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Paper

Optimal Imbalance Management for PV Self-Wheeling Schemes using Model Predictive Control

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As renewable energy adoption increases and electricity market liberalization progresses in Japan, self-wheeling has emerged as a promising scheme that allows producers to supply electricity generated at one location to their own loads at another location via the grid, without selling to the wholesale market. While this scheme facilitates decarbonization and energy cost reduction, it also introduces operational challenges, particularly the risk of imbalance between scheduled and actual power flows due to the variability of PV generation. To address this problem, this paper proposes a Model Predictive Control (MPC) approach that forecasts PV output and imbalance prices, and optimally schedules a battery storage system installed on the PV side to minimize both imbalance penalties and total operational costs during real-time operation. Additionally, a PV forecast adjustment strategy for day-ahead scheduling is introduced to further enhance economic performance. Simulation studies using actual solar radiation and imbalance price data demonstrate improved accuracy in imbalance price prediction and greater effectiveness of the proposed method compared to conventional rule-based strategies.

Keywords: renewable energy, self-wheeling, model predictive control, forecast, battery energy storage system

1. Introduction

The global push toward decarbonization has accelerated the integration of renewable energy sources, with photovoltaic (PV) systems standing out due to their ease of deployment, scalability, and steadily decreasing costs. In Japan, PV has become a cornerstone of national energy strategy, supported by policies such as the Feed-in Tariff (FIT) and Feed-in Premium (FIP) programs[(1)].

During this transformation, self-wheeling has emerged as a flexible mechanism that allows electricity consumers and corporate generators to utilize electricity generated at remote sites for their own consumption. Distinct from conventional retail supply or power purchase agreements, self-wheeling allows electricity to be transmitted across the grid without entering the wholesale market. Participants in this scheme are required only to pay grid usage fees to the transmission system operator (TSO), proportional to the electricity wheeled[(2)]. While self-wheeling contributes to sustainability and enhances user control over energy sourcing, it poses notable operational challenges when intermittent sources like PV are involved.

In Japan's existing market structure, the term "imbalance" denotes the difference between the planned electricity supply/demand in the day-ahead schedule and the actual values observed in real time. To maintain system reliability, the TSO imposes financial penalties or rewards based on the degree to which each participant contributes to these imbalances[(3)]. This mechanism is designed to encourage accurate day-ahead scheduling and promote responsibility in grid participation. For operators of variable renewable energy sources like PV, this creates a strong incentive to improve forecasting accuracy and develop control strategies that minimize the imbalance costs while supporting stable system operation.

With advances in forecasting technologies, a range of methods has emerged to predict PV output. These methods generally fall into three categories: physical models that simulate irradiance based on weather data, statistical models that exploit time series patterns, and hybrid approaches that combine both. Physical models offer interpretability but often struggle with real-time adaptability, while statistical and machine learning techniques, including autoregressive time series models and machine learning algorithms, have demonstrated strong performance in capturing the stochastic nature of PV output[(4)(5)]. More recently, hybrid forecasting methods that integrate physical models with data-driven models have gained attention for balancing accuracy and robustness[(6)]. While much of the existing research has primarily aimed to minimize forecasting errors, recent studies have begun to highlight the economic impact of forecast accuracy, focusing on profit-oriented decision-making in renewable energy operations[(7)–(9)].

Although considerable research has been devoted to forecasting energy spot prices and regulated tariffs, studies on imbalance price forecasting remain limited, largely because Japan is the only country with such a pricing mechanism. Horii et al. proposed the use of generalized additive models

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along with system spot prices to independently forecast imbalance prices for each time slot in a day(10), and further analyzed potential factors influencing imbalance price behavior(11). However, these studies were conducted under the previous imbalance pricing regime, prior to the 2022 revision of the imbalance penalty system(3). More recently, Imai et al. employed a basic “Yesterday” model (predicting imbalance prices based on values from the previous day) and a linear regression model, but their results show limited accuracy, with a root mean squared error (RMSE) reaching nearly half the average price(12).

Many existing studies have proposed the use of corporate Battery Energy Storage Systems (BESS) in combination with PV generation. The BESS is typically employed to mitigate imbalance costs and enhance the profit of PV generators participating in the JEPX spot market(13)(14). For instance, Nakamura et al. evaluated the effectiveness of a BESS in reducing imbalance costs using simple control rules based on the predicted direction of PV forecast error(15). However, these studies primarily target PV generators whose sole cost to be minimized is the imbalance cost. In contrast, a PV self-wheeling entity incurs not only the imbalance cost but also additional retail costs to fully support its load. Furthermore, a PV self-wheeling entity does not directly interact with the JEPX spot market like PV generators. Consequently, the operation of a standard PV-battery system cannot be directly applied to a PV self-wheeling scheme, and the unique business model of PV self-wheeling has not yet been explicitly addressed in the existing literature on PV-battery systems.

This paper presents preliminary research on a self-wheeling project that transmits PV electricity from a distant generation site to a university campus in the Tokyo region as part of the university’s decarbonization strategy. The primary contributions of this study are as follows:

- Formulation of a business model for the PV self-wheeling scheme with a BESS, aiming to minimize both imbalance cost and retail cost.
- Proposal of a Model Predictive Control (MPC) framework for real-time BESS operation, incorporating online imbalance price forecasts generated by Seasonal AutoRegressive Integrated Moving Average (SARIMA) models.
- Introduction of a PV forecast adjustment strategy in day-ahead scheduling to further enhance economic performance.

The remainder of this paper is organized as follows. Section II provides an overview of the self-wheeling scheme and the current imbalance penalty system. Section III describes the proposed MPC framework and the forecasting methodologies. Section IV presents simulation results based on actual historical data, and Section V concludes the paper.

2. PV Self-wheeling

2.1 Self-wheeling Scheme Self-wheeling refers to the practice in which electricity generated at a privately owned facility is transmitted through the transmission network operated by the TSO to a geographically separate load under the same institutional ownership, without any transaction on the wholesale electricity market. This configuration

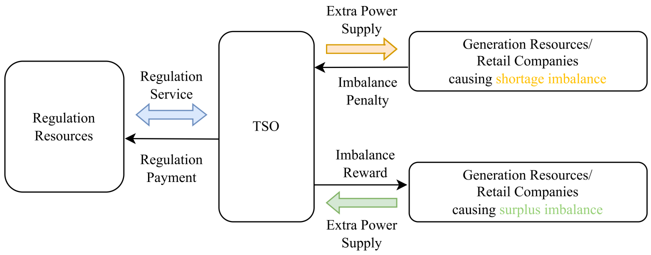


Fig. 1. The imbalance penalty system in Japan

is increasingly adopted by large energy consumers aiming to achieve decarbonization goals and enhance energy autonomy.

The main economic advantage stems from reduced dependence on retail electricity procurement, thereby shielding the consumer from wholesale market price volatility. In addition, electricity delivered via self-wheeling is currently exempt from Japan’s renewable energy surcharge, which is applied to electricity purchased from the grid. As of October 2023, this exemption significantly improves the cost-effectiveness of self-wheeling, particularly for entities deploying large-scale renewable energy systems(16).

