Volatile Market Adaptive Forecaster: Online Learning Framework for Wholesale Market Price Forecasting with Similar Day Classification

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***Abstract*—As electricity market prices are directly tied to generators' revenues, electricity price forecasting is essential for profit maximization. In small, renewable-heavy island systems with grid constraints, wholesale prices fluctuate and often turn negative. This study analyzes the relationship between publicly available datasets and wholesale market prices in Jeju Island to rank key features. The study also proposes the volatile market adaptive forecaster (VOLTA), an integrated classification–forecasting framework capable of responding to rapid price fluctuations, including negative price occurrence. We evaluated the forecasting performance of multiple models using metrics, including MASE in volatile environments featuring price spikes and negative prices. The occurrence of negative prices was identified in advance using a classification model with forecasted demand and precipitation probability as inputs. DNN-based forecasting model was applied to normal price periods. The proposed model achieved improved forecasting accuracy compared to the benchmark models, Rolling ARIMA and BiLSTM.**

***Index Terms*—electricity price forecasting, online learning, negative price pre-detection**

I. Introduction

Wholesale market electricity price has a significant impact on the revenues of market participants. To forecast revenues and establish optimal bidding strategies, market participants have increasingly focused on the field of electricity price forecasting [1]. Many statistical methods based forecasting techniques were initially derived from approaches used in the field of load forecasting [2]. Contreras et al. performed price forecasting using an ARIMA model and showed that introducing explanatory variables can further improve performance [3]. In addition, several studies identified year-wise similar days from historical data and applied them to ANN-based forecasting [4], [5]. Although these methods improved forecasting accuracy to some extent, they failed to fully capture price spikes and rapid price fluctuations caused by the sharp increase in renewable energy penetration.

Conventional batch learning requires pre-specified training data, making it unsuitable for markets with continuous updates. To overcome these limitations, online learning methods have been proposed. The online learning updates the model whenever new inputs arrive, enabling faster and efficient adaptation to changing data streams than batch learning [6]. Kim et al. showed that such online learning–based methods perform well in electricity price forecasting, where prices are sensitive to external factors [7]. However, that study also did not adequately address outliers such as sudden price spikes or negative prices.

The proposed volatile market adaptive forecaster (VOLTA) is an online learning–based price forecasting framework designed for renewable-dominant electricity markets with frequent and severe price fluctuations. Based on the similar-day approach, the VOLTA enhances forecasting stability and accuracy by pre-classifying volatile periods. For this purpose, we performed a Minimum-Redundancy Maximum-Relevance (mRMR) analysis based on publicly available data provided by the Korea Meteorological Administration (KMA) and the Korea Power Exchange (KPX) to select key input features. We evaluated the model against ARIMA and BiLSTM, considering price-scale sensitivity.

The main contributions of this study are as follows:

- To analyze public data and present mRMR-based feature selection results to identify key features of Jeju's wholesale market price.
- To propose an online learning–based classification–forecasting framework capable of adapting to rapid price fluctuations and negative price occurrences in real time.
- To compare multiple models using various metric in volatile environment with price spikes and negative prices.

The remainder of this paper is organized as follows. Section II first introduces the data sources and preprocessing steps, and then provides a detailed description of the proposed model's structure. Section III presents the experimental setup, and Section IV analyzes the experimental results and performance. Finally, Section V discusses the conclusions and directions for future research.

II. Data Collection and Methodology

A. Data and Targets

Since renewable generation is inherently difficult to predict precisely at the time of bidding, we leverage publicly available

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short-term weather forecast information together with demand forecasts as practical proxies for renewable-driven uncertainty. The dataset at time t consists of the electricity price and the following features. Variable names follow those defined by the KMA [8]. To capture the relationship between these proxies and negative-price occurrences while avoiding redundant inputs, the candidate variables are screened using the mRMR method described in Section II-B.

- Demand and price: D_t(electricity demand at t), λ_t^{DA} (electricity price $t-24$), λ_t^{WA} (electricity price $t-168$), I_t^{DA} (indicator of a negative price at $t-24$), I_t^{WA} (indicator of a negative price at $t-168$)
- Meteorological variables: TMP (Temperature), TMX (Maximum temperature), TMN (Minimum temperature), UUU (East-West wind component), VVV (North-South wind component), VEC (Wind direction), WSD (Wind speed), SKY (Sky condition), PTY (Precipitation type), POP (Precipitation probability), PCP (Precipitation amount), REH (Relative humidity).

