TECHNO-ECONOMIC ANALYSIS OF RESIDENTIAL PV-BATTERY ENERGY SYSTEM IN NORDICS

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TECHNO-ECONOMIC ANALYSIS OF RESIDENTIAL PV-BATTERY ENERGY SYSTEM IN NORDICS

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ABSTRACT: Our objective is to discover how the photovoltaic (PV) production profile and home energy management (HEM) strategy affect the economic profitability of an added battery in a residential PV system in a Nordic context. We have included battery usage costs due to degradation – an aspect often overlooked in techno-economic assessments. In the literature, various HEM strategies for PV-battery have been explored, but studies have been limited to conventional south-facing monofacial PV (MPV). This work uses real PV data, including a south-facing MPV and a vertical east-west oriented bifacial (VBPV) system from Finland, combined with a typical residential consumption profile. A rule-based (SCM) and a reinforcement-learning-based (RL) HEM strategy are investigated. These results show that adding a battery (13.5 kWh/5 kW) to a PV system (2.5 kWp) is economically unfeasible with the battery capital expenditures of €9000, increasing annual costs by 137% on average. The break-even capital expenditures ranged between €490–1050, suggesting that batteries must become significantly cheaper to be profitable under the historical electricity prices of Finland. RL outperformed SCM only in 2022 under high electricity prices. The average battery lifetimes for VBPV and MPV were 12.5 and 11.9 years, indicating that PV production profile impacts battery longevity.
Keywords: home energy management, vertical bifacial PV, reinforcement learning, high-latitude location

1 INTRODUCTION

Due to the decreasing investment costs and great variability in electricity market prices, caused by the increasing amount of variable renewable energy (VRE) capacity in the production mix, photovoltaic (PV)-battery systems for households are becoming increasingly popular, even in Nordic countries. By adding a battery to a residential PV system, the self-consumption rate (SCR) can be significantly increased [1], [2], leading to lower need for electricity imports from the grid. The growing number of prosumers has made home energy management (HEM) -strategies of PV and battery an important research area [3], [4]. However, the existing techno-economic studies have focused on the typical south-facing monofacial PV (MPV), and novel orientations of PV combined with an energy storage have been overlooked. Previous studies show that in high latitude locations, a vertical east-west oriented bifacial PV (VBPV) can lead to nearly 10% higher production compared to south-facing MPV [5], [6], as well as higher value of production in a household context due to a better match of the temporal production and consumption profiles [5]. The production profile with the consumption set the boundaries for the battery usage, which is then implemented with a HEM strategy. The use of a battery affects its degradation and consequently its lifetime [3], but this aspect is often neglected when considering the economics of the energy system. In particular, the total throughput of the battery and the cycle depth affect its degradation – deeper cycles reduce the lifetime faster. However, the cycle depth and throughput could be reduced by changing the PV production profile to better match the consumption profile, as enabled by VPBV, leading to a longer battery lifetime.

Typically, simple rule-based HEM strategies are used when performing techno-economic analysis on PV-battery systems, but more sophisticated strategies have been introduced in literature to better control the load and battery usage in a residential energy system. One of the advanced approaches to HEM is reinforcement learning, where the system learns to perform viable actions through exploration and rewarding. One of its greatest advantages is its ability to adapt and improve during its operation [7].

The aim of this work is to discover the effects of PV production profile and HEM strategy on the total economic costs, namely the electricity bill and battery usage cost, in a household with existing PV and added battery. We use real production data from a south-facing MPV system (corresponding to a typical flat rooftop installation) and a VBPV system from Turku, Finland (60 °N, 22 °E), and consumption data representing a typical residential house without electric heating in Finland. We compare the performance of a reinforcement-learning-based HEM strategy with a simple rule-based strategy, to assess how much savings on the electricity bill can be obtained when HEM includes the electricity price information.

