Prediction of PJM Regional Household Hourly Electricity Consumption

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Fundamentals of Data Science

Introduction

As global energy consumption rises, the ability to accurately forecast future energy usage has become increasingly vital. Precise predictions are essential for optimizing resource allocation, reducing operational costs, and ensuring reliable energy delivery in a competitive market. To address this need, our study leverages machine learning techniques to analyze historical energy usage data and predict future consumption trends. By providing data-driven insights, we aim to support utility providers in improving operational efficiency, minimizing waste, and better meeting customer demands.

The dataset used for this study originates from PJM Interconnection LLC, a regional transmission organization (RTO) in the United States founded in 1927. As part of the Eastern Interconnection grid, PJM operates an electric transmission system that spans all or parts of 13 states, including Delaware, Illinois, Indiana, and more. This time-series dataset, which includes household hourly energy consumption data across multiple regions, presents opportunities and challenges in analyzing and forecasting consumption patterns.

This study explores the potential of machine learning to uncover patterns in energy usage by applying diverse predictive models, including the seasonal autoregressive integrated moving average (SARIMA) model, supervised learning approaches, and the Holt-Winters Exponential Smoothing method. The findings aim to provide actionable insights to enhance the efficiency and sustainability of energy management systems.

Pre-processing

Effective data pre-processing plays a big role in preparing time-series datasets like those from the PJM energy consumption dataset for analysis and forecasting. The steps taken in this study focused on cleaning, standardizing, and organizing the data to address common issues such as missing values, duplicate timestamps, and outliers.

Although the dataset required minimal adjustments, missing values and outliers were addressed to enhance data quality:

- **Missing Values:** Missing timestamps were handled to ensure continuity in the time-series data, preserving the hourly frequency necessary for capturing daily and seasonal patterns.
- **Outliers:** Outliers were identified and removed using a threshold of three standard deviations from the mean, ensuring that anomalies did not skew model performance.

To evaluate the forecasting models effectively, the dataset was divided into training and testing subsets. Approximately 80% of the data was used as the training set to analyze historical energy consumption trends. The remaining 20% served as the testing set, enabling a robust assessment of the model's ability to generalize to unseen data.

Method

A. Seasonal Autoregressive Integrated Moving Average (SARIMA) Model

1. Introduction

The SARIMA model, short for Seasonal Autoregressive Integrated Moving Average, is a time-series forecasting method that extends the ARIMA (Autoregressive Integrated Moving Average) model by incorporating seasonality into the predictions. The ARIMA model, in turn, is based on the ARMA (Autoregressive Moving Average) model with the addition of a constant increase component over time. The central idea that binds the AR model class is the concept of autoregression: a feature, or an assumption, of a time-series data in which the current value of the time-series is a function of its past values. That is, it regresses itself, or in other words, the past values of the time-series data can be used to predict its future values if the data is deemed to be autoregressive. Because of this characteristic, the SARIMA model is particularly well-suited for non-linear datasets that exhibit seasonal patterns over time, such as energy consumption, which tends to fluctuate based on the time of day, day of the week, or even month of the year, and then repeats periodically. Intending to mathematically model such a pattern, the SARIMA model considers seven parameters: *p, d, q, P, D, Q,* and *s*:

