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Techno-Economic Assessment of Battery Systems for PV-Equipped Households with Dynamic Contracts: A Case Study of The Netherlands

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Abstract: Dynamic energy contracts, offering hourly varying day-ahead prices for electricity, create opportunities for a residential Battery Energy Storage System (BESS) to not just optimize the self-consumption of solar energy but also capitalize on price differences. This work examines the financial potential and impact on the self-consumption of a residential BESS that is controlled based on these dynamic energy prices for PV-equipped households in the Netherlands, where this novel type of contract is available. Currently, due to the Dutch Net Metering arrangement (NM) for PV panels, there is no financial incentive to increase self-consumption, but policy shifts are debated, affecting the potential profitability of a BESS. In the current situation, the recently proposed NM phase-out and the general case without NM are studied using linear programming to derive optimal control strategies for these scenarios. These are used to assess BESS profitability in the latter cases combined with 15 min smart meter data of 225 Dutch households to study variations in profitability between households. It follows that these variations are linked to annual electricity demand and feed-in pre-BESS-installation. A residential BESS that is controlled based on day-ahead prices is currently not generally profitable under any of these circumstances: Under NM, the maximum possible annual yield for a 5 kWh/3.68 kW BESS with day-ahead prices as in 2023 is EUR 190, while in the absence of NM, the annual yield per household ranges from EUR 93 to EUR 300. The proposed NM phase-out limits the BESS's profitability compared to the removal of NM.

Keywords: residential BESS; day-ahead prices; dynamic energy contracts; techno-economic simulation; linear programming; self-consumption; smart meter data

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1. Introduction

As renewable energy adoption increases globally, understanding the role of a residential Battery Energy Storage System (BESS) in optimizing self-consumption and the response to pricing mechanisms becomes necessary, particularly in countries like the Netherlands where the availability of dynamic energy contracts and policy shifts pose new challenges and opportunities. The Netherlands ranks second globally in solar capacity per capita [1]. By the end of 2022, 25% of Dutch households had PV systems installed [2]. This is due to the favorable Dutch Net Metering arrangement (NM), allowing households with PV to deduct their annual feed-in of electricity from their annual demand, resulting in a short payback period for PV installations [2]. However, it does not give households any financial incentive to increase self-consumption. Meanwhile, the rapid growth of PV systems creates challenges for the Dutch grid such as the overload of the low-voltage grid [3], prompting debates about NM phase-out and removal [4].

While the annual self-consumption of solar power varies widely among households, it averages around 30–37% in European nations [5]. Traditional demand-side management strategies like load shifting offer limited potential for increasing self-consumption [6]. Another way to increase self-consumption is by applying a residential BESS. This is gaining popularity in several European countries, while the Netherlands lags behind in BESS adoption [7].

The profitability of a residential BESS has been studied for several countries. An extensive review of the application of residential BESSs combined with PV in different countries across different incentives and tariff structures can be found in [8]. Flat tariffs, time-of-use tariffs (e.g., high/low tariff), and step tariffs (tariffs depending on consumption level) have been considered, while no study has considered dynamic tariffs based on day-ahead prices. The review suggests that in 2021, a PV-coupled residential BESS is generally not yet profitable, except in specific cases or with the introduction of new incentives. Policy options for enhancing the economic profitability of a residential PV-coupled BESS were explored in [9], highlighting that dynamic tariffs rewarding consumers for discharging at the times most needed by the system is among the most effective options for enhancing profitability. In [10], a review is presented on techno-economic analyses on BESSs in the residential sector in various situations and locations, indicating different results depending on regional conditions such as energy market structures, regulatory frameworks, and renewable energy penetration levels. The Netherlands has not been considered in any of the studies mentioned in these reviews.

The application of residential BESSs in the Netherlands was studied in [11,12]. In [11], residential and community BESSs for households with smart appliances were studied, with dynamic pricing based on a real-time pricing scheme, showing that in 2018, residential energy storage was not feasible due to high battery prices. In [12] (also 2018), it is shown that residential a BESS for increasing self-consumption is not profitable. Here, a fixed consumption tariff and feed-in tariff with a price difference of EUR 0.068 were considered.

In recent years, Dutch households have been able to choose dynamic energy contracts, which are currently offered by several energy suppliers [13]. This allows households to pay and receive hourly day-ahead prices for electricity based on the day-ahead auctions for electricity on the European Power Exchange (EPEX). As these day-ahead prices reflect the supply and demand on the grid, these contracts encourage a consumption and feed-in pattern aligned with system needs. The availability of dynamic contracts, combined with recent debates about phasing out NM, raises the question of whether residential BESSs are becoming profitable in the Netherlands, as these contracts create opportunities to capitalize on price differences.

This study focused on the financial profitability and impact on the self-consumption of a residential BESS controlled based on day-ahead electricity prices for PV-equipped households in the Netherlands. This included different scenarios regarding NM: the current Dutch situation with NM, the proposed NM phase-out, and the case of no NM. To the best of our knowledge, this combination has not been researched before.

As the financial profitability of a BESS depends on the optimality of the control algorithm, aspects that influence a control based on day-ahead prices were studied, such as the minimal required price difference to capitalize on.

This study contributes to a better understanding of the implications of controlling residential BESSs based on day-ahead prices. Although the focus was on the Dutch context, the method for studying profitability with day-ahead prices in case of no NM is applicable to other countries offering dynamic contracts based on day-ahead prices.

The remainder of this paper is organized as follows. In Section Related Work, related work on assessing BESS profitability is presented. In Section 2, the data and methodology are described. Section 3 states the results of residential BESS profitability in all scenarios. Section 4 describes limitations, challenges, and opportunities for future work. Finally, Section 5 presents the conclusion.

Related Work

The profitability of residential BESSs depends on various factors [14]. Among others, the profitability of BESSs depends on household characteristics. For instance, ref. [15] examined optimal PV-BESS sizing in Switzerland, revealing large variations in optimal sizes and profitability between households, even with a comparable annual demand. Similarly, ref. [16] explored the economic viability of PV-BESS applications in Germany across households of different sizes and energy efficiencies, highlighting the role of fiscal treatments in determining profitability.

Appliances present in the house and PV system sizing also affect BESS profitability [17–19]. When the demand response and BESS application for a Portuguese household are compared, it follows that demand response is a better strategy with a modest (1.5 kWp) PV capacity [17]. Energy-efficient appliances can reduce PV revenue and accelerate battery degradation [18], while the presence of an electric vehicle influences the optimal sizing of the PV-BESS [19].

Furthermore, the profitability of a residential BESS can be influenced by the control strategy, as suboptimal control can limit daily profitability or result in faster battery degradation. In [20], a review is presented on recent techniques on the sizing and management of residential BESSs, showing that mathematical optimization techniques such as linear programming (LP) are often used to solve scheduling problems. In [21], linear programming (LP) was used for the daily optimization of electricity costs within a billing period, assuming that a reliable daily prediction for the electricity demand and generation can be made. In [22], reinforcement learning was used for battery control, using LP as a deterministic equivalent for assessing the performance. In [23], a forecast-based operation strategy is presented that can drastically increase battery life, thereby also improving the profitability of BESSs.

The data that are used as input for modeling can influence the estimated profitability of BESSs. The impact of different load profiles on the modeling results regarding tasks like cost-effectiveness and the optimal system configuration of the battery size is considerable, and large variances in profitability between households are to be expected [15]. Aggregated or synthetic profiles tend to overestimate self-consumption and neglect variability between households [24]. Additionally, using low-resolution data leads to smoothing out the consumption profile and, hence, to optimistic financial predictions; therefore, a resolution of 15 min is recommended for a task such as the sizing of PV power and BESS capacity [25], while for other tasks, a higher resolution might be needed. For instance, a 10 min sampling period for load shifting simulations can overestimate PV self-consumption by 30–40% compared to a 1 min sampling period [26].

A residential BESS can be added to PV-equipped households either as part of the PV-system (DC-coupled) or AC-coupled, where an AC-coupled configuration is more easily fitted for existing PV installations, but this comes with a decreased efficiency due to more conversion stages (AC/DC, DC/AC) when charging from PV [10]. Studies on lithium-ion BESS profitability have been conducted, for example, in [11,15,16,24,27,28], revealing a range of different BESS assumptions. These studies employed different values for the depth of discharge, ranging from 100% to values as low as 60% to avoid deep discharges, which are detrimental to lithium-ion batteries [29]. Battery end of life is often expressed as the number of cycles after which 80% of the original capacity is left, and this number varies between 4000 and 6400 cycles, and is sometimes combined with an extra annual degradation factor or a fixed calendar lifetime [15,16,24,27]. In [11,28], it is expressed in years, both assuming a lifetime of 10 years. Furthermore, different assumptions have been made about AC- and DC-coupling, battery charging/discharging efficiency, and inverter efficiency, with mentioned round-trip efficiencies between 84% and 95%, neglecting the influence that factors like charging and discharging power, ambient temperature, and battery age can have on the efficiency [29]. Ref. [30] presents a model assessing battery degradation costs for lithium-ion batteries, using mixed-integer LP to consider factors such as charging/discharging rates and ambient temperature, which influence the battery lifespan and, thus, operational costs.

2. Data and Methodology

To examine residential BESS profitability for Dutch PV-equipped households with a dynamic contract based on day-ahead prices, first a (deterministic) optimal control must be derived. This control depends on the considered scenario for NM. In the current scenario where NM is in place, there is no financial incentive to enhance self-consumption; hence, a method for optimal financial control should solely focus on day-ahead prices. LP can be used to derive this optimal control strategy. When this LP optimization is applied to historical day-ahead prices, profitability for this scenario can be assessed.

The LP objective for optimal battery control must be expanded to examine the financial viability of residential BESSs in the scenarios of NM phase-out and in the absence of NM; as in these two situations, increasing self-consumption is financially beneficial. The LP optimization should now also consider the actual usage and feed-in of a household. To assess profitability in these cases, not only historical day-ahead prices but also realistic household data on electricity consumption and feed-in are required.

The data sources are described first, together with assumptions on the residential BESS, before deriving the LP models.

2.1. Dutch Day-Ahead Prices and Dynamic Energy Contracts

The EPEX day-ahead markets facilitate short-term electricity trading through daily blind auctions across various European countries, including the Netherlands. Hourly prices for the next day are published each afternoon, and historical prices can be accessed online at transparency.entsoe.eu/ (accessed on 1 June 2024).

