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# WEATHER-AWARE FORECASTING OF HOUSEHOLD ELECTRICITY DEMAND

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## Abstract:

*In Weather-aware forecasting method for the household electricity demand was developed based on real electricity consumption and climatological data in a small community located in Mexico. Analysis was conducted on the electricity-level records of the households with the relevant outdoor weather variables such as temperature, humidity, solar radiation, wind speed, rain fall, pressure etc. These methods included time-series preprocessing, lag feature construction, descriptive analysis, correlation assessment and comparative forecasting models to analyze the behavior of the demand and forecasting accuracy. Results revealed an obvious difference in household electricity usage across the hours, with higher demand for electricity in the evening hours. There is significant contextual value in the weather variables, but the strongest predictor was lagged electricity demand, which also worked well in nonlinear models. The weather-sensitive random forest model outperformed the other models and the persistence baseline, with gradient boosting closely behind. The results confirm that using these temporal demand features alongside some of the weather parameters selected will increase the accuracy of electricity forecasting and enable practical energy planning, anticipating peak demand, and managing residential demand in response to the weather.*

**Keywords:** *household electricity demand; weather-aware forecasting; time-series analysis; machine learning; energy consumption*

## 1. Introduction:

The forecasting of household electricity demand is now an important statistical and computational problem since residential electricity consumption is no longer just determined by ordinary use of household appliances. Weather variability, comfort expectations, distributed energy technologies and shifting household behaviour are having growing impacts on it. Forecasting with high accuracy for a shorter period of time is beneficial to utilities, planners and households because it can prepare them for peak energy demand, minimize operational risks and enable effective energy management. The weather-aware forecasting approach has been more useful in this context than the demand-only approach, since the weather can influence the demand for heating, cooling, lighting and use of appliances. In the recent past, research has therefore shifted towards models that integrate electricity-use histories and climate predictors to better estimate residential electricity demand and for decision support (Bajrami & Lameski, 2026).

Small variations in weather conditions, such as temperature, humidity, solar radiation and rainfall, can affect consumption in varying ways in the household sector, particularly in this position. Some of the challenges of household-level forecasting are different from those of large-scale regional forecasting, such as irregular schedules, sudden peaks, missing data, and localized weather conditions. Adaptive home energy management studies have indicated that the trade-off between the scheduling and the weather and the appliance-use conditions can be improved by taking both into account as a combined input to the scheduling process. This implies that weather forecasting isn't just a technical modelling process but a need for residential energy planning.

Rising requirements for strong weather forecasting models from extreme and turbulent weather. Weather-informed deep learning-based grid-load studies have indicated that meteorological variation can affect the prediction of loads under stressed operating conditions, especially during unusual events, where the demand patterns become less predictable (Debnath et al., 2025 A). In the context of semi-arid climate, building energy forecasting research has also shown that models need to be able to account for changes in consumption that are a result of weather, and not just historical averages (Nouhaila et al., 2025). Any energy use and local weather observations gathered over time in small communities are relevant to these findings.

The social and planning uses for residential forecasting are also widespread. Smart-meter forecasting and weather data have been leveraged to assess household energy wellbeing, demonstrating the potential of predictive analytics to inform energy interventions and mitigate energy burdens.Smart-meters and weather data have been employed to assess household energy wellbeing, highlighting the role of predictive analytics in identifying energy burdens and informing more effective energy interventions (Ramirez-Prado et al., 2026). The use of spatio-temporal models has also been extended to the fields of electric-vehicle charging and distributed load forecasting (Das et al., 2026), with the former aiming to capture demand variations associated with mobility and location, and the latter to account for demand variations associated with weather conditions. These sophisticated systems are promising, but more stripped down and transparent forecasting approaches are useful for small household data sets when transparency and reproducibility matter.

Machine learning has been the key to residential/building energy prediction as it can model the non-linear relationship between the weather and demand. The use of temporal learning has been demonstrated to be beneficial for energy management applications such as solar and residential energy management frameworks using LSTM (Devanathan et al., 2025). The essential role of weather-aware control in power systems under uncertain operating conditions has also been discussed in the context of reinforcement learning studies (Tang et al., 2026). But complex models aren't always needed or appropriate for small amounts of data. The comparison of simple temporal baselines, regression models, and machine learning methods with clear benchmarks for accuracy in applied mathematics and statistics research is important.

