Temporal Dependency Analysis in Short-Term Electricity Load Forecasting Using Ensemble Learning

Ilias Zhumagali[1], Meruyert Ramatullayeva[1]Symbat Amanzhol[1], Turlan Turkbenbayev[1] and Dmitry Kachan[2]
[1]*Almaty University of Power Engineering and Telecommunications named after Gumarbek Daukeyev, Baitursynov Str. 126/1, 050013 Almaty, Kazakhstan*
[2]*Mechanical Engineering and Industrial Engineering, Anhalt University of Applied Sciences, Bernburger Str. 55, 06366 Köthen, Germany*
ilias.zhumagali13@gmail.com, meruyert.ramatullayeva@gmail.com, aa.symbat03@gmail.com, turlanturkbenbaev2003@gmail.com, Dmitry.Kachan@hs-anhalt.de

Keywords: Electricity Load Forecasting, Time Series Analysis, Random Forest, Exogenous Weather Variables, Feature Importance, Short-Term Prediction.

Abstract: Accurate short-term electricity load forecasting is essential for reliable operation of modern power systems and smart grid infrastructures. This study investigates the temporal dependency structure of household electricity consumption using supervised machine learning techniques. The forecasting task is formulated as a regression problem based on lagged load values, calendar-related temporal features, and exogenous meteorological variables, including air temperature, relative humidity, precipitation, and wind speed. Linear Regression is employed as a benchmark model, while Random Forest is used as a nonlinear ensemble approach. Model performance is evaluated using Mean Absolute Error, Root Mean Square Error, and Mean Absolute Percentage Error under chronological train-test splitting in order to preserve temporal causality. In addition, lag-window sensitivity analysis, walk-forward validation, multi-step forecasting horizon analysis, and feature importance assessment are conducted. The Random Forest model with weather variables achieved the best one-hour-ahead forecasting performance, with MAE of 0.397, RMSE of 0.552, and MAPE of 54.27%. The results show that recent load history and daily periodicity remain the dominant predictors, while meteorological variables provide a limited but measurable contribution. The findings support the use of ensemble learning for short-term load forecasting analysis and highlight the need for further refinement when applying such models to highly volatile residential consumption patterns.

1 INTRODUCTION

Short-term electricity load forecasting plays an important role in modern power system operation, generation scheduling, demand-side management, and smart grid analytics [1], [2]. Reliable forecasts help system operators anticipate near-future demand, allocate reserves more efficiently, and reduce the risks associated with inaccurate balancing decisions. At the residential level, load forecasting is particularly challenging because household electricity consumption is affected by irregular user behavior, appliance usage patterns, daily routines, and seasonal variations.

Traditional forecasting approaches are commonly based on statistical methods such as autoregressive models and linear regression techniques [3], [4]. These methods are computationally efficient and interpretable; however, they may have limited ability to represent nonlinear relationships and complex temporal dependencies in highly variable residential load data. Machine learning methods have therefore received increasing attention as flexible data-driven alternatives for short-term forecasting tasks [5] - [8].

In electricity consumption analysis, historical load values are usually the primary source of predictive information because they reflect short-term inertia and recurring daily patterns. Nevertheless, external drivers may also influence demand behavior. Meteorological conditions, especially air temperature and humidity, can affect household electricity use through heating, cooling, and ventilation needs. For this reason, the present revised study does not rely exclusively on endogenous lag-based predictors, but also evaluates the contribution of exogenous weather variables to forecasting performance.

The objective of this work is to analyze the temporal dependency structure of household electricity demand and to evaluate the effectiveness of ensemble learning for short-term load forecasting. Linear Regression is used as a benchmark model, while Random Forest is applied as a nonlinear ensemble method. The study further investigates the influence of lag-window length, walk-forward temporal robustness, multi-step forecasting horizons, and feature importance. In addition, a model configuration with meteorological variables is examined in order to assess whether exogenous information improves forecasting quality for residential electricity consumption.