To use the transmission network, self-wheeling entities are required to pay wheeling charges to the TSO based on the volume of electricity transmitted. Unlike conventional retail contracts or third-party Power Purchase Agreements (PPAs), self-wheeling requires that both the generation and the load be owned or controlled by the same entity. Moreover, self-wheeling entities are responsible for imbalance risk: they must submit a day-ahead power transmission schedule, and any deviation between the scheduled and actual power flow results in an imbalance. This imbalance is financially settled under the TSO’s imbalance pricing regime. For variable renewable energy sources such as PV generation, the associated imbalance charges can represent a significant component of operating cost, highlighting the need for accurate forecasting and real-time control strategies.

2.2 Imbalance Penalty Since the deregulation of the electricity sector in Japan in 2016, all market participants, including generators and retail suppliers, have been required to submit their day-ahead operation schedules to the TSO at 30-minute intervals for system operation scheduling. These schedules are expected to be strictly followed during actual operation to maintain system stability in real-time.

Imbalances are classified into two categories. A shortage imbalance occurs when actual generation is less than the scheduled amount or when consumption exceeds the scheduled value. In contrast, a surplus imbalance arises when generation exceeds the scheduled quantity or when consumption falls below it. The structure of the imbalance penalty system is illustrated in Fig. 1. Within this framework, the TSO imposes financial penalties on shortage imbalances and uses the collected payments to compensate surplus imbalances. Settlements are conducted ex-post, and any remaining imbalance that cannot be resolved internally is addressed through the deployment of system regulation resources.

Under the previous system, imbalance prices were computed as a weighted average of the clearing prices in the day-ahead and intraday markets. However, this pricing method did not adequately reflect regional and temporal

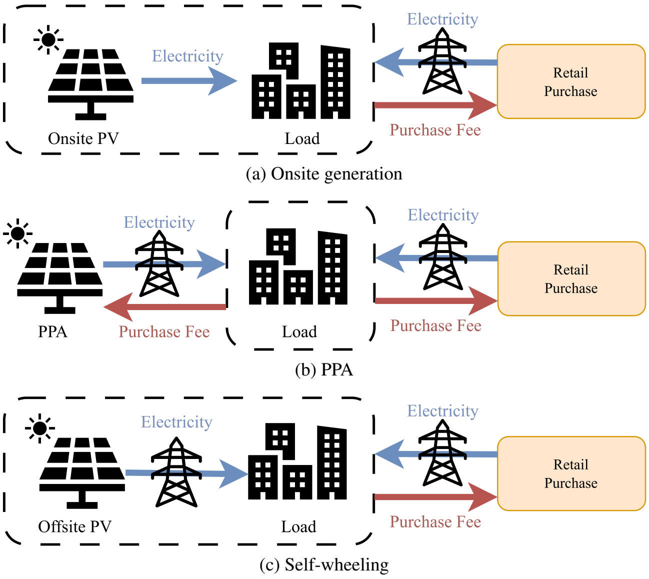


Fig. 2. PV utilization schemes

supply-demand conditions, resulting in weak correlation with actual imbalances(3). To overcome these limitations, a revised imbalance pricing mechanism was introduced in 2022. The updated system accounts for the risk associated with supply shortages, which has become more pronounced due to the growing share of variable renewable energy. While the imbalance prices remain relatively stable under normal grid conditions, they may increase significantly during periods of tight supply. Conversely, during instances of renewable curtailment, the imbalance price may drop to zero to discourage further generation. Moreover, the new system enhances transparency by publishing imbalance prices in real time, enabling more responsive and informed operational decisions.

The allocation of imbalance cost responsibility is the key distinction that sets PV self-wheeling apart from other PV utilization schemes. As shown in Fig. 2, PV utilization from the consumer side can be categorized into three schemes: onsite generation, PPA, and self-wheeling. Their respective imbalance mechanisms are illustrated in Fig. 3.

In Fig. 3, the green and red blocks represent the electricity supplied by the PV system and purchased from the retailer, respectively, and their sum corresponds to the total load. In PV utilization schemes, imbalance can be caused not only by fluctuations in PV generation but also by deviations of the total load from the day-ahead scheduled amount. For example, a surplus imbalance occurs when the actual total load is smaller than the scheduled value, in which case the surplus imbalance reward is received by the retailer; conversely, a shortage imbalance penalty is incurred by the retailer when the actual load exceeds the scheduled amount. The imbalance associated with the total load and that associated with PV generation are independent of each other. As a result, situations may arise in which a shortage imbalance occurs for the total load while a surplus imbalance simultaneously occurs for PV generation. Since this study focuses exclusively on the imbalance arising from PV generation, the imbalance associated with total consumption, which is always settled by the retailer, is omitted from the discussion.

In the onsite generation case, the entity owns PV facilities

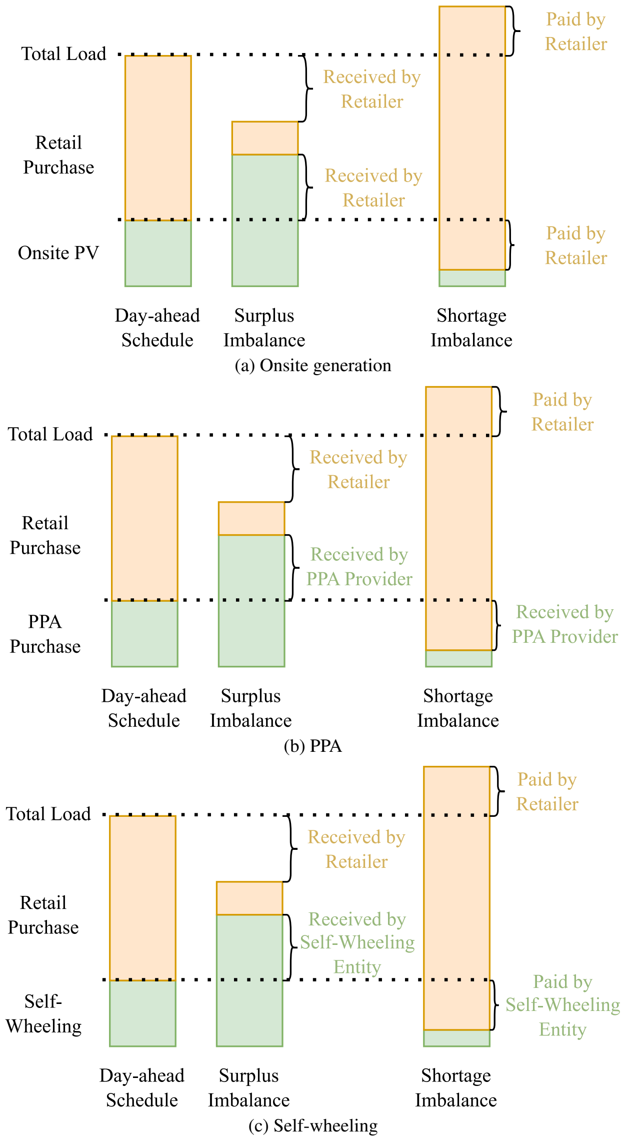


Fig. 3. Imbalance mechanisms of PV utilization schemes

Table 1. Comparison of PV utilization schemes

	PV Ownership	PV Site	Imbalance Cost
Onsite Generation	Yes	Onsite	No
PPA	No	Offsite	No
Self-wheeling	Yes	Offsite	Yes

located close to its load and therefore does not require transmission services. The residual demand is supplied by a retailer. From the TSO's perspective, PV fluctuations are indistinguishable from load fluctuations, and the retailer is responsible for covering the total imbalance caused by both. In the PPA case, the entity contracts with an independent PV generator. Although contractual terms may vary, the PPA provider assumes responsibility for the imbalance arising from PV fluctuations. In contrast, under self-wheeling, the entity directly bears the imbalance associated with PV generation. A summary comparison of these utilization schemes is presented in Table 1.

