Profit-Oriented Criterion of Electricity Price Forecast Considering Charging Duration of Demand-side Responses

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***Abstract*—This paper proposes a novel profit-oriented criterion for evaluating electricity price forecasts used by demand-side response (DR) participants in electricity markets. Typically, DR participants must predict market prices and schedule their bids and operations accordingly. Previous research has shown that a profit-oriented evaluation, focused on accurately identifying price peaks and dips, offers greater economic benefits for DR participants than conventional metrics such as mean-squared error (MSE) or R-squared coefficient. However, the existing criterion does not account for the charging/discharging time of the DR resources, which can reduce accuracy for resources with relatively long response times. To address this limitation, the proposed approach incorporates a moving average filter according to the specific charging/discharging time of each resource. The refined profit-oriented criterion is applied to evaluate seven forecasting methods on day-ahead energy market prices in Japan's JEPX spot market. The amendment enhances the profit-oriented criterion's effectiveness, especially for resources with extended charging/discharging durations.**

***Index Terms*—Demand-side Responses, Electricity Market, Price Forecast, ARIMA models, Deep Learning**

I. Introduction

Electricity market deregulation has further expanded opportunities for DR participation. In these deregulated markets, both generators and consumers can trade electricity through competitive bidding, while ancillary services like frequency regulation are procured via auctions to meet operational needs. As a result, accurate market price forecasting plays a crucial role in shaping market participants' bidding strategies and operational planning.

Numerous forecasting approaches have been explored, ranging from time-series models, such as ARIMA and SARIMA [1], [2], to advanced machine learning techniques. Neural networks, hybrid models, and algorithms like LSTM and CNN have demonstrated their ability to capture complex patterns in electricity price data [3]–[5]. Despite the diversity of methods, most focus on numerical accuracy using conventional metrics such as sMAPE, MSE, and R-squared values [6], [7].

For market participants like generation companies and retailers, precise point forecasts are essential for day-ahead scheduling and trading. However, DRs have different requirements. As shown in [8], an EV aggregator achieved 88.3% of the theoretical maximum revenue despite relying on a forecast with a low R-squared value of 0.2. Typical DRs, including EVs and air conditioners, operate for short durations and contribute limited capacity compared to conventional resources. Furthermore, as price takers in single-price auction markets, DRs cannot influence market prices due to their limited capacity.

Evaluating forecast performance based on actual profits provides the most intuitive and accurate measure but requires detailed DR modeling and market simulations. Moreover, these results are case-specific. A general and convenient profit-oriented criterion is needed to help DRs identify profitable forecasting methods and develop profit-oriented forecast models.

The rest of this paper is organized as follows: Section II identifies the limitations of the original profit-oriented criterion and introduces the proposed method to address the issue. Section III demonstrates the effectiveness of the proposed method through simulations using real historical day-ahead energy market prices in Japan. Finally, the conclusions are drawn in Section IV.

II. Extremum Timing Accuracy

A. Original Form

Conventional evaluation metrics like MSE may not adequately reflect the unique characteristics of DRs. These metrics emphasize the aggregate error across all forecast points, which often fails to align with the operational priorities of DRs, such as:

- Limited participation duration
- Small-scale operations as price-takers

From a profit-driven perspective, the key priority for DRs is accurately pinpointing the timing of market price peaks

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and dips, as these moments present the highest profit potential. Consequently, DRs should focus on scheduling their operations to take full advantage of these opportunities. In this regard, the ability to forecast peak and dip timings with precision becomes a crucial performance metric. To address this requirement, the authors in [9] introduced the Extremum Timing Accuracy (ETA) metric, designed to evaluate forecast performance by specifically accounting for the accuracy of predicting the timing of price peaks and dips:

$$ETA = \frac{\sum_{i \in L\max^Y} T(i) - \sum_{i \in L\min^Y} T(i)}{\sum_{i \in L\max^T} T(i) - \sum_{i \in L\min^T} T(i)} \quad (1)$$

Here, $L\max$ and $L\min$ denote the indexes of local maxima and minima, while Y and T refer to the forecasted and actual price time series, respectively. Similar to the R-squared coefficient, ETA is a normalized metric ranging from 0 to 1, with 1 indicating maximum profitability and 0 representing no profitability. Additionally, the numerator of (1) alone can serve as a performance measure, while the denominator is used solely for scaling ETA to a unit value.