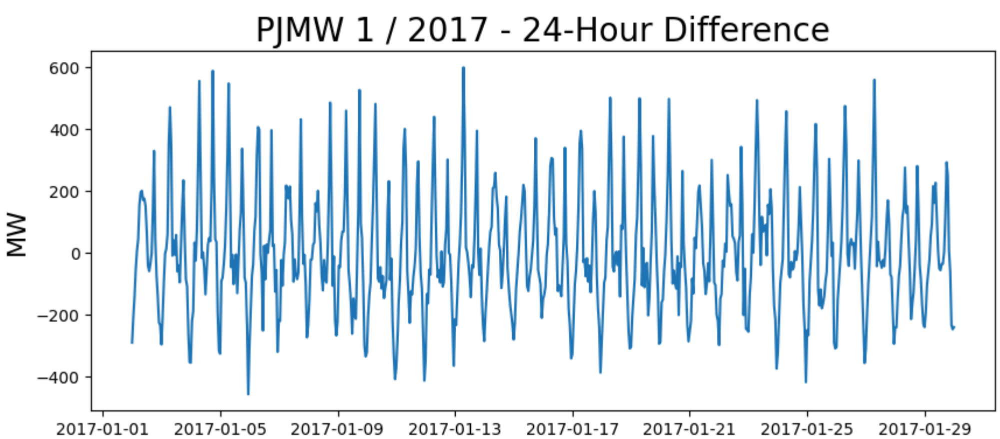
- ***p:*** The number of lag observations included in the model (autoregression).
- ***d:*** The degree of differencing required to make the series stationary.
- ***q:*** The size of the moving average window.
- ***P, D, Q:*** Corresponding seasonal parameters for autoregression, differencing, and moving average.

- ***s:*** The length of the seasonal cycle (e.g. 24 for hourly data to capture daily patterns).

2. Application

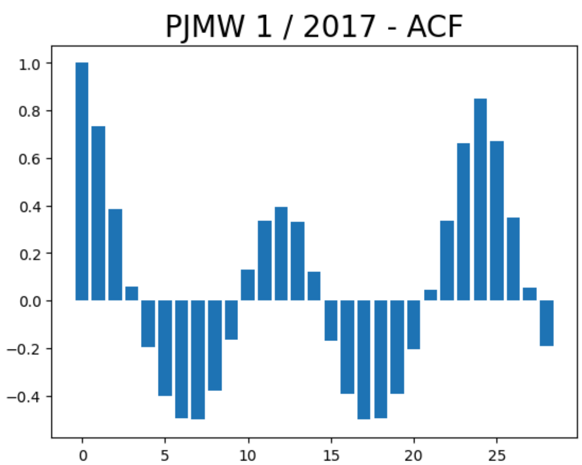
In this study, the SARIMA model was employed to predict hourly energy consumption across various utilities within the PJM dataset. Given the clear seasonal trends in the data (e.g. higher energy consumption during certain times of day or months), the SARIMA model was chosen as one of the primary models for analysis.

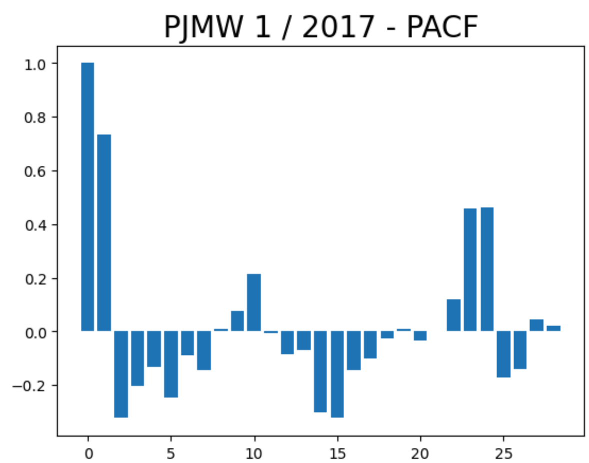
To further quantify our dataset as an eligible candidate for the SARIMA model, we performed the following two operations with the pre-processed datasets. First, recognizing that our raw data is an hourly time series, we took a successive difference between every 24-hour data point:



With a one-month subset of data for January 2017 as an example, the plot above shows the hourly difference with the data points exactly 24 hours later. If there is no seasonality present in our dataset, then this plot should resemble white noise or exhibit random patterns. That is not the case with our dataset, indicating the significant presence of 24-hour short-term seasonality.