2 METHODOLOGY

2.1 Data and electricity contract

Production data was obtained from two real systems of the Turku University of Applied Sciences (TUAS), both located on the same roof in Turku, Finland. Photographs illustrating the two setups are presented in Figure 1. The VBPV system (Figure 1A) consists of four Prism Solar Bi60-375BSTC modules installed vertically, leading to a rated power of 1.18 kWp (indicating the front side rating). The front side is facing east and the rear side facing west. Data is collected every minute. The MPV system is facing south with a tilt of 15 degrees (Figure 1B) and consists of 18 Kingdom Solar KD-250 polycrystalline modules, having a rated power of 4.2 kWp. For this system, data is collected over five minutes. Both production data were on direct current (DC) side and aggregated to one-hour resolution and scaled to resemble 2.5 kWp systems. For the VBPV system, this rated power corresponds to the front side rating. For both systems, data from 2018 to 2022 was used in this work.

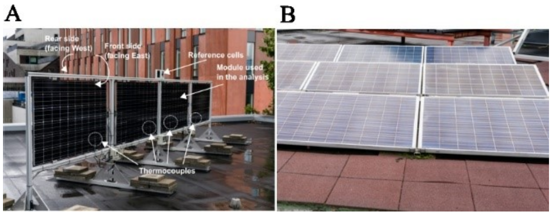

Figure 1: The setups used in this study: A: the vertical bifacial system [8] (@Elsevier, under CC-BY 4.0 licence), and B: the south-facing system. Photos: Nyberg/UTU.

As the electricity consumption data, we utilized the electricity consumer cluster classification data of the Finnish Energy Authority [9]. The profiles are one-year long averages from individual consumption data, and therefore weather/electricity price effects and load peaks are averaged out. We used a profile for a typical detached house without electric heating, having an annual consumption of 5 MWh. The mean monthly electricity consumption for a typical year and scaled PV production data over the years 2018-2022 are presented in Figure 2. The aforementioned scaling of the PV systems to 2.5 kWp was based on matching the monthly production and consumption during the summer months without huge excess production, so that the household can be self-sufficient for those high production months. For a household installation, this system size of 2.5 kWp is relatively small, since typically residential PV systems in Finland are within 5-8 kWp, based on the popular media article [10]. For the two systems, the mean specific yields over the analyzed years were 950 and 900 kWh/kWp for VBPV and MPV, respectively, leading to an average VBPV gain of 4.9%. The greater yield of VBPV is in line with the previous works [5], [6].

In Figure 3, the average daily profiles for each month of 2019 are presented for the production and load. From April to August, there is significant excess production, which can be stored in the battery and used during nighttime. It should be noted that April 2019, depicted in Figure 3, was exceptionally sunny, and that is why the production largely differs from the average of April shown in Figure 2.

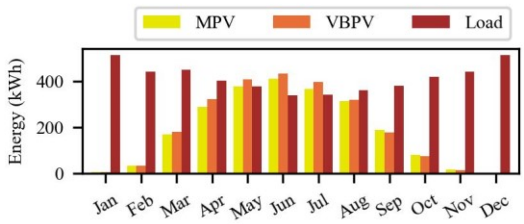

Figure 2: Mean monthly load and PV yields over the years 2018-2022. MPV: south-facing monofacial PV, VBPV: vertical east-west mounted bifacial PV.

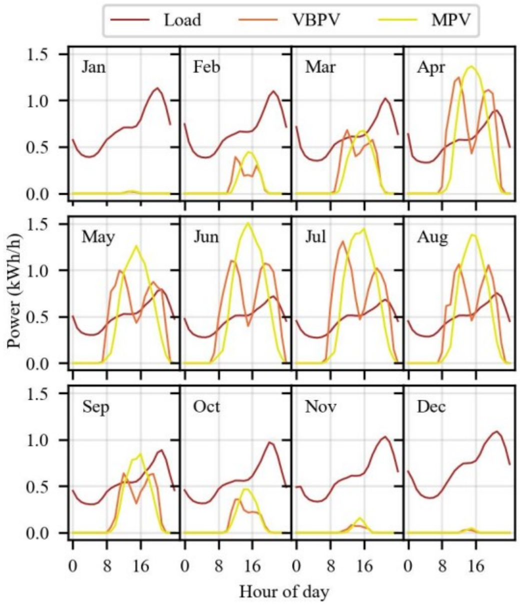

Figure 3: Average daily production and load profiles for each month, obtained using data from 2019. MPV: south-facing monofacial PV, VBPV: vertical east-west mounted bifacial PV.