2 METHODOLOGY

This study develops a supervised machine learning framework for short-term household electricity load forecasting. The methodological design is focused on two related objectives. First, it examines how historical load observations and calendar-related temporal variables explain near-future demand. Second, it evaluates whether the inclusion of exogenous meteorological variables improves forecasting accuracy. The overall workflow consists of data acquisition, preprocessing and hourly aggregation, weather data integration, supervised feature construction, model training, chronological validation, and performance evaluation.

2.1 Dataset Description

The electricity consumption data used in this study were obtained from the publicly available Individual Household Electric Power Consumption dataset [9]. The dataset contains minute-level electrical measurements collected from a single household located in Sceaux, France, approximately 7 km from Paris. The original observation period extends from 16 December 2006 at 17:24 to 26 November 2010 at 21:02.

The raw dataset contains 2,075,259 minute-level records. Among these records, 25,979 values of the target variable, Global active power, were missing and were removed during preprocessing. The variable Global active power represents the household’s total active power consumption and is used as the forecasting target in this study.

To address the reviewer’s concern regarding external explanatory factors, hourly meteorological variables were additionally incorporated for the same geographical area and time period [10]. The weather variables include air temperatures at 2 m, relative humidity at 2 m, precipitation, and wind speed at 10 m. These variables were aligned temporally with the electricity consumption series and used as exogenous predictors in the extended forecasting configuration.

2.2 Data Preprocessing and Hourly Aggregation

The original load data were processed in several stages before model construction. First, the date and time columns were combined into a unified timestamp. Second, Global active power was converted to numeric format, while invalid and missing target values were removed. Third, the minute-level observations were resampled into hourly mean active power values in order to construct a forecasting dataset suitable for short-term hourly prediction.

After cleaning and hourly aggregation, the electricity load series contained 34,168 valid hourly observations covering the period from 16 December 2006 at 17:00 to 26 November 2010 at 21:00. The weather data were then merged with the hourly load series using timestamp alignment. The final merged dataset retained the same 34,168 hourly observations, ensuring a consistent temporal basis for all forecasting experiments.

The overall workflow of the proposed forecasting framework is illustrated in Figure 1.

Figure 1: Overall workflow of the proposed short-term electricity load forecasting framework.

2.3 Time-Series Formulation of the Forecasting Problem

Short-term load forecasting is formulated as a supervised regression problem. Let L(t) denote the hourly mean household active power consumption at time t. The objective is to estimate the future electricity load at forecasting horizon h:

$$\hat{L}(t+h) = f\big(x(t)\big), \tag{1}$$

where $\hat{L}(t+h)$ is the predicted load value h hours ahead, f is the forecasting model, and $x(t)$ is the feature vector available at time t.

In this study, the forecasting horizon h is varied in order to analyze how prediction accuracy changes as the forecast extends further into the future. The main one-hour-ahead prediction task is used for baseline model comparison, while additional experiments consider horizons of 3, 6, 12, and 24 hours.

The feature vector $x(t)$ is constructed from three groups of predictors:

1) Lagged historical load values.
2) Calendar-related temporal attributes.
3) Exogenous meteorological variables.

This formulation makes it possible to investigate both the internal temporal dependency structure of the electricity load series and the additional contribution of external weather conditions.

2.4 Feature Construction

The forecasting features are designed to capture short-term inertia, cyclic demand behavior, and weather-related influences on household electricity consumption.

Lag-based features are constructed from previous load observations. For a selected lag-window length n, the model receives the set of historical values:

$$L(t-1), L(t-2), \ldots, L(t-n). \tag{2}$$

Four lag-window configurations are examined in this study: n = 6, n = 12, n = 24, and n = 48 hours.

This allows assessment of how much historical memory is required for accurate short-term prediction.

Calendar-related temporal features include hour of day, day of week, and month. These attributes are used to represent recurring daily, weekly, and seasonal consumption patterns that are common in residential electricity demand.

In the extended exogenous configuration, four meteorological variables are additionally included:

1) Air temperature at 2 m.
2) Relative humidity at 2 m.
3) Precipitation.
4) Wind speed at 10 m.

