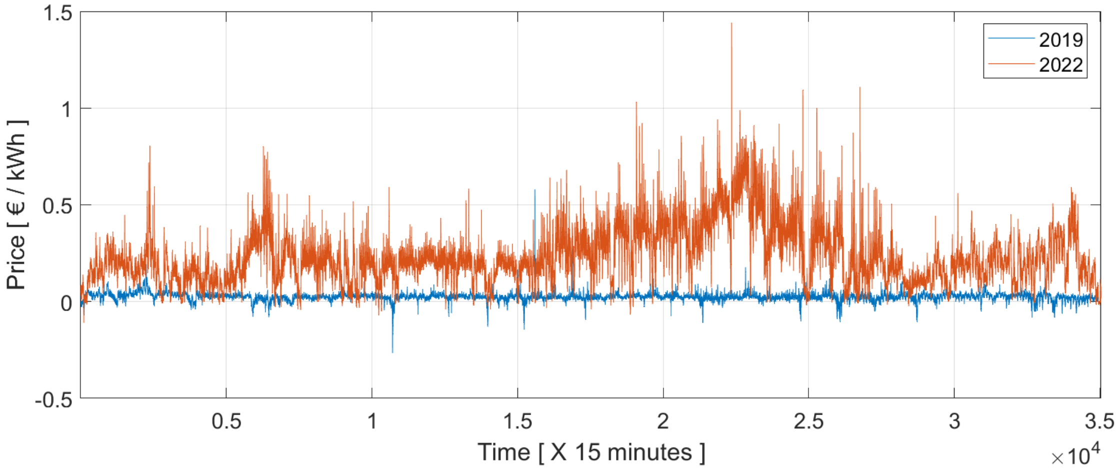


Figure 4. Electricity spot prices in Germany 2019 and 2022.

5.2. MPC-Based Control: Results

Figure 5 depicts the control of BSS power for different yearly seasons with a 5 kWh battery capacity. The electricity prices, the electrical load and the PV power generation vary, but the FITs and the BSS's LCOE don't, from one season to another . The added value of the MPC can be easily observable in the winter and autumn BSS power profiles. The price of electricity during sunny times is higher than the price at night. The cost of storing PV energy for delayed use is higher than the profit achieved by selling it directly to the grid. Part of the excess PV power is sold to the grid rather than stored and used at night when the purchase prices from the grid are lower but still higher than the FITs. The batteries are charged to meet the load demand only during the peak demand times in the night. Non-profitable energy flow is avoided and therefore some BSS cycles are saved. During summer and spring, the price profile of electricity is different. During sunshine hours, due to the high contribution of renewables to total power generation, the prices are their lowest point and are sometimes even negative. Therefore, the BSS charges the batteries from PV power so that they can power most (in spring) or all (in summer) of the demand at night. Thanks to the MPC, energy losses are minimized by beginning to charge the batteries as late as possible.