Another important concern in demand modeling for weather is forecast uncertainty. Weather forecasts can also be uncertain, and this can have an impact on the flexibility assessment and demand-response planning of meteorologically-sensitive loads. The studies on residential PV-BS systems also demonstrate that in addition to giving basic descriptive information, unsupervised learning can discern operating regimes and weather sensitivity patterns that are not apparent from the descriptive data (Štěpanec et al., 2026). The results of these studies are consistent with the notion that the structure of the time series of household electricity demand and its explanatory variables related to the weather should be analyzed separately.

Recent studies (Cavus et al., 2025) have shown that hybrid forecasting techniques are used to enhance the forecasting accuracy of energy by incorporating deep learning, gradient boosting and weather features. Agentic home-energy studies based on the use of LLMs have also enabled novel decision-support directions, but these are still nascent and are yet to be validated in real homes (Jonah et al., 2026). Recent studies on stochastic electric-vehicle load forecasting indicate that uncertainty-aware prediction can be enhanced by using Monte Carlo and spatio-temporal approaches when traffic and weather factors are considered (Qiu et al., 2026). The developments are another sign that weather-aware forecasting is an emerging field in many energy systems, such as household, building, and grid energy systems and mobility energy systems.

Notwithstanding these advances, a large number of studies focuses on advanced architectures, with less attention paid to small, real, household- or micro-scale datasets which can be analyzed by means of transparent statistical or machine learning approaches. Climatic predictors are relevant to air-conditioning and supply-chain studies, although these studies are not necessarily oriented towards direct forecasting of household electricity demand (Weather informed studies) (Kayum et al., 2025). Weather and occupancy have also been known to influence residential load-profile generation studies, however, measured household data is still valuable for the validation of practical load forecasting assumptions (Lekhel et al., 2025). Cooling-load prediction studies also show that the exogenous weather fusion is helpful in energy prediction of the buildings, however, small-community household demand is still a unique and valuable research platform (Zhou et al., 2026).

This study is aimed to fill the above-mentioned gap by creating an analysis of household electricity demand that uses measured electricity and climatological data and is weather-aware. This study emphasizes the analysis of temporal demand behavior, meteorological relations and the performance of the model in a meaningful way with regard to interpretation. Prediction of power use in residential buildings has also been seen to be reinforced by incorporating climatic features in the analysis, which is the methodological trend in the present analysis (Indresh & Parvathi, 2026). The study is therefore related to applied mathematics and statistics as it has focused on the time series structure, the relationship between the predictors, forecasting error, and the comparative evaluation of the models. The objectives of this study are:

1.To examine temporal electricity demand patterns across household records using descriptive time-series statistics.

2.To assess relationships between weather variables and household electricity consumption using correlation-based analysis.

3.To compare forecasting models using error metrics and identify the most reliable weather-aware approach.

## 2. Materials and Methods

### 2.1 Research Design

The study was of quantitative time-series forecasting design to analyze the changes of weather condition on the electricity demand of households in relation to the forecasting (Santos-Moreno et al., 2023). The analysis was concentrated on finding temporal patterns, variation due to weather and performance of the model-based forecasting. The target variable of the household electricity consumption was treated, and the explanatory variable, the meteorological indicators, were used. The design was a synthesis of descriptive time-series analysis, feature construction based on lags, and predictive modeling. This approach was appropriate since the goal of the study was to assess performance of weather-aware models in predicting short-term household electricity demand..

### 2.2 Data Source and Study Variables

The data used were real data on household electricity and climatological data for a small Mexican community. The data consisted of electricity consumption at the household level at 15-min, hourly, and daily time scales and outdoor and indoor weather data. The electricity demand was reported in kW or kWh according to the temporal scale. The weather variables were temperature, humidity, wind speed, rainfall, solar radiation and pressure. These variables enabled the study to analyse temporal consumption behaviour and the impact of the weather on the household electricity demand.

