



Home battery dispatch under a tiered peak power tariff

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Abstract

We consider the problem of operating a battery in a home connected to the grid to minimize electricity cost, which combines an energy charge and a tiered peak power charge based on the average of the N largest daily peak powers in each billing month. With perfect foresight of loads and prices, the minimum cost is the solution of a mixed-integer linear program (MILP), which provides a lower bound on the cost of any implementable policy. We propose a model predictive control (MPC) policy that uses simple forecasts of loads and prices and solves a small MILP at each time step. Numerical experiments on one year of data from a home in Trondheim, Norway, show that the MPC policy attains a cost within 1.7% of the prescient bound, and saves close to three times as much as the best rule-based policy we consider.

Keywords Home battery dispatch · Model predictive control · Peak power tariff

1 Introduction

Retail electricity tariffs typically combine an energy charge, proportional to consumption, with a peak power charge (also called a demand or capacity charge) that reflects the customer's contribution to network peaks (Berg and Savvides 1983; Henderson 1983). These charges have traditionally applied to commercial and industrial customers, but as residential electrification accelerates (heat pumps, electric vehicles, on-site solar), several European countries have extended them to households, with different designs now in use across the Nordic countries, the Netherlands, and parts of central Europe (Wang et al. 2023; Hofmann et al. 2025).

Norway introduced such a tariff on 1 July 2022, motivated by the need to align charges with network costs and defer grid upgrades (Verlo et al. 2020); capacity-based residential tariffs in the Norwegian context have been studied in detail, see, e.g., Bjarghov et al. (2022). Unlike a traditional demand charge proportional to the

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single maximum power draw in a month, the Norwegian tariff applies a *tiered* charge to the *average of the N largest daily peak powers* (typically $N = 3$). The monthly charge is piecewise constant in this average, with jumps at a small number of thresholds. In addition to this grid charge, the energy portion of the bill combines a small time-of-use retail component with the Nord Pool day-ahead wholesale price (Nord Pool 2023).

A home battery can shift consumption to low-price periods and shave peaks to reduce the grid charge. These two objectives interact: greedy energy arbitrage charges the battery at full rate whenever prices dip, driving the grid draw into the highest peak tier. Minimizing total cost requires jointly handling energy prices and the piecewise-constant peak cost.

1.1 Our contribution

We show how to formulate home battery dispatch under the Norwegian tiered peak power tariff as a mixed-integer linear program (MILP). Solved with perfect foresight of future loads and prices, it yields a *prescient* policy, whose cost lower bounds that of any implementable policy; solved on a rolling horizon with forecasts, it yields an implementable *model predictive control* (MPC) policy. On one year of hourly data from a home in Trondheim, the MPC policy comes within 1.7% of the prescient lower bound, and achieves close to three times the savings of the best rule-based policy we consider.

1.2 Related work

Convex energy management. A unified framework for dynamic energy management based on convex optimization appears in Moehle et al., (2019), in which generators, storage, and loads are modeled as a network of devices with convex objectives and constraints. MPC variants that handle forecast uncertainty through scenario-based robust optimization are developed in Wytock et al. (2017). Our formulation follows this modeling approach; the only source of nonconvexity in our problem is the tiered peak power charge, which introduces integer variables.

Battery scheduling under peak power charges. Most prior work on battery scheduling under peak power charges models the charge as a linear penalty on the single largest power draw over the billing period. The simplest methods are rule-based threshold policies, which discharge the battery whenever the load exceeds a target (Karmiris and Tengnér 2013). More sophisticated methods use MPC to jointly trade off peak reduction against energy cost, in both deterministic and stochastic formulations (Raoufat et al. 2018; Kumar et al. 2018; Risbeck and Rawlings 2020). Dynamic programming methods instead carry the running peak in the state and use value-function approximation to manage the curse of dimensionality (Cholette et al. 2022). The Norwegian tariff we consider is different in two ways. The charge is based on the average of the N largest daily peaks rather than a single monthly maximum, and it is tiered and piecewise constant rather than linear in that average. Because of the averaging, a single running peak no longer summarizes the state, and the tiered charge introduces the integer variables that make our problem nonconvex.

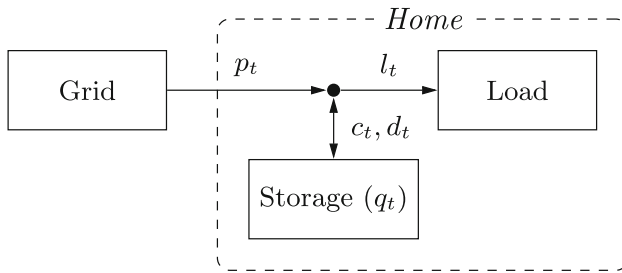


Fig. 1 Grid-connected home with storage. The power flows are the grid draw p_t , the charging and discharging powers c_t and d_t , and the net load l_t . The storage device has an internal charge level q_t

1.3 Outline

In §2 we present a model of the home energy system. In §3 we introduce a running example based on data from a home in Trondheim, Norway. In §4 we formulate the prescient problem as an MILP and establish a lower bound on achievable cost. In §5 we develop the MPC policy and compare it against the prescient bound and three rule-based baselines. In §6 we describe the methods used to generate the forecasts for MPC. Appendix A presents a sensitivity analysis of MPC performance to several problem parameters.

2 Home energy system

We consider a grid-connected home with a battery, as shown in Fig. 1.

2.1 Power balance

We use hourly time steps, indexed by $t = 1, 2, \dots, T$. The load l_t is a net value that can include, for example, photovoltaic generation; it is usually nonnegative. The storage power splits into a nonnegative charging rate c_t and a nonnegative discharging rate d_t . The grid power p_t is the power drawn from the grid, with $0 \leq p_t \leq P$, where $P > 0$ is the maximum grid power. Power balance requires

$$p_t + d_t - l_t - c_t = 0, \quad t = 1, \dots, T - 1.$$

2.2 Storage device

The storage device has a charge level q_t , with dynamics

$$q_{t+1} = \eta_s q_t + h(\eta_c c_t - (1/\eta_d) d_t), \quad t = 1, \dots, T - 1,$$

where $\eta_s, \eta_c, \eta_d \in (0, 1)$ are the storing, charging, and discharging efficiencies, and h is the time period in hours. The initial charge level $q_1 = q_{\text{init}}$ is given; we optionally

impose a terminal constraint $q_T = q_{\text{final}}$. The charge level satisfies

$$0 \leq q_t \leq Q, \quad t = 1, \dots, T,$$

where $Q \geq 0$ is the storage capacity, and the charge and discharge rates satisfy

$$0 \leq c_t \leq C, \quad 0 \leq d_t \leq D, \quad t = 1, \dots, T-1,$$

where C and D are the positive maximum rates.