Consequently, the operational challenges of self-wheeling differ fundamentally from those considered in conventional PV-battery studies, which typically focus on minimizing imbalance costs on the generator or retailer's side(13)–(15). In self-wheeling, the consumer must jointly manage both retail electricity procurement and PV imbalance costs, necessitating distinct optimization strategies. This characteristic makes self-wheeling a particularly important and timely subject of investigation, as its operational implications have not yet been fully explored in the existing literature.

3. Model Predictive Control Scheme

3.1 Overall MPC Scheme MPC is an optimization-based control strategy that updates control decisions at each time step based on the latest system state and forecasts of future conditions(17). Due to its ability to dynamically respond to real-time deviations, MPC is widely applied in load control and electricity-market-related operations, where decisions often rely on predictions of future demand or price signals(18)(19).

Let Gen_A and Gen_0 denote the actual and day-ahead scheduled PV generation submitted to the TSO, respectively. Let I represent the PV generation imbalance and L the load. The operation cost C of the self-wheeling scheme, which is to be minimized, is defined in Eq. (1).

$$C = \sum_{t=1}^{t_{\text{end}}} \left[(L(t) - Gen_0(t))P_R(t) + I(t)P_I(t) + Gen_A(t)P_T \right] \cdots\cdots (1)$$

The first term in Eq. (1) corresponds to the cost of electricity purchased from the retailer, while the second term represents the imbalance cost associated with PV generation. Here, P_R and P_I denote the retail electricity price and the imbalance price, respectively. In the current Japanese imbalance system, both surplus and shortage imbalances are settled at the same imbalance price P_I. Therefore, no distinction is made between surplus and shortage imbalance prices in the proposed model. The third term accounts for the wheeling cost of PV generation. P_T is the wheeling price, which is a fixed tariff independent of time(20).

When a BESS is deployed on the PV side, it can be controlled to charge or discharge in order to adjust the real-time imbalance I:

$$I(t) = Gen_0(t) - Gen_A(t) + B(t) \cdots\cdots (2)$$

where B denotes the battery charge/discharge power output. Under the above setting, L, P_R, and P_T are all known variables, while P_I and Gen_0 are predicted values. However, it is not possible to obtain Gen_A in advance, as Gen_0 already serves as its forecast.

Since there is no local consumption on the PV side, all PV generation must eventually be wheeled to the load site, either directly or after being temporarily stored in the battery. Accordingly, the battery serves only as a temporal buffer, and the net energy charged into the battery over the entire operation horizon is zero:

$$\sum_{t=1}^{t_{\text{end}}} B(t) = 0. \cdots\cdots (3)$$

Moreover, since the wheeling charge P_T is a fixed tariff independent of time, the total wheeling cost depends only on the cumulative wheeled energy $\sum_t Gen_A(t)$, regardless of the

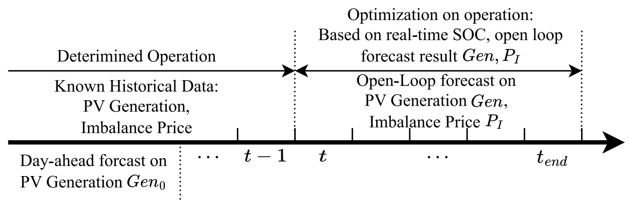


Fig. 4. Proposed MPC scheme

battery charging or discharging operation. For this reason, the wheeling cost in Eq. (1) is formulated solely based on the PV generation $Gen_A(t)$, and the battery output $B(t)$ does not explicitly appear in the wheeling cost term. As a result, the wheeling cost becomes a constant and can be excluded from the objective function without affecting the optimization outcome.

Nevertheless, Gen_A still appears in Eq. (2). Ref. (15) proposed forecasting the sign of $Gen_A(t) - Gen_0(t)$ (i.e., whether it is positive or negative) based on the previous day's result, claiming that approximately 70% accuracy can be achieved. However, this assumption is primitive and lacks rigorous validation. In principle, for any well-calibrated forecasting model that minimizes prediction error, the residuals should approximate a Gaussian distribution with zero mean, implying no consistent bias toward positive or negative deviations. Furthermore, knowledge of only the sign of $Gen_A(t) - Gen_0(t)$ is insufficient for solving a numerical optimization problem.

Given these considerations, the treatment of $Gen_A(t) - Gen_0(t)$ becomes a critical factor in achieving optimal BESS control. This challenge, however, highlights the strength of adopting an MPC framework. During real-time operation at time t, the most recent PV generation data up to $t-1$ can be used to perform an open-loop forecast of PV generation Gen, which then serves as an approximation of $Gen_A(t)$.

The overall MPC scheme is illustrated in Fig. 4.

In the day-ahead stage, a closed-loop forecast of PV generation Gen_0 is performed for the following day and submitted to the TSO as the schedule. At the current real-time operation step t, the BESS actions up to the previous time step $t-1$ have already been executed, while the control decision for time step t is to be determined through optimization. The predictive horizon of the proposed MPC scheme spans from the current time step t to the end of the day, denoted as t_{end}. Gen and P_I over this horizon are updated with an open-loop forecast. Meanwhile, in real-time operation, Gen_0 has already been determined, and therefore the first term representing the retail purchase cost in Eq. (1) becomes a constant and can also be excluded from the objective function.

Ultimately, the final MPC optimization problem at t is formulated as:

$$\min_{B_C(t), B_D(t)} \sum_{\tau=t}^{t_{\text{end}}} I(\tau)P_I(\tau) \cdots\cdots (4)$$

subject to

$$0 \le B_C(\tau) \le 1 \cdots\cdots (5)$$

$$0 \le B_D(\tau) \le 1 \cdots\cdots (6)$$

$$I(\tau) = Gen_0(\tau) - Gen(\tau) + \Delta t \cdot P_{max}[B_D(\tau) - B_C(\tau)] \cdots\cdots (7)$$

$$SOC(\tau) = \Delta t \cdot \frac{P_{\max}}{E} \sum_{\tau'=t}^{\tau} [B_C(\tau') - B_D(\tau')] + SOC(\tau - 1) \quad (8)$$

$$0 \le SOC(\tau) \le 1 \quad (9)$$

$$\Delta t \cdot \frac{P_{\max}}{E} \sum_{t=1}^{48} \frac{(B_C(t) + B_D(t))}{2} \le n \quad (10)$$

$$\Delta t \cdot P_{max} B_C(\tau) \le \max(Gen(\tau) - Gen_0(\tau), 0) \quad (11)$$

$$\Delta t \cdot P_{max} B_D(\tau) \le L(\tau) \quad (12)$$

In this formulation, τ is a dummy time index used for summation from the current time t to the end of the horizon t_{end}. B_C and B_D represent the normalized charge and discharge power of the BESS at time t, which are the BESS control variables to be optimized. $P_{\max}$ and E are the maximum power output and the storage capacity of the BESS, respectively. Eq. (7) defines the PV generation imbalance I after accounting for the BESS's effect. Eq. (8) computes the battery's state of charge (SOC), and the constraint in Eq. (9) ensures it remains within the physically feasible range. The number of charging cycles is limited by Eq. (10) to prevent significant battery deterioration, where n represents the number of charging cycles permitted per day. The inequality in Eq. (11) guarantees that charging occurs only when there is a PV generation surplus, while Eq. (12) limits the discharge power so that it does not exceed the load L, particularly during periods without PV generation. Although such a condition is not explicitly prohibited under current self-wheeling operation rules, it would appear abnormal if a self-wheeling entity were to deliver more energy than its actual demand at night when PV output is absent. This restriction is therefore imposed to reflect a reasonable operational consideration.

