Electric Power Systems Research 264 (2027) 113517

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Averaging favors MPC: How typical evaluation setups overstate MPC performance for residential battery scheduling

Janik Pinter *, Maximilian Beichter, Ralf Mikut, Frederik Zahn, Veit Hagenmeyer

Institute for Automation and Applied Informatics, Karlsruhe Institute of Technology (KIT), Germany

ARTICLE INFO

Keywords:
Battery scheduling
Model predictive control
Net billing
Rule-based control
Timescale effects

ABSTRACT

Residential prosumers with PV-battery systems increasingly manage their electricity exchange with the power grid to minimize costs. This study investigates the performance of Model Predictive Control (MPC) and Rule-Based Control (RBC) under 15/30/60 min averaging commonly used in research, when Net Billing and battery degradation are considered. We simulate five consecutive months for 15 buildings in northern Germany, generating costs at up to 1-min resolution while scheduling at 15/30/60 min. We find that time-averaged evaluations make MPC look consistently better than RBC, yet when costs are recomputed at minute-level ground-truth, the reported advantage shrinks by 69% on average for hourly schedulers. For individual buildings, the finer evaluation can reverse conclusions, and simple RBC can achieve lower total costs than an MPC with perfect foresight. These findings caution against drawing conclusions from coarse averages and show how a fair assessment of battery scheduling approaches can be obtained.

1. Introduction

With the increasing roll-out of residential PV-Battery systems, typical consumers are increasingly turning into prosumers that actively manage their electricity exchange with the power grid. Regulators aim to influence the prosumers energy management to improve grid friendliness and with that reduce the necessity of expensive grid expansions while keeping prosumer economics transparent and fair. For that, their key mechanisms are settlement rules (how imports/exports are accounted for) and tariff structures (how they are priced), which together determine economic incentives and thereby heavily influence the prosumers' energy management strategy. Two of the most common approaches for the prosumers' battery control are Rule-Based Control (RBC) and Model Predictive Control (MPC), which is why many studies compare their performance [1–5]. In this paper, we show how such a comparison is often systematically biased to overestimate the advantages of MPC over RBC. The bias stems from averaging and misaligned timescales between evaluation practices and real-world settlement rules. But in order to fully understand when such a bias occurs, it is important to understand the nuances of different metering and billing settlement rules.

A. *Metering and billing settlement rules*

Metering and billing settlement rules define the frequency at which the amount of exchanged energy with the grid is measured (e.g., instantaneous, hourly, monthly, yearly) and how those measurements are billed [6]. The main forms are:

- **Buy All - Sell All**: All generated electricity is directly fed into the grid (typically under a constant export price for feed-in). All consumed energy is bought from the grid at an import price. Self-consumption is not possible.
- **Net Metering**: Imports a and exports b within a fixed time period called Netting Interval (NI) cancel each other out. Only the net exchange $|a - b|$ over the NI is billed. The price applied to the net exchange depends on the specific regulatory implementation.
- **Net Billing**: Imports a and exports b are measured separately and $|a|$ is billed at an import price and $|b|$ credited at an export price. Self-consumption is possible. Net Billing can be seen as a special form of Net Metering with a very short (instantaneous) NI [6].

* Corresponding author.
E-mail address: janik.pinter@kit.edu (J. Pinter).

https://doi.org/10.1016/j.epsr.2026.113517
Received 14 October 2025; Received in revised form 13 February 2026; Accepted 20 June 2026
Available online 23 July 2026

In this work, we focus on the differences between Net Metering and Net Billing schemes. As of today, there is an ongoing trend towards Net Billing schemes. For example, Denmark introduced Net Metering with an NI of one year in 2010 [7]; because settlement was based on the yearly net $|a-b|$, recorded grid interaction—and thus taxable energy volumes—appeared much smaller. Such a system disproportionally favors prosumers over consumers, which is why, since 2012, new residential PV systems in Denmark are subject to Net Billing instead. Furthermore, the EU Electricity Directive [8] started demanding states to charge prosumers for imports and exports separately since 2019. Therefore, the overall trend in Europe is toward Net Billing for new residential PV contracts. Greece and Cyprus are two recent examples of this transition: Greece abolished its Net Metering scheme, which used a three-year netting period, in 2024, while Cyprus moved new residential PV installations from Net Metering to Net Billing in 2026. The Netherlands plans to abolish its annual Net Metering scheme from the beginning of 2027 onward [9]. See [10] for an overview of selected European states and their settlement practices.

Because the choice of the settlement rule is fundamental for the electricity bill, cost minimization studies should be aware and should make the reader aware of the specific settlement rule they are investigating. Yet, studies rarely specify the settlement rule on which they base their investigation. Although Net Billing is most common, evaluations often average power over 15, 30 or 60 min. This effectively sets the settlement rule to Net Metering with a NI equal to the averaging window, which can misalign research with real-world settlement.

B. Related works

Many studies compare MPC and RBC for residential batteries and typically report notable MPC savings, often assuming perfect forecasts. These results usually arise when evaluation relies on power averaged over 15, 30, or 60 min windows aligned with the controller's scheduling step [1–4,11]. This practice is convenient since it reduces implementation efforts and requires coarser temporal data resolution. However, computing costs from interval averages implicitly assumes Net Metering with a NI equal to the scheduler's step length, i.e., most often 15/30/60 min. Furthermore, coarse temporal aggregation can lead to distorted conclusions regarding estimated self-consumption, as shown in [12]. Under Net Billing, where imports and exports are priced separately, such averaging masks intra-interval fluctuations that add costs for the common case that the export price is lower than the import price. For example, [2] compare RBC and MPC on 30-min averages considering battery degradation and conclude that MPC with perfect forecasts reduces total costs by 12.9% relative to RBC. By only using averages, their cost calculation translates into implicitly assuming that either the load and PV will be constant over each 30-min interval (which does not happen in real-world), or that the evaluation is based on a Net Metering rule with a NI of 30 min.

Beyond single-layer comparisons, several works adopt hierarchical control with a slow scheduling layer and a faster execution layer. The fast layer often focuses on tracking a committed dispatch plan (minimizing plan-tracking error) rather than minimizing monetary costs under Net Billing [13–15]. The authors of [16] implicitly acknowledge the importance of fluctuations by combining a 30-min MPC scheduler with 5-min application. This choice allows for better approximation of costs under a Net Billing scheme. In their setup, the battery power is held constant over an MPC step, so that the 5-min fluctuations are compensated for by the grid. This can be favorable for battery lifetime but may increase the electricity bill significantly due to alternating import/export swings, as our results show later.