Electricity day-ahead spot price data was obtained from Nord Pool [11]. In a spot-price-based contract, the electricity purchase and selling prices of a prosumer are defined as follows:

$$p_{\mathrm{purch}} = p_{\mathrm{spot}} \cdot (1 + \mathrm{VAT}) + p_{\mathrm{trans}} + p_{\mathrm{margin}} \quad (1)$$

$$p_{\mathrm{sell}} = p_{\mathrm{spot}} - p_{\mathrm{margin}}, \quad (2)$$

where p_{spot} is the spot-price, VAT is the value added tax (24%), p_{trans} is the fixed transmission cost, which includes the electricity tax and supply security fee, and p_{margin} is a small margin, determined by the electricity company. The values used for these price components as well as the mean spot price (exc. VAT) are shown in Table I. p_{trans} is location-, year-, and customer-class-dependent, and was obtained for a typical small detached house without electric heating, from the statistics of the Finnish Energy Authority [12]. The margin of 0.4 c/kWh resembles a typical value for this component. The spot prices rapidly increase by the end of 2021 due to the energy crisis.

Table I: Price components for different years. All values are in a unit of c/kWh.

	2018	2019	2020	2021	2022
p_{spot} (mean)	4.68	4.40	2.80	7.23	15.40
p_{trans}	6.93	6.93	6.65	6.65	6.22
p_{margin}	0.4	0.4	0.4	0.4	0.4

2.2 Battery modelling

Battery charge E was obtained each hour based on the previous battery charge and charging/discharging actions:

$$E_{h+1} = E_h + \eta P_h^{\mathrm{CH}} \Delta t - \frac{1}{\eta} P_h^{\mathrm{DCH}} \Delta t, \quad (3)$$

where h depicts the current hour, η is charge/discharge efficiency, obtained from the round-trip efficiency η_{RT} (*i.e.*, the ratio of electric energy that can be obtained from the battery and the amount of electric energy fed to battery) as $\eta = \sqrt{\eta_{\mathrm{RT}}}$. Furthermore, P^{CH} is the charging power, P^{DCH} is the discharging power, and Δt is the time resolution (1 hour). The battery charging and discharging were further limited with the following constraints:

$$0 \leq P^{\mathrm{CH}} \leq \mathrm{MIN}[P^{\mathrm{PV}}, P^{\mathrm{MAX}}, (E^{\mathrm{MAX}} - E)/\eta] \tag{4}$$
$$0 \leq P^{\mathrm{DCH}} \leq \mathrm{MIN}(\eta E^{\mathrm{MAX}}, P^{\mathrm{MAX}}), \tag{5}$$

where P^{MAX} is the maximum charge and discharge power, E^{MAX} is the capacity of the battery, and E is the battery charge. The battery parameters used in this work were based on Tesla's Powerwall battery [13] and are presented in Table II. The capital expenditures were estimated from Finnish mainstream media [14], and they include the installation costs.

Table II: Used battery parameters: P^{MAX} is the maximum charge/discharge power, η_{RT} is the round-trip efficiency, E^{MAX} is the battery capacity, and C_{CAPEX} is the capital expenditures, including installation.