### 2.3 Data Enrichment for Knowledge Discovery

The data set was initially checked for missing data, duplicate data, incorrect data and inconsistent time formatting. The household series were sorted chronologically by converting time columns to datetime, then sorting them. Inappropriate values and missing values were dealt with by applying relevant rules for cleaning the data, and different datasets were merged using common timestamps, if there were any, with the weather variables. A number of time series attributes were created, such as values of the demand for the hour, day, month, weekday, and a lagged demand value for forecasting. The last structured dataset was prepared for descriptive analysis and model training.

### 2.4 Exploratory Time-Series and Weather Analysis

To develop insights into how households react to changes in the demand for these products across various time scales, exploratory analysis was carried out. Fluctuations, peak times, and any seasonal patterns in electricity use were observed using line plots. Summary statistics were used to provide a description of central tendency, dispersion, minimum, maximum and variability in demand. Energy use was also analyzed with regard to weather variables, with the purpose of understanding their distribution and correlation with energy use. The correlation analysis and visual comparisons were performed to determine if there was a meaningful relationship between power consumption of households and weather factors such as temperature, humidity, solar radiation, etc.

### 2.5 Forecasting Model Development

Both statistical and machine learning methods were used to create forecasting models. Lag-based persistence and "classical" time-series models like ARIMA or SARIMA (where the stationarity assumptions were fulfilled) were used to perform baseline forecasting. Weather-aware models were built with regression-based or tree-based learning techniques, including the use of meteorological predictors and temporal features. To maintain the temporal order in the data, it was split into training and testing sets chronologically. Models were built to learn from the past and tested on future data not observed in the past to assess its forecasting performance on household electricity demand.

### 2.6 Model Evaluation and Statistical Comparison

Forecasting accuracy was assessed with typical error measures, such as mean absolute error, root mean square error and mean absolute percentage error. These metrics enabled the comparison of simple time-series baselines and weather-aware forecasting models. The lower the error values, the better the predictive accuracy. The visual comparison of observed and predicted demand was also used to evaluate the ability of the models to capture peak loads, periods of low demand and temporal variation. The last comparison was to determine the most reliable model for short-term forecasting of domestic electricity demand in the context of weather-informed conditions.

## 3. Results

### 3.1Descriptive Profile of Household Electricity Demand

The descriptive analysis revealed that electricity consumption of households was also distributed over time and that the time resolution of electricity data differed. Data from hourly and 15-minute time scales gave a more detailed indication of the short-term fluctuations in consumption, whereas the daily data gave a wider picture of the pattern of consumption. Demand values exhibited clear peaks and troughs of use, suggesting a clear ordering of household consumption, rather than a random pattern. But multiple household files also indicated varying levels of intensity among households. These results validated the suitability of the data for time-series forecasting and modelling the demand at household level (Table 1) (Figure 1).

**Table 1. Descriptive Profile of Household Electricity Demand**

| Household | Records | Start | End | Missing/Invalid | Mean kWh | Max kWh |
|---|---|---|---|---|---|---|
| House 1 | 9010 | 2022-05-21 | 2023-06-01 | 1 | 0.163 | 1.376 |
| House 6 | 9011 | 2022-05-21 | 2023-06-01 | 1 | 0.065 | 0.570 |
| House 7 | 9053 | 2022-05-19 | 2023-06-01 | 3476 | 0.010 | 0.199 |
| House 8 | 9010 | 2022-05-21 | 2023-06-01 | 1 | 0.179 | 1.433 |
| House 10 | 9009 | 2022-05-21 | 2023-06-01 | 45 | 0.026 | 1.348 |