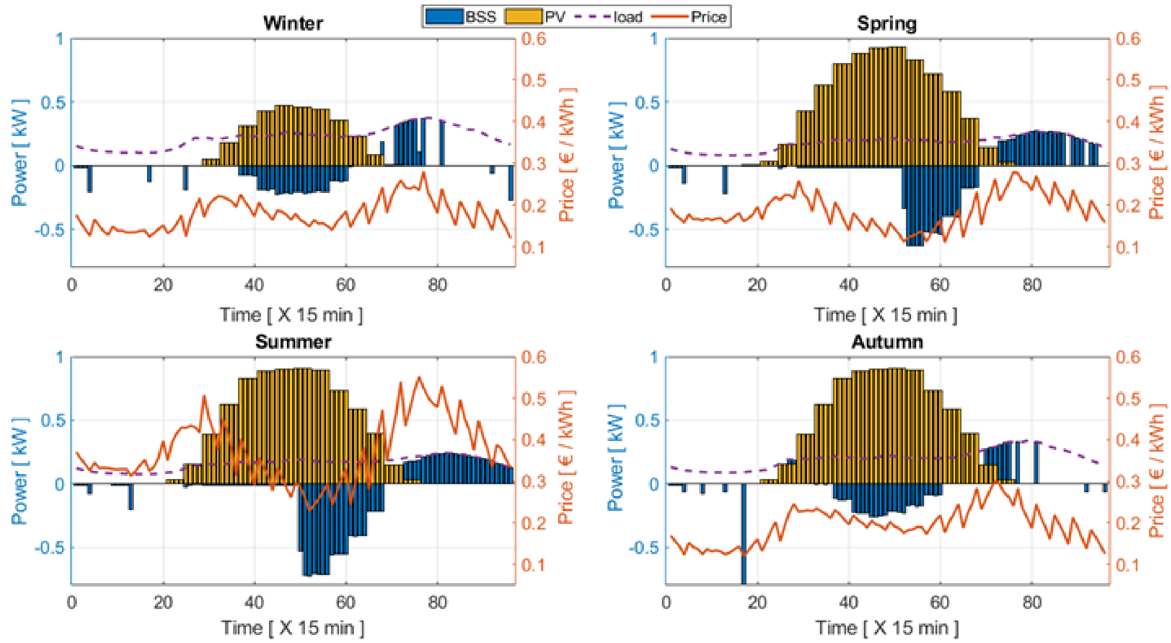
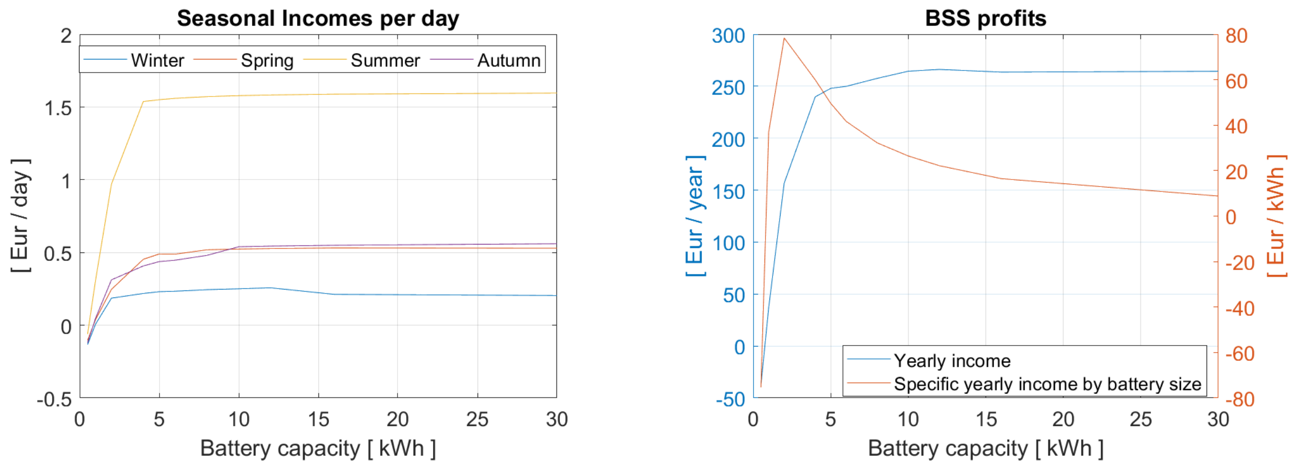
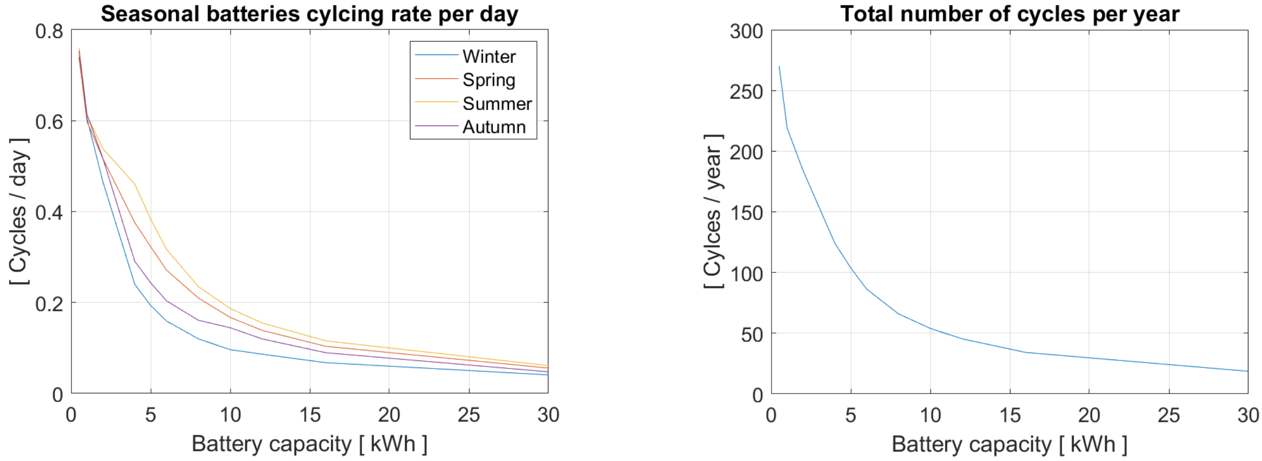