In Figure 1, the daily spreads in the Dutch day-ahead prices, i.e., the highest hourly price minus the lowest hourly price per day, are shown per month from 2021 to 2023. It can be seen that, especially from September 2021 to December 2022, the day-ahead prices in the Netherlands varied a lot but were relatively stable outside this period.

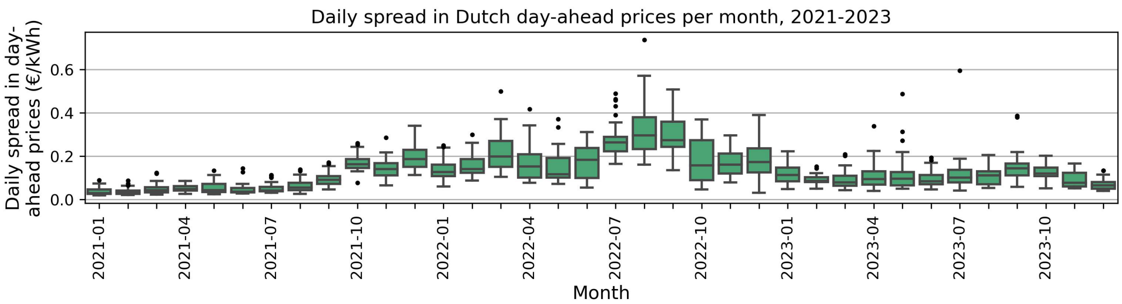


Figure 1. Box plot of daily spreads of the Dutch day-ahead prices summarized per month.

While daily price patterns vary due to factors like weather and the day of the week, a general trend can be described as follows: prices peak in the early mornings and early evenings, while they are lowest at night and during late morning/afternoon hours. Figure 2 illustrates this trend, displaying hourly prices for the first six months of 2021 (chosen for its relative price stability during this period).

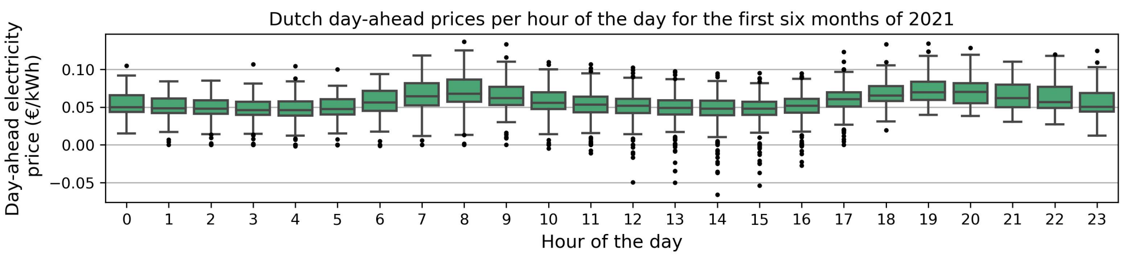


Figure 2. Box plot of Dutch day-ahead prices per hour of the day for the first six months of 2021.

The day-ahead price in the Netherlands is negative at times, meaning that during those hours, an electricity producer has to pay to feed electricity into the grid, while consumers receive payments for their consumption. Negative prices are most prevalent during afternoons, with 72% of the negative prices occurring between 10 am and 6 pm, indicating a surplus of renewable electricity in these hours.

Households equipped with a smart meter can choose a dynamic energy contract based on these day-ahead prices. These households pay their energy provider a fixed monthly connection fee and are then billed or compensated based on the hourly day-ahead prices. Furthermore, taxes are due, and extra charges such as a fixed service fee per kWh may apply.

A dynamic contract influences how NM is applied: while Dutch households without a dynamic contract are guaranteed to receive the full retail price (including taxes) for the fed-in electricity up to the amount of their demand on an annual basis, households with a dynamic contract only receive the current hourly price for their electricity feed-in. Given the trends in the electricity prices illustrated in Figure 2, PV-equipped households usually feed-in most electricity at times of low prices (during the afternoon), while the electricity demand is highest during higher-priced hours (morning, evening). Consequently, a dynamic electricity contract for PV-equipped households might be less beneficial than a fixed contract. In the results below, only the potential benefit of installing a residential BESS, given a dynamic contract, is considered. Whether or not a dynamic contract compared to a fixed contract is favorable for households under the assumed circumstances was not studied.

2.2. Household Data on Electricity Consumption and Feed-In

As outlined in Section Related Work, actual load profiles of high resolutions are needed to obtain reliable estimates on BESS profitability, as well as differences between households to be expected. Furthermore, this study incorporated hourly-varying day-ahead prices that are influenced by factors like the day of the week and the weather. Hence, it is important to use real household data of the same period that reflect the same conditions. This study therefore used smart meter data that were obtained from Energysense, an ongoing smart meter data collection project of household energy consumption in the Netherlands, providing data from 2021 to 2023 with a 15 min resolution.

Only households from Energysense that had PV panels since before 2021 were selected. Furthermore, to ensure high data quality, households that had more than 2.5% missing smart meter readings were discarded, resulting in a total of 225 PV-equipped households. The cumulative meter readings were then converted to 15 min electricity demand/feed-in. Missing values were imputed using the mean of non-missing values at the same time of day in the same month and household, and then scaled to ensure that the yearly totals of the households after imputation remained equal to the actual yearly totals.

The households were binned by their mean annual electricity demand and feed-in over 2021–2023. Bin sizes were chosen such that there were multiple households in almost every bin. The resulting bins are shown in Figure 3.

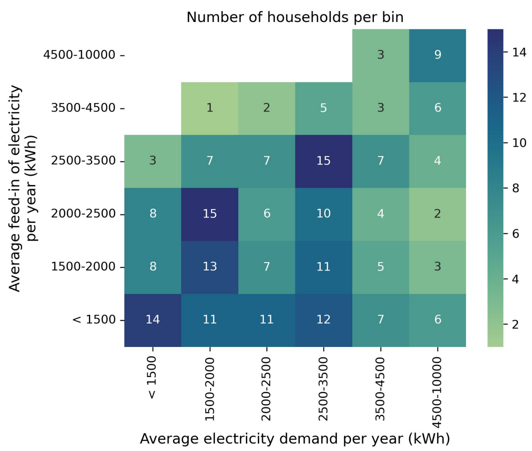


Figure 3. Selected 225 households binned by their mean annual electricity demand and feed-in.

2.3. Battery Assumptions

In this study, a lithium-ion battery was considered. The assumed specifications were chosen to be within the range of assumptions in related work, as mentioned in Section Related Work, and were as follows: The battery was restricted to SoCs between 15% and 90% of the nominal battery capacity. Hence, the maximal depth of discharge is 75%, which is the effective usable battery capacity. Equivalent Full Cycles (EFCs, i.e., the sum of charge/discharge events that add up to one full cycle) were considered in terms of the effective usable battery capacity.

The BESS was assumed to have a (step-wise) degradation of 1.5% of the original capacity after 350 EFCs or 1 year, whichever came first. End of life was determined as the moment that the capacity dropped below 80% of the original capacity, so the BESS reaches end of life after either 4900 EFCs or 14 years, whichever comes first. Furthermore, the BESS was AC-coupled and was assumed to have a simplified round-trip efficiency of 90%.

For this study, a BESS with a capacity of 5 kWh was considered, with a 3.68 kW inverter (the maximum power for a standard group of a fusebox in the Netherlands). The maximum charge and discharge powers were both 3.68 kW. To study the effect of the BESS capacity, a 10 kWh BESS was also considered, for which the other specifications were the same as for the 5 kWh BESS.

The BESS was assumed to be managed by a Battery Management System (BMS) that had real-time information on the lectricity demand and solar surplus of the household. The BESS can be charged in two modes: either by charging at maximum power (possibly charging from the grid) or by charging solely from any surplus of PV power. Likewise, it can be discharged in two modes: either by discharging at maximum power (possibly to the grid) or by discharging for self-use. The BMS can switch between the different charging and discharging modes on an hourly basis.

Although lithium-ion batteries have significantly decreased costs in the last decade, prices have gone up slightly in recent years, and prices are expected to remain at the current level in the near future [2,7]. For this study, a price of EUR 700 per kWh, including an inverter installation and subscription for smart control, was assumed, while the effect of a 50% price reduction to EUR 350 per kWh was also studied. All battery assumptions are summarized in Table 1.

The potential financial yield of a residential BESS in case of a dynamic contract highly depends on electricity taxes and the spread in day-ahead prices. For this study, the potential financial yield of the investment is expressed in terms of potential yield in the first year, where the first year either had price differences as in 2021, 2022, or 2023. Formulas for this are given in Appendix A. It follows that if there are at most 350 EFCs in a year with a BESS price of EUR 3500, an annual profit of at least EUR 277 is needed to recoup the BESS investment within the lifetime of the BESS.

Table 1. BESS specifications: overview of assumed BESS specifications including symbols as used in the remainder of this article.

Variable	Symbol	Value
Original capacity	B	5 kWh
Max charging power	$P_{c,\max}$	3.68 kW
Max discharging power	$P_{d,\max}$	3.68 kW
Mean Wh efficiency	η	0.9 (90%)
Minimum SoC	$s_{\min}$	0.15 (15%)
Maximum SoC	$s_{\max}$	0.90 (90%)
Effective battery capacity	B_{eff}	$(0.75 \times B)$ kWh
Cost	-	EUR 700 per kWh or EUR 350 per kWh
Degradation	d	0.015 (1.5%) of original capacity After 350 EFCs or 1 year
End of life	-	After 4900 EFCs or 14 years

2.4. Minimal Required Yield per Cycle

When controlling a BESS based on day-ahead prices, a choice has to be made about whether or not a spread in prices between a trough and a peak presents a good opportunity to charge and discharge the BESS. See also Figure 4. This leads to the introduction of the minimal required yield per cycle (in EUR), denoted C. A lower value for C results in more yield, but at the cost of relatively more cycles, which in turn leads to the faster degradation of the battery. Therefore, a good value for C can be determined by considering factors such as the cost of the BESS, the battery degradation, and the number of cycles that the battery is expected to last. This minimal required yield per cycle was incorporated in the models for BESS control, and the impact of different choices was studied (Section 3).