An example demonstrating the application of ETA is presented here. Consider a battery storage system as the target DR, operated to charge during low-price periods and discharge during high-price periods based on forecast results. The battery requires one time-step for a full charge or discharge and is restricted to a single charging cycle to minimize battery degradation. The DR forecasts the actual price in a single-price market and submits bids as a price taker, ensuring that the bids are accepted by the market. The system's profit is then calculated based on the actual clearing prices.

Fig.1 compares two forecast results, with additional details summarized in Table I. At first glance, Prediction 2 appears superior, achieving an R-squared value of 0.87 compared to the much lower R-squared value of 0.19 for Prediction 1. However, Prediction 2 fails to accurately capture the timing of the highest and lowest prices, leading to a profit of only 0.62. In contrast, Prediction 1, despite its lower R-squared value, correctly identifies the timing of price peaks and dips. This accuracy enables the system to achieve its full profit potential.

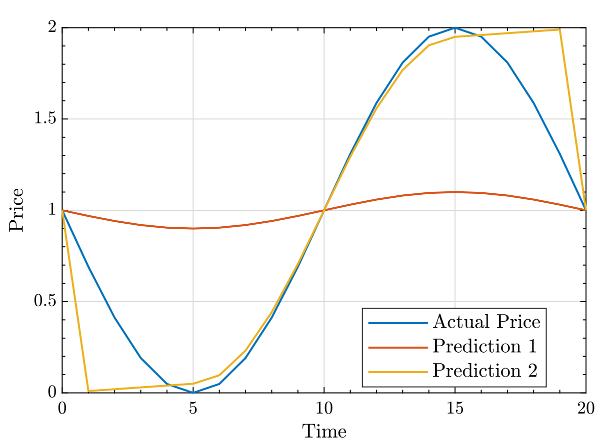


Fig. 1. Example of price forecast result comparison.

TABLE I
DR's Operation Schedule and Profit

	Charge Time	Discharge Time	Profit	R^2
Actual	5	15	2	1
Prediction 1	5	15	2	0.19
Prediction 2	1	19	0.62	0.87

The ETA values for Prediction 1 and Prediction 2 are 1 and 0.31, respectively, corresponding to their profit outcomes. The calculation process is detailed in Table II. For the denominator, the actual price's local maximum and minimum indices are 15 and 5, respectively, resulting in a denominator value of $T(15) - T(5) = 2 - 0 = 2$. For Prediction 1, the local maximum and minimum indices match those of the actual price, making the numerator equal to 2. Thus, the ETA for Prediction 1 is 1. In contrast, Prediction 2 identifies the local maximum and minimum indices as 19 and 1, respectively, with the numerator calculated as $T(19) - T(1)$. Despite achieving a high R-squared value of 0.87, Prediction 2 fails to correctly identify the timing of the price peaks and dips, leading to a much lower ETA of 0.31. This low ETA reflects poor accuracy in predicting extremum timings, proving Prediction 2 unsuitable for DR operations.

The alignment between ETA values and actual profit outcomes underscores its validity as a profit-oriented evaluation metric. With ETA, DRs can efficiently identify the most profitable forecast without the need to develop complex operation models or perform simulations to calculate and compare actual profits directly.

TABLE II
ETA Calculation

	$Lmax$	$T(i)$	$Lmin$	$T(i)$	ETA
Prediction 1	15	2	5	0	$\frac{2-0}{2-0} = 1$
Prediction 2	19	1.31	1	0.69	$\frac{1.31-0.69}{2-0} = 0.31$

B. Considering Charging Duration

The above original form of ETA does not account for the charging duration of DRs. However, as the charging duration increases, it becomes important to consider not only the accuracy of the exact extremum point but also a certain range around it. To address this limitation, a symmetric moving average filter is applied to both the forecasted prices, Y, and the actual prices, T, before calculating the ETA:

$$ETA = \frac{\sum_{i \in L\max^{\bar{Y}}} \bar{T}(i) - \sum_{i \in L\min^{\bar{Y}}} \bar{T}(i)}{\sum_{i \in L\max^{\bar{T}}} \bar{T}(i) - \sum_{i \in L\min^{\bar{T}}} \bar{T}(i)} \quad (2)$$

$\bar{Y}$ and $\bar{T}$ are the forecast result and the actual price smoothed by the moving average filter. The window length of the filter is the length of the charging duration.