Figure 5. Typical power flow and electricity price profile over seasons [31–33].

The average daily generated incomes, using the proposed MPC logic, are basically proportional to the solar power (Figure 6a). However, the volatility of the energy prices and, most importantly, the difference between the prices during sunshine and nighttime or covered periods have the largest impact. For this particular energy system as depicted in Figure 6b, a battery bank of about 2 kWh seems to present a higher profitably per installed storage size at about EUR 80/kWh/year. The financial profit decreases with the increase in BSS storage capacity. The expected total yearly incomes are estimated as the sum of the seasonal incomes, which are obtained by multiplying the daily seasonal income (Figure 6a) with the number of days of each season.



(**a**) (**b**)



(**c**) (**d**)

Figure 6. (**a**) Average daily income by season vs BSS storage capacity; (**b**) Expected yearly incomes and specific income vs BSS storage capacity; (**c**) Cycling rate by season vs BSS storage capacity; (**d**) Yearly cycling rate vs BSS storage capacity.

On the one hand, considering the technically allowed number of cycles over the lifetime of the battery, a 5 kWh lead–acid battery permitting 2500 cycles with 50% depth of discharge would last 25 years and generate about EUR 6250 in this setup. On the other hand, the same battery type with a smaller capacity of 2 kWh, which achieves the best profits per installed storage capacity, would generate about EUR 2100 in 2500 cycles (13.5 year, 184 cycle/year). Negative incomes indicate that the grid-tied PV plant alone would generate more revenue. For the studied case, there is absolutely no interest in adding a BSS, whose capacity is below 1 kWh with FITs and avoided consumption cost as revenues sources.

5.3. Impact of the BSS's LCOE

Figure 7a,b depicts the expected usage rate and revenue of the BSS based on the levelized cost of the BSS. The less expensive the system, the higher the cycling rate and the higher the potential incomes. However, the financially optimal cycling rate is not directly proportional to the LCOE. A 5 kWh BSS with a levelized cost of EUR 0.01/kWh has about 163 cycles per year, whereas a BSS of the same size, acquired at a 7 times higher levelized cost of EUR 0.07/kWh runs about 75 full cycles. As explained before, for a given battery size, the cycling rate induced by the proposed MPC control is highly dependent on the volatility of the electricity prices throughout the day. As soon as the price difference value from one period to the next is higher than the cost of cycling (BSS's LCOE), the MPC triggers a buy operation or a sell operation under the maximum and minimum SOC constraints.