2.3 Cost function

The cost function consists of an energy charge and a peak power charge.

Energy charge. The energy charge is $h \sum_{t=1}^{T-1} (\lambda_t^{\text{tou}} + \lambda_t^{\text{da}}) p_t$, where λ_t^{tou} are time-of-use prices that vary by time of day and season, and λ_t^{da} are day-ahead prices set daily through an auction market.

Peak power charge. The peak power charge is assessed monthly. We assume the time horizon spans K whole months, denoted $k = 1, \dots, K$. Let m_k denote the vector of daily maximum powers in month k , and let z_k denote the average of the N largest entries of m_k , where N is a parameter (typically $N = 3$). When $N = 1$, z_k is simply the maximum daily peak power over the month. We define the sum-largest function $\psi(u, N)$ as the sum of the largest N components of a vector u , so $z_k = \psi(m_k, N)/N$.

The peak power cost in month k is $\varphi(z_k)$, where φ is piecewise constant with the form

$$\varphi(z) = \begin{cases} \beta_1 & 0 \leq z \leq r_1 \\ \beta_2 & r_1 < z \leq r_2 \\ \vdots & \\ \beta_{L-1} & r_{L-2} < z \leq r_{L-1} \\ \beta_L & z > r_{L-1} \end{cases} \quad (1)$$

where $0 < \beta_1 < \beta_2 < \dots < \beta_L$ are the charges, and $0 < r_1 < r_2 < \dots < r_{L-1}$ are the thresholds. When $\varphi(z_k) = \beta_j$, we say that the peak power cost is in tier j . We set $r_L = P$, so the last condition in (1) can be expressed as $r_{L-1} < z \leq r_L$.

Total cost. The overall cost is

$$h \sum_{t=1}^{T-1} (\lambda_t^{\text{tou}} + \lambda_t^{\text{da}}) p_t + \sum_{k=1}^K \varphi(z_k).$$

The first term, the energy charge, is linear in the power values, while the second term, the peak power charge, is nonconvex.

2.4 Policies

Information pattern. We assume that the following quantities are known.

- The system parameters P (max grid power), Q (battery capacity), C (max charge rate), D (max discharge rate), and the efficiencies η_s , η_c , and η_d .
- The initial and final charge levels, q_{init} and q_{final} .
- Time-of-use prices $\lambda_1^{\text{tou}}, \dots, \lambda_{T-1}^{\text{tou}}$.
- The parameter N in the peak power calculation.
- The costs $\beta_1, \dots, \beta_L$ and thresholds $r_1, \dots, r_{L-1}$ specifying the peak power cost tiers.

Day-ahead prices λ_t^{da} are announced daily at 13:00 for the following day, so prices are known 12–35 hours in advance. The load l_t is known at the beginning of period t , but future loads are not known.

Prescient policy. All loads $l_1, \dots, l_{T-1}$ and day-ahead prices $\lambda_1^{\text{da}}, \dots, \lambda_{T-1}^{\text{da}}$ are known in advance. The charging and discharging powers are chosen to minimize total cost subject to the constraints above. This policy is not implementable, but provides a lower bound on the cost achievable by any implementable policy.

Implementable policy. An implementable policy respects the information pattern; in period t , it chooses c_t and d_t based on loads and day-ahead prices known at time t . Future values are not known, but can be forecast from past observations.

3 Running example

We illustrate our methods on a running example using real data from a home in Trondheim, Norway, over 2020–2022. We use 2020–2021 data to fit forecast models (see §6) and 2022 data to evaluate policies. The data and source code are available at <https://github.com/cvxgrp/home-battery-dispatch>.

3.1 The Norwegian electricity tariff

A Norwegian residential electricity bill has three parts: a day-ahead wholesale energy cost, a small retail energy markup, and a grid tariff that includes the tiered peak power charge we study here.

Day-ahead prices. Wholesale electricity is traded on the Nord Pool spot market, which sets hourly prices for each bidding zone one day in advance; Trondheim is in the NO3 zone. The prices vary strongly over the day (morning and evening peaks, a mid-day trough) and over the year, and rose sharply during the 2021–2022 European energy crisis, as shown in Fig. 3.

Retail energy charge. Retailers add a small time-of-use markup to the wholesale price, lower at night and in winter. We use a markup representative of residential contracts available in 2022.

Tiered peak power charge. Introduced in July 2022, Norway’s residential capacity available in 2022 charge ties the monthly charge to the customer’s own peak demand (Verlo et al. 2020). Each distribution network operator sets a schedule of tiers, with a higher charge when the monthly peak exceeds a threshold. We use the schedule of the Trondheim network operator, shown in Table 2. The charge depends

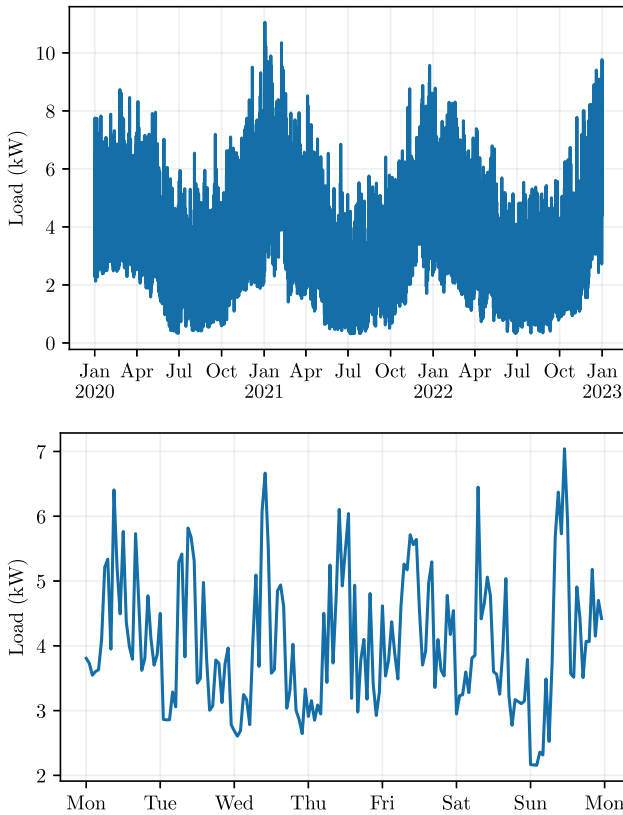


Fig. 2 Hourly loads from a home in Trondheim, Norway. *Top.* Three-year period 2020–2022. *Bottom.* One week in January 2022

on z_k , the average of the $N = 3$ largest daily peaks in the month, which reduces the effect of a single outlier day.