The proposed framework produces the following output:

- Negative price indicator: $y_t = 1\{\lambda_t < 0\}$
- Predicted price $\hat{\lambda}_t$ for times t expected to have non-negative prices.

B. mRMR Feature Screening

The mRMR method is a feature selection algorithm that identifies informative and non-redundant features. The procedure quantifies feature relevance using mutual information $I(\cdot;\cdot)$ between each candidate feature x_j and the target negative-price indicator y. At the m-th selection step, given the set S_{m-1} of previously selected $(m-1)$ features, the next feature is chosen by maximizing the difference between relevance and average redundancy as follows [9]:

$$\max_{x_j \notin S_{m-1}} \left[I(x_j; y) - \frac{1}{m-1} \sum_{x_i \in S_{m-1}} I(x_j; x_i) \right] \tag{1}$$

In Eq. (1), the first term measures relevance to the target, whereas the second term penalizes average redundancy with the previously selected features. This removes redundant features, improving overall efficiency as well as classification and forecasting performance [10]. It is useful for feature selection under redundant input settings. In this study, mutual information was estimated using a k-nearest neighbor estimator ($k = 4$), and continuous variables were discretized into 10 bins. The meteorological inputs considered in the candidate set were obtained from the local short-term forecast records provided by KMA [11].

Fig. 1. ranks the candidate variables according to their mRMR scores for predicting the occurrence of negative prices. Demand is the most informative variable, with an mRMR score of 0.18, and the prior negative-price indicators follow, with scores of 0.07 for the day-ahead indicator and 0.06 for the week-ahead indicator. Among the weather related candidates, precipitation probability is the only variable that yields a positive mRMR score, which is 0.03, whereas the remaining meteorological variables are largely redundant. Based on these results, we construct the negative-price pre-detection model using demand, the prior negative-price indicators, and precipitation probability.

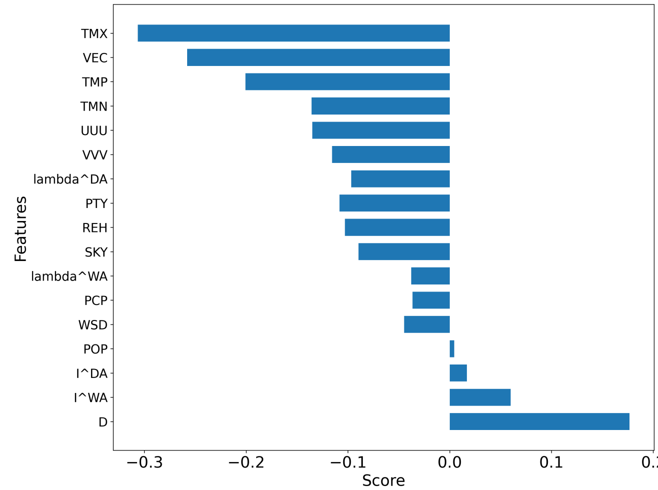

Fig. 1. Feature relevance ranking obtained from the mRMR analysis for Jeju wholesale market dataset

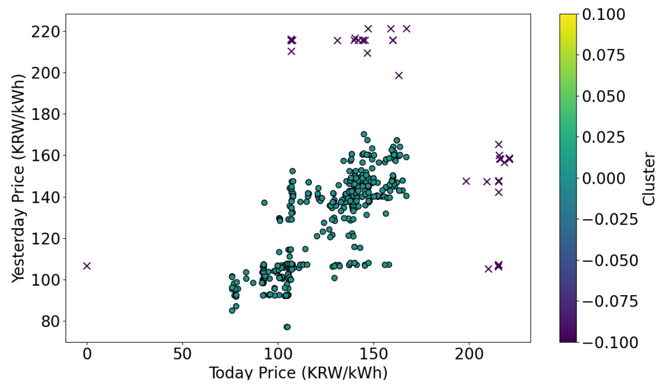

Fig. 2. An example of clustering using DBSCAN

C. DBSCAN-Based Outlier Filtering

Negative prices are rare and can behave as outliers. We apply DBSCAN which is widely used for outlier removal [12], [13]. Using a rolling 90-day window, we run DBSCAN on two-dimensional vectors consisting of λ_t and its lagged value: a 24-hour lag for normal days and a 168-hour lag for special days. Detected outliers are removed before training to stabilize online updates.

For training, we cluster points using the price at time t on the current day and the price at time t on prior days within the past 90 days as the two axes. Data labeled as outliers are excluded from training to enhance model stability. Fig. 2. illustrates outlier extraction using DBSCAN; groups marked "X" represent large deviations from historical prices and are excluded from training.