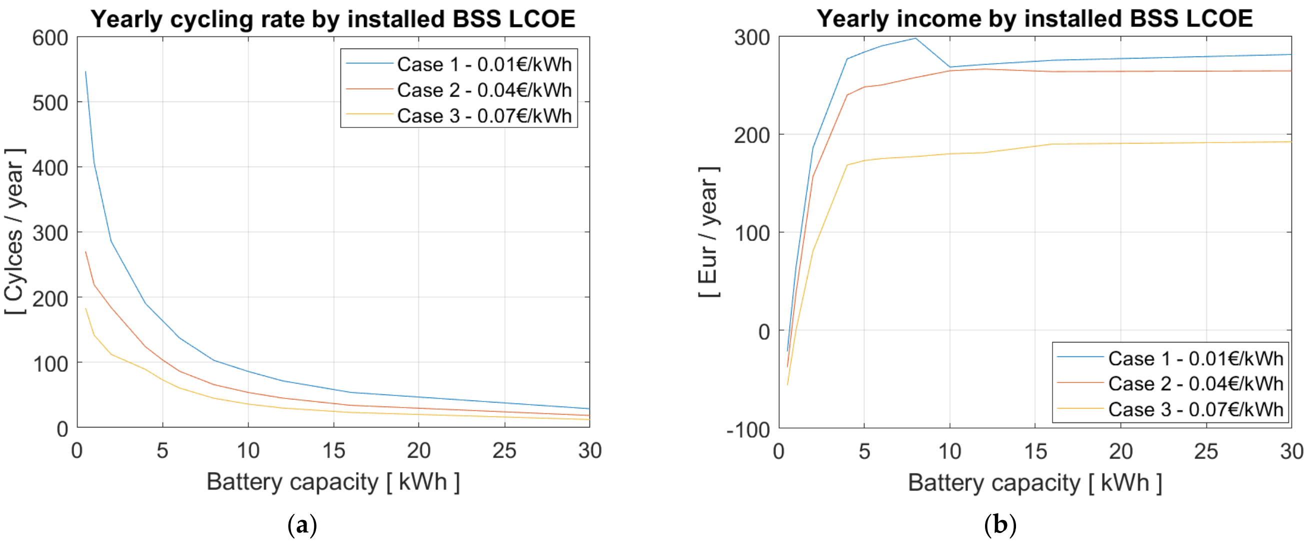


Figure 7. (**a**) Yearly cycling rate vs BSS installed storage capacity by installed BSS's LCOE; (**b**) Yearly expected incomes vs BSS storage capacity by installed BSS's LCOE.

This is well illustrated in Figure 8. In winter, from 20:00 to midnight, the BSS with the cheap EUR 0.01/kWh LCOE charges (buys) at every price dip and discharges (sells) at every peak, even if the price variation is about EUR 0.05. This behavior is simply nonexistent for the case where the BSS's LCOE is EUR 0.07/kWh. Assuming the price variations are purely a market response to production demand, the BSS power profile of the first case can be assimilated to power systems providing auxiliary services, especially reserve provision, to the power grid. In this latter case, complementary revenues for that service could/should be included.

