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Development of System Marginal Price Prediction Model for Electric Vehicle Integration in Power Market

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Executive Summary

This paper introduces a novel approach combining LTSF (Long-term Time-Series Forecasting)-Linear architecture with AsymLoss(Asymmetric Loss), the custom loss function designed to enhance directional accuracy for System Marginal Price (SMP) forecasting in electrical grids. Precise SMP prediction is essential for energy aggregators to effectively participate in electricity markets through electric vehicles vehicle-to-grid (V2G) technology, offering enhanced value propositions for electric vehicle users. We evaluate our proposed methodology against the commonly used time-series model, GRU (Gated Recurrent Unit), and the effectiveness of the proposed model is validated through implementation in real-world market conditions. Along with GRU comparison, common loss functions in time-series problems which are MSE (Mean Squared Error) and DILATE (DIstortion Loss including shApe and TimE) loss compare were processed. Results demonstrate that our proposed approach is particularly well-suited for volatile time-series forecasting problems like SMP prediction. The synergistic effect of LTSF-Linear and AsymLoss shows promising improvements in forecasting accuracy, making it a valuable tool for V2G market participation.

Keywords: AI – V2H&V2G, Smart charging, Artificial intelligence for EVs, Smart grid integration and grid management, Electric Vehicles

1 Introduction

The System Marginal Price (SMP) represents the wholesale electricity price ($/kWh) in electrical grid systems, serving as a crucial indicator of the real-time equilibrium between electricity supply and demand. In the electricity generation landscape, various energy sources are utilized according to their economic efficiency, known as the merit order system. As illustrated in Figure 1 [1], in Korea, nuclear power plants operate as the primary base load due to their low operational costs, followed by coal-fired plants, while Liquefied Natural Gas (LNG) and oil represents the highest cost tier. The SMP mechanism is fundamental for all energy market participants, particularly for energy aggregators who not only facilitates the optimization of energy trading strategies but also enhances profitability by enabling participation in the market at advantageous times such as peak pricing periods.

The global transition toward renewable energy sources presents both promising opportunities and significant technical hurdles. While this transition is essential for environmental preservation, it introduces unprecedented challenges to grid stability primarily due to the unpredictable nature of renewable energy generation.

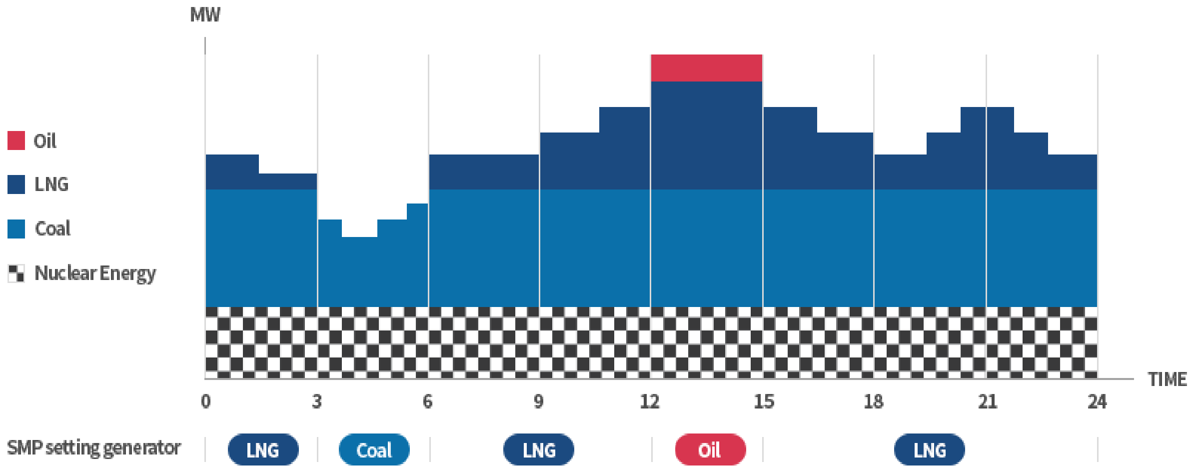

Figure 1. Electricity Market Price Determination [1]

In response to these challenges, the Republic of Korea has launched comprehensive government projects focusing on the integration of electric vehicles into the existing grid infrastructure through Vehicle-to-Grid (V2G) technology. This approach leverages bi-directional on-board chargers (OBC), enabling electric vehicle batteries to function as distributed energy storage systems (ESS), collectively forming Virtual Power Plants (VPPs) when aggregated in large numbers. Through VPPs, these electric vehicles can provide grid services such as Demand Response (DR) and Frequency Regulation (FR). DR programs incentivize power consumers, including EV fleet operators, to adjust their electricity consumption during peak demand periods in exchange for financial compensation. This helps alleviate grid stress, improve system reliability, and optimize energy costs. FR services, on the other hand, are essential for maintaining grid stability by continuously adjusting power supply to keep the frequency at its nominal value, typically 50 or 60 Hz, thereby preventing system imbalances that could lead to power outages. In this market structure, Independent System Operators (ISOs) and Power Exchanges (PXs) provide day-ahead electricity demand forecasts, forming the basis for market participation. Since energy aggregators rely on the sale of electricity back to the grid, their potential profits are directly tied to the System Marginal Price (SMP). Accurate SMP forecasting is crucial, as it allows aggregators to optimize their bidding strategies, maximize revenue, and mitigate financial risks associated with price volatility. Given that SMP values fluctuate based on real-time supply and demand conditions, effective forecasting ensures that VPP operators can strategically schedule energy dispatch, enhancing both economic returns and grid efficiency.