Variable	P^{MAX} (kW)	η_{RT} (-)	E^{MAX} (kWh)	C_{CAPEX} (EUR)
Value	5	0.9	13.5	9000

Battery degradation was based on the model presented by Magnor et al. [15], which accounts for both float and cyclic degradation, with cyclic degradation further divided into micro and macro cycles. Regarding cyclic degradation, we counted only the micro cycles, and excluded the assessment of macro cycles, which is in line with other battery degradation models [16], [17]. For each half cycle, *i.e.*, when battery is charged or discharged monotonically (over ≥ 1 hours), the change in state-of-charge ($\Delta\mathrm{SOC}$) is calculated at the end of the half-cycle and the corresponding maximum number of cycles $N_{\Delta\mathrm{SOC}}^{\mathrm{MAX}}$ is obtained with the following equation:

$$N_{\Delta\mathrm{SOC},h}^{\mathrm{MAX}} = a \cdot |\Delta\mathrm{SOC}_h|^{\mathrm{b}}, \tag{6}$$

where a and b are fitting coefficients. In our work, we used the values for the lithium-ion batteries calculated by Magnor et al. [15], *i.e.*, $a = 1.2698 \cdot 10^6$ and $b = -1.3133$. Based on each half cycle, the corresponding change in state-of-health (SOH) due to cyclic degradation is then obtained as the inverse of the number of cycles:

$$\Delta\mathrm{SOH}_{\mathrm{cyc.},h} = \frac{1}{N_{\Delta\mathrm{SOC},h}^{\mathrm{MAX}}}, \tag{7}$$

when the half cycle finishes at the end of given hour h. During other hours that are not at the end of a half cycle, $\Delta\mathrm{SOH}_{\mathrm{cyc.},h} = 0$. $\Delta\mathrm{SOH}$ of 0 indicates that the battery has not experienced any capacity fade, whereas $\Delta\mathrm{SOH}$ of 1 corresponds to the battery's end-of-life (typically meaning 20% capacity fade). We neglected the effect of temperature on the degradation by assuming a constant battery operation temperature of 25 °C. Therefore, the float degradation was obtained for each hour with the following equation:

$$\Delta\mathrm{SOH}_{\mathrm{float},h} = \frac{1}{d + e \cdot \exp[f \cdot (100 - \mathrm{SOC}_h)]} \cdot \frac{1}{t_{\mathrm{ref}}}, \tag{8}$$

where d, e, and f are again fitting coefficients, and the values $d = 2$, $e = -1.2$, and $c = -0.0275$ calculated by Magnor et al. [15] were used. t_{ref} is the reference calendar lifetime under the temperature of 25 °C, and here it was assumed to be 10 years (corresponding to guarantee by the manufacturer), thus $t_{\mathrm{ref}} = 10 \cdot 8760$. On a given hour, the total degradation $\Delta\mathrm{SOH}$ was obtained as the maximum of the cyclic and float degradation:

$$\Delta\mathrm{SOH}_h = \max(\Delta\mathrm{SOH}_{\mathrm{cyc.},h}, \Delta\mathrm{SOH}_{\mathrm{float},h}). \tag{9}$$

We used a common approach to evaluate the monetary value of this degradation by multiplying the $\Delta\mathrm{SOH}$ with the battery capital expenditures C_{CAPEX} [18], [19]:

$$C_{\mathrm{bat},h} = \Delta\mathrm{SOH}_h \cdot C_{\mathrm{CAPEX}}. \tag{10}$$

2.3 Energy management methods

In this study, three HEM strategies were applied, and the results are compared with a base case, which includes only PV and no battery. Below the strategies are described.

PV without a battery (NO-BATTERY). As a reference case, the electricity bills were calculated for a system without a battery and existing PV. In this case, all PV production is used to cover the load, and the excess is sold to the grid.

Self-consumption maximization (SCM). SCM is a simple rule-based approach that maximizes the amount of self-consumed PV production. All possible production is used to cover the consumption and the excess is stored in the battery. If the battery is full, then the excess production is sold to the grid. Correspondingly, if the consumption is not met with PV production, the battery is discharged, and lastly electricity is purchased from the grid. SCM is a commonly applied strategy in economic PV-battery studies [20], as well as a common reference case for other advanced strategies [21].