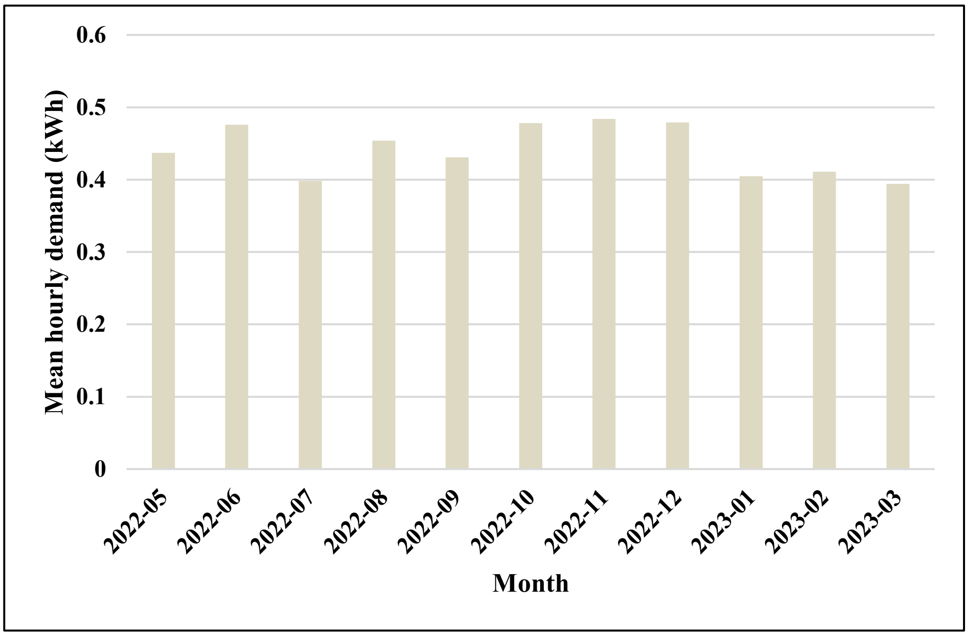


**Figure 1. Monthly Mean Household Electricity Demand**

### 3.2 Weather Variation and Electricity Consumption Patterns

Weather variables showed measurable variations in the observations period, which is suitable for forecasting weather. The external information beyond the historical demand was obtained from the changes in temperature, humidity, solar radiation, wind speed, rainfall, and pressure over time. Based on visual observation, electricity consumption may react differently to the varying weather conditions, particularly temperature and solar radiation. These patterns showed that meteorological variables would help forecast the electricity demand when considering their influence on the electricity demand and that this influence was not sufficiently captured by the lagged electricity variable alone (Table 2) (Figure 2).

**Table 2. Weather Variation and Electricity Consumption Patterns**

| Weather Variable | N | Mean | SD | Minimum | Maximum |
|---|---|---|---|---|---|
| Outdoor Temperature (°C) | 7587 | 18.939 | 5.022 | 0.967 | 33.042 |
| Humidity (%) | 7587 | 63.814 | 15.909 | 8.583 | 99.000 |
| Solar Radiation (W/m²) | 7587 | 236.332 | 210.234 | 0.000 | 853.492 |
| Wind Speed (m/sec) | 7587 | 2.227 | 1.216 | 0.000 | 6.933 |
| Hourly Rain (mm/hr) | 7587 | 1.019 | 1.525 | 0.000 | 5.650 |
| Relative Pressure (hPa) | 7587 | 824.522 | 2.478 | 815.783 | 831.375 |