3.2 Imbalance Price and PV Forecast Obviously, the performance of the MPC depends on the accuracy of the forecast results. Compared to the electricity spot price, the imbalance price is more difficult to forecast since the real-time system imbalance is highly irregular. One primitive approach is to assume that today's imbalance price will be exactly the same as yesterday's[12].

The SARIMA model is commonly used for time series analysis and prediction of future values based on historical values without extra input, and it is widely used in energy spot price forecasting[21][22]. Therefore, it is very suitable to apply SARIMA prediction in the MPC scheme. Especially when related external variables are available, the SARIMA model can be extended to the SARIMAX model to include the impact of external variables through an exogenous regressor term. As the imbalance price is supposed to reflect the value of energy in the power system by definition, it is reasonable to consider the energy spot price as the external variable for SARIMAX forecast of the imbalance price. In this paper, the authors propose to use the SARIMA model for PV generation forecast and use both SARIMA and SARIMAX models for imbalance price forecast, respectively, for performance comparison.

The detailed implementation of the SARIMA/SARIMAX prediction is as follows:

(1) At the beginning of a day, estimate new SARIMA/SARIMAX models for Gen_0 and P_I using historical data up to today.
(2) At time-step t, use historical data up to $t-1$ to predict Gen and P_I from t to the end of the day t_{end}.
(3) If any of the predicted values is lower than 0 (for either Gen or P_I), it is replaced by 0.
(4) Optimize the BESS control Eq. (4) from t to the end of the day t_{end} and execute the BESS control at t.
(5) Repeat from Step 2 until t_{end}.
(6) Repeat from Step 1 on the next day.

Specifically, the PV generation forecast Gen is based on historical measured generation data from the target PV site. The imbalance price P_I is forecast using historical imbalance price data published on Imbalance Price Calculation Service for the corresponding region[23]. Furthermore, in the SARIMAX model, historical JEPX spot market prices are incorporated as exogenous variables[24].

3.3 Day-ahead PV Forecast Adjustment Since the real-time imbalance is directly influenced by the day-ahead schedule Gen_0, one could theoretically submit $Gen_0 = 0$ to intentionally create a surplus imbalance in real-time operation, thereby gaining additional profit, as surplus imbalances are guaranteed to be purchased by the TSO. However, this practice may be regarded as a form of strategic manipulation that undermines system reliability. Moreover, deliberately underreporting Gen_0 increases the reliance on electricity purchased from the retailer, as the updated self-wheeling regulations strictly require that generation and load must be under common ownership[16]. In fact, this constraint is a key feature of the revised self-wheeling rules, designed specifically to discourage such manipulative all-zero day-ahead scheduling.

Nevertheless, it is acceptable for a self-wheeling entity to anticipate periods of high imbalance prices and opt to support the load exclusively via retail purchase during those times. By combining Eq. (1) and Eq. (2), the following expression can be obtained:

$$C = \sum_{t=1}^{t_{\text{end}}} [L(t)P_R(t) + Gen_0(t)(P_I(t) - P_R(t)) - Gen_A(t)P_I(t) + B(t)P_I(t) + Gen_A(t)P_T] \quad (13)$$

Here, $L(t)P_R(t)$, $Gen_A(t)P_I(t)$, and $Gen_A(t)P_T$ are predetermined terms, whereas $B(t)P_I(t)$ depends on the real-time MPC decisions. All terms are independent and decoupled. Consequently, adjusting $Gen_0(t)$ to minimize $Gen_0(t)(P_I(t) - P_R(t))$ contributes directly to the overall cost reduction. Economically, when the retailer's purchase price $P_R(t)$ is lower than the imbalance price $P_I(t)$, it is advantageous to supply the load via retail purchases while allowing PV generation to create surplus imbalance. The BESS can only be charged from the surplus imbalance, as constrained by Eq. (11), so this surplus effectively prepares the battery for future shortage imbalances. From a system operation perspective, this strategy does not compromise stability, as it results in additional PV generation being available during periods of supply scarcity.

Based on this rationale, the following adjustment to $Gen_0(t)$ is proposed to further reduce the operational cost of the self-wheeling scheme:

$$Gen_0(t) = 0, \quad \text{if } P_R(t) < P_I(t) \quad (14)$$

4. Simulation Results

In the simulation, the target self-wheeling project aims to transmit electricity from a PV generation site in Utsunomiya, Tochigi, to a university campus in Tokyo, both located within the same TSO service area in the Kanto region. The PV system has a maximum output capacity of 30 MW, which corresponds to approximately 30% of the campus's peak load. A portion of the load and PV generation profile is shown in Fig. 5. The campus load profile exhibits a pronounced peak around midday and a dip at midnight, aligning well with the generation pattern of PV systems and making it an ideal candidate for PV self-wheeling. The simulation is conducted over a two-month period, from September 1 to October 31, 2023.

4.1 Forecast Result Representative forecast results produced by the SARIMA/SARIMAX models for PV generation and imbalance price are shown in Fig. 6 and Fig. 7, respectively.

Table 2 summarizes the forecasting performance for PV generation and imbalance price using different models, evaluated by the coefficient of determination (R^2).

Subtable 2(a) shows the R^2 values for PV generation forecasts using the SARIMA model. The model achieves a relatively moderate performance in the day-ahead setting, but performs significantly better when used in the MPC framework, indicating that open-loop forecast accuracy is substantially higher.

Subtable 2(b) presents the forecast performance for the imbalance price using three methods: a naïve Yesterday approach, SARIMA, and SARIMAX. All models show

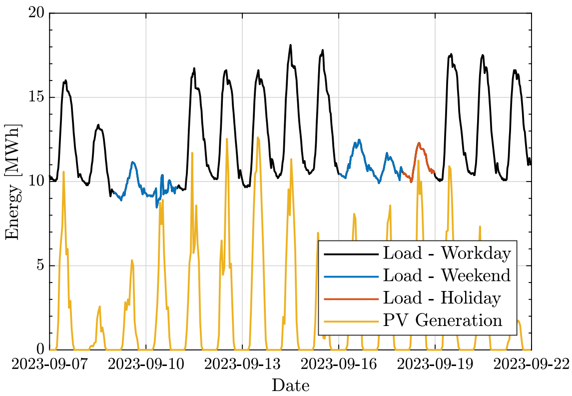


Fig. 5. Load and PV generation profile

Table 2. The performance of the forecast results

(a) The PV generation forecast.

		R^2
SARIMA	Day-ahead	0.7408
	MPC	0.9869

(b) The imbalance price forecast.

		R^2
Yesterday	Day-ahead	-0.4871
	MPC	0.6571
SARIMA	Day-ahead	0.1201
	MPC	0.6938
SARIMAX	Day-ahead	0.2336
	MPC	0.7003

improved accuracy in the MPC setting compared to the day-ahead forecast. Specifically, the Yesterday method yields a poor day-ahead forecast but improves in the MPC setting. SARIMA and SARIMAX both show better performance than the Yesterday method, with SARIMAX slightly outperforming SARIMA in both day-ahead and MPC contexts. Notably, SARIMAX achieves the highest R^2 among all methods for MPC.