These weather variables are temporally aligned with the forecasted hour and are used to evaluate whether external environmental conditions improve forecasting accuracy compared with models relying only on internal load history and calendar information.

2.5 Forecasting Models

Two regression models are applied in this study: Linear Regression and Random Forest. Linear Regression is used as an interpretable benchmark model, while Random Forest is selected as a nonlinear ensemble method capable of capturing more complex relationships among lagged load values, temporal attributes, and weather variables.

The Linear Regression model estimates the future load as a weighted linear combination of input features:

$$L(\widehat{t+h}) = \beta_0 + \beta_1 x_1(t) + \beta_2 x_2(t) + \cdots + \beta_p x_p(t), \quad (3)$$

where β_0 is the intercept term, β_1, β_2, …, β_p are regression coefficients, and $x_1(t)$, $x_2(t)$ …, $x_p(t)$ are the predictors included in the feature vector $x(t)$.

Random Forest is an ensemble learning method that combines the outputs of multiple regression trees.

Each individual tree produces its own load forecast, and the final prediction is calculated as the average of all tree-based outputs:

$$\hat{L}(t + h) = \frac{1}{M} \sum_{m=1}^{m} Tm(X(t)), \quad (4)$$

where M is the total number of regression trees and $Tm(X(t))$ denotes the prediction generated by the m-th tree.

To evaluate the effect of external weather information, both forecasting algorithms are tested under two feature configurations:

1) Endogenous configuration: lagged load values and calendar-related temporal attributes.
2) Exogenous configuration: lagged load values, calendar-related temporal attributes, and meteorological variables.

This design enables a controlled comparison of linear and nonlinear forecasting models, as well as an assessment of whether weather-related predictors improve short-term household load prediction.

2.6 Validation Strategy

A chronological validation strategy is applied in order to preserve the temporal structure of the forecasting problem and avoid information leakage. Since electricity load forecasting is inherently time dependent, random shuffling of observations is not used. Instead, the observations are ordered by timestamp before training and testing.

For the main one-hour-ahead model comparison, lag-window analysis, and forecasting horizon experiments, the first 80% of the available observations are used for model training, while the remaining 20% are reserved for out-of-sample testing. This approach ensures that future load information is never used to predict earlier periods.

In addition to the fixed chronological split, walk-forward validation is conducted to assess the temporal robustness of the final Random Forest model with weather variables. Three sequential expanding-window splits are considered:

1) The first 50% of the data are used for training, and the following 15% are used for testing.
2) The first 65% of the data are used for training, and the following 15% are used for testing.
3) The first 80% of the data are used for training, and the remaining 20% are used for testing.

This validation procedure provides additional insight into how forecasting accuracy changes across different temporal segments of the dataset.

2.7 Evaluation Metrics

Forecasting performance is evaluated using three complementary error metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These indicators provide different perspectives on prediction quality and are widely used in short-term load forecasting studies. MAE measures the average absolute difference between the actual and predicted load values:

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |yi - \hat{y}i|, \quad (5)$$

where:

- yi is the actual load value;
- $\hat{y}i$ is the predicted load value;
- N is the number of test observations.

RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}i)^2}, \tag{6}$$

and assigns stronger penalties to larger deviations. Therefore, RMSE is particularly informative when evaluating errors during local demand peaks or abrupt changes in electricity consumption.

MAPE is calculated as:

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right|. \tag{7}$$

MAPE expresses the forecasting error in percentage terms and enables relative interpretation of model accuracy. However, its magnitude may become large when actual load values are comparatively low. For this reason, MAPE is interpreted jointly with MAE and RMSE rather than as a standalone measure.

3 RESULTS AND DISCUSSION

This section presents the experimental results obtained from the revised forecasting framework. The analysis begins with a comparison of linear and nonlinear models under endogenous and exogenous feature configurations. It then examines the influence of lag-window length, temporal robustness under walk-forward validation, forecasting horizon sensitivity, and the relative importance of individual predictors.