3.2 System parameters

We use one-hour intervals, so $h = 1$. The hourly loads l_t are shown in figure 2, over the full three years (top) and one week in January 2022 (bottom). The system parameters are

$$P = 20 \text{ kW}, \quad Q = 40 \text{ kWh}, \quad C = 20 \text{ kW}, \quad D = 20 \text{ kW},$$

with efficiencies

$$\eta_s = 0.99998, \quad \eta_c = 0.95, \quad \eta_d = 0.95.$$

A complete charge or discharge takes 2 hours at full rate. The storing efficiency η_s corresponds to 1.5% monthly self-discharge, typical for lithium-ion batteries. The charging and discharging efficiencies each represent a 5% loss. We set the initial and

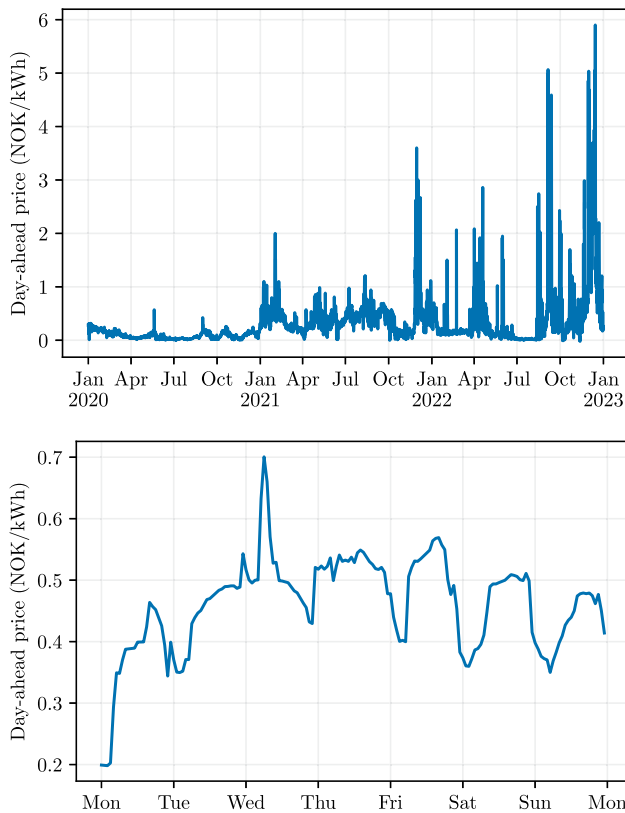


Fig. 3 Day-ahead prices λ_t^{da} for Trondheim, Norway. *Top*. Three-year period 2020–2022. *Bottom*. One week in January 2022

Table 1 Time-of-use prices λ_t^{tou} (NOK/kWh)

	Day (hours 6–21)	Night (hours 22–5)
Winter (Jan–Mar)	0.30	0.21
Remaining months	0.39	0.30

final charge levels to $q_{\text{init}} = q_{\text{final}} = Q/2$. In some experiments we vary Q around its nominal value of 40 kWh to study the effect of storage capacity on cost savings.

3.3 Price parameters

Figure 3 shows day-ahead prices λ_t^{da} for Trondheim, in Norwegian Krone (NOK) per kWh, over the full three-year period (top) and one week in January 2022 (bottom); data are sourced from Nord Pool (2023).

Table 1 shows time-of-use prices, which vary by time of day and season.

Table 2 shows the tiered peak power cost. The monthly charge is β_l when $r_{l-1} < z_k \leq r_l$, where z_k is the average of the $N = 3$ largest daily peak powers in month k .

Table 2 Tiered peak power cost (NOK/month)

Tier l	Threshold r_l (kW)	Cost β_l (NOK/month)
1	2	83
2	5	147
3	10	252
4	15	371
5	20	490

3.4 No storage baseline

Without storage, the cost in 2022 is 25,052 NOK, of which 22,028 NOK is the energy charge and 3,024 NOK is the peak power charge.

4 Prescient problem

In the prescient problem we assume the future loads and day-ahead prices are known in advance. With $h = 1$, the prescient problem is

$$\begin{aligned}
 & \text{minimize} \quad \sum_{t=1}^{T-1} (\lambda_t^{\text{tou}} + \lambda_t^{\text{da}}) p_t + \sum_{k=1}^K \varphi(z_k) \\
 & \text{subject to} \quad p_t + d_t - l_t - c_t = 0, & t = 1, \dots, T-1 \\
 & \quad q_{t+1} = \eta_s q_t + \eta_c c_t - (1/\eta_d) d_t, & t = 1, \dots, T-1 \\
 & \quad q_1 = Q/2, \quad q_T = Q/2 \\
 & \quad 0 \leq q_t \leq Q, & t = 1, \dots, T \\
 & \quad 0 \leq p_t \leq P, & t = 1, \dots, T-1 \\
 & \quad 0 \leq c_t \leq C, & t = 1, \dots, T-1 \\
 & \quad 0 \leq d_t \leq D, & t = 1, \dots, T-1
 \end{aligned} \tag{2}$$

with variables $p, c, d \in \mathbf{R}^{T-1}$ and $q \in \mathbf{R}^T$, giving about $4T$ scalar variables. Here $z_k = \psi(m_k, N)/N$, where m_k is the vector of daily maxima of p_t in month k , and φ is the piecewise constant peak power cost function (1).

4.1 MILP formulation

The piecewise constant function φ can be modeled by introducing binary variables $s_{lk} \in \{0, 1\}$ for tier $l = 1, \dots, L$ and month $k = 1, \dots, K$, with

$$\varphi(z_k) = \sum_{l=1}^L \beta_l s_{lk}, \quad z_k \leq \sum_{l=1}^L r_l s_{lk}, \quad \sum_{l=1}^L s_{lk} = 1.$$

When $s_{lk} = 1$, z_k is assigned to tier l with cost β_l . This adds LK binary variables.

The resulting problem is a mixed-integer convex problem (MICEP); all constraints are convex except the binary constraints $s_{lk} \in \{0, 1\}$. The objective is linear, most con-

straints are linear equalities or inequalities, and the only nonlinearities involve m_k (each entry is the maximum of a subset of the p_t , hence convex) and $z_k = \psi(m_k, N)/N$, which is convex because $\psi(\cdot, N)$ is convex and nondecreasing (Boyd and Vandenberghe, 2004, §3.2.3).