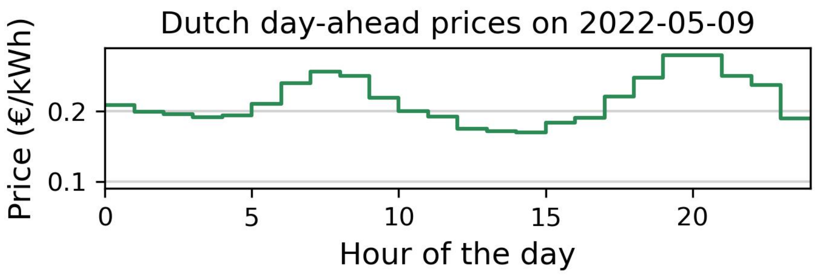


Figure 4. An example of day-ahead prices throughout a day. Although on this day there are two opportunities (two troughs and peaks) for a battery cycle, the financial yield per opportunity differs.

2.5. Optimal Control of Residential BESS with Day-Ahead Prices and NM (DA-NM)

While NM is in place, there is no financial benefit in charging a residential BESS from surplus solar power as opposed to charging from the grid, or to discharge for self-use instead of discharging to the grid. Thus, for optimal financial control, a control algorithm under NM only has to consider the hourly day-ahead prices. This control algorithm can be formulated as an optimization objective with constraints that can be solved using LP, where the objective is to minimize the costs of charging minus the profit of discharging, given the constraints on the BESS.

To formulate the LP objective and constraints, the following variables are defined: let $t \in T$ denote a time period in the optimization window $T = \{0, 1, \ldots, N\}$, where N is the number of time periods in the considered optimization window of duration q (in hours). So, when hourly day-ahead prices are considered and BESS control is optimized for the day ahead, $q = 1$ and $N = 24$. Let p_t denote the day-ahead price during time period t, and let the variables x_t and y_t denote the energy from discharging and charging, respectively, the BESS during period t. The variables x_t and y_t for all $t \in T$ are the decision variables of the BESS control problem. As there are N time periods, there are $2N$ decision variables. The constraints were as follows: x_t and y_t are non-negative and constrained by the maximal discharging and charging power of the BESS, respectively, $P_{d,\max}$ and $P_{c,\max}$. Then, $E_{d,\max} = qP_{d,\max}$ is the maximal amount of energy that can be discharged per time period, and similarly, $E_{c,\max} = qP_{c,\max}$ is the maximal amount of energy that can be charged per time period (constraints 1 and 2 below).

Let B denote the capacity of the battery (in kWh). Let $s_t \in [0, 1]$ denote the SoC at the beginning of period t as a fraction. Requirements on the minimum and maximum SoC values may apply, so that $0 \le s_{\min} \le s_t \le s_{\max} \le 1$, leading to constraint 3 below. The SoC at the beginning of a day is a beforehand-fixed value s_{start}, so $s_0 = s_{\text{start}}$, and similarly, the SoC at the end of the optimization window was set as follows: $s_{N+1} = s_{\text{end}}$. The SoC at the end of each time period t is determined by the SoC at the beginning of that time period and the difference in energy due to charging or discharging during that period (constraint 4 below).

In the case when $C = 0$ and the price $p_t = 0$, LP might say, as the solution, to both charge and discharge within the same time period. As this is undesired behavior, constraints 5 and 6 were added to make sure only either charging or discharging is performed during one time period. This is achieved using the Big M method [31], where M is a large number, and b_t is a binary variable that is 0 if there is discharging during t and 1 if there is no discharging.

To ensure a minimal yield per cycle C, as discussed in Section 2.4, the term $\frac{C}{\eta B_{\text{eff}}} x_t$ was added to the objective. In this term, $B_{\text{eff}} = B(s_{\max} - s_{\min})$ is the effective usable battery capacity. Combined, this leads to a total of $9N$ constraints.

The problem for the optimal control of the battery given the day-ahead prices under the net metering arrangement (DA-NM) formulated as an objective to minimize the costs of charging minus the profit of discharging, taking into account a required yield per cycle C, is then stated as follows:

DA-NM objective: Minimize

$$\sum_{t \in T} (y_t - x_t) p_t + \frac{C}{\eta B_{\text{eff}}} x_t$$

subject to:

1. $0 \leq x_t \leq E_{d,\max} \quad \forall\, t \in T$;
2. $0 \leq y_t \leq E_{c,\max} \quad \forall\, t \in T$;
3. $s_{\min} \leq s_t \leq s_{\max} \quad \forall\, t \in T$;
4. $s_{t+1} - s_t + \frac{(x_t/\eta) - y_t}{B} = 0 \quad \forall\, t \in T$, where $s_0 = s_{\text{start}}$ and $s_{N+1} = s_{\text{end}}$;
5. $x_t \leq M(1 - b_t) \quad \forall\, t \in T$;
6. $y_t \leq M b_t \quad \forall\, t \in T$.

When the DA-NM objective is solved using LP, the result is a control described in terms of electric energies that have to be charged or discharged per time period. For the actual control of a BESS, this must be translated to a corresponding power. The LP solution ensures optimal control under NM for the chosen planning window, given the day-ahead prices, the beforehand chosen values for C, and s_{end}.

Note that when this method is applied to two consecutive optimization windows, the $s_0 = s_{\text{start}}$ of the second window must equal the $s_{N+1} = s_{\text{end}}$ of the first. Given the trends in the Dutch day-ahead prices, which are generally high in the evening but low at night, setting $s_{\text{end}} = s_{\min}$ and optimizing per day usually leads to optimal results. However, this is not guaranteed. For example, the lowest prices during the night sometimes occur at 11 pm, meaning that the optimal control when taking the prices for the day ahead into account might be to start charging at 11 pm the current day.

In applying this method of control to historical day-ahead prices, the financial potential of a BESS and the effect of different values for C were studied, the results of which are shown in Section 3.2.

2.6. Optimal Control of Residential BESS with Day-Ahead Prices (DA) in Case of No NM

To determine optimal control for a residential BESS in the case of no NM, a distinction must be made between prices with and without taxes: when the BESS is charged from the grid, taxes are due, and this is not the case when charging from surplus solar electricity. Likewise, discharging the BESS for self-use essentially saves taxes because otherwise, this electricity would have to be extracted from the grid at the taxed price. Finally, for discharging to the grid, the untaxed price is received.

A deterministic optimal solution for battery control in the case of no NM can be computed when the actual power demand from and supply to the grid for the household is known. This is usually only available as energy per period, where the period is, for example, one minute, a quarter, or an hour, and where a lower resolution might lead to an overestimation of the yield of the battery, since peaks in power that could not be captured by the battery are averaged out over the period [25].

The problem of optimal battery control, given the demand and feed-in from the household, formulated as the LP optimization objective, is as follows: let $t \in T$, N, q, s_t, η, $s_{\min}$, $s_{\max}$, s_{start}, s_{end}, x_t, y_t, $P_{d,\max}$, $P_{c,\max}$, $E_{d,\max}$, $E_{c,\max}$, M, and b_t be as defined in the

DA-NM objective (Section 2.5), leading to constraints 1, 2, 7, 8, 9, and 10. Let U_t be the electric energy used by the household in period t, while F_t is the surplus of solar electric energy in the household in period t. Let p_t be the base price (i.e., without tax) for electricity in period t, while p_t^* is the price including the applicable taxes in period t. Let $z_{d,t}$ be the energy discharged by the BESS for self-use during period t, and $z_{c,t}$, the energy charged from surplus solar energy during period t. Let $g_{c,t}$ be the energy charged by the BESS from the grid during period t, and let $g_{d,t}$ be the energy discharged to the grid during time period t. The variables $z_{d,t}$, $z_{c,t}$, $g_{d,t}$, and $g_{c,t}$, for all $t \in T$, are the decision variables. Thus, as there are N time periods, there are $4N$ decision variables.

Additional constraints are as follows: $z_{d,t}$ and $z_{c,t}$ are limited by U_t and F_t, respectively (constraints 3 and 4). The total energy discharged by the BESS in time period t is then equal to the sum of the energy discharged to the grid and the energy discharged for self-use (constraint 5), likewise for the total energy charged from the grid and from solar surplus (constraint 6). Furthermore, $g_{c,t}$ and $g_{d,t}$ must be non-negative (constraint 11). Combined, this leads to a total of $16N$ constraints.

The minimization objective was then adapted to correct for whether or not taxes have to be paid depending on the source of charging and destination of discharging. Like before, a minimum yield per cycle C is required. The objective for day-ahead (DA)-optimization in case of no NM is now as follows:

DA objective: Minimize

$$\sum_{t \in T} (g_{c,t} - z_{d,t}) p_t^* + (z_{c,t} - g_{d,t}) p_t + \frac{C}{\eta B_{\text{eff}}} x_t$$

subject to:

1. $0 \leq x_t \leq E_{d,\max} \quad \forall\, t \in T$;
2. $0 \leq y_t \leq E_{c,\max} \quad \forall\, t \in T$;
3. $0 \leq z_{d,t} \leq U_t \quad \forall\, t \in T$;
4. $0 \leq z_{c,t} \leq F_t \quad \forall\, t \in T$;
5. $x_t = g_{d,t} + z_{d,t} \quad \forall\, t \in T$;
6. $y_t = g_{c,t} + z_{c,t} \quad \forall\, t \in T$;
7. $s_{\min} \leq s_t \leq s_{\max} \quad \forall\, t \in T$;
8. $s_{t+1} - s_t + \frac{(x_t/\eta) - y_t}{B} = 0 \quad \forall\, t \in T$, where $s_0 = s_{\text{start}}$ and $s_{N+1} = s_{\text{end}}$;
9. $x_t \leq M(1 - b_t) \quad \forall\, t \in T$;
10. $y_t \leq M b_t \quad \forall\, t \in T$;
11. $g_{c,t}, g_{d,t} \geq 0 \quad \forall\, t \in T$.

The result of solving the DA objective with LP is a control described in terms of electric energies that have to be charged or discharged per time period, per source of charging (grid or solar), and destination of discharging (grid or self-use). While the results of the DA-NM objective (Section 2.5) translate directly to the optimal control of the BESS. This DA objective needs data on the actual demand and supply of a household, which is not precisely known beforehand. Using the DA objective for BESS control would therefore require a prediction of the demand and supply, and errors in the prediction lead to suboptimal control. The DA objective can, however, be used to study the financial potential of a residential BESS, given historical data of the households, the results of which are shown in Section 3.3.