These results demonstrate that time-series-model-based approaches, particularly SARIMAX, provide more accurate forecasts of the imbalance price, especially in open-loop forecast. Similarly, PV generation forecasts benefit significantly from the open-loop forecast of the MPC framework.

4.2 Operation Cost The operational cost of the target self-wheeling project under varying battery specifications, as well as different retailer purchase price settings, is presented in Fig. 8. In this study, the battery specifications are characterized by two parameters: the energy capacity (Battery Size, in MWh) and the charging/discharging duration at rated power (Charge Time, in hours), rather than by the conventional pair of power rating (MW) and energy capacity (MWh). In practice, the energy capacity of a single battery module is generally limited to about 10 MWh. Large-scale battery systems, such as those considered in this paper, therefore require the aggregation of multiple modules. In such aggregated systems, an increase in the total energy capacity is typically accompanied by a proportional increase in power output, resulting in a charging/discharging duration that remains within a practical range. By contrast, a direct representation using MW–MWh axes may include unrealistic cases, such as a 100 MWh system with only 1 MW output, which would require 100 hours to charge fully, or a 10 MWh system with only 100 MW output that can be fully charged in 6 minutes. Such configurations are not representative of actual system operation. For this reason, Battery Size and Charge Time are employed as the axes in order to provide a more practical and intuitive representation of feasible battery configurations. The allowable number of charge-discharge cycles per day is set to $n = 2$. The wheeling fee is 7.85 JPY/kWh in the Kanto region, resulting in a total wheeling cost of 51.78 million JPY over the simulation period[25].

In the figure, **SARIMA** and **SARIMAX** represent the cases where the SARIMA and SARIMAX models are used for imbalance price forecasting within the proposed MPC framework, respectively. **SARIMAX-Adjusted** refers to the case where SARIMAX is used for imbalance price forecasting, and the day-ahead generation schedule $Gen_0(t)$ is further adjusted using the method proposed in Section 3.3. The **Oracle** case assumes perfect knowledge of future imbalance prices and serves as a theoretically optimal performance benchmark. The **Rule-based** case denotes a strategy without explicit scheduling, in which the BESS simply absorbs imbalances whenever they occur. Lastly, the **No Battery** case represents the baseline scenario where no BESS is installed to manage PV generation imbalance. All cases other than **SARIMAX-Adjusted** do not apply the day-ahead PV forecast adjustment proposed in Section 3.3, including the **Oracle** case. The detailed simulation conditions and applied methods for each case are summarized in Table 3.

The extent of cost reduction increases with larger battery

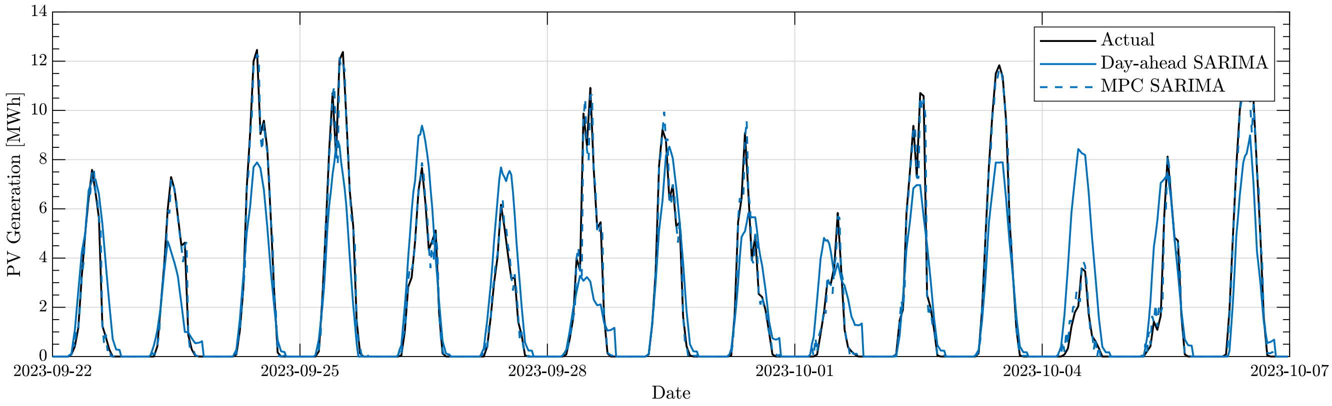


Fig. 6. PV generation forecast result

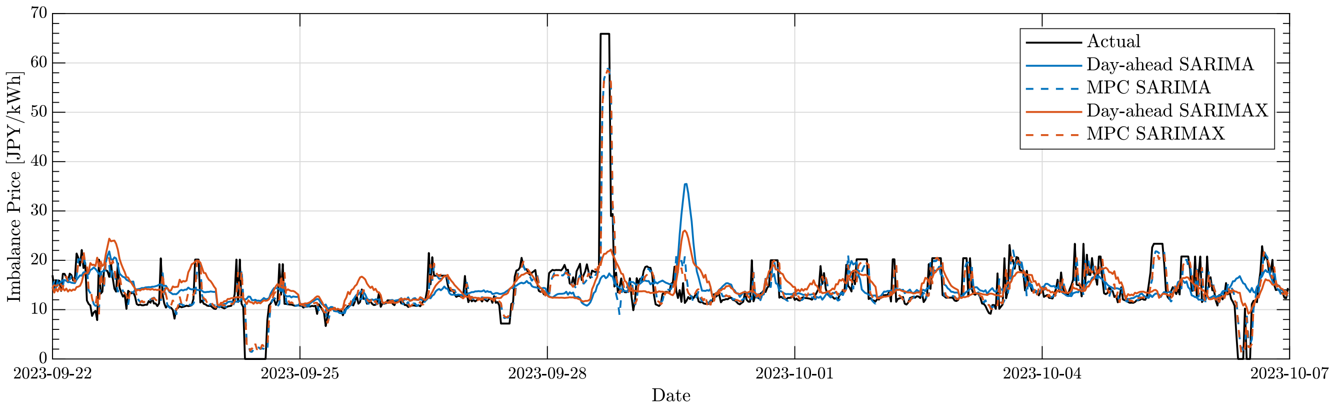


Fig. 7. Imbalance price forecast result

Table 3. Simulation conditions and applied methods

	BESS	PV Forecast	Imbalance Price Forecast	Day-ahead PV Forecast Adjustment
No Battery	x	x	x	x
Rule-Based	o	x	x	x
Oracle	o	SARIMA	Perfect knowledge	x
SARIMA	o	SARIMA	SARIMA	x
SARIMAX	o	SARIMA	SARIMAX	x
SARIMAX-Adjusted	o	SARIMA	SARIMAX	o

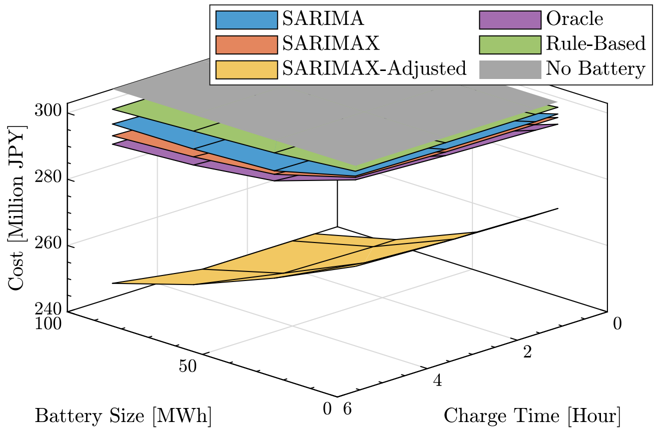
size and shorter charge time. In all cases, the proposed MPC scheme consistently outperforms the simple rule-based operation. The **SARIMAX** case achieves greater cost savings than **SARIMA**, owing to the higher forecasting accuracy of the **SARIMAX** model.