The max and sum-largest functions are piecewise linear and can be represented via linear inequalities, so (2) can be transformed to an equivalent MILP. Domain-specific languages (DSLs) for convex optimization such as CVXPY (Diamond and Boyd 2016) automate these transformations and generate an MILP that can be passed to solvers such as Gurobi Optimization (2023) or open-source alternatives.

4.2 CVXPY implementation

We show how to formulate and solve problem (2) using CVXPY. We assume the parameters from §3 and data vectors `l`, `tou_prices`, `da_prices`, and datetime index `dt` are defined.

```

1 import cvxpy as cp
2 from pandas import unique
3
4 p = cp.Variable(T-1, nonneg=True)
5 c = cp.Variable(T-1, nonneg=True)
6 d = cp.Variable(T-1, nonneg=True)
7 q = cp.Variable(T, nonneg=True)
8 s = cp.Variable((K, L), boolean=True)
9
10 cons = [p + d - l - c == 0,
11         q[1:] == eta_s*q[:-1] + eta_c*c - d/eta_d,
12         q[0] == Q/2, q[-1] == Q/2,
13         q <= Q, p <= P, c <= C, d <= D]
14
15 energy_cost = cp.sum(cp.multiply(tou_prices + da_prices, p))
16
17 peak_cost = 0
18 for k, month in enumerate(sorted(dt.month.unique())):
19     days = unique(dt[dt.month == month].date)
20     m_k = [cp.max(p[dt.date == day]) for day in days]
21     z_k = cp.sum_largest(cp.hstack(m_k), N) / N
22     peak_cost += beta @ s[k]
23     cons += [z_k <= r @ s[k], cp.sum(s[k]) == 1]
24
25 prob = cp.Problem(cp.Minimize(energy_cost + peak_cost), cons)
26 prob.solve()

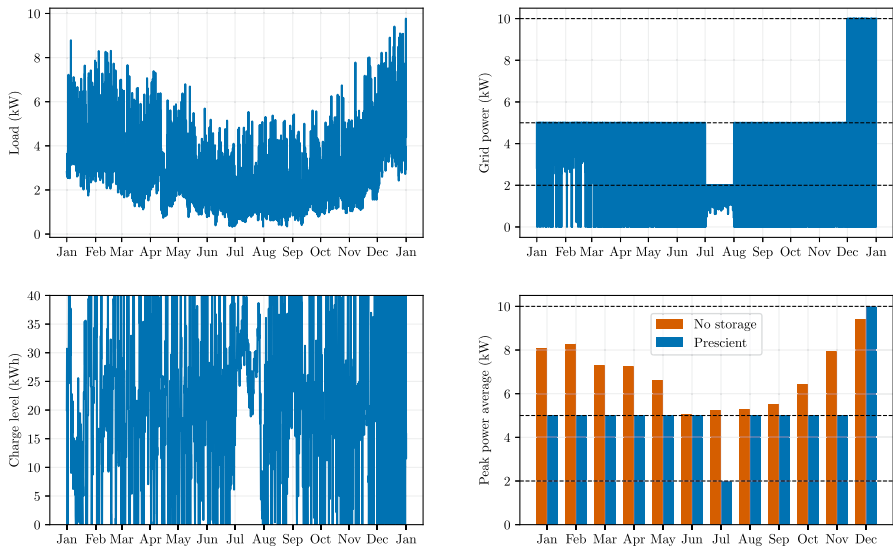
```

Lines 4–8 define variables matching the dimensions in (2). Lines 10–13 encode constraints on power balance, storage dynamics, and bounds. The loop (lines 18–23) builds the tiered peak power cost for each month and adds the corresponding tier constraints, computing daily maxima m_k and the average of the N largest via `cp.sum_largest`.

In roughly 20 lines we formulate and solve problem (2). CVXPY automatically transforms expressions like `cp.max` and `cp.sum_largest` into equivalent linear constraints before passing the problem to an MILP solver.

Table 3 Annual electricity costs (NOK) for 2022 with 40kWh storage

	Energy	Peak power	Total	Savings
No storage	22,028	3,024	25,052	—
Prescient	19,399	1,805	21,204	15.4%

**Fig. 4** Prescient policy with 40kWh storage over 2022. Tier thresholds shown as dashed lines. *Top left.* Load. *Top right.* Grid power. *Bottom left.* Charge level. *Bottom right.* Average peak power z_k

4.3 Running example

We solve problem (2) using 2022 data with CVXPY and Gurobi. After compilation, the problem has 35,783 continuous variables and 60 binary variables. On a laptop with Apple M1 Pro processor, it solves in about 6 seconds.

Costs. Table 3 compares costs with and without storage. The prescient cost is 21,204 NOK, a savings of 15.4% over the no-storage baseline. Roughly two-thirds of the savings come from reduced energy charges.

Power flows. Figure 4 shows the optimal power flows over the year. The policy achieves tier 2 in ten months, tier 1 in July when loads are lowest, and tier 3 only in December when winter peaks are highest. Figure 5 shows one week in detail; the battery charges when prices are low and discharges during load peaks, reducing both energy and peak power costs.

Savings versus capacity. Figure 6 shows annual savings versus storage capacity for 2020–2022. The curves exhibit diminishing returns; in 2022, doubling capacity from 20 to 40 kWh increases savings from 12% to 15%. Without the binary tier constraints, the problem is an LP in Q , so the curves are piecewise-linear and concave (a standard LP sensitivity result); with them, tier transitions introduce small discontinuities but leave the overall shape nearly concave.

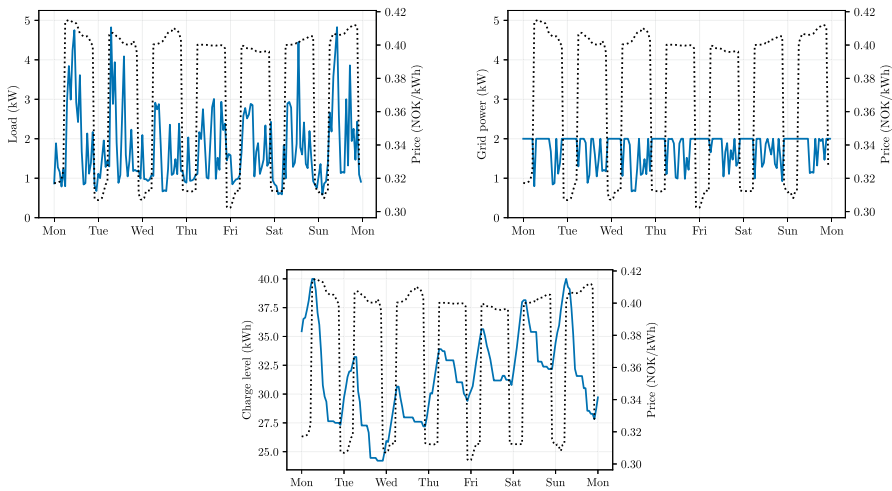


Fig. 5 Prescient policy over one week in July 2022. Electricity prices $\lambda_t^{\text{tou}} + \lambda_t^{\text{da}}$ shown as dotted lines. *Top left.* Load. *Top right.* Grid power. *Bottom.* Charge level