This DA objective can more generally be applied for regions other than the Netherlands, when day-ahead prices of the region and the smart meter data of PV-equipped households in the region are available. Alternatively, a public dataset on households can be used (e.g., the Irish dataset of the household electricity demand over a period of 75 weeks [32]) as long as this is representative for the households in the region, and PV generation can be simulated based on local weather [15].

2.7. Optimal Control of Residential BESS with Day-Ahead Prices in Case of NM Phase-Out

It was recently proposed that as of 2025, the Dutch NM would be phased out. The proposal was that the NM would be phased out in a step-wise manner, allowing for 64% of annual feed-in to be netted in 2025 and 2026, and then this percentage would be reduced by 9% annually until 28% in 2030, and completely removed in 2031 [4]. Although this proposal was voted out, the removal of NM in the future can still be expected, as problems on the Dutch low-voltage grid remain [3]; hence, the consequences of this proposal for residential BESS profitability are studied.

The DA objective derived in the previous section can also be used to study the effect of the proposed NM phase-out when an assumption is made about how this phase-out would be applied for dynamic contracts. In considering the first phase-out step, as long as 64% of the annual feed-in of a household is less than the annual demand of that household, the phase-out can be translated to netting per kWh: for each kWh of feed-in, 64% of the taxes on this kWh may be netted, so that only $(100 - 64) = 36\%$ of the due taxes must be paid on a kWh that is used from the grid. Therefore, the DA objective from Section 2.6 can be applied to study the effect of this phase-out step on the potential yield of a BESS when the following prices are used: p_t are the prices with 64% of the taxes applied, while p_t^* are the prices with full taxes applied. This is similar for the other phase-out steps.

The above is applicable when 64% of the annual feed-in is less than the annual demand, which is true for most households: pre-BESS-installation, this is true, on average, for 89% over the three years. For households for which this assumption does not hold, on average, less than 64% of the taxes per kWh may be netted; thus, more than 36% of the due taxes must be paid, slightly changing the calculations of potential profitability. However, the precise number also depends on how the battery is controlled. For the results in Section 3.4, this assumption is assumed to hold for all considered households.

3. Results

Dynamic contracts based on day-ahead prices create novel opportunities for a residential BESS compared to a contract with fixed electricity prices. For comparison, the results of the increases in the self-consumption and financial potential of a residential BESS for households with fixed contracts are given in Section 3.1. In the remainder of this section, dynamic contracts are considered. For this, the LP objectives defined in Sections 2.5 and 2.6 were implemented in Python (v3.9) with scipy (v1.10.1), using the HiGHS algorithm to solve the LP objectives with the simplex solver [33]. For the DA-NM objective, optimizing for each day in a year took approximately 6 s on a consumer-grade laptop computer. For the DA objective, optimizing for each day in a year for one household took approximately 30 s.

As noted in Sections 2.5 and 2.6, the LP objectives optimize control per day, given fixed values C and s_{end}. However, it is unclear what the optimal values are for both C and s_{end}. Therefore, the results are presented in different values for these variables.

The residential BESSs that were studied are as described in Section 2.3. The taxes were as follows (unless otherwise specified): 21% VAT and an electricity tax of EUR 0.15 per kWh, representing the taxes on electricity in the Netherlands in 2023. The results shown in this section only consider the influence of a residential BESS on the electricity bill, not the total electricity bill.

3.1. Assessment of a BESS with a Fixed Contract

As there is no financial potential for a BESS combined with a fixed contract while NM is in place, only NM phase-out and the removal of NM were considered for fixed contracts. In the case of no NM, households with a fixed contract pay a fixed retail electricity price per kWh for demand p_d from the grid and receive a fixed feed-in tariff per kWh p_f for feed-in to the grid, where p_f will generally be lower than the base price (i.e., the price without taxes) for the demand.

In this case, the BESS will solely be used for increasing self-consumption. A simple control algorithm for this situation, hereafter called the baseline algorithm, is as follows.

Charge when there is a surplus of solar electricity until s_{max} is reached. When there is no surplus of electricity but there is electricity demand, discharge for self-use until s_{min} is reached. In Figure 5 the possible amount of electricity resulting from charging the BESS from solar surplus per household per year based on this baseline algorithm is shown, both for a 5 kWh and 10 kWh BESS. The amounts of electricity that are charged into the BESS are very similar between the years. Therefore, only one year (2023) was considered.

In the case of no NM, the financial yield of a BESS being charged and discharged to use 1 kWh of surplus solar electricity for self-consumption is as follows: $\eta p_d - p_f$, where η is the efficiency of the BESS. For a 5 kWh BESS, at most 1193 kWh of solar electricity is charged into the BESS. Let $p_d =$ EUR 0.35 and $p_f =$ EUR 0.15. Then, every kWh solar charging for self-use yields EUR 0.165, leading to a maximum annual yield of EUR 195 for the household that has the most opportunities to increase self-consumption with the BESS. The median annual yield for a 5 kWh BESS in this case is EUR 129. As an annual yield of EUR 277 is needed to recoup the investment, the investment cannot be recouped by any of the households in this case. If BESS prices would decrease by 50%, then 37% of the households could recoup the investment.

When a lower feed-in tariff $p_f =$ EUR 0.05 is considered, the yield would be EUR 0.265 per kWh charging from PV surplus. Then, the median annual yield is EUR 208, and the maximum is EUR 313. In this case, 5% of the households can recoup the investment. If on top of that, the BESS prices were to reduce 50%, then a residential BESS would be profitable for 90% of the households.

For the case of NM phase-out, a similar reasoning as in Section 2.7 is used: if 64% of the feed-in may be netted, this means that every kWh of feed-in is rewarded for 64% with the retail price and for the remaining 36% with the feed-in tariff. So, let m be the fraction that may be netted. Then, each kWh of feed-in is effectively rewarded with a price of $p_{\mathrm{eff},f} = mp_d + (1-m)p_f$. During the first phase-out step and with $p_f = 0.15$, as shown above, this leads to $p_{\mathrm{eff},f} =$ EUR 0.278 per kWh feed-in. The financial yield of charging a BESS from 1 kWh of solar surplus when NM is at 64% is then $0.9 \times 0.35 - 0.278 =$ EUR 0.037. This is a large reduction compared to the case of no NM, thus limiting the financial potential of a residential BESS. When the phase-out proceeds (so when m becomes lower), the yield per kWh of solar charging increases toward the value of no NM.

In conclusion, with a fixed contract and in the absence of NM, with current electricity, and BESS prices, a residential BESS is not profitable. The proposed NM phase-out further limits the financial potential of a residential BESS.

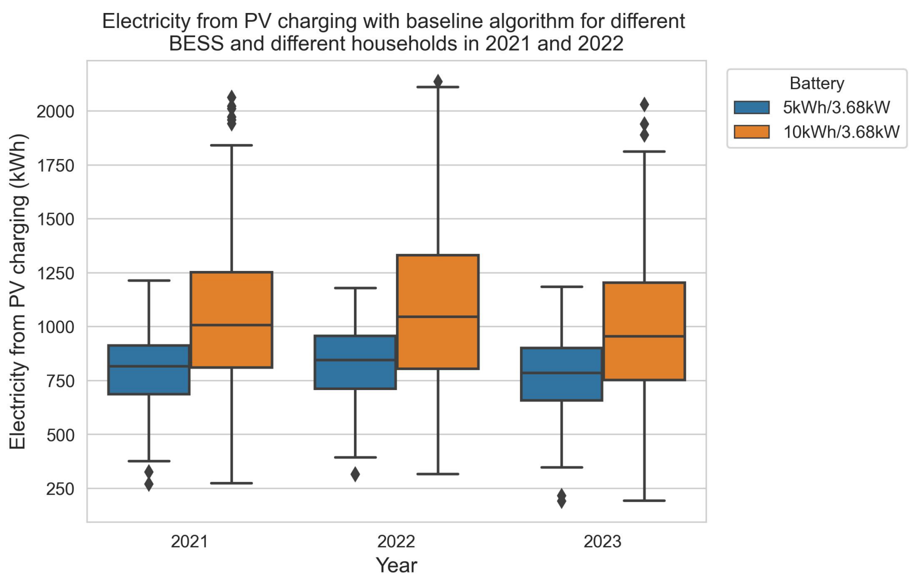
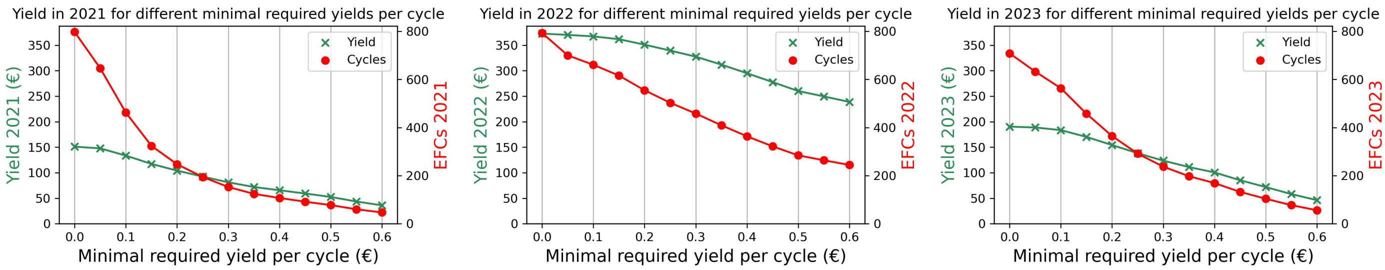


Figure 5. Electricity from charging from PV resulting from the baseline algorithm for a 5 kWh and 10 kWh BESS.

3.2. Assessment of a BESS and a Dynamic Contract with NM

In Section 3.1, the application of a residential BESS combined with a fixed contract was discussed. In the remainder of Section 3, the situation with a dynamic contract is considered. Here, the results on the profitability of a residential BESS under the current Dutch NM are presented.