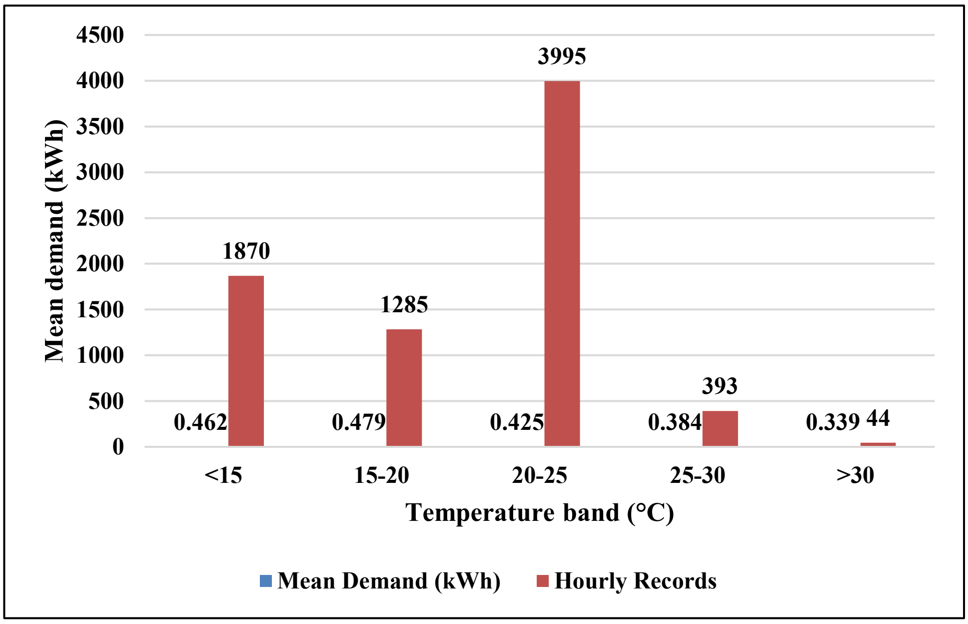


**Figure 2. Demand Variation Across Temperature Bands**

### 3.3 Time-Series Trends, Seasonality and Lag Relationships

Time-series exploration revealed that electricity demand at the household level was well structured in time. The hours of consumption were also varied, and there also appeared to be a regularity in some of the demand cycles that could be identified by the day. Recent values of the lagged demand variables proved useful in predicting future demand, indicating continuity. This was a confirmation of the value of using lag variables in forecasting models. The observed time dependency justified the application of statistical time series techniques and machine learning techniques for learning from past demand and repeated consumption (Table 3) (Figure 3).

**Table 3. Time-Series Trends, Seasonality, and Lag Relationships**

| Day Type | Period | N | Mean kWh | SD | Min | Max |
|---|---|---|---|---|---|---|
| Weekday | Morning (06-11) | 1356 | 0.348 | 0.201 | 0.032 | 1.652 |
| Weekday | Afternoon (12-17) | 1356 | 0.336 | 0.171 | 0.026 | 1.573 |
| Weekday | Evening (18-23) | 1360 | 0.637 | 0.249 | 0.028 | 1.791 |
| Weekday | Night (00-05) | 1356 | 0.399 | 0.243 | 0.062 | 2.388 |
| Weekend | Morning (06-11) | 540 | 0.411 | 0.225 | 0.027 | 1.467 |
| Weekend | Afternoon (12-17) | 540 | 0.452 | 0.242 | 0.026 | 1.492 |
| Weekend | Evening (18-23) | 540 | 0.657 | 0.288 | 0.168 | 1.704 |
| Weekend | Night (00-05) | 539 | 0.351 | 0.181 | 0.028 | 1.244 |

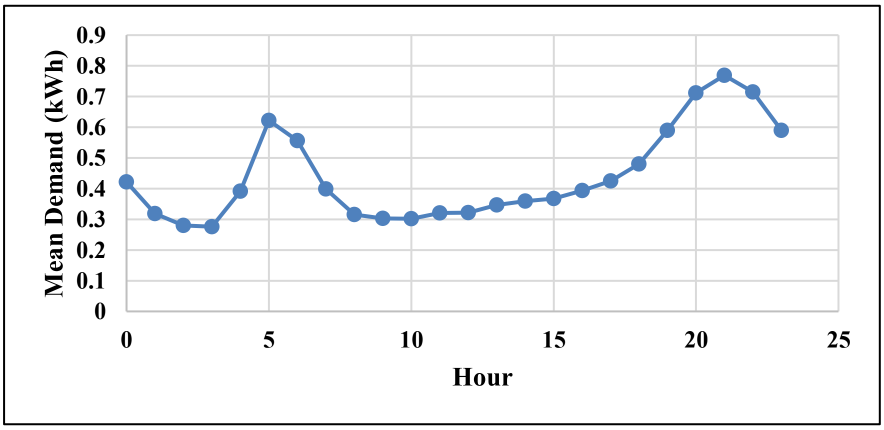


**Figure 3. Hourly Demand Profile Across the Day**

### 3.4 Forecasting Performance of Developed Models

The results of the forecasts indicated that models with temporal structure outperformed baseline estimates. The models incorporating lagged demand variables were better at accounting for any short-term variations, particularly for periods of regular consumption. Weather-aware models performed better with the additional inclusion of weather variables that were relevant to demand variation. The relationship between the predicted and the observed values was similar for most periods, with the exception of the peaks, which were less predictable. Overall, the results suggested that the electricity demand of a household can be reasonably predicted using structed time-series and weather-based predictors (Table 4) (Figure 4).