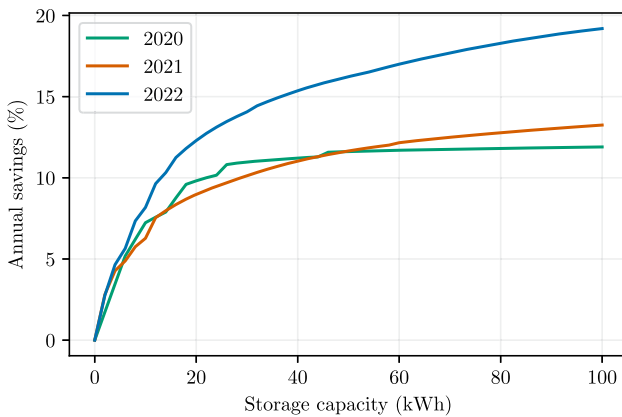


Fig. 6 Annual savings versus storage capacity for 2020–2022

Economic considerations. Figure 6 lets us translate operational savings into a break-even battery cost. Averaging across 2020–2022, a 40 kWh battery saves about 69 NOK/kWh per year, so over a ten-year service life the simple-payback break-even installed cost is roughly 700 NOK/kWh. Residential lithium-ion systems in Norway are installed at around 8,000–12,000 NOK/kWh before subsidy, so a dedicated home battery does not yet pay back on operational savings alone under this tariff. The policy is most valuable, then, for storage that is already owned rather than bought for this purpose alone, such as an electric-vehicle battery operated under vehicle-to-grid (Kempton and Tomić 2005). For such assets the incremental capital cost is negligible, and the savings we report are net.

5 Model predictive control

The prescient problem provides a performance bound but requires perfect foresight. We develop an implementable policy using model predictive control (MPC). At each time step, we solve an optimization problem over a finite horizon using forecasts, apply the first action, and repeat with updated information.

5.1 MPC formulation

At hour t , we observe the charge level q_t and form forecasts of loads and day-ahead prices over a planning horizon of H hours. We let $\hat{l}_{\tau|t}$ and $\hat{\lambda}_{\tau|t}^{\text{da}}$ denote the forecasts for period τ made at time t ; for $\tau = t$ these are the known current values. The forecasting method is described in §6. Let k denote the current month and M the number of months in the horizon. The MPC problem is

$$\begin{aligned}
 & \text{minimize } \sum_{\tau=t}^{t+H-1} (\lambda_{\tau}^{\text{tou}} + \hat{\lambda}_{\tau|t}^{\text{da}}) p_{\tau} + \sum_{j=k}^{k+M-1} \varphi(z_{j|t}) \\
 & \text{subject to } p_{\tau} + d_{\tau} - \hat{l}_{\tau|t} - c_{\tau} = 0, & \tau = t, \dots, t+H-1 \\
 & \quad q_{\tau+1} = \eta_s q_{\tau} + \eta_c c_{\tau} - (1/\eta_d) d_{\tau}, & \tau = t, \dots, t+H-1 \\
 & \quad q_{t+H} = Q/2 \\
 & \quad 0 \leq q_{\tau} \leq Q, & \tau = t+1, \dots, t+H \\
 & \quad 0 \leq p_{\tau} \leq P, & \tau = t, \dots, t+H-1 \\
 & \quad 0 \leq c_{\tau} \leq C, & \tau = t, \dots, t+H-1 \\
 & \quad 0 \leq d_{\tau} \leq D, & \tau = t, \dots, t+H-1
 \end{aligned} \tag{3}$$

with variables $p, c, d \in \mathbf{R}^H$ and $q \in \mathbf{R}^{H+1}$, where the initial state q_t is fixed at the observed value. The terminal constraint $q_{t+H} = Q/2$ prevents myopic depletion of the battery.

The peak power terms require care because the monthly peak averages depend on both past realized and future planned powers. Let $m_{j|t}$ be the vector of daily maxima for month j as evaluated at time t . For days completed before t , the entry is the realized daily maximum (a constant). For each day that intersects the horizon $[t, t+H-1]$, the entry is the maximum of p_{τ} over the hours in that day, which may combine past realized p_{τ} with decision variables p_{τ} for hours $\tau \geq t$. The peak average $z_{j|t}$ is the average of the N largest entries of $m_{j|t}$, or all entries if fewer than N days are represented.

5.2 MILP formulation

Problem (3) has the same structure as (2), with about $4H$ continuous variables. The piecewise constant φ is modeled using binary variables as in §4. A 30-day horizon typically spans two months, giving $2L$ binary variables.

5.3 LP enumeration

An alternative to MILP is enumeration. Since each month selects exactly one tier, we can solve (3) by enumerating over tier assignments. For each assignment the tier variables are fixed and (3) reduces to a linear program. With two months this gives L^2 linear programs; we solve them all and select the minimum-cost solution. This is fast since L is small, and is useful when an MILP solver is unavailable.

5.4 Running example

Simple policies. We compare MPC against three rule-based policies that use only current observations, without forecasts or optimization. All three are clipped to respect charge-level and rate limits.

The *peak shaving* policy discharges when the load exceeds a seasonal target κ_m and charges otherwise,

$$(d_t, c_t) = \begin{cases} (\min\{D, l_t - \kappa_m\}, 0) & l_t > \kappa_m, \\ (0, \min\{C, \kappa_m - l_t\}) & l_t \leq \kappa_m, \end{cases}$$

where κ_m depends on the current month. We use $\kappa_m = 10$ kW in winter (December–February), $\kappa_m = 5$ kW in shoulder months (March–May, September–November), and $\kappa_m = 2$ kW in summer (June–August), matching the upper boundary of tier 3, tier 2, and tier 1, respectively. This loads are much higher in Norwegian winters than in summers.