The DA-NM objective for optimal control with a one-day planning window (Section 2.5) was applied with the day-ahead prices of 2021–2023. The SoC at the end of each day was fixed at $s_{\text{end}} = 0.15$. The day-ahead prices included VAT (since this may be netted under NM). Different values were used for the minimal required yield per cycle C. The results are depicted in Figure 6. As can be seen, lower values for C lead to an increased yield, but at the expense of (many) more EFCs. For example, in 2021, lowering C from 0.5 to 0.25 leads to an increase in the potential yield of EUR 40 at the cost of 114 extra EFCs.



(**a**) 2021 (**b**) 2022 (**c**) 2023

Figure 6. The potential yield (left y-axes) and number of EFCs (right y-axes) for a 5 kWh BESS using DA-NM control on day-ahead prices of 2021–2023 for varying values of the minimal required yield per cycle (x-axes).

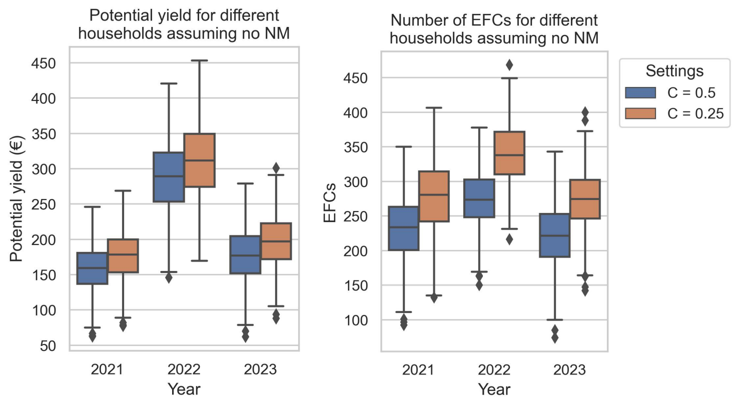
In 2021, the maximal possible yield was EUR 151, and in 2022, a year with unprecedented (differences in) day-ahead prices, the maximal possible yield was EUR 373. For 2023, the maximum was EUR 190. The results under different battery assumptions can be found in Appendix B.

When NM would stay in place, the BESS investment cannot be recouped if day-ahead price differences are as in 2021 or 2023. For day-ahead price differences as in 2022 and with a minimal required yield per cycle $C =$ EUR 0.40, 357 EFCs are performed, yielding a total of EUR 295. This leads to a total yield of approximately EUR 3650 over the lifetime of the battery, slightly more than the EUR 3500 needed to recoup the investment. For $C =$ EUR 0.45, the total profit over the battery lifetime would approximately equal the investment. For lower values of C the BESS would reach the maximum number of cycles, while for higher values of C, the BESS would reach the 14-year limit before the investment could be recouped.

In general, if NM would stay in place, a residential BESS is only profitable if daily price differences are and remain at a higher level than the levels of 2022 and the minimal required yield appropriately chosen. When BESS prices would drop by 50% to EUR 350 per kWh, the investment cannot be recouped with prices as in 2021, or after 12 years, when prices are as in 2023 (and $C =$ EUR 0.20). With prices as in 2022, the payback period would be approximately 6 years.

3.3. Assessment of a BESS and a Dynamic Contract without NM

To study the financial potential of a residential BESS with a dynamic contract in the absence of NM, both VAT (21%) and the electricity tax (EUR 0.15) must be taken into account. First, the DA objective (Section 2.6) is applied to all 225 households for two different values for the minimal required yield per cycle C for 2021–2023. Figure 7a shows the varying annual yields between households as a box plot, and in Figure 7b, the corresponding number of EFCs are depicted. It follows that the potential financial yield varies greatly between households, and also between years. Furthermore, a lower value of C leads to a slightly higher yield at the cost of more EFCs.



(**a**) Potential yield (**b**) Number of EFCs

Figure 7. Potential yield and number of EFCs per year for different households and different values for C (DA optimization for a 5 kWh BESS, $s_{\text{end}} = 0.4$).

The choice of the SoC at the end of each day s_{end} has an influence on the potential yield, as illustrated in Figure 8. Here, the influence of different fixed values of s_{end} on the profitability of a 5 kWh BESS for all households is depicted, indicating that further optimizing control for the SoC at the end of a day per household can improve the potential yield. When s_{end} is fixed throughout the year, $s_{\text{end}} = 0.4$ is optimal for most households.

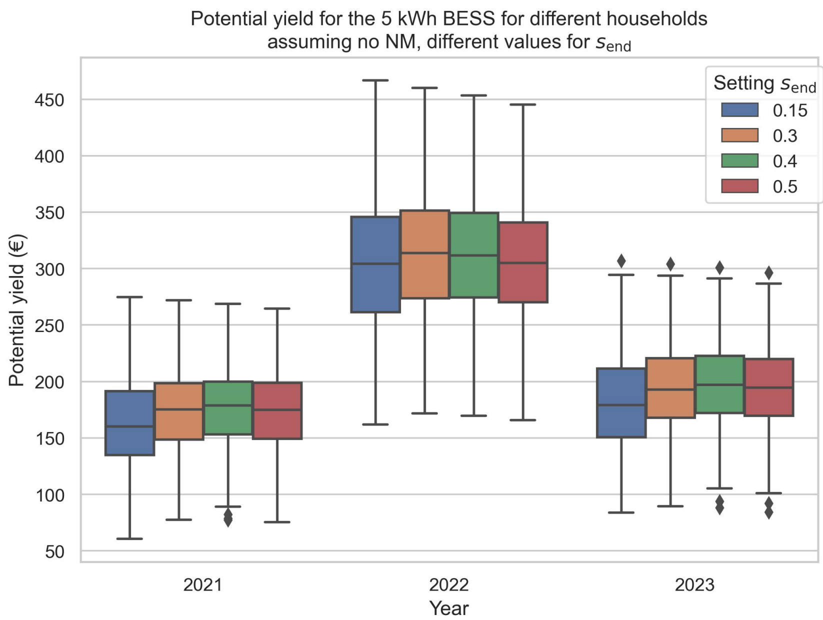


Figure 8. Potential yield for different values for s_{end} for a 5 kWh BESS in 2021–2023 (DA optimization with $C = 0.25$).

The potential annual yield of a 5 kWh BESS averaged per bin of households using the bins from Section 2.2, as well as the minimum and maximum yield per bin, is shown in Figure 9. In general, households that have more annual feed-in also have more opportunities to charge the BESS, and likewise, households that have a higher electricity demand have more opportunities to discharge the BESS at favorable moments; thus, both the pre-installation annual demand and feed-in highly influence the potential yield. This is also reflected in the mean number of EFCs per bin: on average, in 2021, there were only 136 cycles performed in the lower left bin, against 331 in the upper right bin. The results for different battery assumptions—including a capacity increased to 10 kWh—can be found in Appendix C. It follows that mainly households with both high pre-installation annual electricity usage and feed-in see an increased yield with a larger BESS capacity.

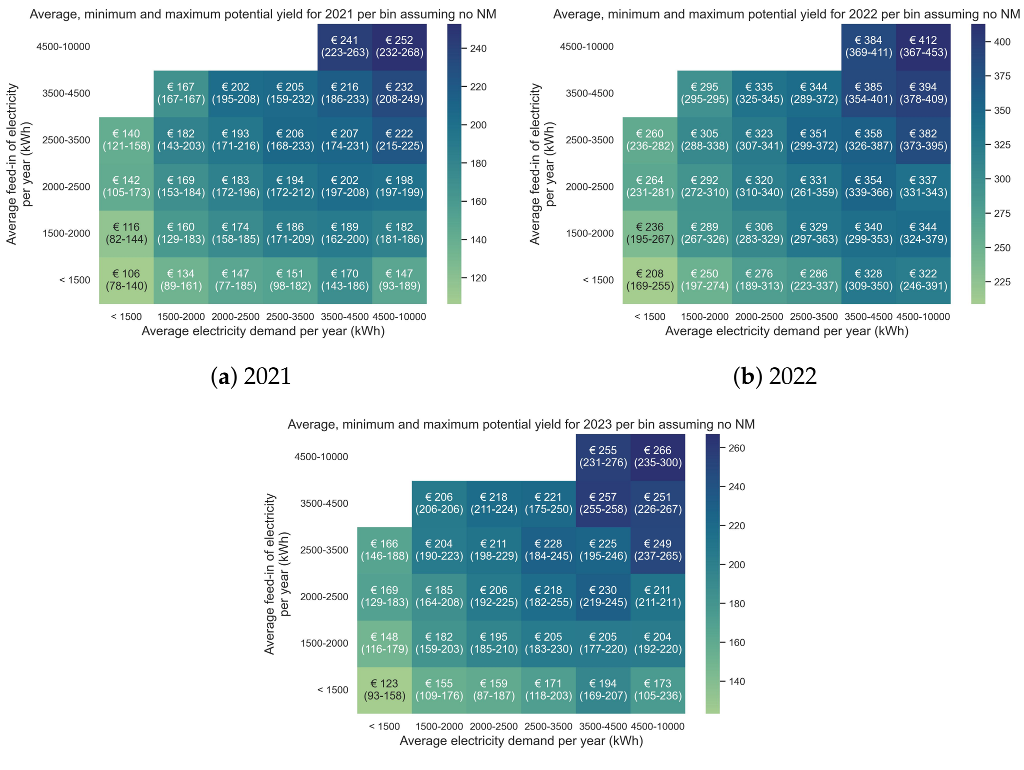
However, Figure 9 also shows that even within a bin, large differences can occur, indicating that not just the average yearly totals but also the specific usage and feed-in patterns (e.g., whether or not peaks in usage coincide with high prices) play an important role, which is similar to what was found in [15].

In Figure 10, the amount of electricity per source of charging for a 5 kWh BESS (either from surplus PV or from the grid) and the destination for discharging (either for self-use or to the grid) is shown for the different households. With prices as in 2021 and 2023, the BESS is mainly used for self-consumption (charging from PV, discharging for self-use), there is little charging from and discharging to the grid. With the prices of 2022, due to the higher spread in prices, there are more opportunities when charging from and discharging to the grid is favorable. However, the BESS is still mostly used for self-consumption.

In conclusion, it follows that BESS profitability differs greatly between households, not only determined through the pre-installation annual feed-in but also by other factors, which is grounds for further study. For optimal control, the SoC at the end of a day s_{end} should be optimized per household, and a proper value for the minimum required yield per cycle C must be chosen to balance the number of EFCs performed and the total yield.