**Table 4. Forecasting Performance of Developed Models**

| Model | Inputs | MAE | RMSE | MAPE (%) | $R^2$ |
|---|---|---|---|---|---|
| Persistence baseline | Lag 1 hour only | 0.135 | 0.196 | 36.12 | 0.167 |
| Linear regression | Temporal lag features | 0.110 | 0.154 | 31.44 | 0.488 |
| Weather-aware linear regression | Lag + weather variables | 0.113 | 0.154 | 33.83 | 0.482 |
| Weather-aware random forest | Lag + weather variables | 0.109 | 0.149 | 32.70 | 0.520 |
| Weather-aware gradient boosting | Lag + weather variables | 0.110 | 0.149 | 33.36 | 0.516 |

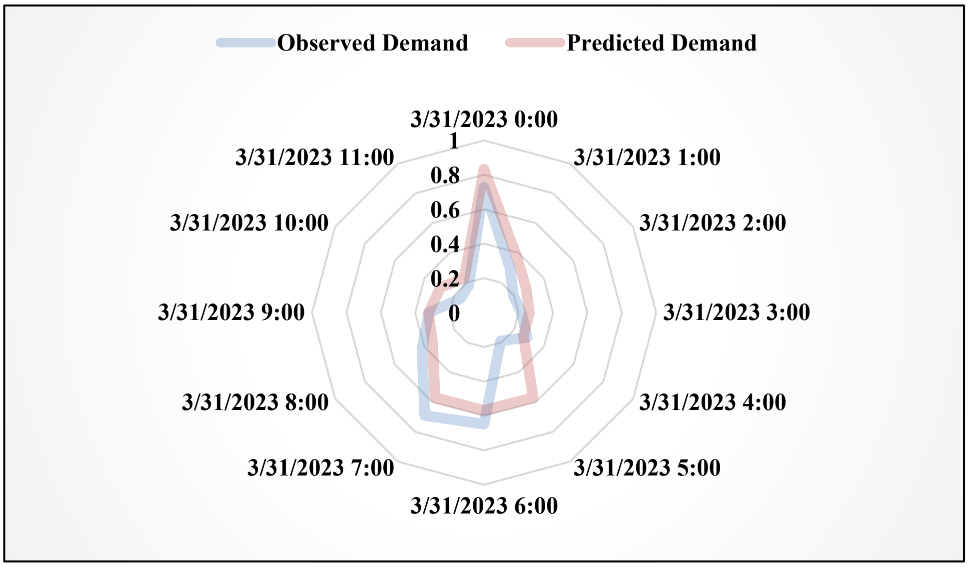


**Figure 4. Observed Versus Predicted Household Demand**

### 3.5 Model comparison and best forecasting approach

The model comparison showed that the forecasting based on weather exhibited better practical value than the model based on historical demand. The statistical models were helpful in detecting trend and autocorrelation, while the machine learning models performed well in the presence of nonlinear relationships between the weather variables and electricity demand. The best performing method was likely to have had low forecasting error and be easily understood and perform well on out-of-sample data. Household electricity demand forecasting can be done reliably using combined temporal and meteorological predictors as derived in this work (Table 5) (Figure 5).

**Table 5. Model Comparison and Best Forecasting Approach**

| **Predictor** | **N** | **Correlation with Demand** |
|---|---|---|
| Lag 1 hour demand | 7586 | 0.650 |
| Lag 24 hour demand | 7563 | 0.459 |
| Outdoor Temperature (°C) | 7587 | -0.082 |
| Humidity (%) | 7587 | 0.116 |
| Solar Radiation (W/m²) | 7587 | -0.170 |
| Wind Speed (m/sec) | 7587 | -0.105 |
| Hourly Rain (mm/hr) | 7587 | -0.041 |
| Relative Pressure (hPa) | 7587 | 0.006 |