Reinforcement learning (RL). As another HEM strategy, a deterministic policy gradient method was applied to control the battery charging and discharging. RL strategies have been shown good performance for HEM [22], [23]. Here, an RL method that includes the information on the electricity price was used to allow a possibility to perform economically viable energy management. An RL problem is defined by a state space *S*, an action space *A*, a reward (or loss) function *R*, and a policy function π. Here, a state *s* ($\forall s \in S$) consists of environmental variables, such as PV production, load, electricity price, and battery charge. An action *a* ($\forall a \in A$) is the result of implementing the policy π on a given state *s*. Here, the action is the amount of battery charging/discharging in a given hour. In the case of deterministic policy function, the action is always the same on a given input state. Electricity bill was used as the loss function. The aim of the loss is to update π so that it would learn actions that lead to lower electricity bill. As a policy function π_θ, a neural network (NN) with three layers, each consisting of 100 neurons with ReLU activation, was used. Notation θ refers to NN parameters, *i.e.* weight matrices and bias vectors of the NN, which were optimized during the model training. Below, the model input, output, and training are described in more detail.

The input vector for given time h depicts the state s, and consists of PV production, load, spot price, electricity purchase and sell price, and the battery charge on the hour h, as well as known spot prices for the next 24 hours, and forecasted production and load for the next 24 hours, leading to 78 input variables. The production and consumption forecasts used in the input were implemented with Naïve forecasting: the load was assumed to be the same as one week ago, and the PV production was assumed to be the same as the day before. The NN produces a scalar output y, which is run through Tanh layer, resulting in a decimal output between -1 and 1. Here, negative outputs indicate battery discharge and positive values battery charge. The output is scaled by multiplying it with P^{MAX} and the absolute value of discharge power is taken, after which the constraints (4) and (5) are checked. PV production that is not used for battery charging is used to cover the load, and remaining PV is sold to the grid, if electricity is not simultaneously bought from the grid. The load that cannot be met with battery discharging or PV production is bought from the grid.

The training of the RL is based on iteratively performing actions that lead to the next state, leading to a realized trajectory τ consisting of multiple consecutive hours. This is called an episode, and one week was used as the length of an episode. After an episode, a loss J, corresponding to the electricity bill, is calculated for the trajectory as the sum of the losses r of each hour:

$$J = R(\theta,\tau) = \sum_{h=0}^{H} r_h(\theta) = \sum_{h=0}^{H} C_{\mathrm{el.bill},h}(\theta) = \sum_{h=0}^{H} (E_{\mathrm{purch},h}(\theta) \cdot p_{\mathrm{purch},h} - E_{\mathrm{sell},h}(\theta) \cdot p_{\mathrm{sell},h}), \tag{11}$$

where H is the length of the episode, $C_{\mathrm{el.bill}}$ is the electricity bill, E_{purch} is the purchased electricity, and E_{sell} is the sold production. This loss depends on the states of the trajectory but also on the parameters θ of the policy π_θ. After completing an episode, π_θ is updated with gradient descent. Adam optimizer was used for this purpose with a learning rate of 10^{-4}. Year 2018 was used for model training. Only the months from March to September were used to ensure data with sufficient PV production. The initial battery charge was randomly generated for each datapoint. The training data was divided into train and validation sets with a common 80/20 random split, and training was monitored by calculating the losses over the whole train and validation sets after each epoch. Early stopping with patience of 20 epochs was applied.

After this initial training, the energy system was simulated over the years 2018-2022 by iterating through each hour of the years and performing HEM with the RL model. In every two weeks, the model π_θ was updated using the data from the previous two weeks over five training epochs. This dynamic training allows the model to produce good policies under changing environment (e.g., the electricity prices experienced a huge raise during 2021-2022).