Furthermore, in the absence of NM, price levels that are at least as high as in 2022 are needed for residential BESSs to become profitable for a large portion of the households, but with an average payback period of 12 years. Otherwise, it is not generally profitable, especially not for households with a lower pre-installation annual usage and feed-in.

Next, a sensitivity analysis was conducted to assess the influence of the electricity tax.



(**a**) 2021 (**b**) 2022

(**c**) 2023

Figure 9. Average yield per bin (top value) and minimum and maximum yield (bottom values), all in EUR, for a 5 kWh BESS, based on the day-ahead prices in 2021–2023 (DA optimization with $s_{\text{end}} = 0.4$ and $C = 0.25$).

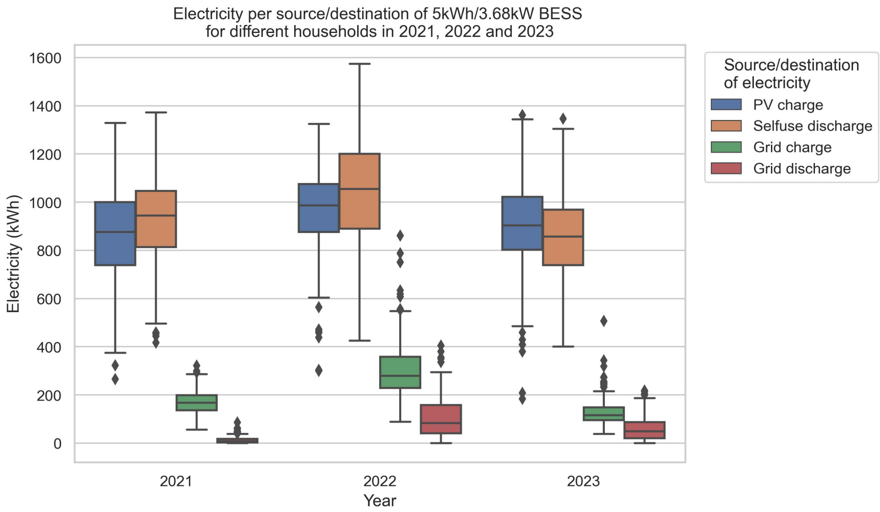


Figure 10. Electricity per source and destination for the different households of, resp., charged and discharged electricity for the 5 kWh BESS with prices as in 2021–2023 ($C = 0.25$, $s_{\text{end}} = 0.4$).

Sensitivity Analysis: Electricity Tax and BESS Price

As seen in Figure 10, the potential yield of a BESS primarily arises from the advantages of self-consumption. Therefore, in this section, a sensitivity analysis was performed on the electricity tax. Electricity tax values of EUR 0.10, EUR 0.15 (used previously), EUR 0.20, and EUR 0.25 were considered, also combined with a 50% reduction in the BESS price, the results of which are shown in Figure 11. A higher electricity tax leads to a higher potential yield, especially for households that already had higher potentials.

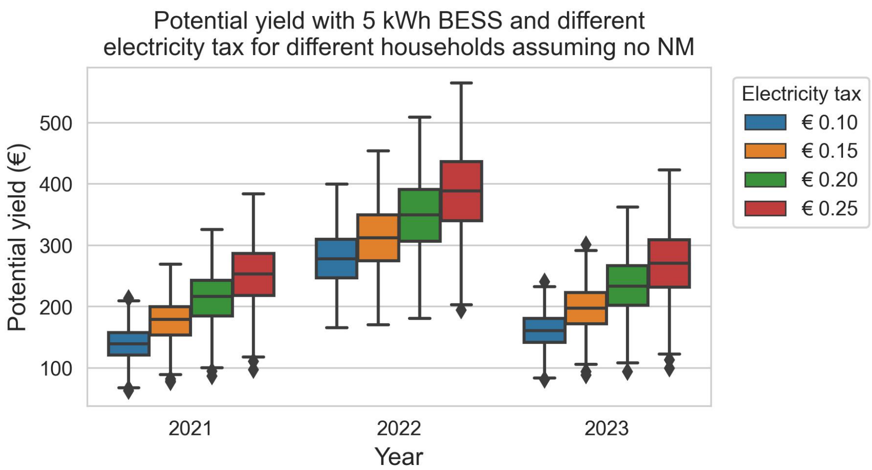


Figure 11. Potential yield for households with prices of 2021–2023 for different values for the electricity tax for a 5 kWh BESS ($C = 0.25$).

The percentage of households that can recoup the investment under these different assumptions are listed in Table 2, showing that a significant drop in battery price or rise in price differences (either by a higher electricity tax or by larger variations in day-ahead prices) is needed for a BESS to become profitable over the lifetime of the BESS for a majority of households when price differences are as in 2021 or 2023. With price differences as in 2022 and a 50% reduction in battery prices, all households can recoup the investment in all cases, with average payback periods from 5 to 7 years.

Table 2. Percentage of households that can recoup the investment in a 5 kWh BESS in the case of no NM for different values of the electricity tax and day-ahead price levels of different years at different BESS prices (DA optimization with $s_{\text{end}} = 0.4, C = 0.25$). In brackets, the mean payback period in years for those households that can recoup the investment is shown.

Electricity Tax	Price Level	% Households When BESS Price Is EUR 3500	% Households When BESS Price Is EUR 1750
EUR 0.10	2021	0%	52% (12 years)
EUR 0.15	2021	0%	82% (10 years)
EUR 0.20	2021	2% (13 years)	92% (9 years)
EUR 0.25	2021	30% (12 years)	95% (8 years)
EUR 0.10	2022	43% (12 years)	100% (7 years)
EUR 0.15	2022	73% (12 years)	100% (6 years)
EUR 0.20	2022	87% (11 years)	100% (5 years)
EUR 0.25	2022	90% (10 years)	100% (5 years)
EUR 0.10	2023	0%	78% (11 years)
EUR 0.15	2023	0%	91% (9 years)
EUR 0.20	2023	16% (13 years)	96% (8 years)
EUR 0.25	2023	44% (12 years)	98% (7 years)

3.4. Assessment of a BESS and a Dynamic Contract during NM Phase-Out

The DA objective can be used to study the effect of the NM phase-out that was proposed, as described in Section 2.7.

In Figure 12, both the scenario of no NM and the scenario where NM is at 64% are depicted for the prices of 2022. It is shown from what source a 5 kWh BESS charges (grid or PV) and to what destination it discharges (grid or self-use), while the values of s_{end} and C are kept the same. It can be seen that in the case of 64% NM, there are more opportunities to charge from and discharge to the grid, while there are fewer favorable opportunities for charging from PV and discharging for self-use compared to the no NM case.

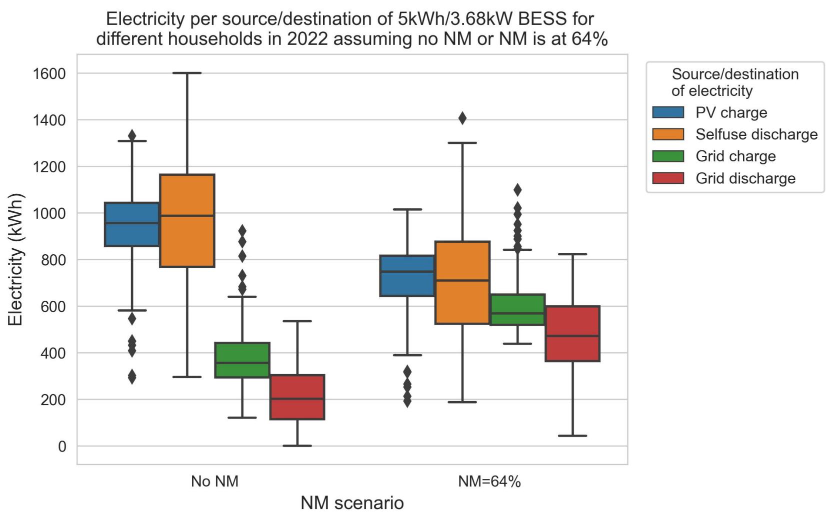


Figure 12. Electricity per source/destination for the 5 kWh BESS during NM phase-out (64% NM) and in the absence of NM with prices as in 2022 (DA optimization with $C = 0.5$, $s_{\text{end}} = 0.15$.)

It follows that NM phase-out creates different opportunities for the BESS compared to the no NM scenario. However, the total potential financial yield during the phase-out is generally lower than without NM, as can be seen in Figure 13. Here, the potential yield in the current and all future scenarios of NM phase-out for all households is depicted. It follows that for most households, the first step of the proposed NM phase-out is less profitable than when NM is in place. During the next steps of the proposed NM phase-out, the profitability of a BESS slightly increases, with the best scenario being the scenario of no NM.

In summary, if NM were to be phased out as proposed, the financial potential of a BESS is limited compared to the situation when NM is completely removed. This is similar to the situation with a fixed contract (Section 3.1).

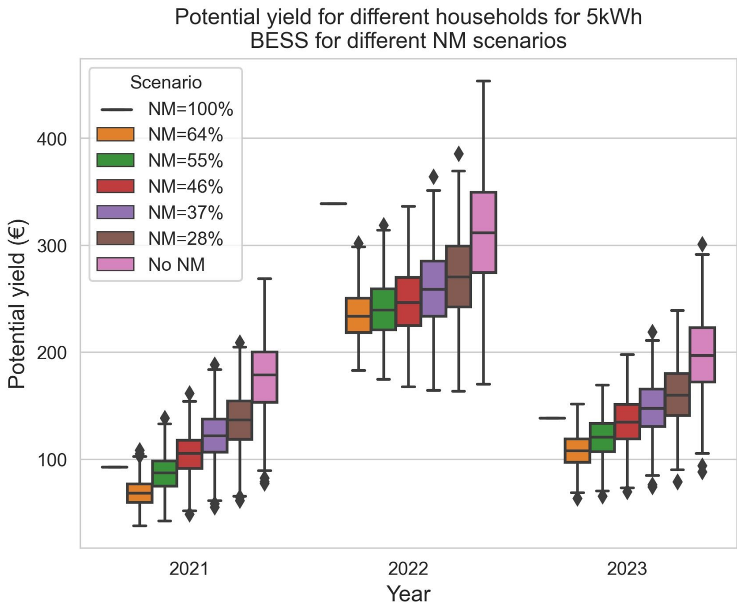


Figure 13. Potential yield for different households in all scenarios: while NM is in place, all steps of NM phase-out, and no NM (5 kWh BESS, $C = 0.25$, $s_{\text{end}} = 0.4$).