Notably, the **SARIMAX-Adjusted** case further enhances cost reduction. However, the degree of improvement diminishes as the retailer purchase price P_R increases. This is because a higher P_R reduces the number of time slots that satisfy Eq. (14), thereby limiting the effectiveness of the proposed adjustment strategy. Currently, the retailer price P_R offered by TEPCO Energy Partner is around 20 JPY/kWh[26]; therefore, the practical benefit of the proposed adjustment is still significant in real-world applications.

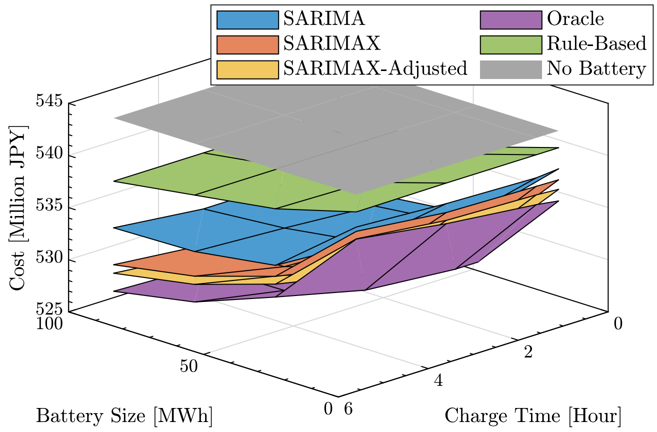
With the Day-ahead PV Forecast Adjustment, when the retailer price P_R is sufficiently low, the self-wheeling entity can choose to meet all load via retail purchases and allow PV generation to become surplus imbalance, thereby profiting from the price difference $P_I - P_R$. In such cases, the adjusted strategy can achieve a lower total cost than the **Oracle** benchmark, as shown in Fig. 8(a). However, since the imbalance price P_I is intended to reflect the system value of energy in real-time, a large and persistent gap between P_R and P_I is unlikely in practice.

To illustrate how the proposed Day-ahead PV Forecast Adjustment works in practice, Fig. 9 presents an operational example on 2023-09-19 for a BESS with a capacity of 10 MWh and a charging time of 1 hour. In this example, the forecasted imbalance price (blue dashed line) exceeds the retailer price $P_R = 20$ JPY/kWh after 15:30. Accordingly, the day-ahead PV generation schedule Gen_0 is adjusted to zero during this period (yellow solid line). The surplus imbalance occurring in the morning is absorbed by the BESS until it becomes fully charged at 10:00. Between 13:00 and 15:00, although a shortage imbalance occurs, the BESS does not discharge because the imbalance price remains relatively low. The BESS starts discharging from 16:00 to 17:00, when the imbalance price reaches its highest level of the day. As a result, compared with the **SARIMAX** case, the **SARIMAX-Adjusted** case generates a larger surplus imbalance during 16:00–17:00, since the scheduled PV generation has been deliberately adjusted to zero in advance. Consequently, the total operational cost on this day is reduced by 5.13%, demonstrating that the proposed Day-ahead PV Forecast Adjustment can effectively improve economic performance by strategically exploiting high imbalance price periods.

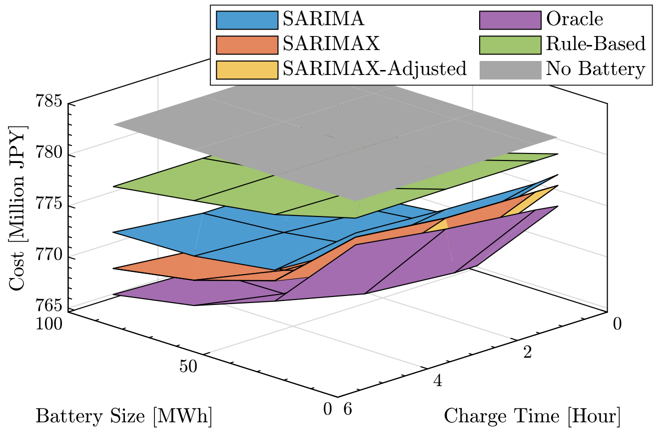
4.3 Imbalance Suppression The absolute value of imbalance across different cases is presented in Fig. 10. Among the tested methods, the total imbalance is lowest



(a) $P_R = 10$



(b) $P_R = 20$



(c) $P_R = 30$

Fig. 8. The operation cost

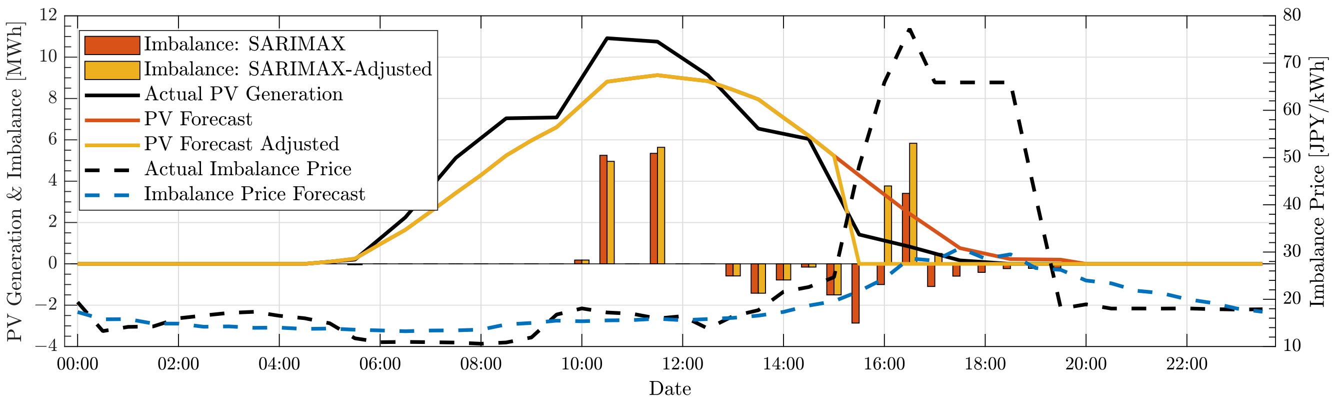
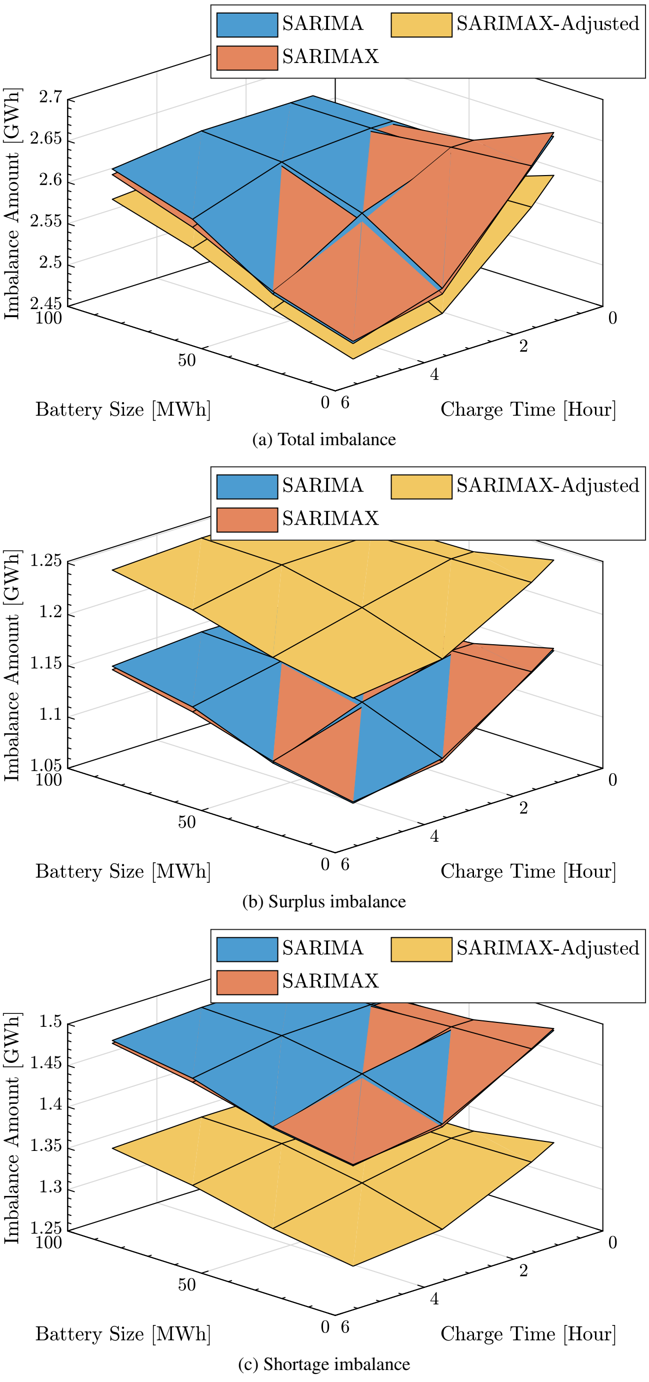