RL with battery cost (RL-BC). We implemented a model otherwise identical to the previously described RL model, but with a different loss function. Since the aim of this work is to study the total operational costs including the battery usage costs, the sum of the electricity bill (Eq. (11)) and battery usage costs (Eq. (10)) was used as the loss function:

$$J = R(\theta,\tau) = \sum_{h=0}^{H} r_h(\theta) = \sum_{h=0}^{H} [C_{\mathrm{el.bill},h}(\theta) + C_{\mathrm{bat},h}(\theta)]. \tag{12}$$

The inclusion of battery usage costs in the loss function allows this strategy for optimizing the operation to lead to smallest total costs. All reinforcement learning models were implemented with Python's open source PyTorch library (version 2.2.0) [24].

3 RESULTS

The electricity bills and battery usage costs for each year are shown in Figure 4 for the different HEM strategies and both PV systems. It is apparent that the total costs of RL and SCM strategies are significantly higher in comparison with NO-BATTERY, because the savings in electricity bill are lower than the total battery usage costs. Especially the float degradation causes high usage costs. The average increases in the total costs for RL and SCM compared with the NO-BATTERY scenario across all years is €670 for VBPV and €698 for MPV. Compared with the NO-BATTERY case, the average relative increase is 137% for both systems. This indicates that the battery with the capital expenditures of €9000 fails to provide economic benefit when added to the existing PV system. In the literature, residential batteries with PV have been reported being economically feasible, especially with lower battery sizes and assuming low battery capital costs [25]–[27]. However, compared with residential scenarios having only PV, it is often the case that added battery does not yet lead to economic benefits, such as presented in [25], [27]–[29], covering cases from Switzerland, Thailand, Germany, and Finland. In [20], the payback time decreased slightly when a small battery was added with PV in Australia, when there was a great difference between time-of-use tariff price (AUD 0.19-0.33/kWh) and feed-in-price (AUD 0.05/kWh).

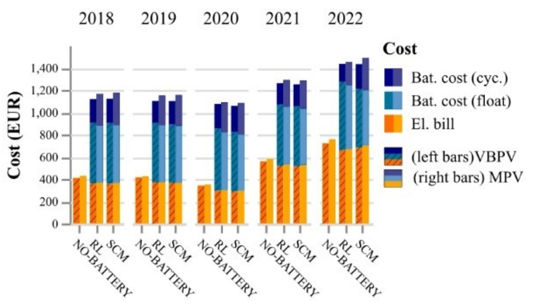

Figure 4: Yearly costs, divided into electricity bill (El. bill) and battery usage cost due to cyclic degradation (Bat. cost (cyc.)) and float degradation (Bat. cost (float)) for vertical bifacial (VBPV) and south-facing monofacial (MPV) systems and for different energy management strategies: NO-BATTERY: PV without battery, RL: reinforcement learning, SCM: self-consumption maximization.

In the presented systems, the addition of the battery becomes profitable (*i.e.*, the total cost is equal to the electricity bill of the corresponding NO-BATTERY case) in all studied cases and years if its capital expenditures are below €490 for the 13.5 kWh battery, compared with the current $C_{\mathrm{CAPEX}} = €9000$ for Tesla's Powerwall. In general, the break-even price varies between €490–720, but reaches its maximum value of €1050, or 78 €/kWh, with MPV and RL during 2022 due to the greatest savings in the electricity bill. It should also be noted that the discounting of the battery cost was neglected, and therefore the break-even prices would be lower in reality than those presented above. There are cheaper battery alternatives in the markets, such as the 13 kWh battery-pack provided by DianKaiShou with a price of €1355 [30]. However, this price is still greater than the highest break-even cost obtained in our study, and it does not include inverter or installation costs. Based on a report by the National Renewable Energy Laboratory [31], the lowest estimated battery system CAPEX will be below €300/kWh by year 2050 with the most optimistic prediction, which is still nearly four times bigger than the highest break-even CAPEX of €78/kWh, obtained here.

