

# Multi-Output Forecasting of Electricity and Gas Fees: A Comparative Study of Deep Learning and Statistical Models

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**Abstract**—Forecasting energy consumption with high accuracy is crucial for effective resource planning and policy decision-making. This study presents a hybrid approach that combines statistical and deep learning models to predict both gas and electricity consumption over an 18-month period. The proposed model integrates GRU, LSTM, VAR, and DFM techniques to improve multi-output time series forecasting. The evaluation is conducted using three widely-used error metrics: RMSE, MAE, and MAPE. Experimental results show that the presented hybrid model outperforms some individual models in predicting electricity consumption and provides competitive accuracy for natural gas forecasting. These findings demonstrate the potential of model fusion strategies in enhancing utility usage prediction for long-term energy management and budgeting.

**Index Terms**—Natural gas, Electricity, Multi-output time series forecasting, Forecasting models, Comparative evaluation, Deep learning, Statistical modeling.

## I. INTRODUCTION

In recent years, the accurate forecasting of utility usage fees has become increasingly important for both consumers and utility providers, particularly in the context of energy pricing, policy planning, and sustainable resource management. Among various utility services, electricity and natural gas represent two of the most critical and widely consumed energy sources worldwide. Their usage patterns are influenced by numerous factors including seasonal variations, economic activity, and consumer behavior. Therefore, developing robust forecasting models that can simultaneously predict multiple energy-related financial metrics—such as electricity and gas usage fees—offers significant practical value for budgeting, load balancing, and strategic planning [1], [2].

Time series forecasting techniques have been widely applied to energy consumption and pricing data. Traditional statistical

models, such as Support Vector Machine (SVM), Polynomial Regression (PR), Auto-regressive Integrated Moving Average (ARIMA) and Seasonal Auto-regressive Integrated Moving Average (SARIMA), have been extensively used due to their interpretability and strong theoretical foundations. However, these models are often limited in capturing non-linear relationships and dynamic temporal dependencies, especially in multi-output scenarios.

With the advent of deep learning, models like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) have shown superior performance in modeling complex sequential data. These models are capable of learning intricate temporal patterns and dependencies, making them well-suited for energy forecasting tasks where data is high-dimensional, seasonally affected, and correlated across multiple variables [3]–[5].

This study presents a comparative analysis of deep learning and statistical models for multi-output time series forecasting, focusing on the prediction of electricity and natural gas usage fees in South Korea from March 2018 to June 2025. We evaluate the forecasting performance of two deep learning models LSTM and GRU and two statistical models Vector Auto-regression (VAR) and Dynamic Factor Model (DFM), using historical fee data of electricity and gas in South Korean Won (KRW), and applying a common set of evaluation metrics including Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The key contributions of this paper summarized as follows:

- 1) We have structured multi-output forecasting framework for utility usage fees using two well-known deep learning and two well-known statistical models.
- 2) A performance comparison of deep learning and statistical models using real-world data were conducted through well-known evaluation metrics.

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- 3) The findings offer insights into the effectiveness of different prediction models for multi-target forecasting applications in energy finance.

The remainder of this paper is organized as follows: Section 2 reviews related work. Section 3 describes the methodology and the dataset used. Section 4 presents the experimental setup and results. Finally, Section 5 concludes the paper with key insights and future directions.

## II. RELATED WORKS

Several works have been conducted in the past on natural gas demand prediction [6], [7]. Wu et al. (2024) proposed a hybrid model combining autoregressive recurrent neural networks with Markov Chain Monte Carlo (MCMC) for probabilistic forecasting of natural gas consumption [8]. Their method generates both point forecasts and confidence intervals, improving accuracy by 5.87% over state-of-the-art baselines. Though focused on gas consumption, the integration of deep learning with probabilistic inference offers valuable insight for broader applications, including residential energy bill prediction.