Overall, related works commonly resort to averaged evaluation and thus conceal three issues that matter under the most prevalent Net Billing: (i) the implicit assumption about a NI equal to the schedulers step, (ii) the additional cost impact of import/export crossings within an interval, and (iii) the additional cost impact of battery degradation in faster execution layers. Whether and how much these factors impact the performances of MPC and RBC differently is not quantified in existing studies. Addressing this gap is the aim of the present work.

C. Contribution

We investigate the performance of RBC and MPC for the operation of residential PV-Battery systems with respect to cost minimization on different timescales. The comparison is based on simulations with real-world measurements from 15 buildings over five consecutive months. The costs we evaluate include the electricity bill and the cost of battery degradation. Our key contributions include the following:

- Identify Net Metering versus Net Billing mismatch: We create awareness of how averaging over 15, 30, 60 min windows implicitly assumes Net Metering settlements when insights are intended for Net Billing.
- Expose common evaluation bias: We demonstrate that averaging over 15, 30, or 60 min systematically overstates MPC performance relative to RBC under Net Billing, which can lead to distorted or wrong conclusions.
- Identify cause of the observed evaluation bias: We show that, for the investigated fast-acting execution rule, battery degradation costs are the primary driver of the systematic bias introduced by coarse-average evaluations.

The remainder of the paper is organized as follows: Section 2 introduces the problem. In Section 3, the investigated RBC and MPC models are presented. Section 4 contains the experimental setup, battery specifications, pricing tariffs, and data. Section 5 contains the results. Section 6 discusses the obtained insights. Section 7 concludes the paper.

2. Problem formulation

We investigate residential buildings equipped with PV panels and a battery system. We consider the point-of-view of the residents and try to leverage the battery system to minimize costs, considering the electricity bill and battery degradation. The general structure of this setup is sketched in Fig. 1. Here, the net-load $p_L(k)$ is shared between the controllable battery power $p_B(k)$ and the grid power $p_G(k)$ such that

$$p_L(k) = p_B(k) + p_G(k). \tag{1}$$

We assume that the battery power $p_B(k)$ is set by a controller. The net-load $p_L(k)$ is given from time series measurement data. The grid power $p_G(k)$ thus results from the difference between $p_L(k)$ and $p_B(k)$.

In this study, all powers are averaged over predefined time intervals, with k denoting the index of the interval. Because this paper revolves around averaging effects, Fig. 2 illustrates different averaging choices for the same underlying net-load. This illustrates how different averaging choices can cause different battery decisions and hence different costs. The smaller the averaging window, the better the costs can be approximated under Net Billing.

We formalize this with two timescales: Δgt for the ground-truth data resolution and ΔNI for the Netting Interval used for settlement. Since we focus on Net Billing settlement, we set $\Delta NI = \Delta gt$. As a result, the finest data resolution selected directly sets the Netting Interval in the cost calculation. The smaller Δgt (and thus ΔNI), the better the cost approximation for a Net Billing settlement rule. We next describe the control schemes that determine the controllable battery power $p_B(k)$.

3. Battery control schemes

This section outlines the battery control approaches investigated in this study. We first introduce a purely Rule-Based Control (RBC) approach. We then present a two-level Model Predictive Control (MPC) approach that combines slower forecast-based planning with faster rule-based execution.

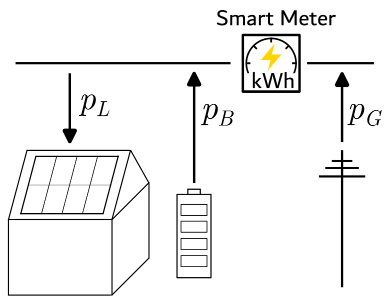

Fig. 1. General setting. The residential net-load p_L, the battery power p_B and the grid power p_G are in balance.

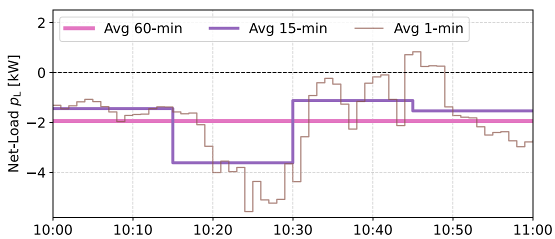

Fig. 2. Net-load p_L averaged over three resolutions. High-resolution data can better approximate costs under Net Billing.

A. Rule-based control

Typical RBC is a fast-acting reactive control strategy that controls battery power without relying on forecasts or price information. We implement the most commonly used rules (see e.g. [2,17]), i.e.,

- **RBC:** Charge during PV surplus and discharge during load surplus such that the grid exchange becomes zero and no battery constraints are violated.

We introduce an additional timescale Δc that denotes the control frequency at which the battery system can be operated. We set $\Delta c = \Delta gt = \Delta NI$ and with that assume that RBC can act in real-time to account for ground-truth changes. With that, we neglect phenomena like delayed battery response times observable in real-world [18].

B. Two-Level model predictive control

MPC is a proactive control strategy that relies on forecasts to determine a control action. MPC for residential battery scheduling thus typically considers upcoming prices as well as forecasts $\hat{p}_L$ in load and PV generation. At each planning step, an optimization problem is solved for a selected prediction horizon. However, only the first control action is applied before a re-optimization occurs after a predefined time has passed. The optimization problem used in this study is the following:

$$\min_{p_B} \quad C^{imp}(p_G^{imp}) + C^{exp}(p_G^{exp}) + C^{deg}(p_B) \tag{2a}$$

s.t. for all $k \in \mathcal{K}$

$$p_G(k) = \hat{p}_L(k) - p_B(k) \tag{2b}$$

$$e(k+1) = e(k) - \Delta s\left(p_B^{ch}(k)\eta^{ch} + \frac{p_B^{dis}(k)}{\eta^{dis}}\right) \tag{2c}$$