The electricity bills and the total battery usage costs of VBPV are systematically lower than those obtained with MPV. On average, the annual electricity bill is 2.4% (or €12) and the battery usage cost 5.0% (or €38) lower than with MPV. This means that the battery added to MPV degrades 5% faster compared with the battery with VBPV. The average $\Delta\mathrm{SOH}$ for VBPV is 8.0%-point/a and 8.4%-point/a for MPV, resulting battery lifetimes of 12.5 and 11.9 years, respectively (20% capacity fade). The lower electricity bill of VBPV is expected based on the literature [5], and the lower battery usage costs are due to the better temporal match between the production and load of VBPV compared with MPV, leading to lower cyclic degradation. Due to the orientation of VBPV, it produces power earlier in the morning and later in the evening compared with south-facing MPV, providing higher SCR and lower need for battery storage. Additionally, on sunny days, the VBPV produces more electricity, leading to a fully charged battery and selling of the excess production. This way the battery throughput is smaller compared with the south system, where the battery is constantly charged and discharged. This can be seen in Figure 5, which displays the operation of SCM (Figure 5A and B) and RL (Figure 5C and D) strategies over three days in May 2022. All three days have excess production, in which case the battery is charged. Regarding MPV with SCM, excess PV production is sufficient to charge the battery fully only on the second day, leading to deep daily cycles (Figure 5A). Due to the greater production of VBPV, battery stays fully charged during days and remaining production is exported (Figure 5B), which causes less battery usage and cyclic degradation. However, since the battery charge stays higher with VBPV, the float degradation is higher (Eq. (8)) and therefore leads to higher float battery costs compared with MPV.

When the battery is added to the PV system, the SCR increases on average (regarding SCM and RL) from 58% to 87% with VBPV and from 54% to 91% with MPV, leading to 30 and 37%-point increases, respectively. MPV leads to higher SCR with the added battery due to lower total production which causes less production exports. By calculating the additional total costs and additional self-consumed electricity when using a battery compared with NO-BATTERY, the average costs of added self-consumption are 100 c/kWh for VBPV and 86 c/kWh for MPV.

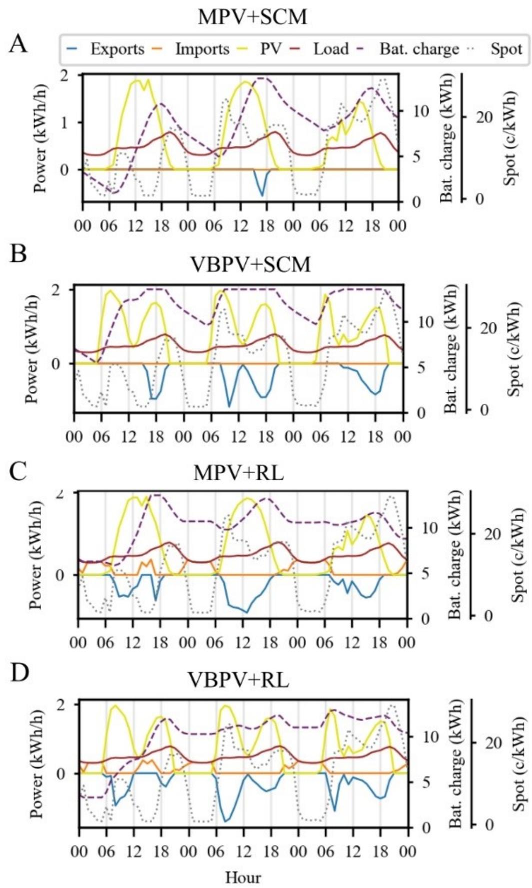

Figure 5: Operation examples on 15-17th of May 2022, A: MPV (south-facing monofacial PV) with SCM (self-consumption maximization), B: VBPV (vertical bifacial PV) with SCM, C: MPV with RL (reinforcement learning), and D: VBPV with RL.