Aliyuda Ali et al. (2021) developed a deep neural network (DNN) model for monthly natural gas price prediction, leveraging fully connected layers and ReLU activation to capture temporal dynamics [9]. Trained on 281 months of data, their DNN significantly outperformed five mainstream machine learning models, achieving an  $R^2$  of 0.9937. This demonstrates the strong potential of deep learning in energy forecasting tasks relevant to commodity pricing and resource planning — a foundation applicable to residential energy consumption prediction as well.

Rahman et al. (2023) proposed a hybrid VMD-LSTM deep learning model for day-ahead electricity price forecasting in the U.S. energy market [10]. Their work addressed common limitations in previous studies by clearly specifying input features, incorporating renewable energy variables such as temperature and wind speed, and emphasizing data preparation and normalization. Using data from the MISO market, their model achieved a low mean absolute error (0.3107), demonstrating strong predictive accuracy and setting a benchmark for incorporating renewable energy factors in electricity price forecasting.

Ding et al. 2024 developed a deep learning framework tailored for green electricity price forecasting by explicitly incorporating environmental value attributes of electricity [11]. To handle the complexity of price formation in the emerging green electricity market, they introduced a quantification index for environmental value and applied the Whale Optimization Algorithm (WOA) to optimize LSTM network parameters. Their model, validated on data from North China's green electricity market, achieved 91.7% prediction accuracy, demonstrating the effectiveness of including sustainability-related factors in electricity price modeling.

## III. METHODOLOGY

In this study, we utilised natural gas and electricity consumption data of a tenant, which were collected from two South Korean energy providers: Daesung Energy [12], and the Korea Electric Power Corporation (KEPCO) [13]. The dataset spans approximately 88 months (equivalent to 7 years and 4 months). Following data collection, we performed a comprehensive preprocessing stage to transform the raw, real-world time-series data into a clean, scaled, and model-ready format. This step was essential to ensure that each forecasting algorithm—whether deep learning-based or statistical—could operate effectively and contribute meaningfully to the proposed hybrid forecasting approach.

The primary objective of this study is to propose a hybrid forecasting pipeline that achieves higher accuracy and faster performance compared to existing multi-output forecasting models, including well-established deep learning techniques such as GRU and LSTM, and robust statistical approaches such as VAR and DFM. Notably, we aim for the proposed hybrid model to perform at least comparably to these individual models, even in scenarios where one type (e.g., deep learning or statistical) may underperform.

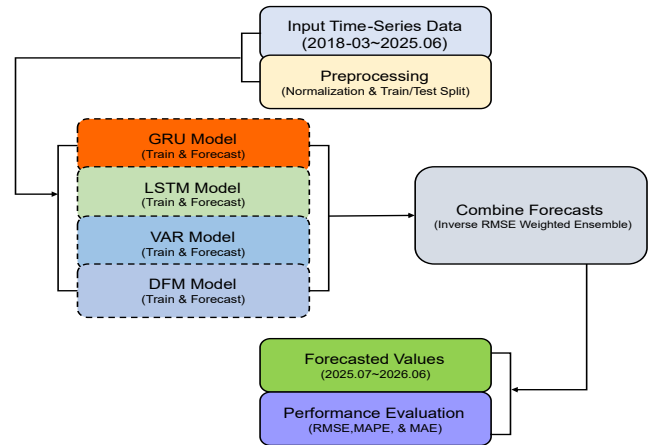


Fig. 1. Proposed hybrid time-series forecasting pipeline.

Furthermore, we seek to analyse how much energy—natural gas or electricity—is consumed monthly by foreign tenants, identify which energy type is more frequently used, and explore potential reasons behind this pattern. To accomplish this, we employed four well-known forecasting models: GRU, LSTM, VAR, and DFM. The two deep learning models were selected for their effectiveness in multi-output forecasting, while the two statistical models were chosen for their accuracy and widespread application in similar tasks.