$$e^{\min} \le e(k) \le e^{\max} \tag{2d}$$

$$p_B^{\min} \le p_B(k) \le p_B^{\max} \tag{2e}$$

$$p_G(k) = p_G^{imp}(k) + p_G^{exp}(k) \tag{2f}$$

$$p_G^{imp}(k)\, p_G^{exp}(k) \ge -10^{-8} \tag{2g}$$

$$p_G^{imp}(k) \ge 0, \qquad p_G^{exp}(k) \le 0 \tag{2h}$$

$$p_B(k) = p_B^{ch}(k) + p_B^{dis}(k) \tag{2i}$$

$$p_B^{ch}(k)\, p_B^{dis}(k) \ge -10^{-8} \tag{2j}$$

$$p_B^{dis}(k) \ge 0, \qquad p_B^{ch}(k) \le 0. \tag{2k}$$

The objective is to minimize total costs consisting of electricity import costs C^{imp}, electricity export revenues C^{exp} and battery degradation costs C^{deg}. In general, this optimization problem is relatively standard. For brevity, we refer to related works that derive and state all the necessary equations separately [2]. Nevertheless, we shortly introduce the variables and equations. p_B denotes the battery power and is the only decision variable and thus the only degree of freedom of the system. Eq. (2b) states that battery power p_B, grid power p_G and forecasted net-load $\hat{p}_L$ need to be in balance. The SoE dynamics in Eq. (2c) update the battery state e over each step of length Δs, with charging/discharging efficiencies η^{ch}/η^{dis}. The battery's physical constraints are defined by minimum/maximum SoE $e^{\min}/e^{\max}$ and battery power $p_B^{\min}/p_B^{\max}$. Eqs. (2f)–(2h) and (2i)–(2k) enable the modeling of grid power as imports p_G^{imp} and exports $p_G^{\exp}$, as well as the split of battery power into charging/discharging power p_B^{ch}/p_B^{dis} respectively. The relaxation of the complementary constraints in (2j) and (2g) enables nonlinear solvers to handle the problem without introducing binary variables.

All powers indexed with k represent averages over the k-th timestep. To formalize this, we introduce a fourth and final timescale Δs. The scheduler step length Δs describes the time between subsequent optimization steps, commonly 60/30/15 min. In this work, Δs may differ from the control/ground-truth/settlement timescale, so $\Delta s \neq \Delta c = \Delta gt = \Delta NI$ can hold. In those instances, MPC issues one setpoint per Δs and cannot react to intra-interval fluctuations. To address this issue, we mirror real-world implementations and add a fast-acting RBC layer on top of the MPC as a second layer to deal with intra-interval fluctuations. Two variants are investigated:

- **MPC Const-Grid:** Adjust the battery power such that the grid exchange follows the MPC-planned value. The fluctuations are compensated by the battery system and the grid exchange remains constant (if possible).
- **MPC Const-Bat:** Keep battery power fixed at the MPC setpoint during Δs, shifting all fluctuations to the grid.

These two fast-acting rules do not necessarily represent cost-optimal control policies. Instead, they represent two transparent and directly interpretable choices for applying the MPC schedule at a finer control resolution: either the planned grid exchange p_G or the planned battery power p_B is maintained within the scheduling interval. In fully averaged evaluations, this distinction typically remains hidden because intra-interval fluctuations are not resolved explicitely. Making the execution layer explicit is therefore necessary to assess how an MPC schedule behaves once it is applied under a finer control and settlement resolution.

4. Experimental setup

This section contains the setup of the performed simulations. Section A describes the data we use for simulation and forecasting. Section B contains the forecasts needed for the MPC approaches. The battery specifications and degradation costs are described in Section C. Section D describes the selected import/export prices. Finally, Section E describes further configurations of the experiments.

A. Data

We build our investigation on the data presented in [19], which provides high-resolution electricity consumption for several Single-Family Houses (SFH) in an enclosed district in northern Germany. We select a total of 15 buildings according to their data availability for this study. All of the buildings feature a respective heat pump. As no individual on-site PV measurements are available, we construct realistic net-load series by combining the building's load measurements with PV measurements from three nearby PV sites included in the dataset (east-, south-, and west-facing). We randomly assign one of the three orientations (and with that one of the three PV measurements) to each building. We furthermore scale each newly created residential PV system according to its building size. For that, we map a given number of PV panels to each building according to its documented building area. The total number of PV panels varies between 16 and 38 panels per building. With that, we create a high-resolution dataset based on real-world measurements for 15 single-family buildings spanning approximately 2 years and 5 months of residential net-load data in a 1-min resolution.

B. *Forecasting*

Our MPCs rely on forecasts of the upcoming net-load. To separate forecasting quality from timescale effects, we evaluate two forecast types:

- **Ideal Forecasts:** Ideal interval-average forecasts of net-load built from ground-truth.[1]
- **Real Forecasts:** Data-driven realistic forecasts of net-load using Kolmogorov-Arnold Networks [20].

We predict 24 hours of residential net-load in three resolutions (60, 30, and 15 min), yielding a horizon of 24, 48 and 96 interval averages, respectively. To obtain the realistic forecasts, we employ Kolmogorov-Arnold Networks in an autoregressive manner, relying purely on historical net-load. No exogenous variables like weather forecasts or calendric features are included. We split the data chronologically and perform time-series cross-validation: the first year is used for training, the second for validation, followed by a five-month test period (mid-July to mid-December). For each building, we train locally [21], evaluating 125 randomly sampled hyperparameter configurations from a predefined grid and select the model with the best validation performance. We then generate rolling 24-h forecasts over the test set.

C. *Battery specifications*

The selected battery specifications are listed in Table 1. To obtain realistic battery degradation costs, we follow [2] and refer to the warranty guarantee of a specific battery model [22], ensuring that the capacity retention will be above 60% usable energy until a minimum discharged energy of 42.69 MWh is reached. We assume that the battery can be resold after 60% maximum capacity remains for 10% of its original value. The degradation costs are calculated according to

$$c^{deg} = \frac{\text{Investment Costs} - \text{Salvage Return}}{\text{Lifetime Discharged Energy}} = \frac{4000€ - 400€}{42690\,\text{kWh}} = 0.084€/\text{kWh}. \quad (3)$$

Note that we do not consider a continuous degradation, meaning that during our simulation the maximum battery SoE $e^{\max}$ is constant over time. This is justifiable since our evaluation is based on 5 months of simulation and during those the maximum discharged total energy is below 1400 kWh.

We compute the battery degradation costs according to

$$C^{deg} = c^{deg} \sum_{k\in\mathcal{K}} \frac{p_B^{dis}(k)}{\eta^{dis}} t_k, \quad (4)$$

where t_k denotes the duration of timestep k in hours. Note that the degradation costs are derived from discharged battery power only, since the selected warranty defines its guarantees over the batteries total energy output, i.e., its discharged energy only.

[1] *Ideal Forecasts* refer to the exact 60/30/15 min averages over the next 24 hours. They specifically do not include any information about intra-interval fluctuations within each average.