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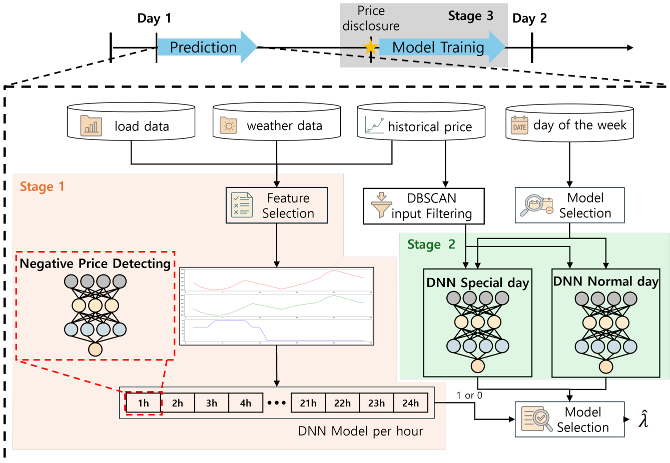

Fig. 3. Overall configuration of the framework

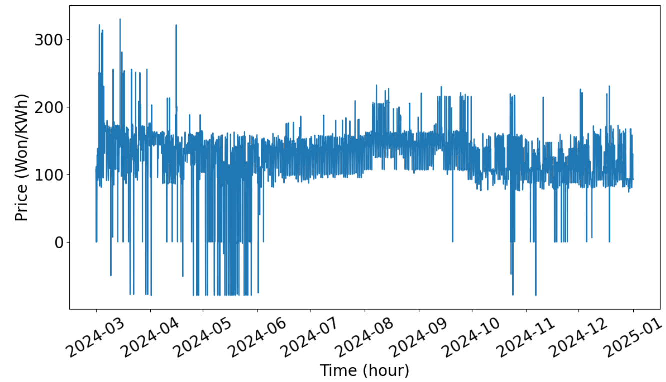

Fig. 4. Jeju wholesale market price from March to December 2024

D. Overall Framework Configuration

Fig. 3. illustrates the the VOLTA framework, which runs daily in three stages. Stage 1 trains hour-specific DNN classifiers to pre-detect negative-price hours. For hours where the negative-price ratio is below 5%, training is skipped to avoid overfitting caused by class imbalance. Stage 2 forecasts prices using one of two DNN forecasters: a Special-Day DNN or a Normal-Day DNN. Special days are defined as Mondays and Saturdays, for which week-ahead information (D−7) and Normal-Day DNN uses day-ahead information (D−1) for all remaining days. The final output is fixed to zero when Stage 1 predicts a negative-price regime. Otherwise it takes the selected DNN forecast. Stage 3 updates the corresponding DNN online after realized prices arrive, excluding negative-price samples and removing DBSCAN outliers. The Special-Day DNN and the Normal-Day DNN are updated separately using samples from the corresponding day type.

III. Simulation Configurations

A. Experimental Data Setup

The proposed framework was tested on the Jeju Island electricity market to demonstrate and evaluate its performance.

In Jeju Island, only ten centrally dispatched generators are in operation, and available capacity fluctuates due to preventive maintenance and grid constraints [14]. Jeju Island represents an environment in which wholesale market price forecasting must explicitly account for both negative prices and price spikes given its renewable-dominant generation mix. Jeju Island operates an independent power system with a total installed capacity of 2,045 MW, including 1,116 MW of renewable energy generation [15]. In addition, the high share of solar and wind power generation leads to wholesale market price volatility driven by changes in solar irradiance and wind speed.

The wholesale market price data used for training are shown in Fig. 4. Hourly wholesale market price data from March 8 to December 30, 2024, were used for model training, while performance evaluation was conducted for the period from April 7 to December 30 2024. Because the proposed framework employs an online learning scheme, training and evaluation datasets partially overlap in time, reflecting the model's continuous adaptation to newly arriving data. The dataset covers the period from March 1 to December 30, 2024, including both market and meteorological variables. The demand data was obtained from the KPX and correspond to the hourly demand in Jeju Island used in the day-ahead generation plan [16]. The average wholesale market price was 125.5 won/kWh, with 264 occurrences of negative prices including zero, and negative price were treated as zero.

B. Comparative Algorithms for Benchmarking

To evaluate the proposed algorithm, we implemented several benchmark models. First, a rolling ARIMA model was retrained daily using the most recent 30 days of data. Second, we applied a BiLSTM network, which was also retrained daily based on the same 30-day window to capture nonlinear temporal dependencies in price dynamics. Both benchmark models relied solely on historical electricity price data for training and prediction.