As illustrated in Figure 2, the proposed VPP framework aggregates EVs at scale and implements a sophisticated 24-hour scheduling strategy that optimizes charging and discharging patterns based on predicted SMP fluctuations. This optimization process strategically schedules charging during periods of low SMP and discharging during high SMP periods, while simultaneously ensuring that each State-of-Charge (SoC) of electric vehicle remains within acceptable bounds to accommodate predetermined user mobility patterns and plug-in/out schedules. This dual-objective optimization approach effectively balances the competing demands of maximizing aggregator profits through market participation while maintaining reliable vehicle availability for EV owners.

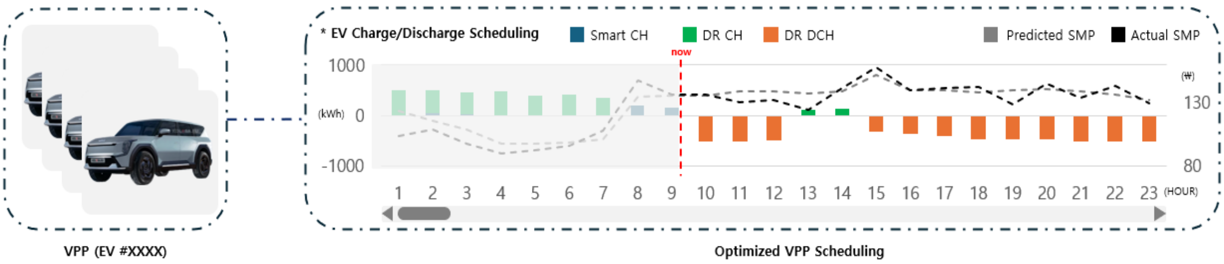

Figure 2. Optimized EV Scheduling According to SMP

2 Literature Review

Time-series forecasting in volatile markets such as electricity has been extensively studied over the past decades, with approaches ranging from classical statistical methods to advanced deep learning architectures. This section reviews notable contributions across this spectrum while highlighting persistent challenges in accurate prediction of highly dynamic data. Traditional statistical models such as the

Autoregressive Integrated Moving Average (ARIMA) [2] and its seasonal extension with acceptance of exogenous variable, SARIMAX, have been widely applied due to their interpretability and ability to capture linear trends and seasonality. For instance, SARIMAX has been employed in various energy market studies for forecasting electricity demand and pricing with relatively strong performance in stable conditions. However, these models often fall short in volatile contexts, as they are not designed to handle non-linearities [3] or complex temporal dependencies that frequently arise in SMP data. Machine learning algorithms have emerged as powerful alternatives, offering improved capabilities in non-linear relationships. Boosting-based methods such as Random Forest, XGBoost, and CatBoost not only offer greater flexibility and often outperform linear models by capturing non-linear interactions between input features but also have shown promising results in various range of forecasting competitions and real-world applications [4,5]. Yet even these models may struggle to capture the sequential dependencies inherent in time-series data, especially for long-term forecasts or under conditions of rapid fluctuation. The advent of deep learning has introduced more sophisticated architectures specifically in tasks requiring the modeling of temporal dynamics. Recurrent Neural Networks (RNNs), and more specifically their advanced variants such as Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM) networks, are capable of learning complex temporal dependencies. The Long Short-Term Memory (LSTM) network, introduced by Hochreiter and Schmidhuber [6], addresses the vanishing gradient problem of standard RNNs, allowing the model to capture longer-term dependencies. Similarly, Gated Recurrent Units (GRUs), a simplified variant of LSTMs proposed by Cho et al. [7], have shown comparable performance with reduced computational complexity. These architectures have been applied with considerable success in energy price forecasting and load prediction tasks. In parallel, WaveNet, a deep generative model originally designed for audio data [8], has been adapted for time-series forecasting. Its use of dilated causal convolutions allows for the modeling of long-range temporal dependencies without recurrence, making it highly suitable for multistep and multivariate time-series applications [9]. In recent studies, the LTSF-Linear (Linear Transformer for Time Series Forecasting) model has gained attention for its notable performance in multistep forecasting tasks. Unlike complex recurrent or convolutional architectures, this approach leverages simply designed linear transformations that capture temporal dependencies while maintaining computational efficiency. Zeng et al [10]. demonstrated that this streamlined architecture outperforms state-of-the-art models on standard benchmarks, challenging the conventional wisdom that increased model complexity necessarily yields better performance.

Along with research in time-series forecasting models, recent studies have explored combining deep learning architectures with specialized loss functions tailored for time-series data. Conventional loss functions used in model training, such as Mean Squared Error (MSE) and Mean Absolute Error (MAE), prioritize point-wise accuracy without adequately considering the temporal alignment of predictions. This limitation is particularly problematic for energy market forecasting, where accurate prediction of trend changes and extreme values is crucial for effective bidding strategies. To address this shortcoming, The DILATE (DIstortion Loss including shApe and TimE) loss function, proposed by Le Guen and Thome [11], represents an advancement in this direction. By decomposing the loss into shape and temporal terms, DILATE encourages predictions that preserve both the magnitude and timing of significant pattern changes. Therefore, the integration of DILATE within deep neural networks demonstrates improved performance in modeling non-stationary signals and predicting multiple future time steps. However, it still exhibited notable weaknesses in accurately capturing critical signal features such as peaks and valleys, values that are particularly important for energy aggregators when formulating market bids.