Table 1
Selected battery specifications.

$e^{\min}$ [kWh]	$e^{\max}$ [kWh]	$p_B^{\min}$ [kW]	$p_B^{\max}$ [kW]	$\eta^{ch/dis}$ [%]
0.0	13.8	-5.0	5.0	98

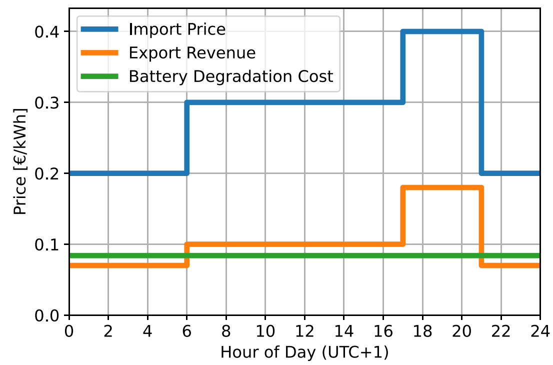

Fig. 3. Selected prices for imports c^{imp} and exports $c^{\exp}$ with constant battery degradation costs c^{deg}.

D. *Pricing scheme*

We calculate the total import/export costs according to

$$C^{imp} = \sum_{k\in\mathcal{K}} c^{imp}(k) p_G^{imp}(k) t_k \quad (5)$$

$$C^{exp} = \sum_{k\in\mathcal{K}} c^{exp}(k) p_G^{exp}(k) t_k, \quad (6)$$

with $c^{imp}(k)$ and $c^{\exp}(k)$ representing the €/kWh prices for imports and exports respectively. Fig. 3 depicts the selected tariff structure for the grid exchange and battery degradation. We orient the exchange prices at a typical three-level residential Time-of-Use pricing scheme, characterized by lower prices during nighttime and a high-pricing period during the typical evening high net-load peak. We use this pricing structure to keep the battery scheduling behavior and resulting cost dynamics easy to interpret, while ensuring sufficient daily cost variation for MPC approaches to exploit during optimization. Because generally, the more prices vary throughout the day, the more an MPC approach can leverage them to minimize costs. Furthermore, to align the prices with EUs directive of promoting self-sufficiency [10], we select a tariff structure that specifically does not incentivize arbitrage. That is, $c^{imp}(t_0) > c^{\exp}(t_1) \forall t_0, t_1$. Finally, it can be seen that at night, discharging the battery system to export energy is a net loss for the residents because the degradation costs surpass the export revenue.

E. *Configuration*

We simulate battery control for five consecutive months of data from mid-July to mid-December 2020 for 15 buildings. We design two main experiments. For each experiment, we simulate battery control using the different battery control models described in Section 3. Each model is furthermore evaluated three times using different scheduling interval lengths:

$$\Delta s \in \{60, 30, 15\}\ \text{min}, \quad (7)$$

with the respective 60/30/15 min forecasts described in Section 4.B. The difference between the two main experiments is the ground-truth data resolution Δgt:

- **Fully Averaged Evaluation**: The ground-truth data resolution equals the scheduling interval length, i.e., $\Delta gt = \Delta s$. Only coarser averages with length Δs are used to assess the models' performances. This reproduces a typical evaluation strategy as described in Section 1.B.

- **Fine-Resolution Evaluation**: The ground-truth data resolution is fixed at $\Delta gt = 1$min. The models' performances are based on the aggregation of 1-min averages. All models now rely on faster-acting rule-based behavior with control frequency $\Delta c = \Delta gt \neq \Delta s$. This evaluation strategy aims to obtain more realistic performance assessments under Net Billing settlement rules.[2]

All models and evaluations are solved in Python using the optimization modeling language Pyomo [23] with IPOPT [24] as the solver. The implementation is published as an open-access repository along with this paper. All presented results can be reproduced using the provided code [25].

5. Results

The experiment results are reported in Tables 2 and 3. Both tables contain mean results across the 15 buildings. Table 2 corresponds to the Fully Averaged Evaluation with $\Delta s = \Delta gt$. Here, the terms "(Ideal)" or "(Real)" indicate whether the results are achieved using ideal or realistic forecasts. Additionally, the label "MPC (Ideal)" does not contain a specified MPC rule (neither Const-Grid nor Const-Bat), because both rules yield the same result, hence it is omitted. Table 3 shows the Fine-Resolution Evaluation with $\Delta s \neq \Delta gt$.

Each table reports imported energy, exported energy, their associated costs, discharged energy and degradation costs. Total Costs is the sum of the electricity bill and degradation costs and serves as the main performance indicator for the present work. The relative performance (Rel. Perf.) describes the change of Total Costs relative to RBC. Finally, Mean Rank represents the consistency of model performance. It is calculated by averaging the ordinal rank of the Total Costs of each model across the 15 simulated buildings.[3] In the following, the results of the tables are visualized and discussed in detail.

We begin with a few general observations. At first, we want to draw attention to the Fully Averaged Evaluation in Table 2. Within each configuration, models are ordered from lowest to highest Total Costs. For each configuration Δs, MPC (Ideal) ranks best, RBC second, and MPC (Real) third. An observation that may seem counterintuitive is that Total Costs increase for all models as the scheduling step Δs decreases. Here, $\Delta gt = \Delta s$ holds. Therefore, a smaller Δs also leads to a finer ground-truth resolution that reveals more fluctuations that need to be handled by the battery. This increases costs, because $c^{imp} > c^{\exp}$ holds. Further, the relative performance of MPC (Ideal) over RBC is -12.41% for $\Delta s = 30$min, aligning with the -12.9% cost reduction reported in [2].[4]

In the Fine-Resolution Evaluation in Table 3, the ranking of the models also is consistent, with an MPC (Ideal) performing best by achieving the lowest Total Costs. Here, we want to highlight two observations: First, RBC's Total Costs of 251.65€is constant across Δs. RBC does not schedule, it reacts to the ground-truth, which is fixed at $\Delta gt = 1$min here. Second, MPC (Ideal) Const-Bat results in highest Total Costs. Fixing the battery setpoint over each scheduling interval shifts all intra-interval fluctuations to the grid and induces frequent import/export swings. The results highlight how important intra-interval fluctuations are under Net Billing. Even with imperfect forecasts, combining MPC with an effective fast rule that compensates for fluctuations can beat an ideal-forecast MPC paired with a poor fast rule.

[2] Note that in reality, Net Billing stems from instantaneous measurements and not from 1-min averages. To be precise, with this setup, we aim to approximate Net Billing by investigating the performance under Net Metering with a Netting Interval $\Delta NI = 1$min.