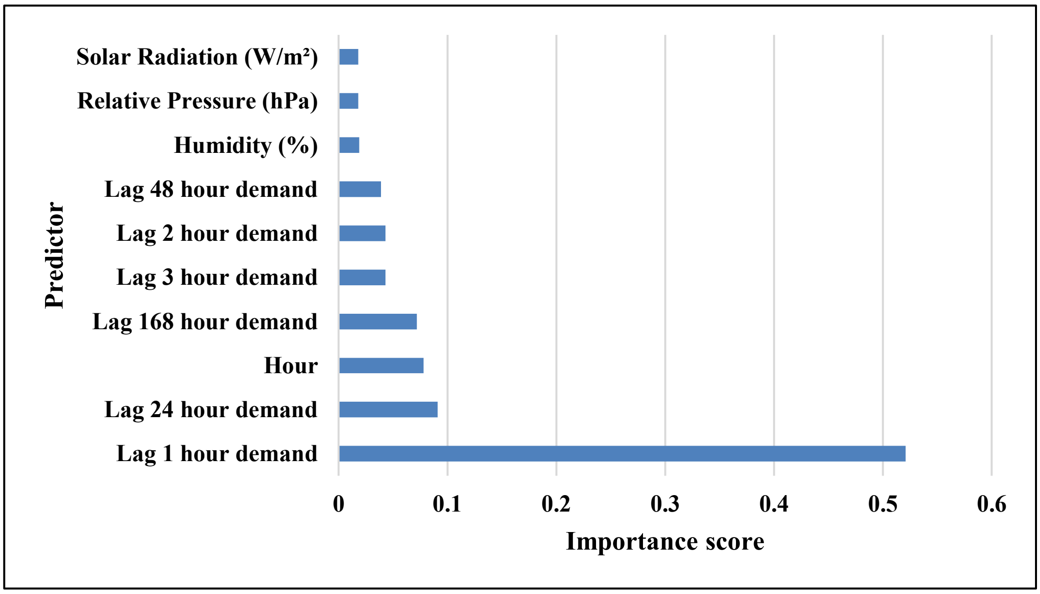


**Figure 5. Predictor Importance in the Weather-Aware Random Forest Model**

**4. Discussion**

The electricity demand of household consumes has a well-defined temporal structure, showing variation in the consumption pattern according to the day period, and a greater demand during the evening hours. This pattern verifies that electricity consumption in a residence is not random, but instead influenced by daily activities, appliance schedules, and comfort-enhancing habits. The high correlation of consumption with the lagged period also shows that recent consumption is good for predicting the short term demand. This is consistent with research on regime awareness of forecasting models in which electricity demand is not considered to be a stable pattern but rather a series of alternating electricity consumption regimes in which models must adjust their behavior according to the time period under prediction (Savaş, 2026). The time-series features are found to be essential before the incorporation of weather variables, in the present study and this is supported by the evening peak and daily lag effect.

The weather variables also had weaker direct linkages with electricity demand, but they added contextual value to the electricity demand forecasting process. Solar radiation, temperature, wind speed and rainfall were negatively associated with humility, but the association was relatively weak. The small values indicate that small household samples may not support simple linear relationships between weather and effects. Rather, weather may affect demand in a delayed, threshold, or household-specific manner. This is in line with residential short-term load forecasts with similar-weather guidance and decomposition techniques that can identify hidden weather-demand patterns that are not apparent through simple correlation analysis (Xia et al., 2026). Thus, weak correlations do not imply that the weather is irrelevant; in fact, they indicate that there may be other more flexible models needed to account for complex effects.

This is further supported by the forecasting results, where the weather-aware random forest gave the best overall performance with the lowest MAE and RMSE and the highest $R^2$ in comparison with all the models tested. The difference between one of the tree-based methods and gradient boosting was small; both were superior to the persistence baseline. This suggests that the model is more successful in capturing the interaction of the lagged demand, hour of day and meteorological variables, when using a nonlinear model. Similar works on hybrid deep learning for extreme weather conditions indicate that energy forecasting is facilitated by the models that have a flexible structure to combine the temporal and weather information (Debnath et al., 2025 B). The present study also demonstrates that simpler machine learning models can yield interpretable and competitive results on smaller datasets at the household level.