4. Discussion and Future Work

The results of this study show that, with current BESS prices and recent day-ahead price levels, a residential BESS controlled based on day-ahead prices is not generally profitable in the Netherlands, and in the near future, it might only be profitable in specific situations. Similar results hold for fixed contracts. This might change when BESS prices become lower. However, a significant decrease in BESS prices is not expected in the near future [7].

4.1. Residential BESS Adoption

In this study, only potential financial benefits of a residential BESS were considered. However, other aspects should also be considered before stimulating the adoption of residential BESSs, including the environmental impact of a BESS through a life cycle assessment [28] and effects on the grid. Moreover, it should also be considered what prospected payback period do households consider an attractive investment for a BESS.

An option to incentivize residential BESSs could be a government subsidy. However, the proposed NM phase-out would limit the financial potential of a BESS for PV-equipped households. During NM and NM phase-out, any subsidy on a residential BESS would therefore (partially) serve to counteract the negative effects of the existing NM subsidy on BESS profitability, while these households already benefit from NM. Furthermore, a scenario of high penetration of residential PV-BESS might lead to an unfair distribution of network charges, taxes, and levies in the favor of households that are in possession of such a system [5]. On the other hand, minimizing the uncertainty in expected revenues in future years by offering long-term and transparent electricity tariffs is important for residential BESS adoption [9].

4.2. Research Assumptions and Shortcomings

For this study, smart meter data with a resolution of 15 min were used, thus averaging out peak loads shorter than 15 min. Also, the effect of factors like charging and discharging power on the efficiency of the battery were neglected. Both might lead to errors in the estimated amount of self-consumption and financial yield, as noted in Section Related Work.

As seen in Section Related Work, battery assumptions can vary a lot between studies, limiting the comparability of similar studies. Also, a more detailed model for battery degradation and efficiency could be incorporated [30]. However, such a model needs to be accompanied with good estimates of future day-ahead price differences, which remains a challenge. Therefore, this work focused on annual yields with different historical price levels and used a simplified model for battery degradation, leading to rough estimates on the payback period.

In this study, the main focus was on the profitability of a residential BESS combined with a dynamic contract based on day-ahead prices, as this is currently available in the Netherlands. Residential BESS control based on day-ahead prices does not necessarily solve the problems on the low voltage grid: a pricing mechanism based on day-ahead prices can lead to increased peak demands at the household level [34]. Control based on other price incentives might be more favorable for the grid and could lead to extra revenue. For example, when the provision of frequency restoration reserves (FRRs) is added a second application for residential BESSs, there is a small drop in the self-consumption rate, but a significant increase in annual revenue [12]. Finally, as electric vehicles are becoming more popular, the possibilities of using an existing electric vehicle instead of a residential BESS for increasing self-consumption can be promising.

A residential BESS must be sized properly, which depends on various aspects [20]. In this study, the BESS capacity was fixed at 5 kWh or 10 kWh. As seen in Section 3.3, when NM is removed, mainly households with high annual electricity usage and feed-in pre-BESS-installation might benefit from the larger capacity. Therefore, this should be taken into account when sizing a residential BESS. Furthermore, it can be studied which aspects other than pre-installation annual feed-in and demand affect BESS profitability, for example, by incorporating information on appliances present in the household. Furthermore, battery types other than lithium ion might be favorable, depending on the electricity usage and PV generation [35].

Financial profitability depends on the optimality of the control algorithm. For this study, an optimal (deterministic) control was derived per day, where two variables were fixed beforehand: the required minimal yield per cycle C and the SoC at the end of each day s_{end}. It follows from Section 3 that when controlling the BESS based on day-ahead prices, an optimization of C is needed to determine whether a price difference presents a good opportunity to charge or discharge the BESS, and thereby limit the number of cycles.

As seen in Section 3.3, for different households, different values of s_{end} are optimal in the case of no NM, and this could be optimized. In [21], a similar problem was encountered when a residential BESS was controlled to minimize the monthly electricity bill, and reinforcement learning was used to optimize the value of s_{end} per day. This could also be promising for optimizing the minimal required yield per cycle C.

Only a deterministic optimal control was offered for the situations of NM phase-out and removal combined with a dynamic contract. For actual control in these cases, prediction models are needed, while errors in the prediction could lead to reduced profitability. Furthermore, an ideal control would not only take into account the household profile but also assess battery degradation, and thereby try to increase the battery life [23].

When applying machine learning techniques for control, challenges arise, such as the predictability of solar generation and household demand or modeling and data availability. For example, creating a separate model for each household requires historical data of each household and the maintenance of many models, while if a clustering of similar households can be used, this not only decreases the number of models needed but also increases the amount of available training data for (new) households.

5. Conclusions

The potential financial profitability and increase in PV self-consumption by applying a residential BESS was studied for Dutch PV-equipped households with a dynamic contract based on day-ahead prices. Both the current Dutch situation (with NM) and proposed future situations were studied. For the current situation with NM, an optimal control algorithm was derived using LP in order to study financial profitability. For the recently proposed phase-out of NM and for the general case where there is no NM, only a deterministic optimal control could be derived using LP. This was then combined with smart meter data from Dutch households in order to study economic feasibility and increase in self-consumption.

The results show that with the current BESS prices and electricity price levels, controlling a residential BESS based on electricity prices in the Netherlands is not generally profitable. Only when BESS prices are significantly lower or when electricity price differences are larger (e.g., when electricity taxes are higher), could a residential BESS become profitable for a large fraction of the households. The NM phase-out limits the potential of a residential BESS compared to the situation without NM. In particular, in the cases of NM removal or phase-out, the potential yield and increase in self-consumption differ greatly between households, with higher numbers for households with both a high annual pre-installation electricity demand and feed-in. Furthermore, when controlling a BESS based on day-ahead prices, a valid choice about the minimal required yield per cycle—i.e., what price differences should be capitalized on—must be made, as this affects profitability and the number of cycles and, thereby, battery degradation. Finally, further investigation should be conducted on optimal BESS sizing and control per household, as well as on additional price incentives that could not only increase BESS profitability but also be more favorable for the grid.

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Data Availability Statement: Data are only available upon request due to restrictions. The Python-code, including examples, can be found at https://github.com/mariondam/Wattflex/tree/main/residential_battery_control (accessed on 1 June 2024).

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

Appendix A. Estimation of the Payback Period of a Residential BESS

The payback period or, in the case of no possible recoupment, the total yield over the lifetime of the BESS is estimated as a function of the potential yield in the first year and battery degradation. Degradation within a year is ignored during the calculation of the annual yield and the assumptions shown in Table 1 are used, so the BESS has a lifetime of 4900 cycles or 14 years, whichever comes first.

Let Y be the computed potential financial yield of a residential BESS in the first year ($n = 0$) after BESS installation. Then, after a year or 350 cycles, whichever comes first, the degradation d is applied step-wise, leading to a decrease in the annual yield Y of the same amount. This is expressed in formulas below.

When 350 EFCs per year or less are performed, the BESS lasts 14 years. After n years only $(1 - dn) \times 100\%$ of the original capacity is left; hence, only a fraction of $(1 - dn)Y$ of the original yield Y can be achieved in year n. Using this, the total yield over the battery lifetime (14 years) can be expressed in terms of the annual yield Y, and is given by

$$\sum_{n=0}^{13}(1 - dn)Y = \sum_{n=0}^{13}(1 - 0.015n)Y = 12.635Y \quad \text{(A1)}$$

With this, it can be estimated whether or not the BESS investment can be recouped. A 5 kWh BESS costs EUR 3500. In using Equation (A1), if there are at most 350 EFCs in a year, an annual profit of $Y = \frac{3500}{12.635} \approx$ EUR 277 is needed in the first year to recoup the investment before the BESS reaches its end of life.

If there are more than 350 EFCs performed per year, then the BESS reaches its end of life after 4900 EFCs. Let n_c be the number of EFCs per year. In this case, it is assumed that after the first n_c EFCs, a fraction of $\frac{350}{n_c}$ of Y is earned, and then degradation is applied. In continuing this step-wise degradation per n_c EFCs, the total yield over the lifetime of the BESS, expressed in terms of the annual yield in the first year Y, is then given by

$$\sum_{n=0}^{13}(1 - dn)\frac{350Y}{n_c} = \sum_{n=0}^{13}(1 - 0.015n)\frac{350Y}{n_c} = 12.635\frac{350Y}{n_c} \quad \text{(A2)}$$

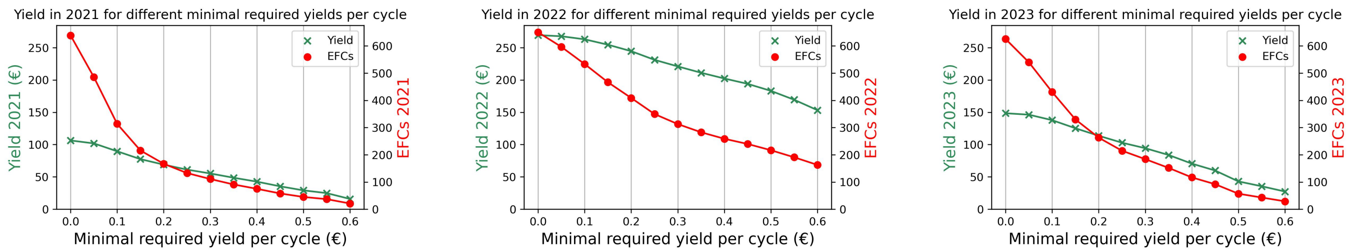
For example, if $n_c = 400$ EFCs are performed in the first year with a yield of $Y = 317$, then the total profit over the battery lifetime is approximately EUR 3505; hence, the investment can be recouped, but the total calendar lifetime is only 12.25 years.

Appendix B. DA-NM Optimization with Different BESS Assumptions

Instead of the BESS specifications as given in Table 1, different specifications were studied for DA-NM optimization.