Fig. 9. Example of **SARIMAX-Adjusted** Operation on 2023-09-19

in the **SARIMAX-Adjusted** case compared to both the **SARIMA** and **SARIMAX** cases. In the **SARIMAX-Adjusted** case, parts of the day-ahead generation schedule Gen_0 are deliberately set to zero according to the adjustment strategy proposed in Section 3.3. This results in larger surplus imbalances during certain periods. However, these surplus imbalances not only generate additional imbalance revenue but also contribute to charging the BESS. The stored energy can later be used to mitigate shortage imbalances, thereby reducing the overall imbalance level more effectively.

Notice that as the rated power output increases (corresponding to a shorter charge time), the imbalance amount, particularly the surplus imbalance, also increases. This is because the self-wheeling entity's objective is not simply to reduce imbalance, but to minimize the overall operational cost. As discussed in Section 3.3, creating surplus imbalance can in fact be profitable when timed appropriately. Fig. 11 illustrates the imbalance with a 10 MWh BESS when the charging time is set to 0.5 h and 5 h. The BESS with higher rated power output can clearly generate a larger surplus imbalance, whereas the difference in shortage imbalance remains relatively small and is mainly influenced by the real-time MPC operation.

During the simulation period, the total surplus and shortage imbalances in the Tokyo area were approximately 510 GWh and 1195 GWh, respectively. In contrast, the surplus and



(a) Total imbalance

(b) Surplus imbalance

(c) Shortage imbalance

Fig. 10. The absolute amount of imbalance

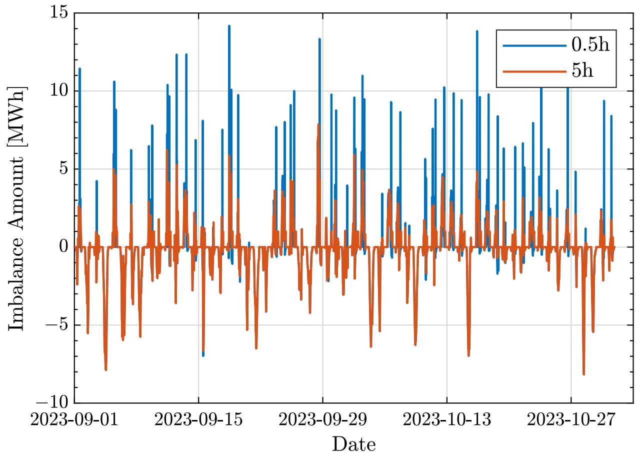


Fig. 11. Imbalance with different BESS charging time

shortage imbalances caused by the target self-wheeling project were only about 1.2 GWh and 1.4 GWh, respectively, as shown in Fig. 10. Given that the imbalance attributable to the self-wheeling project is negligible compared to the overall system imbalance (0.12%～0.24%), its impact on the imbalance price can be reasonably disregarded.

4.4 The Effect of P_R on Deliberate Underreporting of Gen_0 As discussed in Section 3.3, some entities may deliberately underreport Gen_0 to gain additional profit. In this analysis, it is assumed that the entity applies a scaling coefficient k to Gen_0 to simulate underreporting behavior. The effect of the retailer purchase price P_R on the incentive to underreport Gen_0 under the proposed MPC scheme is illustrated in Fig. 12.