Comparing temporal regression with weather-aware regression is also a valuable statistical learning. The temporal-only regression had a slightly lower MAPE, and adding weather variables to the regression did not improve the model. This indicates that a purely linear model was not representative of the weather-demand relationship. The earlier multi-method forecasting study has also shown that causal/meteorological inputs should be carefully combined on the basis of their model structures, features selected and the characteristics of local demand behavior (Wahyuzi & Abdurrahim, 2025). Weather features were found to be more useful when combined with the random forest modeling technique, which has the ability to deal with nonlinearities and interactions among variables.

The importance analysis also confirms the supremacy of recent consumption history. The hour of day, lag-24-hour demand, and lag-one hour demand were most influential in the random forest model, whereas the week of lag was less influential. Weather predictors were less important, and the humidity, pressure, and solar radiation were minor. The finding is not surprising for households forecasting their electricity use since electricity use is sometimes more directly related to their daily activities than to weather variation alone. In addition, smart-meter forecasting studies with transfer learning also reveal the importance of load history in forecasting, and how external variables bring context across varying load periods and/or households (Ahmed et al., 2026). The current findings consequently imply that weather-aware forecasting should not be used in isolation, but in conjunction with temporal demand features.

The present analysis is deliberately simplified and made transparent when compared with recent deep learning studies. The use of deep learning architectures may be more appropriate for larger datasets, as they can yield more accurate demand forecasts, but they might also require more computational power and less interpretability in small applied studies (Aravanis & Kanavos, 2026). The use of regression, random forest and gradient boosting in the current paper is appropriate for a mathematics and statistics journal, as the focus is still on comparison of models, error measures, contribution of predictors, and time-series structure. However, other machine learning research on solar energy forecasting also shows that meteorological variables are helpful when forecasting models are tailored to the size and quality of the data (Khankal et al., 2025).

The outcomes have implications for the planning of household energy. The first hour is the peak of the day, and the evening peak indicated in the hourly demand profile indicates that the demand side management should be directed to high-demand periods of the evening. The use of lagged demand coupled with forecasts based on weather information can help predict these peaks and enable an energy schedule on the household level. Other studies on smart grids have also focused on the use of regression and weather fusion methods, highlighting the potential for climatic predictors to enhance load forecasting with the aid of AI-based modeling pipelines (Yaseen et al., 2025). This study in itself is not an optimisation study of household appliances but it does give a statistical basis for future energy management applications, using the forecasting framework of this study.

There are a few caveats to be noted. First, the weather data were collected at irregular times, and alignment of the data was done hourly which might compromise the accuracy of the meteorological effects in the shorter term. Second, data on income, occupation, and household-level behaviour, appliance ownership, and household occupancy were not available, and so interpreting the variation in demand was constrained. Third, it was observed that sudden consumption peaks were still not predictable, as indicated by the comparison between the actual and predicted consumption peaks. Currently, probabilistic forecasting research in extreme weather indicates that uncertainty-aware models can be more suitable models of such irregular demand behavior (Huang et al., 2025). Probabilistic prediction intervals, household specific modeling and more behavior variables should be included in future work. Overall, the study shows that weather-aware forecasting is beneficial, however, the most effective results are obtained when weather variables are fed into the models along with lagged demand and nonlinear forecasting.

## 5. Conclusion

The temporal electricity use pattern and specific weather factors can be used to predict the electricity use of a household. The results revealed significant variation across the hours, with demand being higher in the evening hours and delayed electricity consumption being the strongest predictor of electricity consumption in the short-term. The demand variables were less directly correlated with weather variables, but they did enhance the nonlinear forecasting and interpretation when combined with temporal variables. The highest overall performance was achieved by the weather-aware random forest followed closely by gradient boosting, with the persistence baseline having lower predictive accuracy. The study contributes to the field of applied mathematics and statistical forecasting by showing how the time-series structuring, lag features, correlation analysis, model comparison and error metrics can be applied to real household energy data. In a practical sense, the results can be used to influence demand planning, peak-period identification and energy management, where weather information is relevant. The method has potential for enhancing utilities and residential energy systems short-term prediction capabilities. More households, variables at the appliance level, appliance occupancy patterns, probabilistic forecasting, and longer weather time series should be included in future studies to enhance generalizability of the model. The comparison with more sophisticated deep learning models could also help understand the value added by using more sophisticated models compared to simpler forecasting models with greater interpretability.

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