By neglecting small, high-frequency perturbations in real-world prices, the price at which the DR charges can be approximated by a convex curve with a single minimum point.

Conversely, the price at which the DR discharges can be approximated by a concave curve with a single maximum point. Taking the charging scenario as an example, a DR with a charging duration of k time-steps will operate at the k lowest values on the curve.

By applying the moving average filter, all price information within the range of interest to the DR is effectively captured and consolidated into the new extremum point. The theorem supporting this statement, along with its proof, is provided in the Appendix. Additionally, the moving average process smooths out small high-frequency perturbations, leaving only the significant peaks and dips in the price data that are most critical for the DRs.

The ETA values that account for the DR's charging duration in the previous example are presented in Table III. The profit ratio is the ratio of the profit achieved using the given forecast to the profit achievable with a perfect price forecast. When the charging duration is 1 time-step, the moving average window length is also set to 1, equivalent to not applying any moving average. Under this circumstance, the ETA matches the original ETA that does not consider the charging duration. As the charging duration increases, the ETA adjusted for the charging duration aligns perfectly with the profit ratio, demonstrating improved evaluation performance compared to the original ETA.

TABLE III
ETA VALUES CONSIDERING CHARGING DURATION

Charging Duration	1	2	3	4	5
ETA	0.310	0.459	0.588	0.710	0.811
Profit Ratio	0.309	0.460	0.588	0.716	0.809

III. SIMULATION RESULT

A. DR Model

The simulation focuses on a demand-side battery storage system as the target DR, which operates by purchasing charging power from a single-price energy spot market during low-price periods and maximizing profit by selling power back to the market during high-price periods. The daily operational schedule of the DR is formulated as the optimization problem outlined in (3):

$$\underset{State(t)}{\text{maximize}} \quad P_{\max}\sum_{t} Y(t)State(t) \tag{3a}$$

$$\text{subject to} \quad SOC(t) = SOC_{\text{initial}} - P_{\max}\Delta t \sum_{t} State(t), \tag{3b}$$

$$0 \le SOC(t) \le 1, \tag{3c}$$

$$-\sum_{t} State(t) \le n \text{ if } State(t) < 0 \tag{3d}$$

The DR aims to maximize its one-day profit with the objective function (3a) and a given forecast result $Y(t)$. $P_{\max}$ is the DR's maximum power output, and $State(t) \in [-1, 1]$ represents the charging and discharging schedule to be optimized. The state-of-charge (SOC) is computed through constraint (3b) and restricted by constraint (3c). To mitigate severe battery degradation, the maximum number of charging cycles per day is regulated by constraint (3d), where n denotes the upper limit. Δt is the length of the market time-step.

In this simulation, the capacity of the DR is $10\,\mathrm{MWh}$. The maximum power output varies depending on the charging duration. As a price-taker in the market, the DR's profit is calculated by (4), where $State(t)$ is the optimized charging and discharging schedule derived from (3). $T(t)$ represents the actual market clearing price.

$$Profit = P_{\max}\Delta t \sum_{t} T(t)State(t) \tag{4}$$

B. ETA Validation

The target market is the energy wholesale market in Japan: the Japan Electric Power eXchange (JEPX) spot market. The JEPX spot market operates as a day-ahead, single-price market with a 30-minute time step. Participants are required to submit their bids by 10:00 AM one day before the actual production and delivery [10]. The JEPX spot clearing prices for the period from April 2023 to March 2024 are forecasted using the following seven models:

- **Yesterday** Assume today's market clearing price is exactly the same as yesterday's.
- **Conventional SARIMA**
- **LSTM Neural Network** A recurrent neural network with LSTM units that can effectively capture and retain long-term dependencies in sequential data.
- **Just-In-Time (JIT)** Generate predictions by identifying and using the most relevant pre-stored past data points for the current situation.
- **Partial Least Squares (PLS)** Reduce high-dimensional, correlated predictors (such as temperature, weather conditions, etc.) into a smaller set of uncorrelated latent variables and use these latent variables to construct a linear regression model.
- **Support Vector Regression (SVR)** Use support vectors to derive a regression model with most of the errors being kept within a specified error margin.
- **Ensemble** An ensemble model of JIT, PLS and SVR.