Finally, we implemented a multi-output forecasting framework that integrates these four models and compares their predicted outputs against the actual data. The prediction data span from January 2024 to June 2025, covering a period of 18 months (or 1 year and 6 months). In total, we compared the performance of five models, including our proposed hybrid forecasting approach. To assess prediction accuracy, we

employed three widely recognized evaluation metrics: RMSE, MAE, and MAPE. After model training, each approach independently forecasts a 12-month horizon (from July 2025 to June 2026). Our aim in predicting the next 12-month is to evaluate how well the proposed hybrid model preserves temporal dynamics and demonstrates generalization ability. To construct the final hybrid forecast, we adopt an ensemble weighting strategy based on the inverse RMSE evaluated over the final 12 months of the training period. The weight assigned to each model  $i$  is computed as:

$$\text{Weight}_i = \frac{1}{\text{RMSE}_i} \quad (1)$$

The weights are normalized to sum to one. The hybrid forecast at each time step  $t$  is then derived through a weighted combination of individual model predictions as follows:

$$\text{Hybrid}_t = w_1 \cdot \text{GRU}_t + w_2 \cdot \text{LSTM}_t + w_3 \cdot \text{VAR}_t + w_4 \cdot \text{DFM}_t \quad (2)$$

This ensemble method enables the hybrid model to leverage the unique strengths of both data-driven and statistical paradigms, yielding more stable and accurate multi-output predictions across the forecast span. Figure 1 illustrates the proposed hybrid time-series forecasting pipeline.

#### IV. RESULTS

This section presents the experimental results of the proposed hybrid time-series forecasting approach for gas and electricity consumption. The evaluation is conducted using three widely used error metrics: RMSE, MAE, and MAPE. The results are reported for five forecasting models—GRU, LSTM, VAR, DFM, and a hybrid approach—applied to both gas and electricity datasets. The performance of each model is compared in terms of predictive accuracy.

The accurate prediction of multiple output variables is essential, particularly when dealing with time-series data. To achieve reliable forecasts, it is beneficial to employ multiple well-established models, whether statistical or deep learning-based. In our case, the proposed hybrid approach, while visually appearing less aligned with the actual data, demonstrates competitive performance in terms of error metrics compared to other models used in this study.

Figure 2, subplot a. shows the complete time series of gas and electricity consumption over 88 months, ranging from March 2018 to June 2025. The X-axis represents the timeline, while the Y-axis indicates the energy expenditure in KRW. Notably, the prediction period spans from January 2024 to June 2025 — a total of 18 months. Our primary objective is to compare the predicted values against the actual observed data. From the line plot, it can be observed that gas utility bills increase between November 2024 and April 2025, followed by a slight decrease in May and June. On the other hand, electricity bills exhibit relatively small fluctuations between January 2024 and February 2025, with alternating increases and decreases. However, beginning in February 2025, the predicted electricity costs show a sharp rise through June 2025

— which contradicts the actual trend. Figure 2, subplot b. provides a focused view of this prediction window (January 2024 to June 2025), highlighting that the predicted gas bill steadily increases to a significantly high level, extending even beyond the evaluation period up to January 2026.

Based on our investigation and the visualizations presented in Figure 3—specifically, subplots a. GRU model, b. LSTM model, c. VAR model, and d. DFM model—we observe that the energy user had higher electricity consumption from March 2018 to December 2022. However, there is a noticeable and continuous increase in gas usage beginning in January 2023 and continuing through January 2024. This observation aligns with the trend seen in Figure 2, b., where gas utilization exceeds electricity consumption. A potential explanation for this shift is the arrival of the user's family members to Korea in December 2022. This implies that foreign migrants accompanied by family members may prefer cooking at home rather than dining out, in order to reduce expenses associated with restaurant meals. Moreover, such households are more likely to use heating systems and hot water during the winter, further contributing to increased gas consumption. Finally, it is notable that the GRU and LSTM models predict a continued increase in gas usage until June 2025, which aligns closely with the actual trend. In contrast, the VAR and DFM models forecast an increase in electricity usage over the same period, diverging from the observed data.