3.1 Baseline Model Comparison and Effect of Weather Variables

The first experiment evaluates one-hour-ahead forecasting performance using a 24-hour lag window. Four model configurations are compared: Linear Regression with endogenous temporal features, Linear Regression with additional weather variables, Random Forest with endogenous temporal features, and Random Forest with additional weather variables. The results are summarized in Table 1.

Table 1 shows that Random Forest consistently outperforms Linear Regression in both feature configurations. For the endogenous models, the nonlinear ensemble approach reduces MAE from 0.452 to 0.399 and RMSE from 0.606 to 0.555. This confirms that short-term household electricity demand contains nonlinear temporal relationships that are not fully captured by a purely linear baseline.

The inclusion of meteorological variables produces a modest improvement in both models. For Linear Regression, MAPE decreases from 64.19% to 63.11%. For Random Forest, MAE decreases from 0.399 to 0.397, RMSE decreases from 0.555 to 0.552, and MAPE decreases from 54.47% to 54.27%. Although the gain is limited, the result indicates that weather conditions provide additional explanatory information beyond historical load and calendar-related temporal features.

The Random Forest model with weather variables achieves the best overall one-hour-ahead performance and is therefore used as the principal configuration for the subsequent lag-window, walk-forward, forecasting horizon, and feature importance analyses. At the same time, the remaining MAPE above 50% indicates that residential household load remains highly volatile and difficult to predict accurately using a compact feature set. Consequently, MAPE is interpreted together with MAE and RMSE rather than in isolation.

The visual behavior of the best-performing configuration is illustrated in Figure 2, which compares actual hourly household load values with the predictions generated by the Random Forest model with weather variables for a representative segment of the test period.

Table 1: One-hour-ahead forecasting performance with and without weather variables.

Model	Feature Configuration	MAE	RMSE	MAPE (%)
Linear Regression	Endogenous	0.452	0.606	64.19
Linear Regression	Endogenous and Weather	0.450	0.605	63.11
Random Forest	Endogenous	0.399	0.555	54.47
Random Forest	Endogenous + Weather	0.397	0.552	54.27

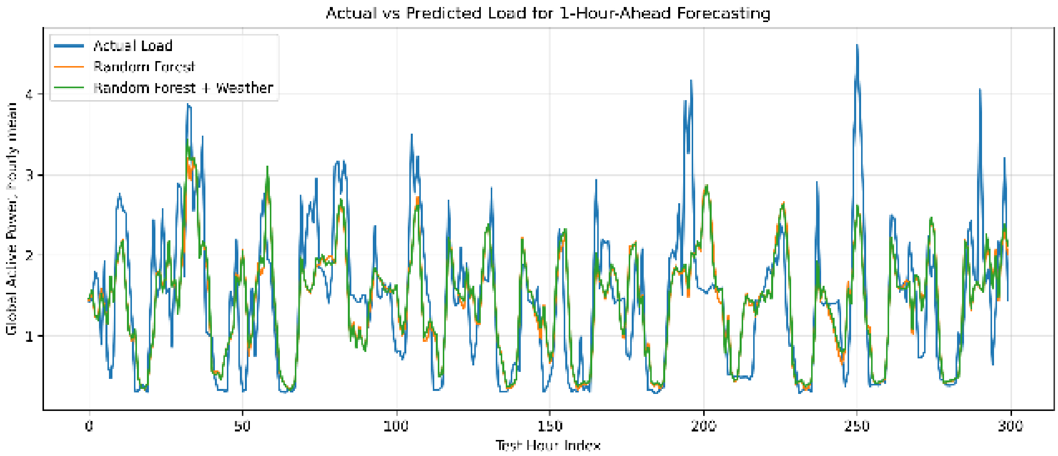

Figure 2: Actual and predicted household electricity load for one-hour-ahead forecasting using Random Forest with weather variables.

As shown in Figure 2, the model follows the general temporal evolution of household electricity demand and reproduces the main fluctuations in the test sequence. The predicted curve responds to changing demand levels and captures the broader short-term pattern of the observed load.