The *energy arbitrage* policy uses the current price to decide when to charge and discharge. Let $\lambda_t = \lambda_t^{\text{tou}} + \lambda_t^{\text{da}}$ be the retail price at hour t , and $\bar{\lambda}_t$ its median over the calendar day that contains t . The policy charges at full rate when the current price is below the median and discharges against the load otherwise,

$$(d_t, c_t) = \begin{cases} (0, \min\{C, (Q - q_t)/\eta_c\}) & \lambda_t < \bar{\lambda}_t, \\ (\min\{D, l_t\}, 0) & \lambda_t \geq \bar{\lambda}_t. \end{cases}$$

The threshold is the daily median rather than a fixed hour schedule, so the policy tracks the prevailing day-ahead price curve.

The *capped arbitrage* policy merges the two by capping the grid draw at the seasonal target κ_m during charging,

$$(d_t, c_t) = \begin{cases} (0, \min\{C, (Q - q_t)/\eta_c, \kappa_m - l_t\}) & \lambda_t < \bar{\lambda}_t, \\ (\min\{D, l_t\}, 0) & \lambda_t \geq \bar{\lambda}_t. \end{cases}$$

Charging is thus clipped both to the charge level and to the tier cap, so the policy exploits energy arbitrage when prices are low but never drives the grid draw above its seasonal tier.

Table 4 Comparison of policies for 2022 with 40 kWh storage. Costs in NOK

	Energy	Peak power	Total	Savings
No storage	22,028	3,024	25,052	—
Peak shaving	22,009	2,225	24,234	3.3%
Energy arbitrage	21,088	5,880	26,968	−7.7%
Capped arbitrage	20,779	3,024	23,803	5.0%
MPC (energy-only)	18,774	5,880	24,654	1.6%
MPC	19,279	2,289	21,568	13.9%
Prescient	19,399	1,805	21,204	15.4%

MPC parameters. We run MPC with horizon $H = 720$ hours (30 days) and $N = 3$, matching the tariff definition, using the forecasts described in §6. With $L = 5$ tiers, the horizon spans two months, giving $2L = 10$ binary variables. Solving the MILP with Gurobi, each step takes around 0.2 seconds. Sensitivity to H , N , and the forecast method is reported in Appendix A.

Costs. Table 4 compares all policies. MPC achieves a total cost of 21,568 NOK, a savings of 13.9% relative to no storage and within 1.7% of the prescient bound. Peak shaving achieves 3.3% savings by reducing peak power charges in shoulder and summer months but forgoes energy arbitrage; even with a seasonal target, the policy is sometimes too aggressive in summer (the battery depletes serving routine load) and too passive in winter (loads rarely exceed the target, so the battery stays idle). Energy arbitrage reduces energy cost by nearly a thousand NOK but, by charging at full rate whenever prices fall below the daily median, drives peak power into tier 5 every month, giving a total cost *higher* than no storage. Capped arbitrage, which clips the grid draw during low-price charging to the seasonal target, avoids this failure and achieves 5.0% savings.

The gap between the best rule-based policy (5.0%) and MPC (13.9%) is almost a factor of three, and quantifies the value of forecasting and joint optimization. To isolate the contribution of modeling the peak power charge, we also report an MPC variant that ignores it (energy-only). This policy achieves the lowest energy cost but, like energy arbitrage, hits tier 5 every month, yielding savings of only 1.6%. The jump from 1.6% to 13.9% shows that most of the value of MPC comes from jointly handling energy and peak charges; arbitrage alone is not enough.

Power flows. Figure 7 shows the MPC power flows over the year. MPC achieves tier 2 in fewer months than prescient, since forecast errors make it harder to anticipate the highest load days. The weekly detail in figure 8 shows similar coordination to prescient, with timing differences due to uncertainty in load and price forecasts.

6 Forecasting

In this section we describe a simple method to forecast a scalar time series $x_1, x_2, \dots$ using historical data, following Moehle et al. (2019, Appendix A).

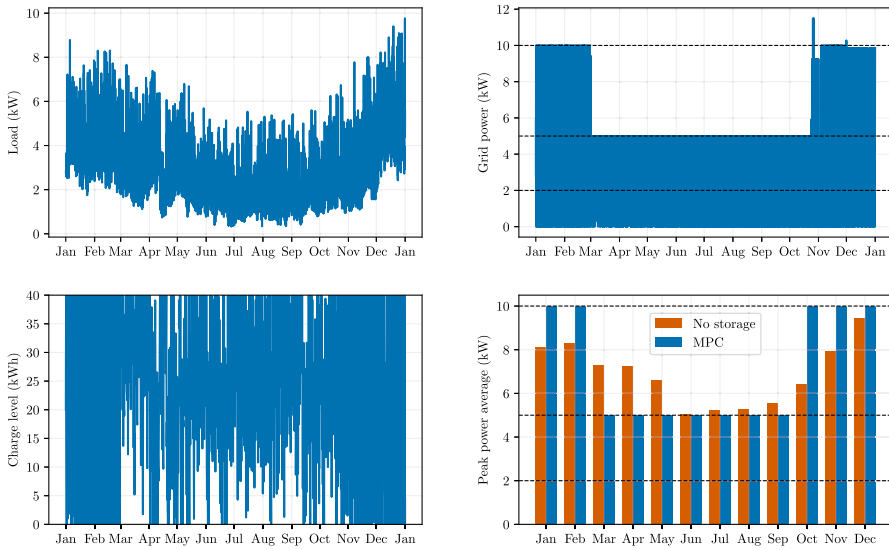


Fig. 7 MPC policy with 40kWh storage over 2022. Tier thresholds shown as dashed lines. *Top left.* Load. *Top right.* Grid power. *Bottom left.* Charge level. *Bottom right.* Average peak power z_k

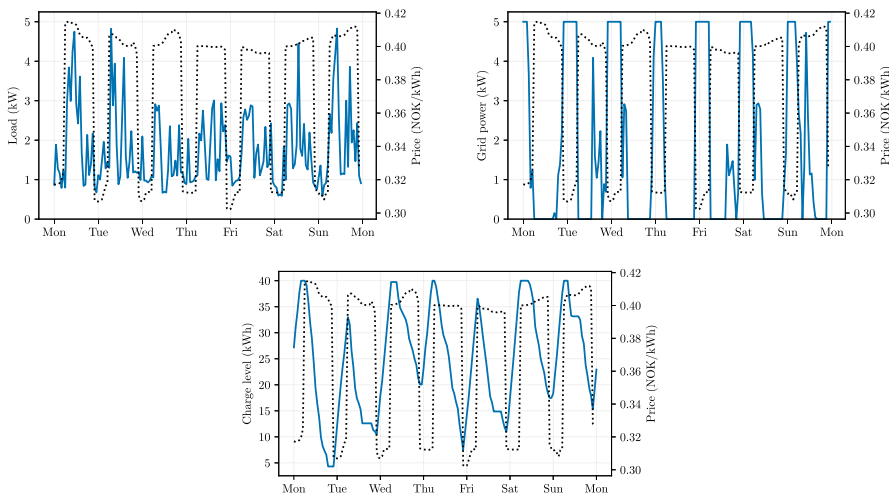


Fig. 8 MPC policy over one week in July 2022. Electricity prices $\lambda_t^{\text{tou}} + \lambda_t^{\text{da}}$ shown as dotted lines. *Top left.* Load. *Top right.* Grid power. *Bottom.* Charge level