In the context of SMP forecasting, achieving satisfactory prediction involves more than simply minimizing standard error metrics. The accurate capture of temporal dynamics and structural patterns within the SMP trajectory is essential for optimizing electricity market trading strategies. Time-series forecasting challenges temporal misalignment such as time offset and time warping, as illustrated in Figure 3, can significantly degrade the quality of strategy formulation and must therefore be explicitly addressed. Building on this motivation, we propose a hybrid approach that integrates the lightweight yet highly effective LTSF-Linear model with a custom-designed loss function, AsymLoss. This asymmetric objective combines DTW-based temporal alignment penalties with mechanisms that emphasize structural reliability. Specifically, AsymLoss penalizes large prediction errors more heavily in a temporally aware manner, reinforces directional consistency by aligning the gradient signs of predictions and targets, and highlights critical points such as SMP peaks and valleys to preserve key structural patterns in the time series. This integrated approach shows promise in handling non-linear and volatile time-series forecasting challenges such as characteristic of electricity markets.

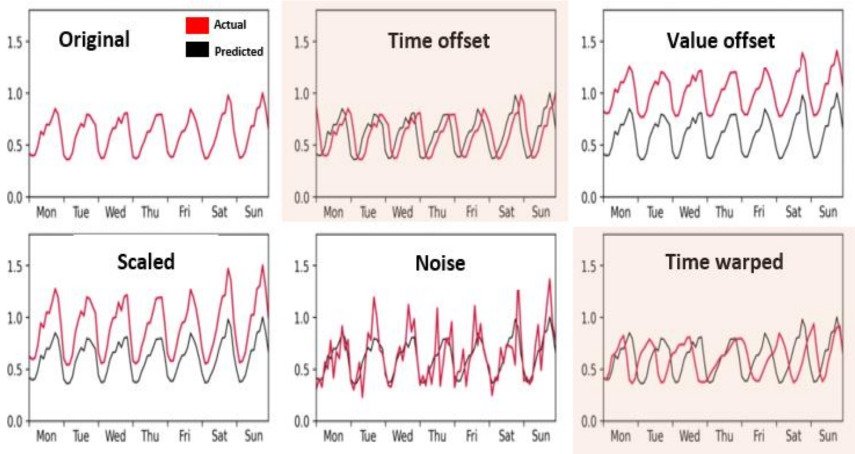

Figure 3. Time-Series Forecasting Error Types

3 Methodology

3.1 Time-Series Analysis

Time Series Prediction Models use k historical data points y(i,t-k:t) at time t, along with exogenous variables, x(i,t-k:t) and static metadata si (e.g., SMP classification: mainland, Jeju) to derive the predicted value, $\hat{y}$(i,t+n) along n, the forecast horizon as shown in (Eq.1). Based on the usage of exogenous variables, these models are classified into univariate and multivariate time series, while they are further categorized as single-step or multi-step predictions depending on the size, n, of the prediction horizon.

$$\widehat{y_{i,t+n}} = f(y_{i,t-k:t}, x_{i,t-k:t}, s_i, n) \qquad (1)$$

In this study, for simplicity, we adopted a univariate multi-step forecasting approach using only historical SMP (System Marginal Price) values. A look-back window of 7 days (k=168 hours) was used as input, and the forecasting horizon was set to 24 hours (n=24 hours) to support next-day bidding decisions. The model was designed to generate forecasts with an hourly stride, producing updated predictions every hour.

3.2 Datasets

The SMP data analyzed in this study were acquired from the Korea Power Exchange (KPX) [13]. Recordings spanning from January 1, 2021, to December 31, 2023, at a frequency of every hour, resulting in a total of 26,280 data samples. As shown in Fig. 3, we utilized three years (2021-2023) of Jeju Island SMP data. This testbed was chosen for its dynamic SMP fluctuations due to high reliance on renewable energy. The model was trained using data from 2021-2022, and its performance was validated by predicting the entire period of 2023.