##### A. Performance Evaluation

To assess the performance of our gas and electricity bill prediction models, we employed three widely used error evaluation metrics: RMSE, MAE, and MAPE. These metrics provide complementary perspectives on model accuracy. RMSE, defined as

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}, \quad (3)$$

quantifies the square root of the average squared differences between the actual ( $y_i$ ) and predicted ( $\hat{y}_i$ ) values. It is particularly sensitive to large deviations, thus emphasizing models' performance in handling outliers. MAE, given by

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|, \quad (4)$$

measures the average absolute error and is more robust to outliers, offering a balanced view of overall prediction accuracy. Lastly, MAPE, expressed as

$$\text{MAPE} = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right|, \quad (5)$$

evaluates the average percentage error relative to actual values, making it useful for comparing predictions across scales, though it becomes unstable when actual values are close to zero.

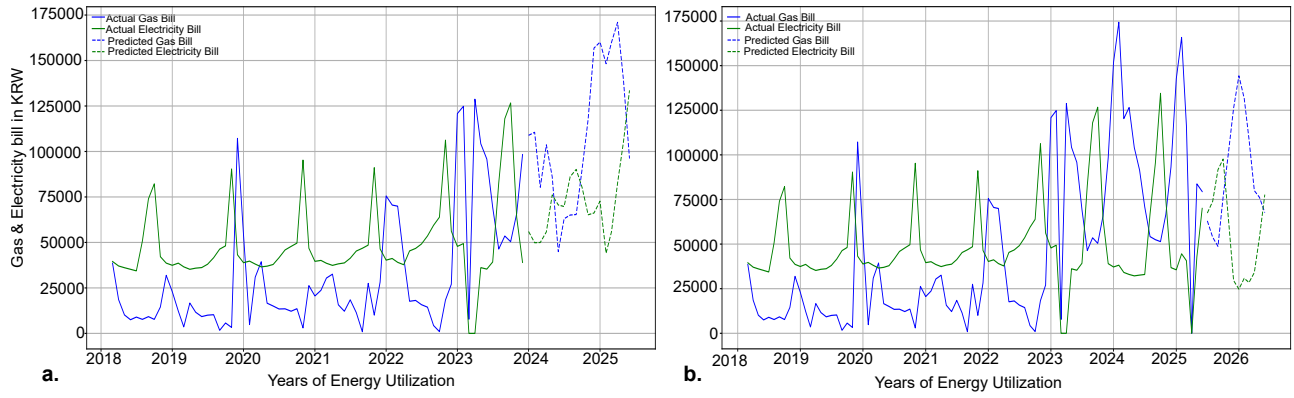


Fig. 2. Hybrid Model Forecasting of Energy Consumption: a. January 2024–June 2025; b. July 2025–June 2026.