Nevertheless, local deviations remain visible during sharper changes in consumption. Abrupt peaks and rapid transitions are smoothed by the model, which is consistent with the RMSE value reported in Table 1. This behavior is typical for residential load forecasting, where individual appliance usage and irregular household activity can generate sudden variations that are difficult to infer from historical load, calendar attributes, and weather information alone.

The figure therefore supports the numerical results: the Random Forest model with weather variables provides a reasonable short-term representation of load dynamics, but it does not eliminate the intrinsic volatility of single-household electricity consumption.

3.2 Lag-Window Sensitivity Analysis

To evaluate the influence of historical memory length on forecasting performance, the Random Forest model with weather variables was tested using lag windows of 6, 12, 24, and 48 hours. This experiment assesses whether the inclusion of a longer sequence of previous load values provides additional predictive benefit for one-hour-ahead household electricity forecasting. The results are presented in Table 2.

Table 2: Lag-window sensitivity analysis for Random Forest with weather variables.

Lag Window (h)	MAE	RMSE	MAPE (%)
6	0.410	0.565	58.26
12	0.399	0.554	54.96
24	0.397	0.552	54.27
48	0.397	0.553	54.00

Table 2 shows that expanding the lag window from 6 to 12 hours produces a clear improvement in forecasting accuracy. MAE decreases from 0.410 to 0.399, while MAPE decreases from 58.26% to 54.96%. This indicates that very short historical windows may not provide sufficient temporal context for household load prediction.

A further increase from 12 to 24 hours leads to a smaller additional improvement. The 24-hour window achieves MAE of 0.397, RMSE of 0.552, and MAPE of 54.27%, indicating that one full daily cycle of historical information is useful for representing recurring residential demand patterns.

The 48-hour configuration yields the lowest MAPE value of 54.00% and a marginally lower MAE than the 24-hour configuration. However, the difference is very small, and RMSE slightly increases from 0.552 to 0.553. Therefore, the results suggest that most of the useful historical information is already captured within a 24-hour window, while extending the memory to 48 hours provides only limited additional benefit.

The behavior of MAE across the tested lag-window configurations is illustrated in Figure 3.

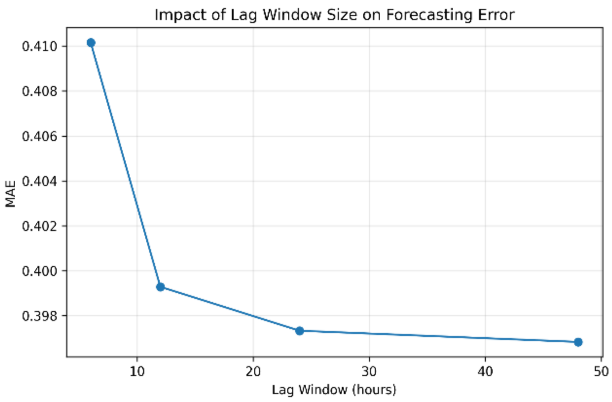

Figure 3: Impact of lag-window size on MAE for Random Forest with weather variables.

Figure 3 confirms that the largest improvement occurs when the historical window is increased from 6 to 12 hours. Beyond 24 hours, the MAE curve becomes nearly flat, which reinforces the conclusion that extending the lag structure further does not substantially improve short-term forecasting performance. This finding supports the use of a compact 24-hour lag window as a balanced configuration for the subsequent analysis.

3.3 Walk-Forward Validation

To assess the temporal robustness and generalization capability of the selected forecasting configuration, walk-forward validation was conducted using three sequential expanding-window splits. In each split, the Random Forest model with weather variables was trained only on earlier observations and evaluated on a later unseen period. The results are summarized in Table 3.

Table 3: Walk-forward validation results for Random Forest with weather variables.