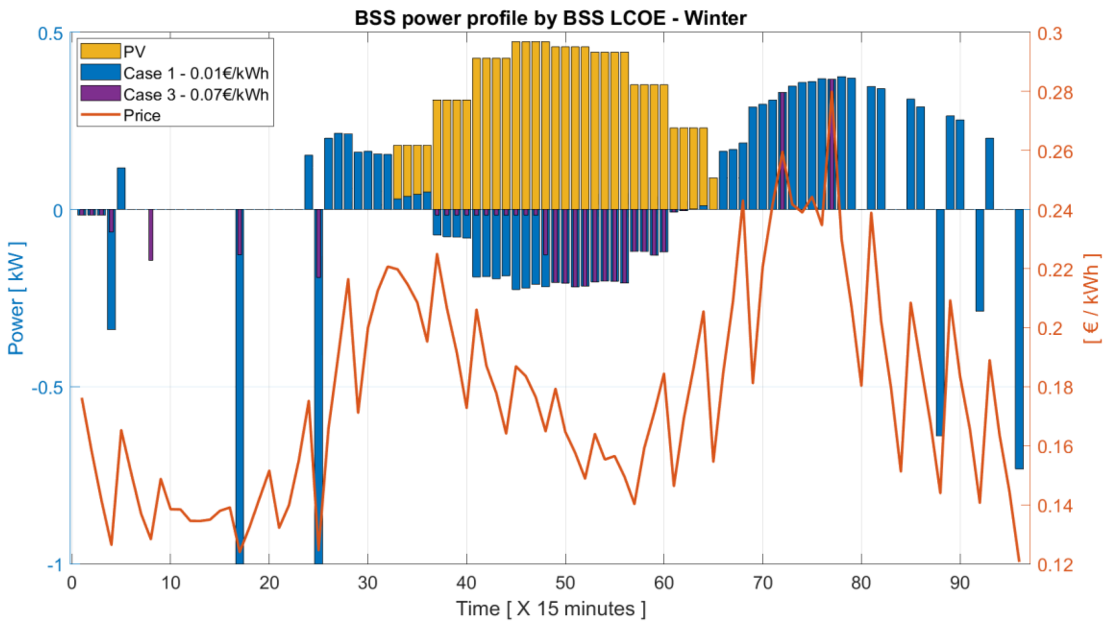


Figure 8. Comparison of BSS power flow in winter with differences in BSS's LCOE.

6. Discussion

The profitability of the BSS as described in this work is strongly influenced by the volatility of electricity prices. Therefore, this strategy can only be applied in a limited number of markets. Furthermore, the constantly increasing number of commercial BSSs providing grid support services, such as negative reserve, mean that the volatility of prices decrease as BSSs can quickly respond to power demand.

The levelized costs of energy for utility-scale BSSs have considerably decreased and will likely continue on the same trend. This means residential BSSs will also become more accessible and make residential BSSs more profitable. Advanced control strategies, such as MPC, will no longer be as important and will likely generate additional profits from price volatility as the LCOE of BSSs, like the LCOE of PV panels, will be lower than the cost of electricity from the grid.

The cost of electricity discussed in this work considers only the production cost with no distribution cost, taxes, or other expenses in addition to electricity provision. For homeowners, by taking these avoided expenses into account as complementary profits, the projected BSS is likely more profitable than the values presented in the present work. However, installation, monitoring, and maintenance costs are missing. Further investigations are necessary to evaluate other financial indicators, such return on investment and net actual value, because these service costs depend on the country or region of installation.

7. Conclusion

In this paper, a brief review of the electrical energy context in 2022 is presented. The trend looks financially promising as the purchase price of PV panels and battery energy storage are becoming cheaper and cheaper.

Lab experiments have shown that BSS self-consumption to supply power electronics and data monitoring are relatively high compared to the natural self-discharge of batteries. This should be considered while modelling BSSs.

A new approach of MPC for BSSs has been investigated. The methodology optimizes the achievable profits of BSSs with a direct inclusion of the levelized cost of BSSs. It is demonstrated that a reasonable yearly cycling rate of the BSS is reached, ensuring good usage and the good health of the batteries. The proposed control does not overreact to small electricity price variations until it is financially worthwhile. The trio composed of FITs, electricity cost, and the LCOE of BSS represents the most determining factors. Ancillary grid service provision can represent a substantial source of revenue for BSSs in addition to FITs and avoided costs.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

$\boldsymbol{BIN}_{buy}$	Binary variable for buying power from the grid
$\boldsymbol{BIN}_{BSS-}$	Binary variable for discharging the BSS's batteries
$\boldsymbol{BIN}_{BSS+}$	Binary variable for charging the BSS's batteries
$\boldsymbol{BIN}_{sell}$	Binary variable for selling power to the grid
$\boldsymbol{E}_{BSS}, max$	Maximum BSS storage capacity
$\boldsymbol{FIT}$	Electricity feed-in tariff
$\boldsymbol{\eta}_{BSS-}$	BSS discharging efficiency
$\boldsymbol{\eta}_{BSS+}$	BSS charging efficiency

$\boldsymbol{P_{BSS,loss}}$ BSS's batteries self-discharging rate
$\boldsymbol{P_{BSS-}}$ BSS discharging power
$\boldsymbol{P_{BSS+}}$ BSS charging power
$\boldsymbol{P_{BSS-,max}}$ BSS maximum discharging power
$\boldsymbol{P_{BSS+,max}}$ BSS maximum charging power
$\boldsymbol{p_{buy}}$ Electricity price
$\boldsymbol{P_{buy}}$ Power bought from the grid
$\boldsymbol{P_{buy,max}}$ Subscribed maximum power from the grid
$\boldsymbol{P_{load}}$ Load's power
$\boldsymbol{P_{sell}}$ Power fed back to the grid
$\boldsymbol{P_{sell,max}}$ Subscribed maximum power fed into the grid
$\boldsymbol{P_{pv}}$ PV plant power
$\boldsymbol{SOC}$ BSS state of charge
$\boldsymbol{SOC_{max}}$ Maximum allowed state of charge
$\mathbf{SOC}_{min}$ Minimum allowed state of charge