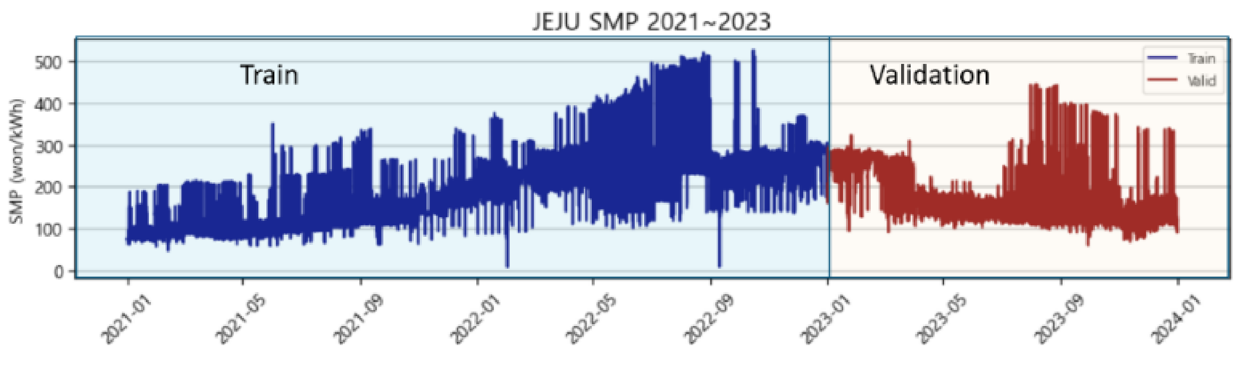

Figure 4. Jeju Island SMP 2021 – 2023 Data

Comprehensive statistical analyses were conducted to examine the characteristics of the SMP data and determine the selection of appropriate forecasting models and loss functions. In this analysis, we utilize price returns, defined as Returns = SMP(t) - SMP(t-1), which are commonly preferred in time-series analysis as they facilitate the identification of patterns in price movements and volatility. Furthermore, the following statistical measures were utilized to analyze the data: standard deviation to quantify the dataset's variability and dispersion, skewness to measure distributional asymmetry, and kurtosis to evaluate the heaviness of the distribution tails. The metrics reveal significant deviations from normal distribution characteristics, as illustrated in Figure 5. The distribution exhibits a slight positive skewness (0.1023) and extremely high kurtosis (23.0798), far exceeding the kurtosis value of 3.0 typically associated with normal distributions. This high kurtosis indicates a fat-tailed distribution, meaning extreme price movements occur more frequently than would be expected under normal distribution assumptions. Furthermore, the standard deviation of 11.7498 demonstrates considerable price volatility in the market. These statistical characteristics provide compelling evidence for the necessity of an asymmetric approach to SMP forecasting, as conventional symmetric loss functions would prove inadequate in capturing these distinctive distributional properties and asymmetric risk patterns.

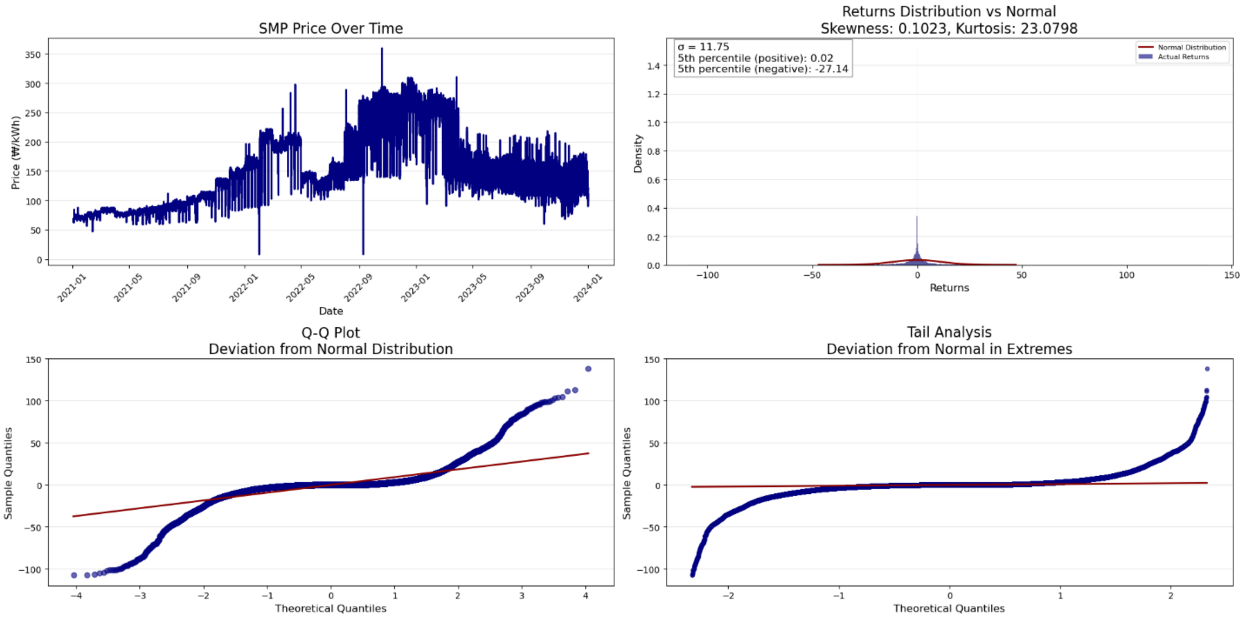

Figure 5. Statistical Plots of SMP

3.3 LTSF-Linear Model

Our study employed the LTSF-Linear model [1], which exhibited notably strong performance in multi-step time-series forecasting tasks when compared to more complex transformer-based architectures, while maintaining architectural simplicity. The LTSF-Linear model challenges the conventional assumption that complex architectures such as deep recurrent networks or attention-based Transformers are necessary to achieve high forecasting accuracy.

The core idea behind LTSF-Linear is simple: it replaces heavy architectural components with a single linear layer that directly maps historical input sequences to future predictions. Despite this simplicity, the model performs competitively, and often outperforms more sophisticated alternatives, particularly in multistep forecasting tasks. This is achieved through its direct modeling of temporal dependencies using a learned projection matrix that transforms input sequences of shape $[B, C, T_{in}]$ into output sequences of shape $[B, C, T_{out}]$ where:

- B represents the batch size which indicates how many sequences are trained at once.
- C denotes the number of channels. (i.e. the number of variables. For univariate forecasting C = 1)
- T_{in} is the length of the input window.
- T_{out} is the length of the forecast horizon.

For each batch, the model learns a set of linear weights that operate independently on each channel to map the temporal information from T_{in}, in this case past 168 hours of SMP values, to T_{out}, in this case next 24 hours SMP predictions.

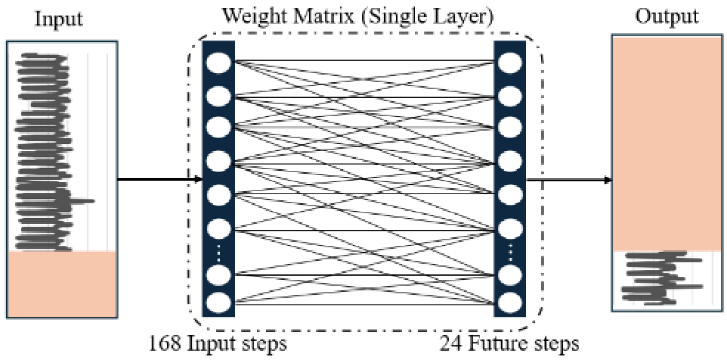

Figure 6. Illustration of the LTSF-Linear Model

As illustrated in Figure 5, the LTSF-Linear model essentially applies a channel-independent linear transformation over the time dimension, capturing temporal patterns through weight matrices trained to estimate future values based on past trends. This structure is not only computationally efficient but also less prone to overfitting due to fewer parameters than conventional deep learning models, making it particularly well-suited for practical forecasting scenarios with limited data or high volatility, such as the electricity market.