First, the maximum charging and discharging power were both assumed to be 5.0 kW instead of 3.68 kW. This leads to an average increase of less than 1% in the annual profit and number of EFCs. This is due to the fact that with the original assumptions, it takes only slightly over one hour to fully charge or discharge, while in the new scenario, it takes less than an hour, resulting in small price differences when hourly prices are considered.

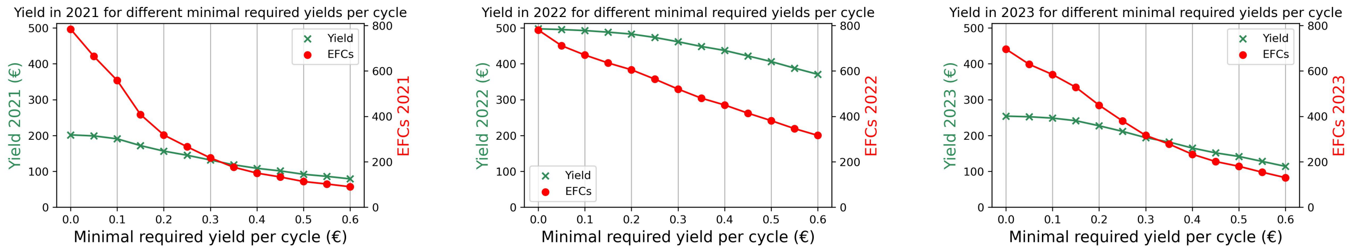
If the maximum charging and discharging power are set to 2.5 kW, while keeping the other specifications as in Table 1, the number of EFCs and annual yield drop, on average, respectively, 28% and 32%. Fully charging and discharging now takes 1 h and 19 min; thus, a larger portion of the charging and discharging is performed in, respectively, the second-cheapest or second-most expensive hour, which satisfies the minimal required yield less often. The results are shown in Figure A1. The investment in the BESS cannot be recouped in this case.



(**a**) 2021 (**b**) 2022 (**c**) 2023

Figure A1. The potential yield (left y-axes) and number of EFCs (right y-axes) for a 5 kWh BESS with a maximum charging and discharging power of 2.5 kW instead of 3.68 kW using DA-NM control on day-ahead prices of 2021–2023 for varying values of the minimal required yield per cycle (x-axes).

When not only the charging and discharging power are increased to 5.0 kW but also the effective usable battery capacity is 100% (i.e., the minimum SoC is 0% and the maximum SoC is 100%), while keeping all other specifications as in Table 1, the annual yield and number of EFCs increase, on average, by 57% and 34%. The results are shown in Figure A2. When battery degradation assumptions are kept the same—thus disregarding the fact that deeper discharges are unfavorable for battery life—the investment cannot be recouped with prices as in 2021 and 2023. With prices as in 2022, the payback period is 9 years (if $C = 0.45$).



(**a**) 2021 (**b**) 2022 (**c**) 2023

Figure A2. The potential yield (left *y*-axes) and number of EFCs (right *y*-axes) for a 5 kWh BESS with an effective usable battery capacity of 100% instead of 75% and maximum charging and discharging power of 5.0 kW instead of 3.68 kW using DA-NM control on day-ahead prices of 2021–2023 for varying values of the minimal required yield per cycle (*x*-axes).

Finally, the BESS is assumed to have an efficiency of 95%, while all other specifications are as in Table 1. In this case, the number of EFCs and annual yield increase, on average, respectively, by 19% and 16%.

Appendix C. DA Optimization with Different BESS Assumptions

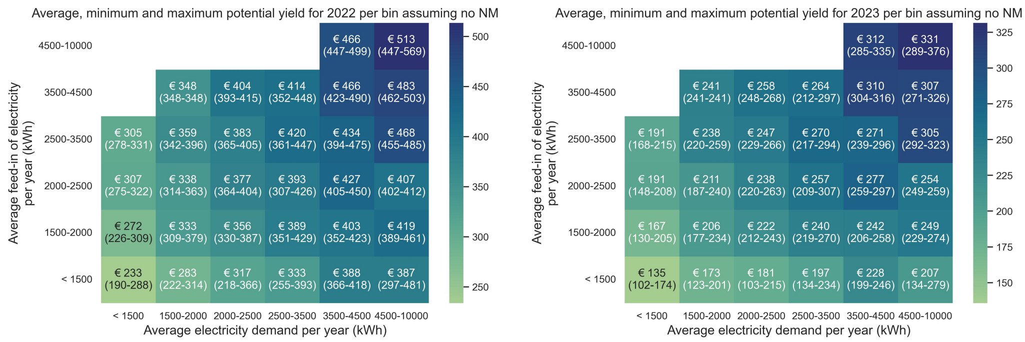
Instead of the BESS specifications as given in Table 1, different specifications were studied for DA optimization. (As seen in Figure 9, the results of 2021 and 2023 are very similar. Therefore, the figures per household bin only include 2022 and 2023).

First, the maximum charging and discharging power were both assumed to be 5.0 kW instead of 3.68 kW. This leads to an increase of at most 1% in the average annual yield per bin. If the maximum charging and discharging power are set to 2.5 kW while keeping the other specifications as in Table 1, the average potential annual yield decreases at most 1%, similarly for the total number of EFCs. This is mostly explained by the fact that the yield is mainly driven by increasing self-consumption (as seen in Section 3.3), while powers over 2.5 kW are rare in the 15 min smart meter dataset: taking the median for all households, only 0.3% of the 15 min intervals in a year have an average demand of over 2.5 kW, and only 0.1% of the intervals have an average demand of over 3.68 kW. For feed-in, this is 2.8% and 2.2%, respectively.

If not only the maximum charging and discharging power are increased to 5.0 kW but also the effective usable battery capacity is 100% (i.e., the minimum SoC is 0% and the maximum SoC is 100%), the average annual yield increases by at most 25%. The results are shown in Figure A3.

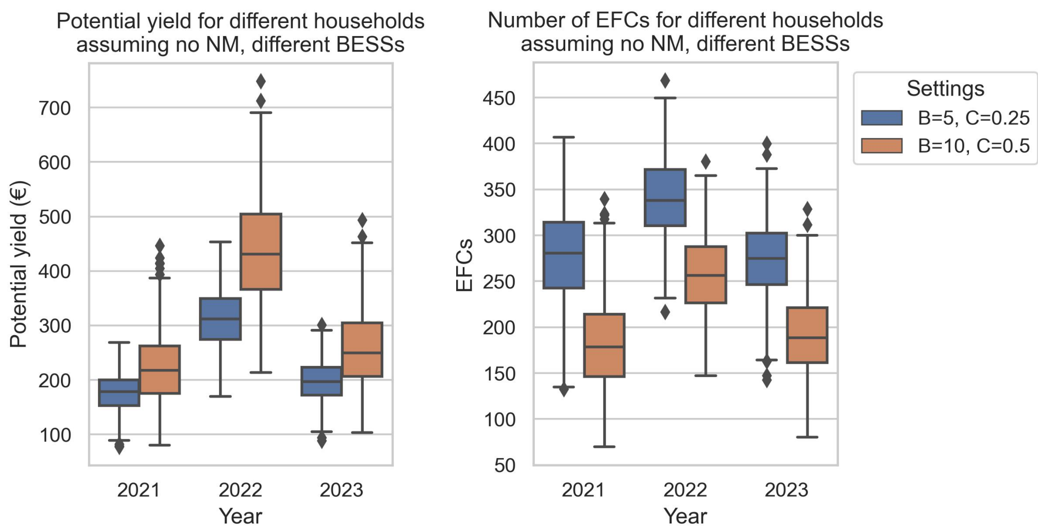
If the BESS is assumed to have an efficiency of 95%, while all other specifications are as in Table 1, the average annual yield increases by at most 15%.

Finally, when the BESS capacity is expanded to 10 kWh, while the other specifications are as in Table 1, the spread in the potential yield between the households becomes larger, as can be seen in Figure A4. Households with both a high pre-installation annual demand and feed-in benefit more from a BESS with a higher capacity than households with a low annual demand and feed-in.



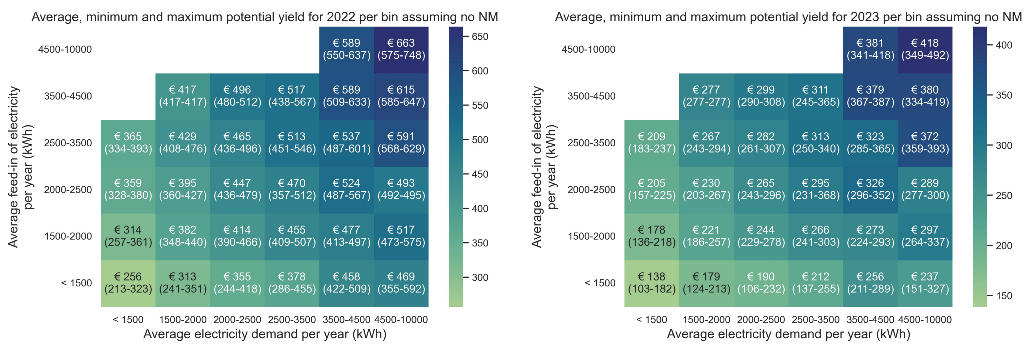
(**a**) 2021 (**b**) 2022

Figure A3. Average yield per bin (top value) and minimum and maximum yield (bottom values), all in EUR, for a 5 kWh BESS with a maximum charging and discharging power of 5 kW and a 100% effective usable battery capacity based on the day-ahead prices in 2022 and 2023 (DA optimization with $s_{\text{end}} = 0.4$ and $C = 0.5$).



(**a**) Potential yield (**b**) Number of EFCs

Figure A4. Comparing the potential yield and number of EFCs for different BESSs. DA optimization for different households and a 5 kWh and 10 kWh BESS ($B = 5$ and $B = 10$) per year, assuming no NM, $s_{\text{end}} = 0.4$ and different values for C.



(**a**) 2022 (**b**) 2023

Figure A5. Average yield per bin (top value) and minimum and maximum yield (bottom values), all in EUR, for a 10 kWh BESS, based on the day-ahead prices in 2022 and 2023 (DA optimization with $s_{\text{end}} = 0.4$ and $C = 0.5$).

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