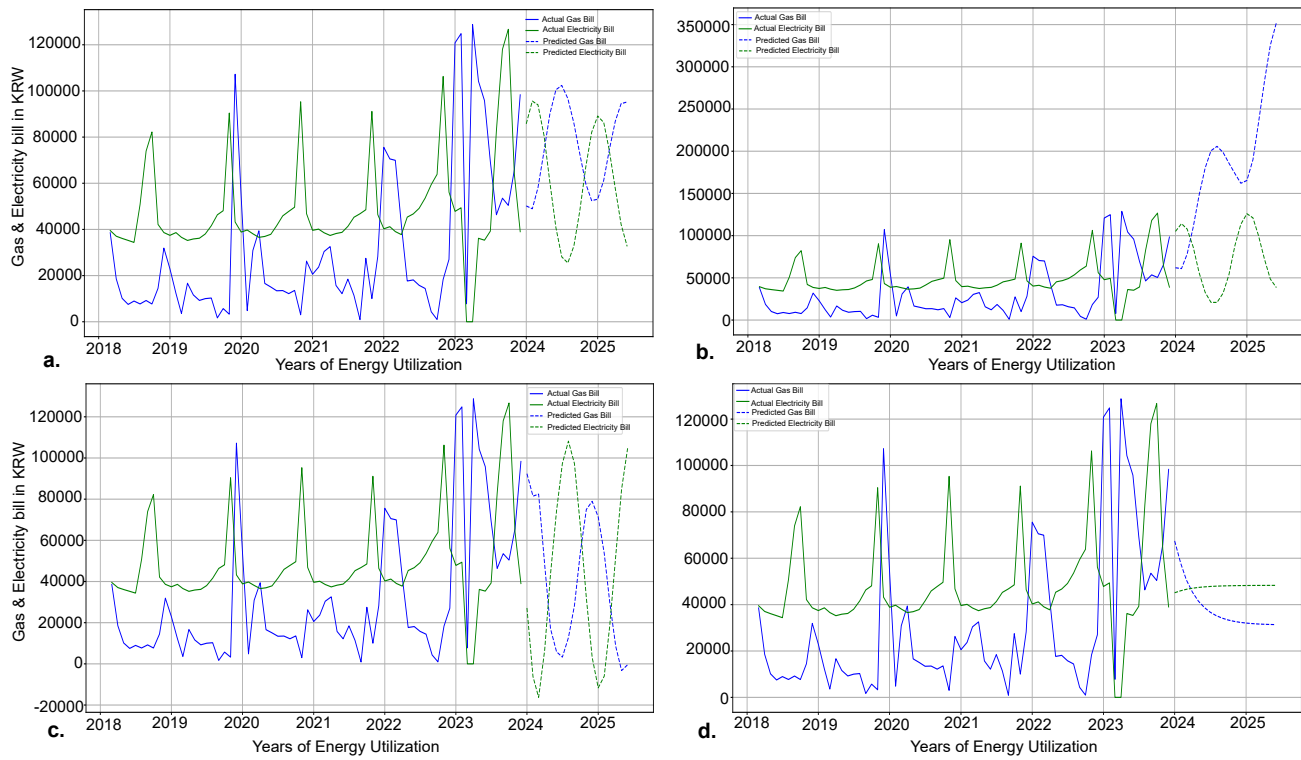


Fig. 3. Gas and Electricity Bill Prediction from January 2024 to June 2025 Using: a. GRU; b. LSTM; c. VAR; and d. DFM.

In our study, these metrics were calculated for each model—GRU, LSTM, VAR, DFM, and a Hybrid ensemble—across an 18-month forecast period for both gas and electricity usage. Notably, we visualized the total predicted gas and electricity values over the 18-month forecast period in KRW using a clustered bar chart, as shown in Figure 4, with subplot a. representing gas usage predictions and subplot b. for electricity usage predictions. On the X-axis, we highlight the total predicted values by the proposed and utilized models, while the Y-axis displays the list of prediction models. The

objective is to compare the cumulative forecasts of each model against the actual totals, providing insight into each model's overall predictive alignment with real-world trends. For gas predictions, the VAR, DFM, Hybrid, and LSTM models tend to overestimate the actual values, whereas the GRU model demonstrates predictions that are comparatively closer to the actual trend. In the case of electricity fee forecasting, most models produce results closely aligned with the actual values, with VAR and DFM showing particularly strong agreement. Meanwhile, GRU, LSTM, and Hybrid models also show

competitive performance. The performance evaluation results for both natural gas and electricity predictions are summarized in Table 1.

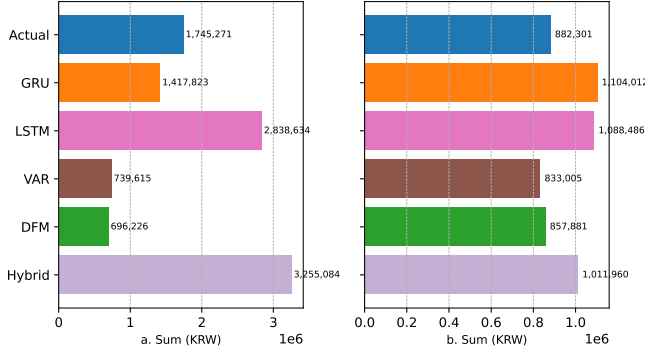


Fig. 4. Total predicted values (in KRW) across the 18-month forecast period by each model compared to actual trend., a. Total gas usage prediction; b. Total electricity prediction.