3.4 AsymLoss Function

While the LTSF-Linear model demonstrates strong performance in long-term forecasting tasks, it is commonly paired with conventional loss functions such as Mean Squared Error (MSE). MSE minimizes the squared differences between predicted and true values, placing greater emphasis on larger errors, whereas MAE computes the average of absolute differences, treating all errors equally regardless of magnitude, making it effective for optimizing point-wise accuracy. However, both do not account for temporal alignment or directional consistency, often leading to forecasts that fail to preserve important structural patterns in the time series, such as trend shifts or peak positions.

To address limitations in traditional loss functions and construct a shape-preserving loss function to enhance directional accuracy in time series forecasting, we introduce Asymmetric Loss (AsymLoss), a custom designed loss function which combines three key components for robust temporal pattern matching. The structure of AsymLoss is composed of 3 different components: Temporal Dynamic Time Warping (DTW) component, directional component and peak-valley component, as illustrated in Fig 5.

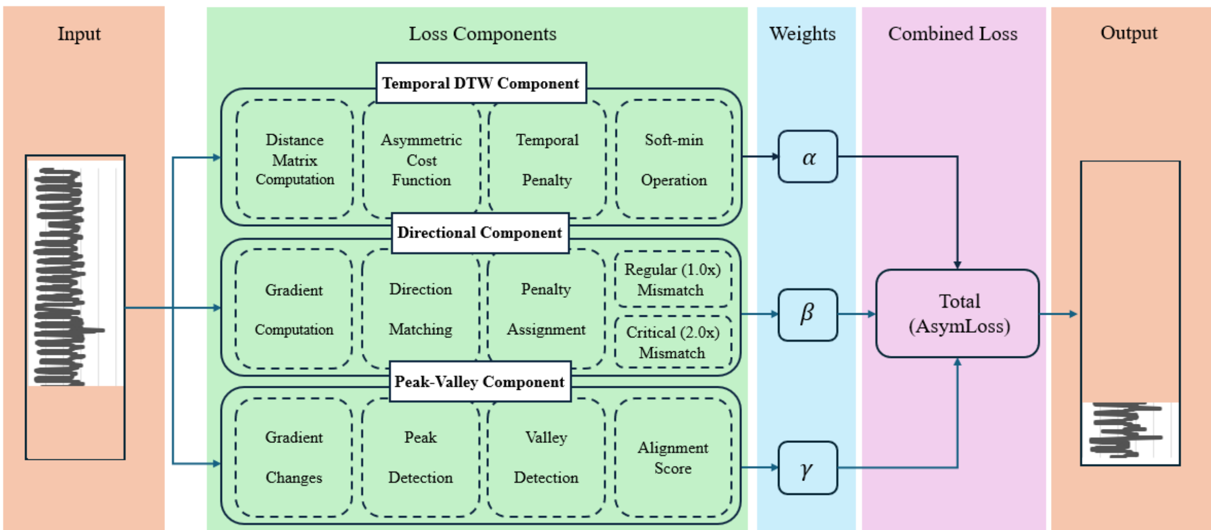

Figure 7. Illustration of the AsymLoss Structure

3.4.1 Temporal DTW Component

Dynamic Time Warping (DTW) is an algorithm that measures similarity between two temporal sequences by finding the optimal alignment between them. Traditional DTW treats all differences equally. Unlike traditional DTW, the temporal DTW component incorporates asymmetric alignment costs with temporal coherence. Given input sequences $X = \{x_1, ..., x_n\}$ and target sequence $Y = \{y_1, ..., y_m\}$, the distance matrix D is computed using an asymmetric cost function (2).

$$D(i,j) = \left(x_i - y_j\right)^2 \cdot f_{asym}(i,j) \quad (2)$$

$$where \quad f_{asym}(i,j) = 1 + \max\left(0, y_j - mean(Y)\right) * (1 + \max\left(0, -\left(x_i - y_j\right)\right) \quad (3)$$

The first term applies an adaptive penalty proportional to the magnitude of target values, ensuring greater emphasis on significant observations and the second term adds extra penalty for underestimation. To maintain temporal consistency within the alignment, a temporal penalty term is incorporated:

$$\tau(i,j) = w|i - j| \quad (4)$$

where w denotes the temporal weight coefficient and $|i - j|$ represents the temporal distance between indices in the respective sequences. This constraint discourages excessive warping that would violate the inherent temporal structure of the data. The optimal alignment is computed using soft-DTW recursion (5):

$$R(i,j) = D(i,j) + \min_\gamma(\mathrm{R(i-1,j-1), R(i-1,j), R(i,j-1)} \quad (5)$$

where $\min_\gamma$ represents a smoothed minimum operation controlled by parameter γ (6).

$$\min_\gamma(a_1, \ldots, a_n) = -\gamma log(\sum_{i=1}^{n} \exp\left(-\frac{a_i}{\gamma}\right) \quad (6)$$

As γ approaches 0, the operation approaches a regular minimum, while larger γ values produce a smoother approximation. The resultant soft-DTW distance provides a differentiable measure of temporal alignment quality that accounts for both value differences and temporal distortion, thereby enhancing capacity of the model to preserve structural patterns in forecasted sequences.