[3] For example, a model with a Mean Rank of 1.00 means that for 15 out of 15 buildings, this model achieved lower Total Costs than the others.

[4] To be precise, [2] only reports absolute values, i.e., 759$ for RBC and 661$ for MPC (Ideal), which yields a reduction of total costs by -12.9%.

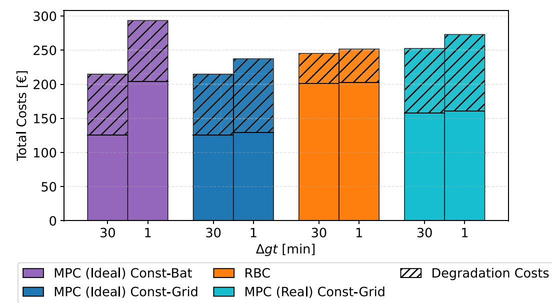

Fig. 4. Total Costs for two different ground-truth resolutions Δgt with an MPC scheduler step length of $\Delta s = 30$min. All MPC approaches lead to comparatively high battery degradation costs when compared to RBC.

A. *Impact of battery control strategies and imperfect forecasting on cost composition*

In Fig. 4, the total costs of the different models for a scheduling step length of $\Delta s = 30$min are displayed. All MPC schedulers contain a fair amount of degradation costs, whereas the majority of the costs of RBC stem from electricity costs. The main reason for that is that MPCs actively use the battery system to leverage prices. A battery controlled via RBC on the other hand is in many cases fully charged during summer, and fully discharged during winter. This reduces battery usage at the cost of higher electricity bills.

Furthermore, all approaches lead to higher costs when applied to finer time resolution $\Delta gt = 1$min. The additional costs are mostly caused by battery degradation, except for the constant-battery MPC. We also see that MPC Const-Grid with ideal and real forecasts achieve similar degradation costs, but differ in electricity costs.

Finally, while perfect-forecast MPC can perform slightly better than RBC, the margin is relatively small. With realistic forecasts, MPC can underperform RBC in our setup, making the practical advantage of MPC questionable for this scenario.

B. *Systematic underestimation of total costs under averages*

Fig. 5 shows the total costs for all configurations. Here, it can be seen that averaging leads to cost underestimation: in each case, the bars in the left block ($\Delta gt = \Delta s$) are lower than their counterparts on the right. See for example MPC (Ideal) Const-Grid for $\Delta s = 30$min: Averaging over 30-min intervals underestimates total costs by $(237.40€ - 214.83€)/214.83€ = 10.5\%$ as shown in Fig. 5. Table 4 contains the relative underestimation of Total Costs for all configurations. It can be seen that the underestimations of costs for RBC are substantially lower than the ones of MPC. This effect is further analyzed in the following subsection.

C. *Systematic bias in MPC vs. RBC comparison under averages*

To omit forecasting-related effects and because the constant battery setpoint rule underperforms, we focus in this and the following subsection exclusively on the comparison of MPC (Ideal) Const-Grid versus RBC.

When costs are computed from averages (Table 2), MPC performs clearly better. With a scheduling step length of $\Delta s = 30$min, the averaged evaluation shows a 30.44€ reduction of Total Costs relative to RBC. Under Net Billing, however, real operation includes intra-interval fluctuations that cause costs. When the same controllers are evaluated at finer resolution (Table 3), MPC's advantage drops to 14.25€. This is a shrinkage of MPC's presumed advantage of $1 - 14.25/30.44 = 53\%$. We call this metric the shrinkage S and formally define it as

$$S = 1 - \frac{TC^{RBC}(\Delta s \neq \Delta gt) - TC^{MPC}(\Delta s \neq \Delta gt)}{TC^{RBC}(\Delta s = \Delta gt) - TC^{MPC}(\Delta s = \Delta gt)}, \quad (8)$$

Table 2
Fully Averaged Evaluation: $\Delta s = \Delta gt$.

Model	Imports [kWh]	Costs Imports [€]	Exports [kWh]	Costs Exports [€]	E. Discharged [kWh]	Degradation [€]	Bill [€]	Total Costs [€]	Rel. Perf. [%]	Mean Rank [-]
Schedule Step Δs = 60min ——— Ground-Truth Resolution Δgt = 60min										
MPC (Ideal)	1191.19	**250.77**	1149.04	123.78	1039.20	87.29	**125.01**	**212.31**	-12.55	1.00
RBC	**1132.74**	322.04	1122.48	120.93	**496.66**	**41.72**	201.05	242.77	-	2.20
MPC (Real) Const-Grid	1304.44	298.72	**1262.46**	**138.74**	1078.74	90.61	158.35	248.96	2.55	2.80
Schedule Step Δs = 30min ——— Ground-Truth Resolution Δgt = 30min										
MPC (Ideal)	1192.76	**251.40**	1149.64	124.13	1065.63	89.51	**125.31**	**214.83**	-12.41	1.00
RBC	**1135.01**	322.61	1123.68	121.23	**523.20**	**43.95**	201.32	245.27	-	2.20
MPC (Real) Const-Grid	1291.19	295.27	**1247.55**	**135.98**	1128.68	94.81	157.72	252.53	2.96	2.80
Schedule Step Δs = 15min ——— Ground-Truth Resolution Δgt = 15min										
MPC (Ideal)	1193.69	**251.88**	1149.59	124.29	1090.02	91.56	**125.63**	**217.19**	-12.30	1.00
RBC	**1136.74**	323.08	1124.43	121.37	**547.49**	**45.99**	201.65	247.64	-	2.13
MPC (Real) Const-Grid	1289.26	294.92	**1243.67**	**135.10**	1183.89	99.45	158.30	257.75	4.08	2.87

Table 3
Fine-Resolution Evaluation: $\Delta s \neq \Delta gt$ = 1min.