C. Implementation Details and Hyperparameter Settings

Simulations were conducted in Python 3.9.12, with deep learning models implemented in PyTorch 2.3.1 and clustering modules in scikit-learn 1.5.2. The hyperparameter of the classification, forecasting, and DBSCAN models are summarized in Table I .

IV. Simulation Results

A. Distinguishing Special Days

Fig. 5. compares absolute errors relative to the previous day (D-1) and the previous week (D-7) for each day of the week. Most days exhibited lower errors when referenced to the previous day. For Mondays and Saturdays, the average error based on the previous week was lower than that based on the previous day.

This finding indicates that weekly patterns provide a more reliable reference for these days. The VOLTA classifies Mondays and Saturdays as special days, applying week-ahead

979-8-3315-8138-1

TABLE I
MODEL HYPERPARAMETERS

Model	Hyperparameter	Value
Online Learning	Look back days	30
	Classification activation thershold	0.05
Prediction DNN	epochs	50,000
	loss	L1 Loss
	optimizer	Adam
	learning rate	0.0001
	activation	LeakyReLU negative slope 0.5
	dense layer	(2, 128), (128, 64, 32), (32,1)
Classification DNN	epochs	2,000
	loss	BCE Loss
	batch size	2
	optimizer	Adam
	learning rate	0.1
	activation	LeakyReLU negative slope 0.2
DBSCAN	epsilon	30
	MinPts	30

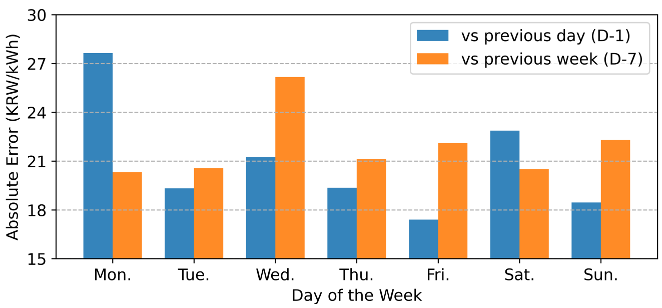

Fig. 5. Mean absolute errors of Jeju Electricity Prices

models for those periods, while day-ahead models are used for regular weekdays.

B. Capturing Negative Price

Table II summarizes the hourly frequency of negative price occurrences from April to December 2024. Negative prices occurred in 264 out of 6,600 total hours (4%), peaking at 13:00 with a 17.5% occurrence rate. The time window between 11:00 and 14:00 consistently showed high frequencies exceeding 10%, indicating that these hours are particularly important for enhancing the model's ability to detect negative prices.

The proposed VOLTA includes an hour-specific negative price pre-detection module, enabling the framework to determine whether to train a separate classifier for each time slot. Because the negative-price proportion directly impacts learning efficiency, the VOLTA skips training for hours with a ratio below 5%.

The performance of the negative-price pre-detection was analyzed using the confusion matrices in Table III. For VOLTA, the precision was 64.5%, whereas DA Rolling ARIMA and BiLSTM recorded precisions of 45.0% and 35.3%, respectively. Since DA Rolling ARIMA and BiLSTM do not include an explicit pre-detection module, we treated non-positive forecasts as negative-price predictions when constructing their confusion matrices, enabling a direct comparison of false-positive levels across models.

TABLE II
HOURLY FREQUENCY OF NEGATIVE PRICE OCCURRENCES SINCE APRIL 2024

Time	Count	Ratio(%)	Time	Count	Ratio(%)
1	1	0.4	13	48	17.5
2	1	0.4	14	34	12.4
3	4	1.5	15	21	6.5
4	4	1.5	16	18	6.5
5	6	2.2	17	9	3.3
6	8	2.9	18	2	0.7
7	2	0.7	19	0	0
8	5	1.8	20	1	0.4
9	9	3.3	21	1	0.4
10	24	8.7	22	0	0
11	28	10.2	23	0	0
12	38	13.8	24	0	0

TABLE III
CONFUSION MATRICES FOR NEGATIVE-PRICE PRE-DETECTION

	VOLTA		DA Rolling ARIMA		BiLSTM	
	Pred(+)	Pred(-)	Pred(+)	Pred(-)	Pred(+)	Pred(-)
Actual(+)	100	160	18	242	30	230
Actual(-)	55	6141	22	6174	55	6141

C. Overall Results

Table IV and Fig. 6 summarize the comparative forecasting performance among the three models. The VOLTA framework achieved an SMAPE of 16.88%, an MAE of 16.02, and a MASE of 0.83, outperforming both benchmark models in all evaluation metrics. Compared with the DA Rolling ARIMA model (SMAPE 20.80%, MAE 18.44, MASE 0.96) and the BiLSTM model (SMAPE 20.75%, MAE 18.52, MASE 0.96), the VOLTA demonstrates consistently superior accuracy and stability across the testing period.