3.4.2 Directional Component

The directional component of AsymLoss addresses a fundamental limitation in conventional error metrics by explicitly quantifying trend alignment between predicted and target sequences. This component is designed to penalize directional inconsistencies that may persist even when point-wise error metrics indicate satisfactory performance. Initially, for each time step t, two gradients are computed: $\nabla x_t = x_{t+1} - x_t$ for predicted sequence gradient and $\nabla y_t = y_{t+1} - y_t$ for target sequence gradient. Direction matching is evaluated through two binary indicators: a general mismatch indicator and a critical error indicator. I_(mismatch(t)) = 1 if $\mathrm{sign}(\nabla x_t) \neq \mathrm{sign}(\nabla y_t)$ which is 1 when the gradients have opposite signs. A critical error indicator, I_(critical(t)), equals 1 when the model predicts a decrease while the target increases (1 if $\nabla y_t > 0$ and $\nabla x_t < 0$). The directional penalty combines both indicators with different weights: P_(dir(t)) = I_(mismatch(t))+ 2·I_(critical(t)). To account for the varying significance of directional errors based on the magnitude of target movements, we employ a local importance weight:

$$\mathrm{w(t)} = \frac{|\nabla y_t|}{mean(|\nabla y|} \quad (7)$$

This weighting scheme ensures that deviations during sharp transitions are penalized more heavily than those in flat regions. The final directional loss is then computed as the summation of the weighted directional penalties across the entire sequence:

$$L_{dir} = \sum_{t=1}^{T-1} w(t) \cdot P_{dir}(\mathrm{t}) \quad (8)$$

where T represents the sequence length. This formulation effectively captures the directional patterns in time series data, providing a complementary optimization objective to the temporal alignment component.

3.4.3 Peak-Valley Component

The peak-valley component is designed to enhance the model sensitivity in time series data, specifically turning points such as local maxima (peaks) and minima (valleys). To explicitly penalize misalignment of these turning points, this component first identifies peaks and valleys in both the predicted and target sequences by analyzing the directional change of consecutive gradients. Peak and valley features are detected using gradient sign changes:

$$\mathrm{peaks(t)} = \max\left(0, \nabla \mathrm{x_t} \cdot (-\nabla \mathrm{x_t}^{+1})\right) \quad (9)$$

$$valleys(t) = \max\left(0, (-\nabla \mathrm{x_t}) \cdot \nabla \mathrm{x_t}^{+1}\right) \quad (10)$$

Consequently, the alignment score between detected features are computed as:

$$L_{peak-valley} = \mathrm{mean}\left(\left|peaks_x - peaks_y\right|\right) + \mathrm{mean}\left(\left|valleys_x - valleys_y\right|\right) \quad (11)$$

where $peaks_x$, $peaks_y$, $valleys_x$ and $valleys_y$ represent the detected peaks and valleys in predicted and target sequences respectively. By incorporating this feature, the component explicitly encourages the model to preserve crucial structural characteristics of the time series, ensuring more interpretable and contextually meaningful forecasts. This is particularly advantageous in applications where the timing and magnitude of turning points are of high operational or economic importance, such as SMP bidding case.

3.4.4 Final Loss

The final AsymLoss combines the above three components with weighted contributions. Each component addresses a distinct aspect of temporal prediction quality: structural alignment, trend consistency, and pattern sensitivity, respectively. The combined loss is expressed as a weighted sum of the individual components:

$$L_{Asym} = \alpha \cdot L_{DTW} + \beta \cdot L_{dir} + \gamma \cdot L_{peak-valley} \quad (12)$$

The hyperparameters, α, β and γ control the relative influence of each component and are selected based on the volatility regime of the target domain. To maintain consistent performance across SMP market, two distinct hyperparameter sets are implemented: $\alpha = 0.8$, $\beta = 0.14$, $\gamma = 0.06$, placing greater emphasis on global temporal alignment for stable periods and $\alpha = 0.6$, $\beta = 0.28$, $\gamma = 0.12$, enhanced sensitivity to directional trends and structure inflections for volatile periods. To seamlessly adapt across varying temporal dynamics, a volatility-aware ensemble weighting mechanism is introduced. This approach allows the model to interpolate between stable and volatile configurations based on real-time market variability, enhancing flexibility and generalization across fluctuating regimes.

4 Simulation Results

To evaluate the effectiveness of the proposed LTSF-Linear model and asymmetric loss (AsymLoss) in sequence forecasting, extensive experiments were conducted comparing multiple time-series state-of-the-art models using diverse loss combinations. The experiments were designed to assess both prediction accuracy and the ability to capture essential structural dynamics of SMP.

4.1 Experimental Setup

We compared five distinct model-loss combinations to isolate the effects of both architectural choices and loss function designs. These include: (1) gated recurrent unit architecture (GRU) with the standard mean squared error (MSE), serving as the baseline with a conventional recurrent architecture and standard loss, (2) LTSF-Linear model with MSE, allowing us to isolate the effect of model architecture using the same conventional loss, (3) LTSF-Linear with DILATE loss function, introducing a shape-aware loss for comparison with AsymLoss, (4) GRU + AsymLoss, allowing us to isolate the effectiveness of AsymLoss, and finally our primary interest, (5) LTSF-Linear with AsymLoss configuration to evaluate the synergistic effect.