The JEPX clearing price forecast with conventional SARIMA and a three-layer LSTM neural network is reported in [11]. The forecast with JIT, PLS, SVR, and the ensemble model is provided by Fuji Electric Co., Ltd. and reported in [12], [13]. A fraction of the actual JEPX clearing price and the forecast results are shown in Fig. 2

Fig. 3 and Fig. 4 present the ETA values and profit ratios for the target DR across varying charging durations, assuming no limitation on allowable charging cycles. The original ETA values are represented by dashed lines, which appear as horizontal due to the fact that the original ETA does not account for charging duration. In contrast, the solid lines depict the ETA

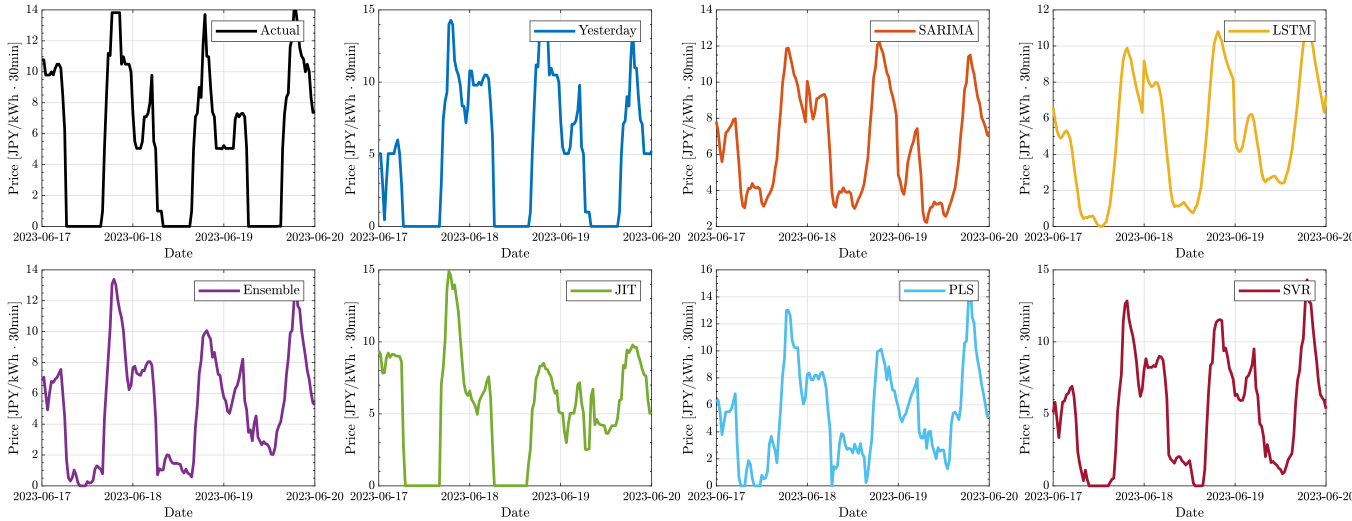


Fig. 2. The actual JEPX clearing price and seven forecast results.

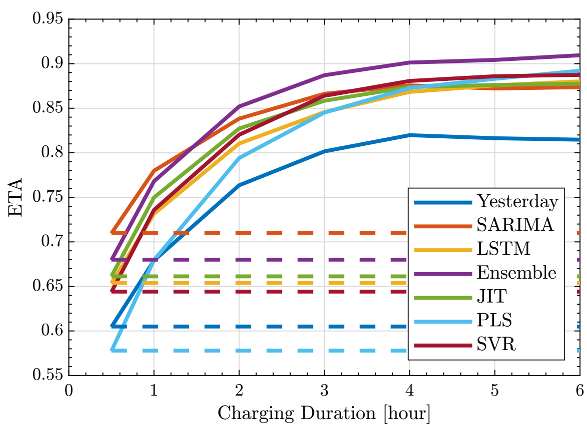


Fig. 3. ETA with different charging durations.