6.1 The baseline-residual forecast

The baseline-residual forecast is given by

$$\hat{x}_{\tau|t} = b_{\tau} + \hat{r}_{\tau|t},$$

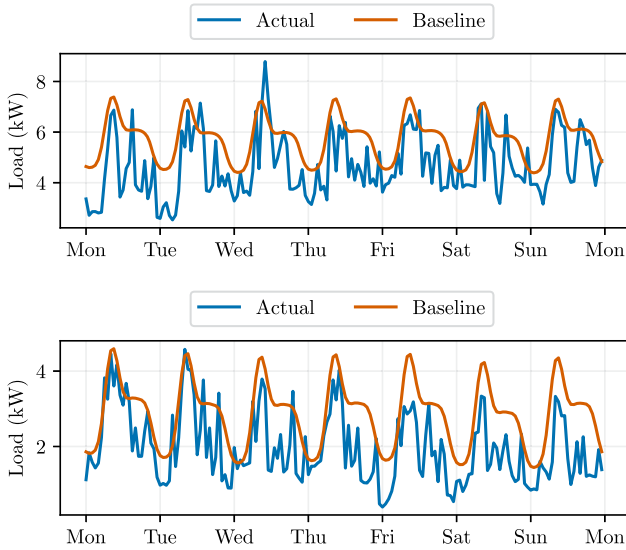


Fig. 9 Baseline component (orange) and actual load (blue). *Top.* One week in January 2022. *Bottom.* One week in June 2022

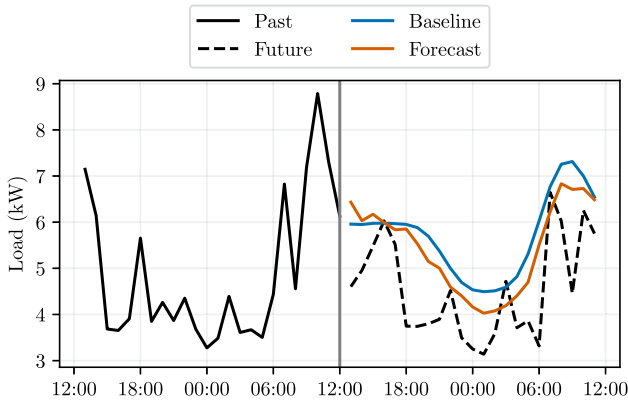


Fig. 10 Load forecasts for a test day in May 2022, with vertical line marking the forecast hour. Black solid and dashed lines show realized and future load; blue shows the baseline component; orange the forecast (baseline + AR)

where $\hat{x}_{\tau|t} \in \mathbf{R}$ is the prediction of quantity x at time $\tau \geq t$, made at time t . The forecast is the sum of a seasonal baseline b_{τ} , capturing periodic patterns (diurnal, weekly, annual), and an autoregressive residual $\hat{r}_{\tau|t}$ that accounts for short-term deviations from the baseline. The baseline depends only on τ ; the residual depends on both τ and the time t at which the forecast is made.

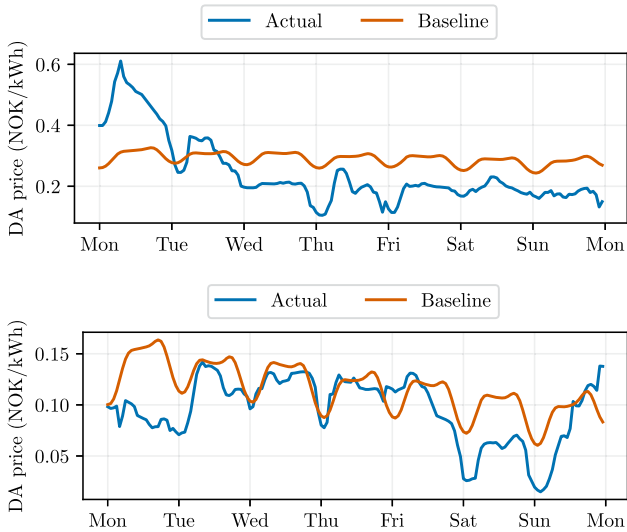


Fig. 11 Baseline component (orange) and actual day-ahead prices (blue). *Top.* One week in January 2022. *Bottom.* One week in June 2022

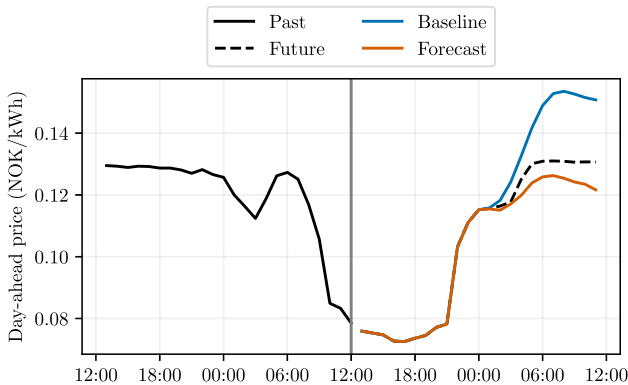


Fig. 12 Price forecasts for a test day in May 2022, with vertical line marking the forecast hour. Black solid and dashed lines show realized and future prices; blue shows the baseline component; orange the forecast (baseline + AR)

Baseline component. A simple model for the baseline is a sum of K sinusoids,

$$b_t = \beta_0 + \sum_{k=1}^K \left(\alpha_k \sin \left(\frac{2\pi t}{P_k} \right) + \beta_k \cos \left(\frac{2\pi t}{P_k} \right) \right),$$

where α_k and β_k are the coefficients and P_k are the periods. In the usual case of Fourier series, the periods have the form $P_k = P/k$, where P is the fundamental period. Here we include terms for daily, weekly, and annual variation.