Fig. 6 illustrates the cumulative absolute forecasting error from April to December 2024. The cumulative error of the VOLTA (blue dashed line) grows more slowly than that of BiLSTM and DA Rolling ARIMA, indicating better adaptability to recent price dynamics. After May, all models show a steady increase in cumulative error, but the gap between the VOLTA and the benchmarks widens slightly over time. These results confirm that the VOLTA provides improved responsiveness to changing market conditions while ensuring robust prediction accuracy under high volatility.

Fig. 7. presents results for 13–15 May 2024, a period that includes negative prices. VOLTA achieves SMAPE 0.49 and MASE 1.88, whereas BiLSTM and DA Rolling ARIMA record SMAPE values of 0.71 and 0.80 and MASE values of 2.64 and 2.17, respectively. It is worth noting that May 13, 2024, is a Monday, which VOLTA treats as a special day meaning the transition from weekend price patterns to weekday price patterns. BiLSTM does not capture the tran-

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TABLE IV
PERFORMANCE COMPARISON OF THE PROPOSED VOLTA MODEL AND OTHER BENCHMARKS

	SMAPE(%)	MAE	MASE
The proposed VOLTA	16.88	16.02	0.83
DA Rolling ARIMA	20.80	18.44	0.96
BiLSTM	20.75	18.52	0.96

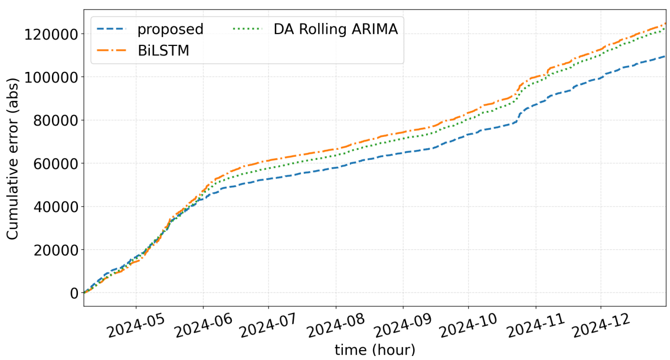

Fig. 6. Cumulative error from 7 April to 14 July 2024

sition to the zero-price level on Monday (from weekend to weekday), whereas VOLTA and DA Rolling ARIMA produce values closer to zero during several zero-price segments. DA Rolling ARIMA produces lower values than BiLSTM during these events, but it often remains above zero and does not consistently reach the zero level. VOLTA shows sharper transitions around the zero-price segments because it integrates a negative-price classifier with the forecasting model and sets the final forecast to zero whenever the classifier predicts a negative-price regime.

V. CONCLUSION

This study proposes a forecasting framework for electricity price forecasting in island systems such as Jeju Island, combining pattern classification with online learning. It pre-detects negative price periods and selects between day-ahead and week-ahead inputs based on day-of-week patterns, improving performance even under rapid price fluctuations. Precision is about 64.5%, because the model was intentionally trained only on hours whose historical negative-price frequency exceeds 5% to mitigate class-imbalance bias, although this thresholding inevitably excludes some low-frequency regimes and can contribute to missed detections. Future work will develop forecast confidence intervals and evaluate bidding strategies in real-time electricity markets.

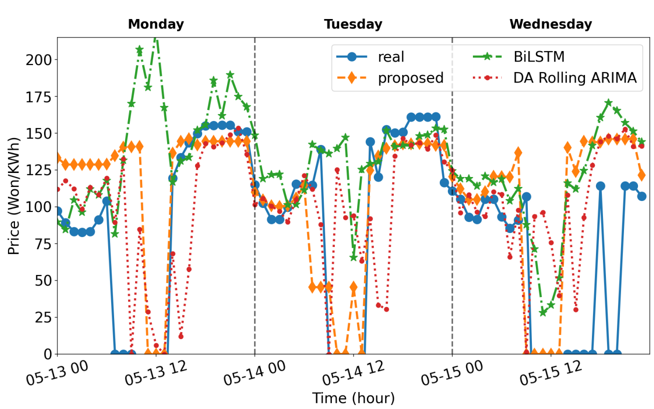

Fig. 7. Forecasting results from 13 to 15 May 2024

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