Model	Imports [kWh]	Costs Imports [€]	Exports [kWh]	Costs Exports [€]	E. Discharged [kWh]	Degradation [€]	Bill [€]	Total Costs [€]	Rel. Perf. [%]	Mean Rank [-]
Schedule Step Δs = 60min ——— Ground-Truth Resolution Δgt = 1min										
MPC (Ideal) Const-Grid	1207.75	**256.79**	1153.98	124.28	1329.11	111.65	**130.55**	**242.19**	–3.76	1.20
RBC	**1139.61**	323.93	1125.71	121.54	**587.12**	**49.32**	202.33	251.65	–	1.80
MPC (Real) Const-Grid	1318.83	303.31	1266.00	139.08	1347.95	113.23	162.60	275.83	9.61	2.00
MPC (Ideal) Const-Bat	1671.39	404.92	**1629.33**	**181.42**	1039.26	87.30	221.54	308.83	22.72	4.00
Schedule Step Δs = 30min ——— Ground-Truth Resolution Δgt = 1min										
MPC (Ideal) Const-Grid	1202.98	**255.36**	1150.83	124.25	1288.74	108.25	**129.14**	**237.40**	–5.66	1.13
RBC	**1139.61**	323.93	1125.71	121.54	**587.12**	**49.32**	202.33	251.65	–	1.87
MPC (Real) Const-Grid	1300.82	298.40	1248.83	136.09	1336.25	112.25	160.75	272.99	8.48	3.07
MPC (Ideal) Const-Bat	1583.96	377.07	**1540.85**	**171.06**	1065.41	89.49	204.05	293.54	16.65	3.93
Schedule Step Δs = 15min ——— Ground-Truth Resolution Δgt = 1min										
MPC (Ideal) Const-Grid	1199.80	**254.38**	1149.56	124.28	1242.28	104.35	**128.14**	**232.49**	–7.61	1.00
RBC	**1139.61**	323.93	1125.71	121.54	**587.12**	**49.32**	202.33	251.65	–	2.13
MPC (Real) Const-Grid	1294.77	296.78	1243.67	135.08	1321.32	110.99	160.20	271.19	7.76	3.27
MPC (Ideal) Const-Bat	1472.98	341.53	**1428.90**	**157.74**	1089.99	91.56	181.84	273.40	8.64	3.60

Table 4
Relative underestimation of Total Costs. By how much are costs underestimated when evaluations are performed using $\Delta gt = \Delta s$ instead of Δgt = 1min.

	MPC (Ideal) Const-Bat	MPC (Ideal) Const-Grid	RBC	MPC (Real) Const-Grid
Δs = 60 min	45.5%	14.1%	3.7%	10.8%
Δs = 30 min	36.6%	10.5%	2.6%	8.1%
Δs = 15 min	25.9%	7.0%	1.6%	5.2%

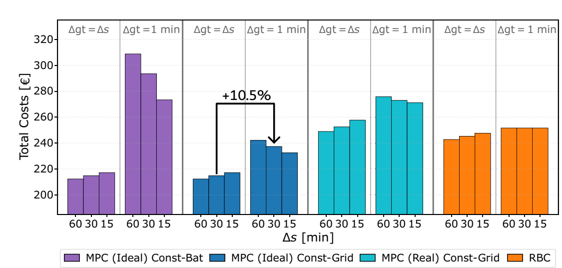

Fig. 5. Total costs for varying scheduler step lengths Δs. Left-hand blocks indicate Fully Averaged Evaluations ($\Delta gt = \Delta s$). Right-hand blocks indicate Fine-Resolution Evaluations (Δgt = 1min). Averaging hides costs. Average evaluations using $\Delta gt = \Delta s$ underestimate costs across all experiments. The bigger Δs, the bigger the underestimation.

Table 5
Shrinkage—How much of MPC's advantage over RBC is lost once fluctuations are considered.

Δs	60 min	30 min	15 min
Shrinkage	69%	53%	37%

with TC standing for Total Costs. Table 5 contains the shrinkages for all three scheduling step lengths Δs. The potential advantage of MPC shrinks by as much as 69%, which is far from negligible. If decisions are based on averaged evaluations alone, a reduction of this magnitude could change the preferred control strategy.

Up until now, all shown results are based on the average over the 15 simulated buildings. Fig. 6 shows the shrinkage for each building individually.[5] Building-level variability is high, and the general trend persists: as Δs decreases, shrinkage becomes smaller. However, at the same time, forecasting at shorter steps is more challenging, making the assumption of ideal forecasts less justifiable. Moreover, in several cases the shrinkage exceeds 100%, i.e., the expected advantage not only de-

[5] Note that the mean shrinkage visualized in Fig. 6 does not perfectly equal the mean shrinkage in Table 5. They differ because Table 5 contains the shrinkage of an average building, whereas the figure plots the average shrinkage of a building.

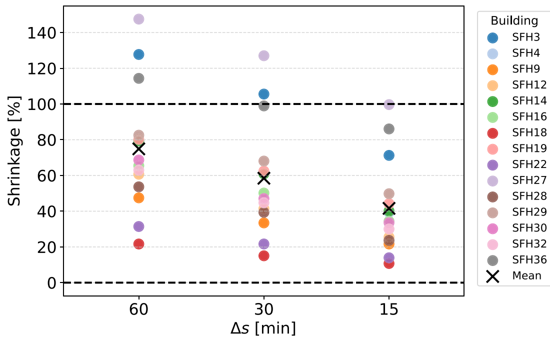

Fig. 6. Individual building shrinkage for different scheduling step lengths Δs. The higher the shrinkage, the more of MPCs presumed advantage over RBC decreases once fluctuations are considered. Shrinkages over 100% indicate that all advantage is lost and RBC leads to better performance than an MPC with ideal forecasts.

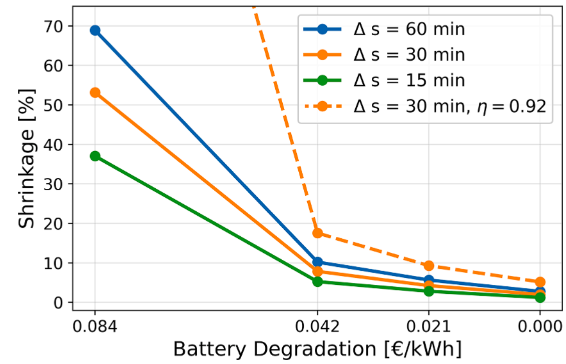

Fig. 7. Impact of decreasing battery degradation costs on the shrinkage.

creases but reverses, and RBC outperforms MPC even under perfect forecasts for individual buildings. For instance, for SFH3 at $\Delta s = 60$min, the Fully Averaged Evaluation indicates MPC savings of 18% (30€) relative to RBC. However, the Fine-Resolution Evaluation shows RBC is better by 4% (8€). Hence, the presumed advantage shrinks by 128%. In this specific case, an average-based evaluation would recommend the wrong controller.