Split	MAE	RMSE	MAPE (%)
1	0.460	0.645	57.60
2	0.417	0.591	57.68
3	0.397	0.552	54.27

Table 3 demonstrates that the forecasting model maintains a comparable level of performance across different temporal segments of the dataset, although the magnitude of the error varies over time. The first split produces MAE of 0.460 and RMSE of 0.645, indicating relatively higher prediction difficulty in the corresponding testing period. In the second split, MAE decreases to 0.417 and RMSE to 0.591. The third split provides the best performance, with MAE of 0.397 and RMSE of 0.552.

The MAPE values remain within a relatively narrow range from 54.27% to 57.68%. This indicates that the model does not experience an extreme collapse in generalization capability when evaluated on later unseen intervals. At the same time, the differences among splits confirm that residential household load is temporally heterogeneous and that forecasting accuracy depends on the characteristics of the specific evaluation period.

Overall, the walk-forward validation results support the temporal consistency of the proposed forecasting framework while also highlighting the persistent challenge of accurately modeling irregular household electricity consumption.

3.4 Multi-Step Forecasting Behavior

The effect of forecasting horizon length was evaluated for 1-, 3-, 6-, 12-, and 24-hour-ahead prediction tasks. For all horizons, the Random Forest model with weather variables and a 24-hour lag window was used. This experiment examines how forecasting accuracy changes as the target prediction point moves further into the future. The results are presented in Table 4.

Table 4: Multi-step forecasting performance of Random Forest with weather variables.

Forecast Horizon (h)	MAE	RMSE	MAPE (%)
1	0.397	0.552	54.27
3	0.423	0.580	58.90
6	0.428	0.587	60.12
12	0.435	0.597	61.58
24	0.444	0.606	64.07

Table 4 shows a gradual deterioration in forecasting performance as the prediction horizon increases. The one-hour-ahead configuration achieves the best accuracy, with MAE of 0.397, RMSE of 0.552, and MAPE of 54.27%. When the horizon is extended to 3 hours, MAE increases to 0.423 and MAPE rises to 58.90%.

The degradation continues for longer forecasting horizons. At 24 hours ahead, MAE reaches 0.444, RMSE increases to 0.606, and MAPE rises to 64.07%. This pattern indicates that the available lagged load history, calendar attributes, and weather variables become progressively less informative as the forecasted time point moves further away from the latest known observations.

Although the error increase is not abrupt, the results clearly demonstrate that the proposed framework is most suitable for ultra-short-term forecasting, particularly within the 1- to 3-hour-ahead range. For longer prediction horizons, more advanced temporal modeling strategies or richer explanatory information may be required.

The increase in forecasting error across prediction horizons is illustrated in Figure 4.

Figure 4 visually confirms the progressive growth of MAE as the forecasting horizon extends. The curve rises most noticeably between the one-hour and three-hour horizons and continues to increase more gradually thereafter. This behavior reflects the accumulation of prediction uncertainty in multi-step residential load forecasting and supports the conclusion that short-term temporal dependencies are most informative for near-future demand estimation.

3.5 Feature Importance Analysis

To identify the predictors that contribute most strongly to one-hour-ahead load forecasting, feature importance analysis was performed for the Random Forest model with weather variables. This analysis provides additional interpretation of the forecasting framework by showing which historical, temporal, and meteorological variables have the greatest influence on the model output.

The relative importance of the most influential predictors is shown in Figure 5.

Figure 5 shows that the most influential predictor is the immediately preceding load value, load_lag_1, with an importance score of approximately 0.260. This confirms the strong short-term inertia of household electricity demand, where the current consumption level is highly informative for the next-hour forecast.

The second most important predictor is load_lag_23, followed by the cyclic hour-related variables. This result indicates that daily periodicity plays a substantial role in the forecasting process. The prominence of load values observed approximately one day earlier, together with hour-of-day indicators, supports the interpretation that residential demand contains recurring daily behavioral patterns.