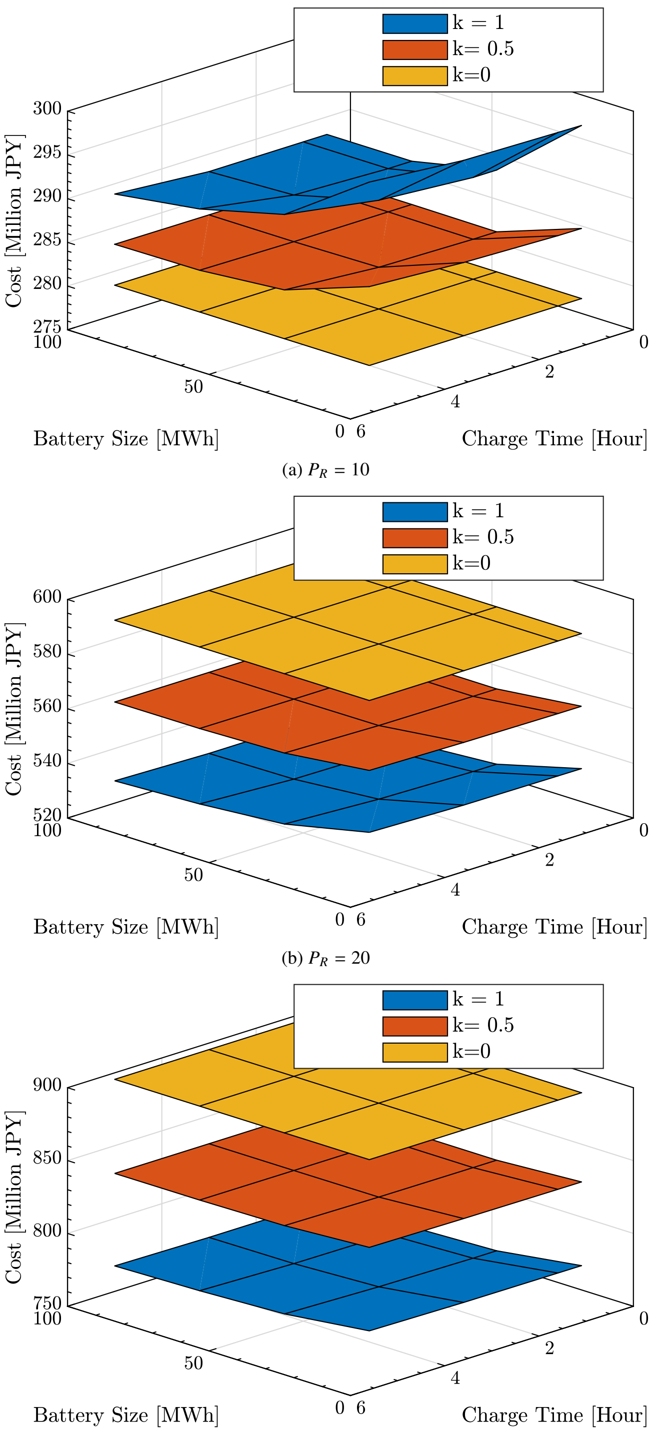
The results show that when P_R = 10 JPY/kWh, underreporting Gen_0 can indeed reduce the operational cost. However, since a retailer procures electricity from wholesale markets such as the JEPX spot market and sells it at the retail price P_R to make a profit, it is highly unlikely that electricity would be offered at a price lower than the wholesale market average, which was around 12 JPY/kWh in the Kanto region in 2023. Thus, such a low retail contract is unrealistic. While wholesale prices may decline with large-scale renewable penetration or rise sharply with fuel price surges, both the retailer price P_R and the imbalance price P_I should remain closely tied to the wholesale market. For this reason, under more realistic values of P_R, deliberate underreporting of Gen_0 actually increases the operational cost. Consequently, the proposed MPC scheme does not incentivize manipulative scheduling and preserves the integrity of the imbalance pricing system.

4.5 Effect of PV Size on Total Cost Reduction The maximum power output of the PV generation site is set to be 30 MW in the above simulation. To further demonstrate the feasibility of the proposed strategy, the total cost reduction with different levels of PV injection is shown in Fig. 13. The purchase price P_R is 20 JPY.

Compared with the simple rule-based operation, the proposed operation strategy achieves approximately a 2.5% cost reduction when a large-capacity, fast-charging battery is employed. The cost reduction is influenced not only by the battery specifications but also by the PV system size. As the PV size decreases, a greater portion of the power supply must be procured from the retailer. Consequently, not only does the total operational cost increase with decreasing PV capacity, but the cost savings achievable through battery operation also diminish.

5. Conclusions

This paper proposed an MPC-based BESS operation strategy for a PV self-wheeling scheme, considering realistic imbalance regulation rules in the Japanese power system. Forecasting models based on SARIMA and SARIMAX were applied to predict PV generation and imbalance prices, enabling cost minimization in real-time operation. The simulation, conducted for a campus-scale self-wheeling

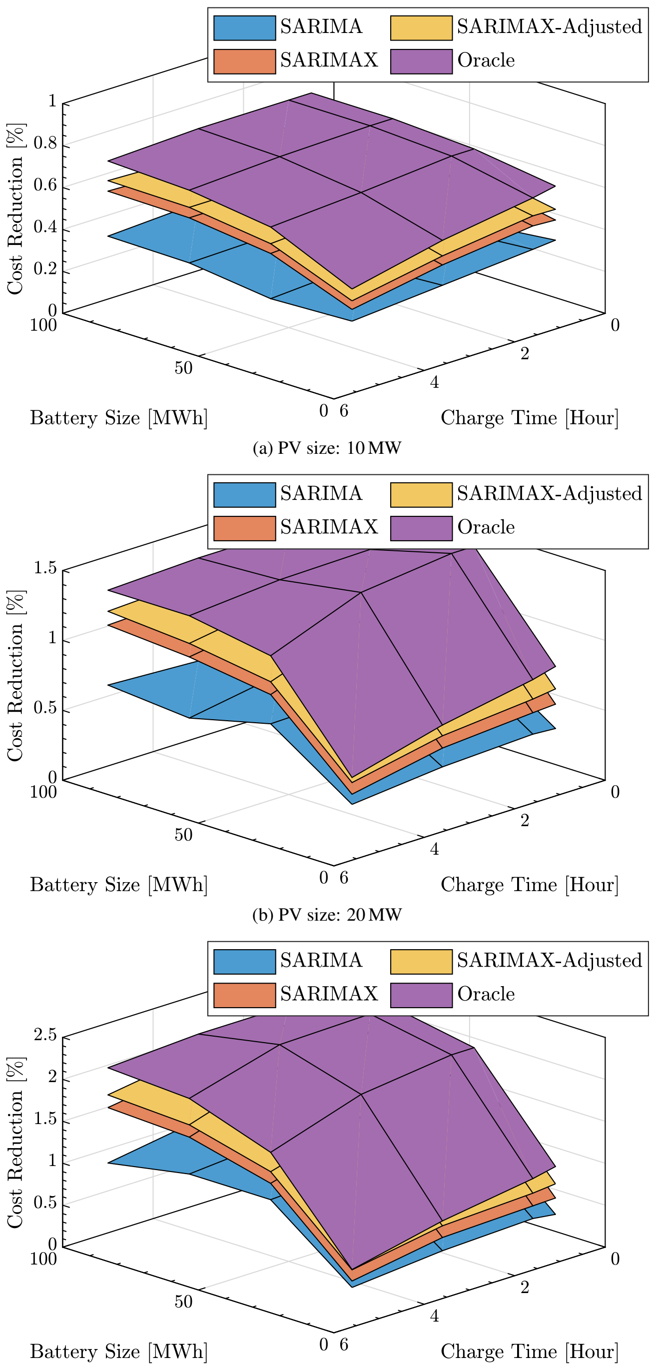


(a) P_R = 10

(b) P_R = 20

(c) P_R = 30

Fig. 12. The effect of P_R on deliberate underreporting of Gen_0



(a) PV size: 10 MW

(b) PV size: 20 MW

(c) PV size: 30 MW

Fig. 13. The effect of PV size on total cost reduction

project in the Kanto region, demonstrated that the proposed MPC scheme significantly outperforms baseline strategies such as rule-based control and no-battery scenarios. The **SARIMAX-Adjusted** case, which incorporates a novel day-ahead PV generation adjustment method, achieved additional cost reduction, especially under moderate retailer purchase prices.

In addition to economic gains, the proposed day-ahead PV generation adjustment approach not only reduces costs but also achieves the lowest total imbalance amount among the tested cases. This is accomplished by utilizing surplus PV energy to both earn revenue and charge the BESS for potential shortage mitigation. Further analysis shows that the MPC scheme remains legitimate in the face of potential strategic underreporting of generation schedules. Under realistic retailer purchase price settings, any attempt to manipulate Gen_0 results in increased operational costs, thereby aligning individual incentives with system-level reliability objectives. These findings underscore the potential of the proposed approach to enhance both economic efficiency and operational integrity in future self-wheeling implementations. The proposed framework thus offers a practical and scalable solution for integrating distributed renewable energy within deregulated electricity markets.

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