Additionally, we want to highlight that not a single building has a shrinkage below 0%. Across all 45 simulations (15 buildings × 3 scheduler step lengths Δs), the advantage of MPC never increases relative to RBC when a more realistic evaluation is applied. The underlying reason for that is that intra-interval fluctuations under RBC are more often absorbed by the grid (whenever the battery is fully charged or depleted). Because of the fast-acting Const-Grid rule, the MPC controlled battery system is used more to counteract fluctuations, leading to increased degradation costs. This makes the battery degradation cost the deciding factor on how strongly averaging favors MPC. This statement is more thoroughly investigated in the following subsection.

D. Impact of battery degradation costs on shrinkage

To understand how battery degradation costs influence the shrinkage and to estimate how these effects might change as battery prices continue to fall, we rerun our simulations using three additional degradation costs, i.e., 0.042€/kWh, 0.021€/kWh, and 0.00€/kWh. The results are shown in Fig. 7. The shrinkage values at 0.084€/kWh align with those in Table 5. As degradation costs decrease by half, shrinkages fall to 10% and below, demonstrating that degradation is what drives most of the bias introduced by coarse averaging. Interestingly, even when degradation costs are eliminated entirely, small positive shrinkages remain (i.e., 2.79%, 2.00%, 1.25% for $\Delta s = 60, 30, 15$min respectively). This occurs because the increased use of MPC-controlled batteries to counteract fluctuations leads to higher energy losses caused by charge-discharge inefficiencies.

Since real battery systems can show substantially lower system efficiencies once inverter losses and power-dependent efficiencies are considered [27], we also evaluate the $\Delta s = 30$min case with $\eta = 0.92$. The resulting dashed line in Fig. 7 shows that lower efficiency amplifies the shrinkage compared with the $\eta = 0.98$ case. This reinforces that coarse averaging hides not only degradation-related costs, but also conversion losses from the additional battery usage induced by the fast-acting execution layer.

Thus, coarse-average evaluations overlook fluctuation effects that lead to an increased battery usage of MPC-controlled systems, which causes additional degradation costs as well as energy losses which in our setup systematically favor MPC over RBC.

6. Discussion

In our evaluation, Net Billing is approximated with 1-min averages. Thus, we underestimate costs even for the Fine-Resolution Evaluation and with that also understate the reported effects and drawn conclusions. Under this approximation, our results show that a fair comparison of battery scheduling methods must consider high-resolution fluctuations and the controller's response to them. By contrast, studies focusing on Net Metering settlements or on tracking a committed schedule can reasonably use a simpler coarse-average evaluation that ignores within-interval variability.

Limitations: Degradation is modeled per discharged kWh only. We do not consider SoE-dependent, calendar or rate-dependent aging effects. High SoE is known for accelerating aging, which is why some scheduling approaches specifically try to delay charging [26]. The negligence of this effect likely skews our results in favor of RBC. However, this just affects the relative performance between RBC and MPC and does not impair our main contribution, i.e., the systematic favoring of MPC in fully averaged evaluation setups.

Moreover, the investigated fast-acting rules are deliberately straightforward execution strategies; more sophisticated cost-aware rules could reduce battery usage or alternating import/export scenarios and thereby change the absolute performance gap between MPC and RBC as well as the reported averaging effects.

Implications for practice and policy: Even with time-varying prices, RBC provides a strong baseline. This is strengthened by the fact that we do not consider additional installation, integration, and maintenance costs typically associated with real-world MPC deployments. RBC is also straightforward to enhance with simple rules (e.g., pre-charging at night to a target SoE during winter). Yet, RBC is generally less grid-friendly than MPC: midday PV spikes, for instance, are more likely to be fully shifted to the grid. This hints at a misalignment between common Net Billing tariffs and grid objectives. If policymakers want prosumers to adopt MPC and react to price changes, pricing and settlement should be designed so MPC realistically outperforms RBC by a clear margin. Levers include widening price variations, introducing capacity-based tariffs, and also adjusting settlement rules, as we have shown in this work. For example, regulators could employ Net Metering with a short netting interval (such as 15 min) instead of Net Billing.

7. Conclusion

This paper investigates performance of Model Predictive Control (MPC) and Rule-Based Control (RBC) for residential battery systems regarding the minimization of costs and battery degradation. We investigate timescale effects, specifically the justifiability of performing evaluations based on 15/30/60 min averages. We find that under Net Billing, averaged evaluations underestimate total costs and can overestimate the advantages of MPC over RBC significantly.

For a better scientific practice, we recommend researchers to specify their settlement assumptions and state clearly when, if, and why the investigated settlement rule does not match the true underlying settlement rule. To elaborate, if performance is measured on 30-min averages, the investigated results actually represent performance on a Net Metering scheme with an NI of 30 min, instead of Net Billing.

To conclude, averaging hides fluctuations that cause real costs and impact different battery control methods differently. Thus, in order to obtain a solid foundation for a fair comparison between different battery control approaches, accounting for high frequency fluctuations is a necessity that should not be neglected by only considering coarse averages. Future work can focus on investigating other fast-acting rule strategies that might synergize better with slow-planning MPCs.

CRediT authorship contribution statement

Janik Pinter: Writing – original draft, Visualization, Software, Methodology, Conceptualization; **Maximilian Beichter:** Writing – review & editing, Software, Conceptualization; **Ralf Mikut:** Writing – review & editing, Supervision; **Frederik Zahn:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization; **Veit Hagenmeyer:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

The authors thank the Helmholtz Association for the support under the "Energy System Design" program and the German Research Foundation as part of the Research Training Group 2153 "Energy Status Data: Informatics Methods for its Collection, Analysis and Exploitation".

Data availability

The data and code are published as an open-access repository along with the present work [24].