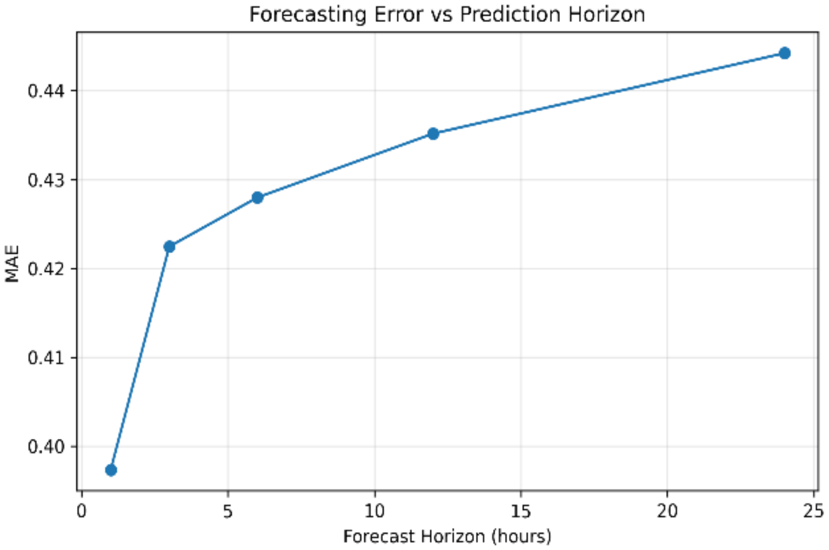

Figure 4: Forecasting error versus prediction horizon for Random Forest with weather variables

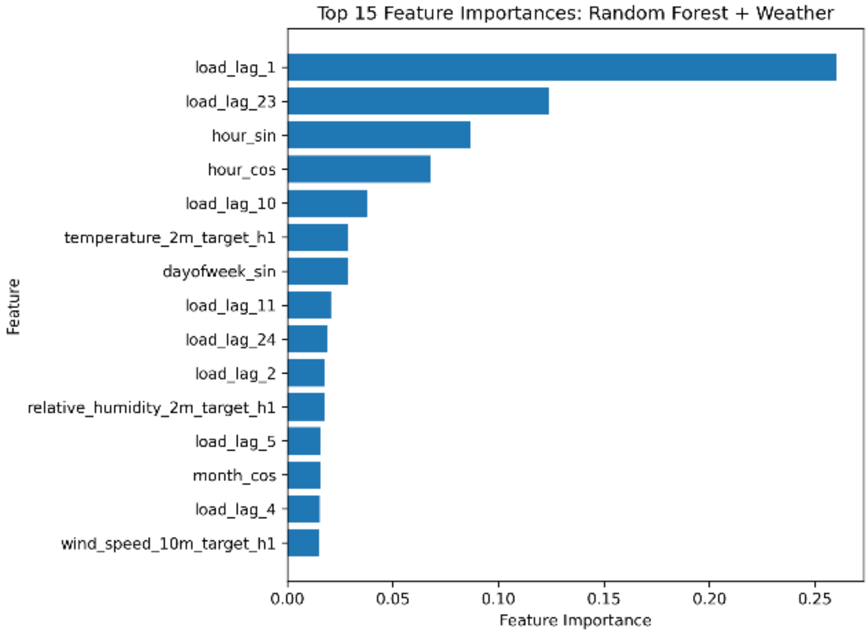

Figure 5: Feature importance ranking for the Random Forest model with weather variables.

Among the meteorological variables, air temperature appears within the ten most influential predictors. Although its contribution is smaller than that of the dominant lag-based features, its presence confirms that weather conditions provide measurable additional information for short-term household load prediction. This finding is consistent with the model comparison results in Table 1, where the inclusion of weather variables produced a modest improvement in forecasting accuracy.

Overall, the feature importance analysis demonstrates that the proposed model is primarily driven by recent load history and daily cyclic behavior, while exogenous weather information acts as a secondary but relevant explanatory factor.

4 CONCLUSIONS

This study investigated short-term household electricity load forecasting through a supervised machine learning framework focused on temporal dependency analysis. In response to the need for a more comprehensive forecasting design, the revised methodology incorporated not only lagged load observations and calendar-related temporal features, but also exogenous meteorological variables, including air temperature, relative humidity, precipitation, and wind speed.