References

1. International Renewable Energy Agency. Statistics Time Series. 20 July 2022. Available online: https://www.irena.org/Data/View-data-by-topic/Capacity-and-Generation/Statistics-Time-Series (accessed on 1 October 2022).
2. IRENA. *Renewable Power Generation Costs in 2021*; International Renewable Energy Agency: Abu Dhabi, United Arab Emirates, 2022.
3. International Energy Agency. Global Installed Solar PV Capacity by Scenario, 2010–2030. Available online: https://www.iea.org/data-and-statistics/charts/global-installed-solar-pv-capacity-by-scenario-2010–2030 (accessed on 1 October 2022).
4. IRENA. *Renewable Power Generation Costs in 2020*; International Renewable Energy Agency: Abu Dhabi, United Arab Emirates, 2021.
5. European Commission-Directorate-General for Energy. Clean Energy for all Europeans Package. 17 January 2019. Available online: https://energy.ec.europa.eu/topics/energy-strategy/clean-energy-all-europeans-package_en (accessed on 1 October 2022).
6. FERC. *Reports on Demand Response and Advanced Metering*; Federal Energy Regulatory Commission: Washington, DC, USA, 2022.
7. Bahramara, S.; Mazza, A.; Chicco, G.; Shafie-khah, M.; Catalão, J.P.S. Comprehensive review on the decision-making frameworks referring to the distribution network operation problem in the presence of distributed energy resources and microgrids. *Int. J. Electr. Power Energy Syst.* **2020**, *115*, 105466.
8. Luthander, R. Self-Consumption of Photovoltaic Electricity in Residential Buildings. Ph.D. Thesis, Uppsala University, Uppsala, Sweden, 2018.
9. Maekawa, J.; Shimada, K.; Takeuchi, A. Sustainability of renewable energy investment motivations during a feed-in-tariff scheme transition: Evidence from a laboratory experiment. *Jpn. Econ. Rev*. **2021**, *73*, 83–101.
10. Organisation for Economic Co-operation and Development. Renewable Energy Feed-In Tariffs. 1 April 2020. Available online: https://stats.oecd.org/Index.aspx?DataSetCode=RE_FIT (accessed on 19 September 2022).
11. Dijkgraaf, E.; van Dorp, T.P.; Maasland, E. On the effectiveness of feed-in tariffs in the development of solar photovoltaics. *Energy J*. **2018**, *39*, 81–99.
12. Nolden, C. *Performance and Impact of the Feed-in Tariff Scheme: Review of Evidence*; Department of Energy and Climate Change; London, UK, 2015.
13. Sevilla, F.S.; Knazkins, V.; Park, C.; Korba, P. Advanced Control of Energy Storage Systems for PV Installation Maximizing Self-Consumption. *IFAC-Pap*. **2015**, *48*, 524–528.
14. Rafii-Tabrizi, S.; Hadji-Minaglou, J.-R.; Scholzen, F.; Capitanescu, F. Optimal Operation of Nearly Zero Energy Buildings using Mixed Integer Linear Programming. In Proceedings of the International Conference on Smart Energy Systems and Technologies (SEST), Porto, Portugal, 9–11 September 2019.
15. Montero, I.; Miranda, M.T.; Barrena, F.; Sepúlveda, F.J.; Arranz, J.I. Analysis of photovoltaic self-consumption systems for hospitals in southwestern Europe. *Energy Build.* **2022**, *269*, 112254.
16. Cieślak, K.J. Multivariant Analysis of Photovoltaic Performance with Consideration of Self-Consumption. *Energies* **2022**, *15*, 6732.
17. Weniger, J.; Tjaden, T.; Quaschning, V. Sizing of Residential PV Battery Systems. *Energy Procedia* **2014**, *46*, 78–87.
18. Goebel, C.; Cheng, V.; Jacobsen, H.-A. Profitability of Residential Battery Energy Storage Combined with Solar Photovoltaics. *Energies* **2017**, *10*, 976.
19. Ershad, A.M.; Ueckerdt, F.; Pietzcker, R.C.; Giannousakis, A.; Luderer, G. A further decline in battery storage costs can pave the way for a solar PV-dominated Indian power system. Renew. *Sustain. Energy Transit*. **2021**, *1*, 100006.
20. Hoppmann, J.; Volland, J.; Schmidt, T.S.; Hoffmann, V.H. The economic viability of battery storage for residential solar photovoltaic systems—A review and a simulation model. *Renew. Sust. Energy Rev.* **2014**, *39*, 1101–1118.