References

[1] J. Lee, P. Zhang, L.K. Gan, D.A. Howey, M.A. Osborne, A. Tosi, S. Duncan, Optimal operation of an energy management system using model predictive control and Gaussian process time-series modeling, IEEE J. Emerg. Sel. Top. Power Electron. 6 (4) (2018) 1783–1795. https://doi.org/10.1109/JESTPE.2018.2820071

[2] B. Banfield, D.A. Robinson, A.P. Agalgaonkar, Comparison of economic model predictive control and rule-based control for residential energy storage systems, IET Smart Grid 3 (5) (2020) 722–729. https://doi.org/10.1049/iet-stg.2020.0090

[3] J. Salpakari, P. Lund, Optimal and rule-based control strategies for energy flexibility in buildings with PV, Appl. Energy 161 (2016) 425–436. https://doi.org/10.1016/j.apenergy.2015.10.036

[4] L. Becchi, E. Belloni, M. Bindi, M. Intravaia, F. Grasso, G.M. Lozito, M.C. Piccirilli, A computationally efficient rule-based scheduling algorithm for battery energy storage systems, Sustainability 16 (23) (2024). https://doi.org/10.3390/su162310313

[5] A. Groß, C. Wittwer, M. Diehl, Stochastic model predictive control of photovoltaic battery systems using a probabilistic forecast model, Eur. J. Control 56 (2020) 254–264. https://doi.org/10.1016/j.ejcon.2020.02.004

[6] C. Ziras, L. Calearo, M. Marinelli, The effect of net metering methods on prosumer energy settlements, Sustain. Energy Grids Netw. (2021). https://doi.org/10.1016/j.segan.2021.100519

[7] K. Gram-Hanssen, A.R. Hansen, M. Mechlenborg, Danish PV prosumers' time-shifting of energy-consuming everyday practices, Sustainability 12 (10) (2020). https://doi.org/10.3390/su12104121

[8] European Union, Directive (EU) 2019/944 on common rules for the internal market for electricity and amending Directive 2012/27/EU, 2019, (EUR-Lex). accessed 19 Sep 2025, https://eur-lex.europa.eu/eli/dir/2019/944/oj/eng.

[9] Netherlands Enterprise Agency, Netting scheme for solar panels ends per 2027, 2026, (https://business.gov.nl/amendments/netting-scheme-solar-panels-ends/). Accessed: 7 July 2026.

[10] K. Varga, M. Bartek-Lesi, A. Diallo, B. Dézsi, The changing regulatory landscape of household self-consumption, Technical Report, REKK, 2024.

[11] P. Benalcazar, M. Kalka, J. Kamiński, Transitioning from net-metering to net-billing: a model-based analysis for Poland, Sustain. Energy Technol. Assess. 72 (2024). https://doi.org/10.1016/j.seta.2024.104073

[12] A. Burgio, D. Menniti, N. Sorrentino, A. Pinnarelli, Z. Leonowicz, Influence and impact of data averaging and temporal resolution on the assessment of energetic, economic and technical issues of hybrid photovoltaic-battery systems, Energies 13 (2) (2020) 354. https://doi.org/10.3390/en13020354

[13] M. Pasqui, F. Gerini, M. Jacobs, C. Carcasci, M. Paolone, Self-dispatching a renewable energy community by means of battery energy storage systems, J. Energy Storage 114 (2025). https://doi.org/10.1016/j.est.2025.115837

[14] R.R. Appino, J.A. Gonzalez Ordiano, R. Mikut, T. Faulwasser, V. Hagenmeyer, On the use of probabilistic forecasts in scheduling of renewable energy sources coupled to storages, Appl. Energy 210 (2018) 1207–1218. https://doi.org/10.1016/j.apenergy.2017.08.133

[15] D. Werling, B. Heidrich, H.K. Çakmak, V. Hagenmeyer, Towards line-restricted dispatchable feeders using probabilistic forecasts for PV-dominated low-voltage distribution grids, in: Proc. ACM e-Energy, 2022, pp. 395–400. https://doi.org/10.1145/3538637.3538868

[16] M. Bird, R. Andraos, S. Acha, N. Shah, Lifetime financial analysis of a model predictive control retrofit for integrated PV-battery systems in commercial buildings, Energy Build. 332 (2025). https://doi.org/10.1016/j.enbuild.2025.115459

[17] N. Müller, M. Marinelli, K. Heussen, C. Ziras, On the trade-off between profitability, complexity and security of forecasting-based optimization in residential energy management systems, Sustain. Energy Grids Netw. 34 (2023). https://doi.org/10.1016/j.segan.2023.101033

[18] S. Beichter, M. Beichter, A. Nöthel, J. Pinter, J. Galenzowski, K. Förderer, F. Wiegel, T. Moser, S. Waczowicz, R. Mikut, V. Hagenmeyer, BEOP: a framework enabling validation of real-world energy management systems, in: Proc. IEEE PEDG, 2025, pp. 799–804. https://doi.org/10.1109/PEDG62294.2025.11060365

[19] M. Schlemminger, T. Ohrdes, E. Schneider, M. Knoop, Dataset on electrical single-family house and heat pump load profiles in Germany, Sci. Data 9 (2022). https://doi.org/10.1038/s41597-022-01156-1

[20] Z. Liu, Y. Wang, S. Vaidya, F. Ruehle, J. Halverson, M. Soljačić, T.Y. Hou, M. Tegmark, KAN: Kolmogorov–Arnold networks, 2025. https://doi.org/10.48550/arXiv.2404.19756

[21] P. Montero-Manso, R.J. Hyndman, Principles and algorithms for forecasting groups of time series: locality and globality, Int. J. Forecast. 37 (4) (2021) 1632–1653. https://doi.org/10.1016/j.ijforecast.2021.03.004

[22] BYD, Battery-Box Premium Limited Warranty, 2026, (https://www.bydbattery-box.com/uploads/downloads/bydbatteryboxpremiumhvlimitedwarrantyaustrali-aenv10-5e99918928a8b.pdf). Accessed: 19 Sep 2025.

[23] M.L. Bynum, G.A. Hackebeil, W.E. Hart, C.D. Laird, B.L. Nicholson, J.D. Siirola, J.-P. Watson, D.L. Woodruff, Pyomo - Optimization Modeling in Python, 67 of *Springer Optimization and Its Applications*, Springer International Publishing, Cham, Cham, 2021. https://doi.org/10.1007/978-3-030-68928-5

[24] A. Wächter, L.T. Biegler, On the implementation of an interior-point filter line-search algorithm for large-scale nonlinear programming, Math. Program. 106 (2006) 25–57. https://doi.org/10.1007/s10107-004-0559-y

[25] J. Pinter, F. Zahn, M. Beichter, R. Mikut, V. Hagenmeyer, Averaging favors MPC, 2026. https://github.com/JaMoPinter/MPC-vs-RBC.

[26] T.M.N. Bui, M. Sheikh, T.Q. Dinh, A. Gupta, D.W. Widanalage, J. Marco, A study of reduced battery degradation through state-of-charge pre-conditioning for vehicle-to-grid operations, IEEE Access 9 (2021) 155871–155896. https://doi.org/10.1109/ACCESS.2021.3128774

[27] N. Orth, L. Meissner, J. Weniger, Stromspeicherinspektion, 2026, (https://www.stromspeicher-inspektion.de). Accessed: 10 May 2026.