To fit the $2K + 1$ coefficients $\beta_0, \alpha_1, \beta_1, \dots, \alpha_K, \beta_K$ to historical training data $x_1, \dots, x_T$, we use a pinball (quantile) loss with ℓ_2 regularization. The pinball loss for quantile $\eta \in [0, 1]$ is

$$L_\eta(u) = \max\{\eta u, (\eta - 1)u\} = (\eta - 1/2)u + (1/2)|u|.$$

Being piecewise linear, it is less sensitive to outliers than squared error. Choosing $\eta < 0.5$ biases forecasts toward overestimation, while $\eta > 0.5$ biases toward underestimation. We find the coefficients by minimizing

$$\sum_{t=1}^T L_\eta(b_t - x_t) + \lambda \sum_{k=1}^K v_k(\alpha_k^2 + \beta_k^2),$$

where $\lambda > 0$ is the regularization parameter and $v_k = k^2$ penalizes higher harmonics more heavily. The ℓ_2 penalty shrinks coefficients without zeroing them out, since all harmonics contribute to a smooth baseline. The problem is convex and readily solved; good values for η and λ can be chosen by cross-validation (Hastie et al., 2001, §7.10), (Boyd and Vandenberghe, 2018, §13.2).

Residual component. The residuals are $r_t = x_t - b_t$, $t = 1, \dots, T$. We fit an autoregressive (AR) model to predict the next L residuals from the previous M ,

$$(\hat{r}_{t+1|t}, \dots, \hat{r}_{t+L|t}) = \Gamma(r_{t-M+1}, \dots, r_t),$$

where $\Gamma \in \mathbf{R}^{L \times M}$ is the parameter matrix. We find Γ by minimizing

$$\sum_{t=1}^T \sum_{\tau=t+1}^{t+L} L_\eta(\hat{r}_{\tau|t} - r_\tau) + \lambda \|\Gamma\|_F^2,$$

where $\|\cdot\|_F$ is the Frobenius norm; good values for η and λ can be chosen by cross-validation.

6.2 Running example

Load forecasting. We apply the baseline-residual method to load. The baseline captures diurnal (24h), weekly, and annual periodicities with 4 harmonics each, giving periods

$$\begin{aligned} P_1 &= 24/1, \quad P_2 = 24/2, \quad P_3 = 24/3, \quad P_4 = 24/4, \\ P_5 &= 168/1, \quad P_6 = 168/2, \quad P_7 = 168/3, \quad P_8 = 168/4, \\ P_9 &= 8760/1, \quad P_{10} = 8760/2, \quad P_{11} = 8760/3, \quad P_{12} = 8760/4. \end{aligned}$$

We fit these 25 parameters on two years of hourly data (2020–2021). Figure 9 shows the baseline component against actual load for one week each in January and June 2022.

For the residual component, we fit an AR model to predict residuals over the next 23 hours from the previous 24. The 23×24 parameter matrix Γ is fit using quantile regression with ℓ_2 regularization on the same training period. Figure 10 compares the baseline component alone to the full forecast (baseline + AR) for a test day in May 2022.

Forecasting day-ahead prices. We apply the same method to day-ahead prices. Since prices are announced at 13:00 for the next day, the known horizon varies from 12 to 35 hours depending on the time of day. Figure 11 shows the baseline component against actual prices for one week each in January and June 2022. Figure 12 compares the baseline component alone to the full forecast (baseline + AR) for a test day in May 2022.

7 Conclusions

We have developed an MPC policy for operating a home battery under a tariff that combines an energy charge with a tiered peak power charge based on the average of the N largest daily peaks. The tiered charge makes the problem a mixed-integer linear program, which we solve either directly or by enumerating tier assignments and solving a sequence of linear programs; both are fast and reliable. On a year of real data from a home in Trondheim, MPC with simple forecasts comes within 1.7% of the prescient bound and saves nearly three times as much as the best rule-based policy we consider. The formulation is not specific to this tariff or to chemical batteries. The same MILP applies to any piecewise-constant peak charge and to other storage assets, including thermal storage and electric-vehicle batteries under vehicle-to-grid operation.

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Data Availability Code to reproduce the examples is available at <https://github.com/cvxgrp/home-battery-dispatch>.

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A Sensitivity analysis

We study the sensitivity of MPC performance to three design choices: the planning horizon H , the peak power parameter N , and the forecast method. All other parameters are held at their default values from §5.

MPC horizon. Table 5 shows MPC cost as a function of the planning horizon H . A horizon of one day ($H = 24$) performs poorly because the controller cannot anticipate peak power charges beyond the current day; the peak power cost is 3,633 NOK at $H = 24$, versus 2,289 at $H = 720$. Performance improves with longer horizons up to $H = 720$ (30 days), which spans a full billing month. Doubling the horizon to $H = 1440$ does not improve performance further; the natural planning horizon is one billing month, since peak power charges reset monthly.

Peak power parameter N . The tariff defines the monthly peak average z_k as the mean of the N largest daily maxima. Table 6 compares $N = 1$ and $N = 3$. The difference is negligible (5 NOK over the year). With $N = 1$, the controller optimizes against the single worst day in each month; with $N = 3$ (the actual tariff definition), it can tolerate occasional peaks as long as their average stays low. The cost is nearly the same either way, because a policy that limits the largest daily peak also limits the average of the largest three.

Forecast method. Table 7 compares MPC using the full baseline+AR forecast to a baseline-only variant that omits the autoregressive residual component. The improvement from the AR correction is modest (90 NOK, or 0.4%) and comes entirely from reduced peak power charges (2,289 versus 2,394). The AR model helps the controller anticipate near-term load peaks, which improves peak shaving; the seasonal baseline alone captures the price patterns that drive energy arbitrage.

Table 5 MPC cost versus planning horizon H . Costs in NOK

H (hours)	Energy	Peak power	Total	Savings
24 (1 day)	19,213	3,633	22,846	8.8%
168 (1 week)	19,234	2,618	21,852	12.8%
360 (2 weeks)	19,280	2,513	21,793	13.0%
720 (30 days)	19,279	2,289	21,568	13.9%
1440 (60 days)	19,352	2,289	21,641	13.6%

Table 6 MPC cost versus peak power parameter N . Costs in NOK

N	Energy	Peak power	Total	Savings
1	19,274	2,289	21,563	13.9%
3	19,279	2,289	21,568	13.9%

Table 7 MPC cost versus forecast method. Costs in NOK

Forecast	Energy	Peak power	Total	Savings
Baseline only	19,264	2,394	21,658	13.5%
Baseline + AR	19,279	2,289	21,568	13.9%

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