The experimental results showed that Random Forest consistently outperformed Linear Regression in one-hour-ahead forecasting. The best-performing configuration, Random Forest with weather variables, achieved MAE of 0.397, RMSE of 0.552, and MAPE of 54.27%. The inclusion of weather information produced a modest but measurable improvement compared with the endogenous-only Random Forest model, indicating that meteorological conditions contribute additional explanatory value, although they do not dominate the forecasting process.

Lag-window sensitivity analysis demonstrated that extending historical memory from 6 to 24 hours improves model accuracy, while further expansion to 48 hours provides only marginal additional benefit. This finding suggests that a one-day historical window is sufficient to capture most of the relevant short-term temporal structure in the analyzed residential load series.

Walk-forward validation confirmed that the forecasting framework maintains broadly consistent performance across sequential temporal segments, while still reflecting the intrinsic heterogeneity of household electricity consumption. Multi-step horizon analysis further revealed that forecasting accuracy gradually deteriorates as the prediction horizon increases, supporting the conclusion that the proposed approach is most appropriate for ultra-short-term applications, particularly within the 1- to 3-hour-ahead range.

Feature importance analysis showed that the immediately preceding load value, daily lag-related information, and hour-of-day variables are the dominant predictors. Air temperature also appeared among the most influential variables, confirming that weather effects are present but secondary relative to internal load dynamics.

Overall, the study demonstrates that ensemble learning can effectively capture nonlinear temporal dependencies in household electricity demand and that the inclusion of meteorological variables provides a limited but meaningful enhancement. At the same time, the remaining MAPE values indicate that single-household load forecasting remains a challenging problem due to irregular consumer behavior and abrupt demand fluctuations. Future research should therefore consider richer behavioral indicators, appliance-level information, probabilistic forecasting strategies, and advanced temporal models to further improve predictive robustness.

REFERENCES

[1] M. G. Pinheiro, S. C. Madeira, and A. P. Francisco, “Short-term electricity load forecasting-A systematic approach from system level to secondary substations,” Applied Energy, vol. 332, p. 120493, 2023.

[2] A. A. Mamun, M. Sohel, N. Mohammad, M. S. H. Sunny, D. R. Dipta, and E. Hossain, “A comprehensive review of the load forecasting techniques using single and hybrid predictive models,” IEEE Access, vol. 8, pp. 134911-134939, 2020.

[3] J. W. Taylor and P. E. McSharry, “Short-term load forecasting methods: An evaluation based on European data,” IEEE Transactions on Power Systems, vol. 22, no. 4, pp. 2213-2219, 2007.

[4] T. Hong, P. Wang, and H. L. Willis, “A naive multiple linear regression benchmark for short-term load forecasting,” in Proc. IEEE Power and Energy Society General Meeting, Detroit, MI, USA, pp. 1-6, 2011.

[5] Y. Wang, Q. Chen, T. Hong, and C. Kang, “Review of smart meter data analytics: Applications, methodologies, and challenges,” IEEE Transactions on Smart Grid, vol. 10, no. 3, pp. 3125-3148, 2019.

[6] M. Imani, “Electrical load-temperature CNN for residential load forecasting,” Energy, vol. 227, p. 120480, 2021.

[7] P. Ran, K. Dong, X. Liu, and J. Wang, “Short-term load forecasting based on CEEMDAN and Transformer,” Electric Power Systems Research, vol. 214, p. 108885, 2023.

[8] X. Wen, J. Liao, Q. Niu, N. Shen, and Y. Bao, “Deep learning-driven hybrid model for short-term load forecasting and smart grid information management,” Scientific Reports, vol. 14, p. 13720, 2024.

[9] G. Hebrail and A. Berard, “Individual Household Electric Power Consumption,” UCI Machine Learning Repository, 2006.

[10] H. Hersbach et al., “The ERA5 global reanalysis,” Quarterly Journal of the Royal Meteorological Society, vol. 146, no. 730, pp. 1999-2049, 2020.