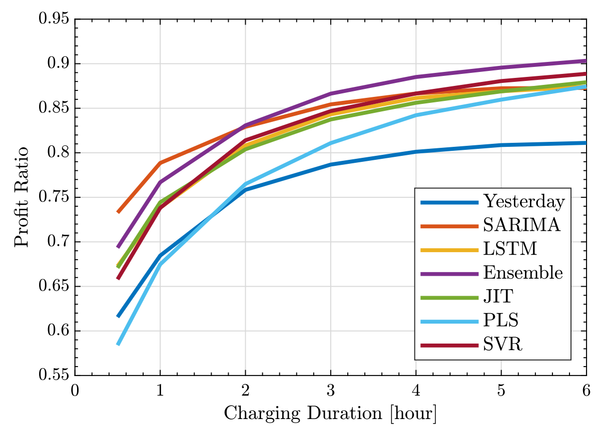
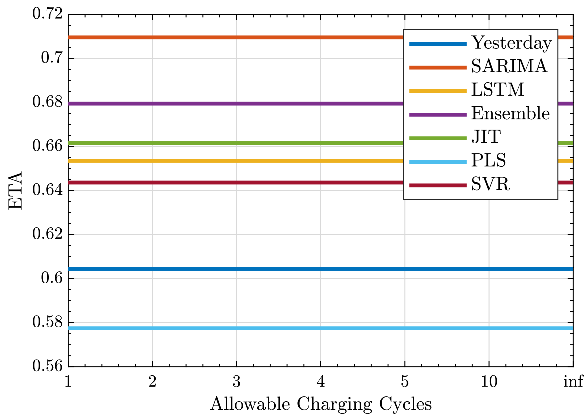


Fig. 4. Profit ratio with different charging durations.

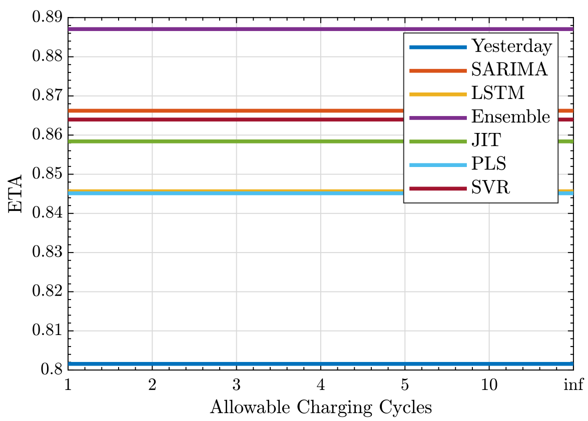
that incorporates the charging duration. Figure 4 shows the variation in profitability across the seven forecasting methods as a function of charging duration. When charging duration is ignored, the straight lines fail to capture the impact of increasing duration on profitability. Additionally, the ranking of methods becomes inaccurate at longer charging durations. For instance, while the Ensemble method shows an increase in profitability with longer durations, the original ETA continues to rank SARIMA as the most profitable method. However, once the charging duration is considered, the ETA values evolve with the charging duration and follow a trend that closely aligns with the profit ratio.

Fig. 5 and Fig. 6 show the profit ratio and ETA under different allowable charging cycles per day k. The results show that the profit is minimally influenced by the number of allowable charge cycles, especially when the charging duration is sufficiently long. The reason is that, in most cases, the clearing price exhibits only 1 to 2 dominant peaks and dips per day, which are the most critical opportunities for DR to generate profit. Increasing the allowable charge cycles beyond this point can only target peaks and dips of less prominence, contributing little to the overall profit. The ETA formulation (2) is independent of the allowable charging cycles, therefore Fig. 5 shows only horizontal straight lines. However, the overall ranking order of the forecast methods based on ETA is still highly consistent with that based on the profit ratio.

To quantitatively evaluate the effectiveness of the conventional R-squared value and the ETA, the Kendall rank correlation coefficient between these metrics and the profit ratio are calculated. The analysis includes 49 scenarios, where the charging duration varied between $0.5, 1, 2, 3, 4, 5, 6$ hours, and the allowable charging cycles per day k takes values from $1, 2, 3, 4, 5, 10, \infty$. The Kendall rank correlation coefficient is a common statistical measure that quantifies the ordinal relationship between two ranked datasets [14]. A high Kendall rank correlation coefficient indicates that the two metrics tend to rank the forecast results similarly, which suggests a strong agreement in their evaluation of the forecast methods. The