Although RL has the information on the current and near future electricity prices allowing it to perform energy arbitrage, its typical operation on 2018-2021 is nearly identical to SCM (*i.e.*, the exports, imports, and battery charge curves of RL presented in Figure 5 are similar to those of SCM), leading to similar electricity bills and battery usage costs. Only during 2022 RL reaches notably lower total costs compared with SCM. This difference in 2022 is due to the high spot prices as well as high variability in the price during 2022, which offered great possibility for energy arbitrage. This can be seen in Figure 5: during high electricity prices, RL strategy sells the excess production rather than stores it into the battery, which leads to good profits and avoids stressing the battery. With SCM strategy, the battery is heavily utilized, and production is only sold to the grid when the battery is full. During the three-day period presented in Figure 5, the electricity bills for VBPV and MPV were €-0.14 and €-2.30 with SCM, and €-0.97 and €-2.00 with RL. Although RL tries to minimize the electricity bill, its electricity bill over the three-day period is higher for VBPV compared with SCM. This is because the starting battery charge is higher in the case of SCM, and because RL is trained with an episode length of one week, in which case the three-day

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period depicted in Figure 5 does not represent the full optimization horizon. During the years 2018-2021, when the electricity prices were on a conventional level (the prices increased rapidly at the end of 2021), the RL provides no economic benefit over SCM. This result indicates that the potential to gain profits from utilizing the intra-day spot-price fluctuations is small, when electricity prices are at conventional levels. However, due to the rapid increase in installed and planned VRE capacity, e.g., wind energy increased from 6.7 GW to 7.7 GW during 2024 from January to September [32], the high fluctuations in the electricity prices might be the new norm. These fluctuations in the prices favor the utilization of electricity-price-aware HEM methods, such as the RL presented in this work. The RL method could also be further optimized, *i.e.*, by tuning the model hyperparameters, to reach lower electricity bills.

When the battery usage cost is included in the loss function of RL-BC, the battery stays practically unused, indicating that the added battery is non-profitable. During the simulation period, there are hardly any situations where using the battery would lead to higher electricity bills savings than the total battery usage costs, thus the RL-BC model learns not to use the battery. It is possible that there are such periods where utilizing the battery would lead to bigger electricity bill savings than the battery usage costs, especially during high spot-prices in 2022. However, since the number of these possible periods is so small, the model cannot learn to utilize the battery regardless of the dynamic training.

4 CONCLUSIONS

The objective of this work was to discover how the PV production profile and HEM strategy affect the economic profitability of an added battery in a residential PV system in the Nordics. We showed that, on average, VBPV leads to 2.4% (€12) lower annual electricity bills as well as 5.0% (€38) lower degradation and battery usage costs compared with a typical south-facing MPV system, because of the higher production and better temporal match between the production and load profiles. The corresponding average battery lifetimes for VBPV and MPV were 12.5 and 11.9 years, respectively. However, the battery capital expenditures of €9000 (including installation) was found to be too high for the 13.5 kWh/5 kW battery to be an economically profitable addition to a PV system, increasing the total annual costs by around 137%, compared with a base case with PV and no battery. The break-even battery capital expenditures varied between €490–1050 (€36/kWh–€78/kWh), depending on the year, HEM strategy, and PV orientation. These break-even costs are much smaller than the predicted future battery system capital expenditures, such as €300/kWh for 2050 [31]. The capital expenditures should decrease and/or electricity peak prices should increase significantly to make an added battery economically viable.

The electricity-price-aware RL reduced electricity bill and battery usage cost significantly only during 2022 compared with the rule-based SCM. During other years, the two strategies performed equally. This equal performance suggests that only in cases where the electricity prices are high and have huge fluctuations, significant savings can be obtained with a more advanced HEM strategy. However, due to high increases in planned and installed VRE, high fluctuations in electricity prices can be the new norm, in which case more advanced HEM strategies, as well as the added battery in the first place, could become more viable.

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