TABLE I  
EVALUATION METRICS FOR GAS AND ELECTRICITY FORECASTING

| Model  | Gas             |                 |                 | Electricity     |                 |                 |
|--------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|        | RMSE            | MAE             | MAPE            | RMSE            | MAE             | MAPE            |
| GRU    | <b>44110.15</b> | 48687.03        | 505606.44       | 48933.24        | 41221.10        | 310300.28       |
| LSTM   | 144066.74       | 117565.26       | 1474858.59      | 47214.18        | 40155.99        | 193356.51       |
| VAR    | 67042.57        | 58037.19        | <b>47237.39</b> | 59810.32        | 50548.78        | 291685.53       |
| DFM    | 70413.72        | 61784.36        | 175258.79       | 46009.21        | 39982.13        | 268290.25       |
| Hybrid | 163135.48       | <b>10338.94</b> | 201639.97       | <b>44110.15</b> | <b>38233.87</b> | <b>38664.41</b> |

Notably, for natural gas prediction, the RMSE values indicate that the Hybrid model exhibited the highest error, followed by LSTM, DFM, VAR, and GRU. This suggests that the GRU model achieved the lowest RMSE, and thus the best performance under this metric. When evaluating using the MAE, the ranking of model performance changed, with LSTM showing the highest error, followed by DFM, VAR, GRU, and finally the Hybrid model, which recorded the lowest MAE. Lastly, based on the MAPE, the models ranked from highest to lowest error as follows: LSTM, GRU, Hybrid, DFM, and VAR. Accordingly, the VAR model achieved the lowest MAPE, suggesting superior performance in proportional error estimation. These variations across metrics highlight the importance of using multiple evaluation criteria to obtain a comprehensive assessment of predictive accuracy. For electricity prediction, the RMSE results indicate that the Hybrid model achieved the lowest error. The remaining models, ranked from highest to lowest error, are DFM, LSTM, GRU, and VAR. Similarly, when evaluated using MAE, the Hybrid model again demonstrated the best performance with the lowest error, followed by DFM, LSTM, GRU, and VAR. However, when using MAPE for evaluation, the Hybrid model still recorded the lowest error, while the ranking of the remaining models slightly changed to LSTM, DFM, VAR, and GRU. These results further reinforce the consistency of the Hybrid model's performance across all three metrics for electricity usage prediction.

## V. CONCLUSION

In this study, we conducted a comprehensive comparative analysis of deep learning and statistical models for the multi-output time series forecasting of electricity and natural gas usage fees in South Korea. By leveraging real-world data spanning from March 2018 to June 2025, we evaluated the predictive capabilities of four models: LSTM and GRU as representative deep learning approaches, and VAR and DFM as statistical baselines. Additionally, the exploration of hybrid time-series pipeline could yield improved results by combining the strengths of both statistical and deep learning approaches. The results, measured using RMSE, MAE, and MAPE demonstrate that deep learning models are generally more effective in capturing the complex temporal dependencies and non-linear relationships inherent in utility fee data.

Our findings suggest that deep learning approaches hold significant promise for enhancing the accuracy and reliability of energy cost forecasting, especially in multi-target scenarios where multiple energy sources must be predicted concurrently. These insights are valuable not only for researchers and practitioners in the field of energy informatics but also for policymakers and utility companies aiming to improve planning, pricing strategies, and resource allocation.

For future work, we plan to develop a novel time-series forecasting algorithm tailored specifically for multi-output energy cost prediction. In addition, incorporating exogenous variables such as weather conditions, economic indicators, or consumer profiles may further enhance the robustness and accuracy of forecasting models.

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