For all experiments, we maintained consistent hyperparameter settings across all model-loss combinations to ensure fair comparison. The number of epochs was set to 30, a choice driven by practical application requirements that constrained training and inference to complete within an hour. All models were trained with a batch size of 32 and a learning rate of 0.001, using the Adam optimizer with default beta parameters

For the evaluation, we employed multiple evaluation criteria to provide a comprehensive performance assessment. Mean Absolute Percentage Error (MAPE) was used to measure relative prediction error. Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) were utilized to quantify absolute error with higher penalties for larger deviations. Additionally, Dynamic Time Warping (DTW) was applied to capture temporal alignment between predicted and actual sequences. A lower DTW value indicates a closer alignment and higher structural similarity between predicted and actual sequences, while a higher DTW value reflects poorer alignment and greater temporal distortion

4.2 Comparative Analysis

A comprehensive evaluation using one year of SMP data was conducted and Table 1 summarizes the quantitative performance metrics across all model-loss combinations. The baseline (1) GRU + MSE model demonstrated moderate performance with MAPE of 8.76% and MSE of 341.30, representing conventional approaches in time series forecasting. When comparing architectures with the same loss function, the (2) LTSF-Linear + MSE outperformed the (1) GRU + MSE configuration across all error metrics, indicating the inherent advantage of the linear transformer architecture for SMP forecasting tasks. While the (3) LTSF-Linear + DILATE configuration achieved improved accuracy in terms of MAPE and MSE (compared to standard loss functions, it registered the highest DTW value among all tested models. This suggests that despite its shape-aware design, DILATE loss struggled to capture temporal alignment effectively in SMP forecasting applications.

The effect of the AsymLoss function is evident when comparing models with the same architecture but different loss functions. (4) GRU + AsymLoss showed notable improvement over (1) GRU + MSE, particularly in DTW, demonstrating AsymLoss effectiveness in enhancing temporal alignment even in recurrent architectures. Especially the (5) LTSF-Linear + AsymLoss configuration achieved the highest performance across all metrics and the remarkable reduction in DTW (58.6% lower than the DILATE configuration) highlights the exceptional capability of our proposed approach in maintaining structural and temporal fidelity in SMP predictions.

Table 1: Performance Comparison of Model-Loss Combinations

Model-Loss Combination	MAPE (%)	MSE	RMSE	DTW
(1) GRU + MSE	8.76	341.30	18.47	94477.87
(2) LTSF-Linear + MSE	7.63	230.71	15.19	104219.33
(3) LTSF-Linear + DILATE	6.44	202.47	14.23	110075.08
(4) GRU + AsymLoss	8.04	304.68	17.46	73681.83
(5) LTSF-Linear + AsymLoss	**5.07 ▲**	**146.71 ▲**	**12.11 ▲**	**43162.98 ▲**

To validate practical utility, forecasted SMP values from models were implemented in the real-world market conditions. While optimal EV scheduling typically involves complex algorithms with numerous variables, a simplified bidding strategy is applied in this experiment: EVs charge when SMP is at or below the 30% and discharge when SMP reaches or exceeds the 80% of daily SMP prices (13, 14). Constant power rate was assumed acroos all time periods. A volatile test case was selected from the dataset and it is characterized by large variance and significant differences between local peaks and valleys, a pattern commonly associated with inaccurate charge-discharge decisions due to misaligned or poorly predicted SMP trajectories. Such conditions emphasize the importance of directional accuracy and peak-valley alignment in real-time applications.

$$Charge\ at\ time\ t\ SMP_t \leq\ Price_{30}\ for\ t = 0{,}1 \ldots, 23 \quad (13)$$

$$Discharge\ at\ time\ t\ SMP_t \geq\ Price_{80}\ for\ t = 0{,}1 \ldots, 23 \quad (14)$$

Figure 7 illustrates the forecasted SMP trajectories for each model-loss configuration alongside the actual market data, offering a qualitative comparison of predictive fidelity under a volatile scenario. The baseline model, (1) GRU + MSE, fails to effectively capture temporal dynamics, resulting in misaligned trends and inaccurate peak timings that directly lead to wrong charge-discharge decisions. In contrast, (LTSF-Linear models combined with both (2) MSE and (3) DILATE demonstrate improved temporal structure recognition. However, they still exhibit notable misalignment around local extrema and inaccurately detect trend reversals, which compromises decision reliability. The (4) GRU + AsymLoss configuration successfully identifies directional changes, yet the predicted variances diverge significantly from actual values, reducing their reliability for real-time strategies. Notably, the proposed (5) LTSF-Linear + AsymLoss model exhibits superior ability in capturing overall trend structures, key inflection points, and directional shifts. Although certain sudden changes remain partially over or underestimated, this configuration achieves the best balance between structural consistency and temporal precision.