21. Li, Q.; Liu, Y.; Guo, S.; Zhou, H. Solar energy storage in the rechargeable batteries. *Nano Today* **2017**, *16*, 46–60.
22. Yue, X.; Zhang, J.; Dong, Y.; Chen, Y.; Shi, Z.; Xu, X.; Li, X.; Liang, Z. Reversible Li Plating on Graphite Anodes through Electrolyte Engineering for Fast-Charging Batteries. *Angew. Chem.* **2023**, *62*, e202302285.
23. Castillo-Cagigal, M.; Caamaño-Martín, E.; Matallanas, E.; Masa-Bote, D.; Gutiérrez, Á.; Monasterio-Huelin, F.; Jiménez-Leube, J. PV self-consumption optimization with storage and Active DSM for the residential sector. *Sol. Energy* **2011**, *85*, 2338–2348.
24. Sigalo, M.B.; Pillai, A.C.; Das, S.; Abusara, M. An Energy Management System for the Control of Battery Storage in a Grid-Connected Microgrid Using Mixed Integer Linear Programming. *Energies* **2021**, *14*, 6212.
25. Marocco, P.; Ferrero, D.; Martelli, E.; Santarelli, M.; Lanzini, A. An MILP approach for the optimal design of renewable battery-hydrogen energy systems for off-grid insular communities. *Energy Convers. Manag*. **2021**, *245*, 114564.
26. Ranaweera, I.; Midtgård, O.M.; Korpås, M.; Farahmand, H. Control Strategies for Residential Battery Energy Storage Systems Coupled with PV Systems. In Proceedings of the International Conference on Environment and Electrical Engineering and Industrial and Commercial Power Systems Europe, Milan, Italy, 6–9 June 2017.
27. Nagpal, H.; Avramidis, I.-I.; Capitanescu, F.; Heiselberg, P. Optimal energy management in smart sustainable buildings—A chance-constrained model predictive control approach. *Energy Build*. **2021**, *248*, 111163.
28. Townsend, A.; Gouws, R. A Comparative Review of Lead-Acid, Lithium-Ion and Ultra-Capacitor Technologies and Their Degradation Mechanisms. *Energies* **2022**, *15*, 4930.
29. Utsunomiya, T.; Hatozaki, O.; Yoshimoto, N.; Egashira, M.; Morita, M. Self-discharge behavior and its temperature dependence of carbon electrodes in lithium-ion batteries. *J. Power Sources* **2011**, *196*, 8598–8603.
30. Huang, Z.; Wong, S.-C.; Tse, C.K. An Inductive-Power-Transfer Converter with High Efficiency Throughout Battery-Charging Process. *IEEE Trans. Power Electron*. **2019**, *34*, 10245–10255.
31. Rafii-Tabrizi, S. Smart Electrical and Thermal Energy Supply for Nearly Zero Energy Buildings. Ph.D. Thesis, University of Luxembourg, Luxembourg, 2020.
32. CREOS. Versorgung der Kunden auf Grundlage Synthetischer Lastprofile. CREOS, 2022. Available online: https://www.creos-net.lu/de/lieferanten/strom/synthetische-lastprofile.html (accessed on 17 July 2022).
33. Fraunhofer Institute for Solar Energy Systems ISE. Electricity Production and Spot Prices in Germany. 17 November 2021. Available online: https://energy-charts.info/charts/price_spot_market/chart.htm?l=en&c=DE (accessed on 19 October 2022).