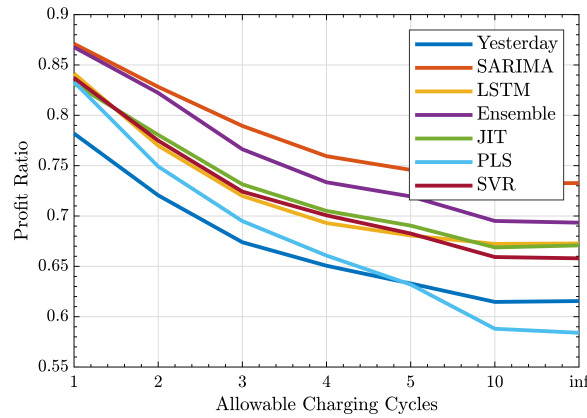


(a) Charging duration: 0.5 hour

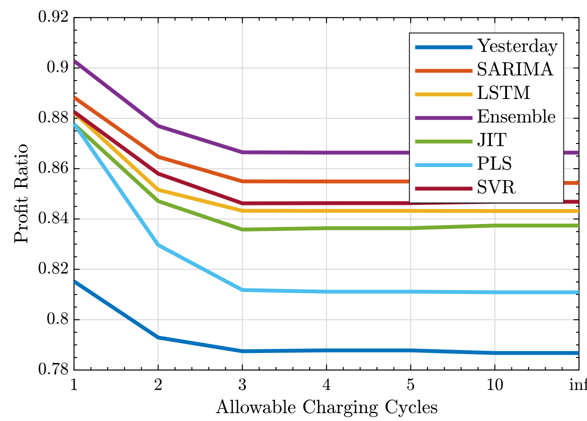


(b) Charging duration: 3 hour

Fig. 5. ETA with different allowable charge cycles.



(a) Charging duration: 0.5 hour



(b) Charging duration: 3 hour

Fig. 6. Profit Ratio with different allowable charge cycles.

TABLE IV
AVERAGE KENDALL RANK CORRELATION COEFFICIENT.

	R^2	ETA	
		Not Considering Charging Duration	**Considering Charging Duration**
Kendall Rank Correlation Coefficient	0.66	0.77	0.88

average Kendall rank correlation coefficients are presented in Table IV.

The Kendall rank correlation coefficient for the R-squared value shows only a moderate agreement with the profit ratio, indicating a limited alignment. In contrast, the coefficient of 0.77 for the original ETA reveals a stronger correlation with the profit ratio. Notably, when accounting for charging duration, the Kendall rank correlation coefficient for ETA further increases to 0.88, indicating an even stronger concordance with the profit ratio. This result implies that with charging duration considered, the ranking of the seven forecasting methods remains highly consistent between the ETA and the profit ratio. Consequently, the refined ETA proves to be a reliable metric for approximating the profit ratio and for evaluating the profitability of forecast results.

IV. CONCLUSIONS

This paper proposes a novel method for incorporating the charging duration of DRs into the profit-oriented criterion, ETA. The original form of ETA loses accuracy when the DR has a long charging duration. To address this issue, the proposed method applies a symmetric moving average filter with a window length corresponding to the DR's charging duration. By integrating this approach, the accuracy of ETA is significantly enhanced, particularly for scenarios with long charging durations.

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Appendix

Theorem 1. *Let $f(x)$ be a discrete convex function with a unique minimum point, and let its k smallest values occur within the interval $x \in [a, b]$. Suppose a symmetric moving average filter with a window length of k is applied to $f(x)$ and the filtered function is $\bar{f}(x)$. Then, the minimum point of $\bar{f}(x)$ is located at $x = \frac{a+b}{2}$.*

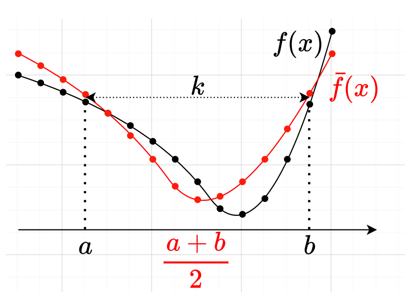

Fig. 7. Illustration of the convex function $f(x)$ and the filtered function $\bar{f}(x)$.

Proof. The symmetric moving average filter with a window length of k calculates the filtered value $\bar{f}(x)$ at each point i by averaging $f(x)$ over a symmetric interval of width k:

$$\bar{f}(i) = \frac{1}{k} \sum_{x=i-\frac{k}{2}}^{i+\frac{k}{2}} f(x)$$

Since $f(x)$ is convex and its k smallest values lie within $x \in [a, b]$, $\frac{1}{k}\sum_{x=a}^{b} f(x)$ is the minimum value of $\bar{f}(x)$. Moreover, because the filter is symmetric, the minimum of $\bar{f}(x)$ must occur at the midpoint of the interval $[a, b]$. Thus, the minimum point is:

$$x = \frac{a+b}{2}.$$

$\square$