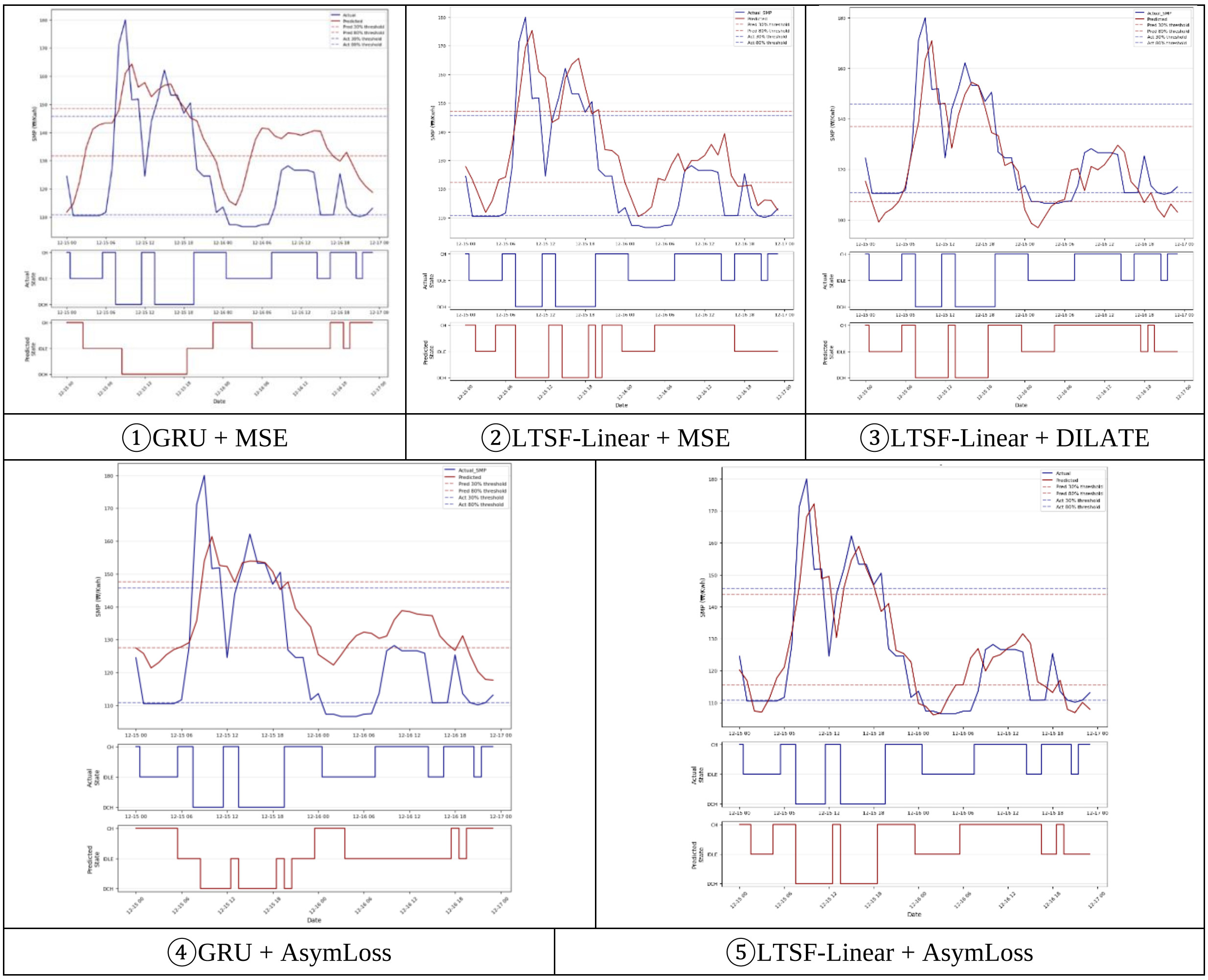

Figure 8. Forecasted SMP for Each Model-Loss Configuration Compared to Actual Market Prices

Table 2 presents the resulting charge and discharge SMP prices derived from forecasted outputs of each model under the rule-based strategy. While all models managed to produce at least one reasonably aligned charging or discharging price, most exhibited imbalances or inconsistencies that limit their reliability for practical application. Notably, with the exception of the (3) LTSF-Linear + DILATE configuration, one of the predicted SMP values deviated by more than 10% from the actual values, raising concerns about their real-time applicability. In contrast, the proposed (5) LTSF-Linear + AsymLoss model demonstrated closer alignment with actual SMP prices, providing a economical benefit. These results reinforce the practical value of the model in V2G market operations, where accuracy directly impacts profitability.

Table 2: Determined SMP Price for Each Model-Loss Configuration

		① GRU + MSE	② LTSF-Linear + MSE	③ LTSF-Linear + DILATE	④ GRU + AsymLoss	⑤ LTSF-Linear + AsymLoss
Actual SMP Price (₩/kWh)	CH	**110.74**				
	DCH	**145.65**				
Forecasted SMP Price (₩/kWh)	CH	131.59 (+19%)	122.28 (+10%)	**107.19 (-3%)**	127.48 (+15%)	**115.45 (+4%) ▲**
	DCH	**148.55 (+2%)**	**147.16 (+1%)**	136.98 (-6%)	**147.52 (+1%)**	**143.91 (+1%) ▲**

5 Conclusion

As renewable energy adoption increases to reduce greenhouse gas emissions, maintaining real-time balance between electricity supply and demand has become increasingly challenging. Electric vehicles, through vehicle-to-grid technology, offer a promising solution by providing flexible, distributed energy resources capable of dynamic market participation.

Our LTSF-Linear model with AsymLoss function outperformed conventional approaches, particularly during volatile market periods. By accurately capturing directional changes and predicting turning points, the model delivers substantial economic benefits for EV scheduling strategies, demonstrating its practical utility for V2G implementation in dynamic electricity markets.

This work supports ongoing national efforts in advanced energy demand management, including participation in the “2024 First Energy Technology Development Program” led by the Korea Institute of Energy Technology Evaluation and Planning (KETEP). The developed SMP forecasting model will serve in real-world V2G markets to determine optimal bidding prices for thousands of EVs, positioning our approach as a core technology for energy demand management.

Future work will focus on developing lightweight versions of the loss function for more practical applications and incorporating additional exogenous variables to enhance forecasting accuracy. Through these continued efforts, we aim to advance V2G implementation and contribute to the sustainable integration of renewable energy resources into power systems.

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Presenter Biography

Jaeyun Jung received his Bachelor's degree in Mechanical Engineering from The University of Auckland in 2018 and began the professional career at Hyundai Motors Company at the same year. His initial work focused on the advanced HEV/EV system development, and he currently specializes in optimizing V2X scheduling algorithms and developing V2G-related forecasting models through machine learning and deep learning methodologies.