In addition, we also applied the autocorrelation function (ACF) and partial autocorrelation function (PACF) on the above-mentioned 24-hour difference across our dataset. ACF and PACF attempt to measure the degree of similarity between a time-series data and its lagged version, indicating autoregression:

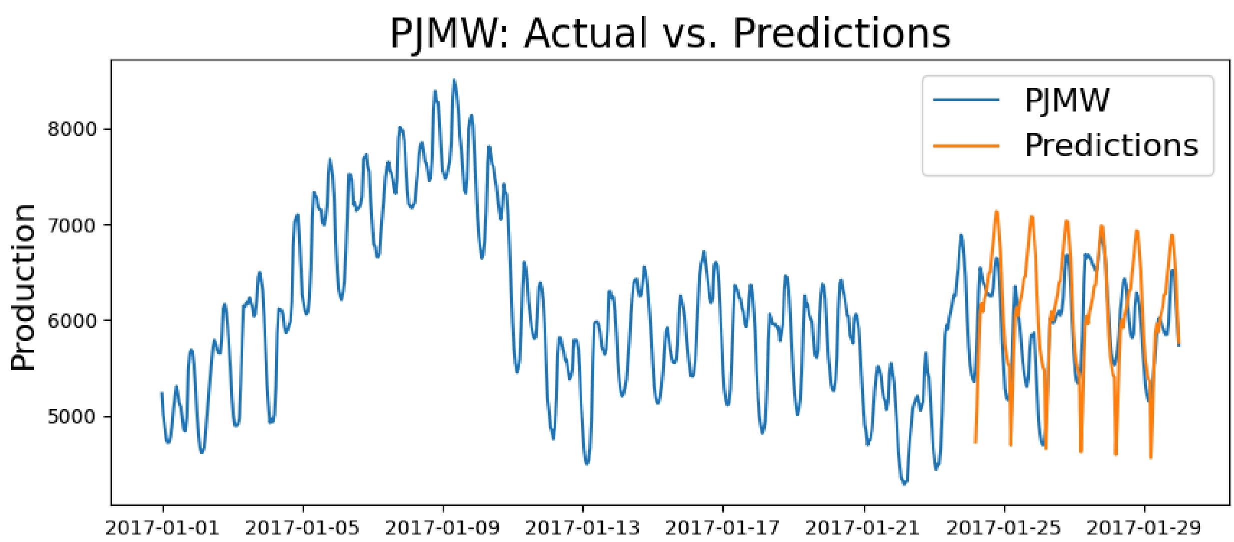




As expected, the results confirmed the presence of 24-hour seasonality in our hourly datasets. Therefore, we set the seasonality parameter of our SARIMA model as 24.

3. Results and Observations

The SARIMA model effectively captured short-term fluctuations and the seasonal patterns of such fluctuations in the dataset, demonstrating its ability to adapt to complex time-series data. With a Mean Absolute Percent Error (MAPE) of approximately 7.2% for most utilities, the model showcased strong predictive performance. However, the Root Mean Squared Error (RMSE) varied significantly across utilities, ranging from 1,466.49 for well-behaved datasets to over 34,000 for utilities with higher variability in energy consumption, highlighting the impact of dataset characteristics on model accuracy.

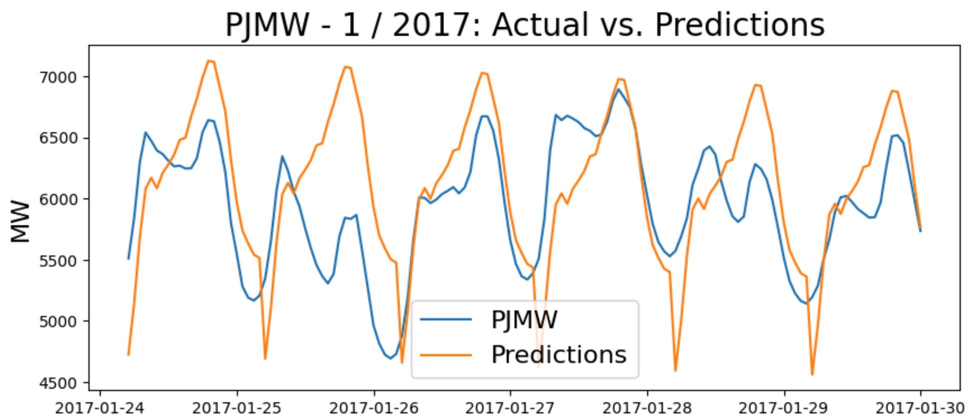


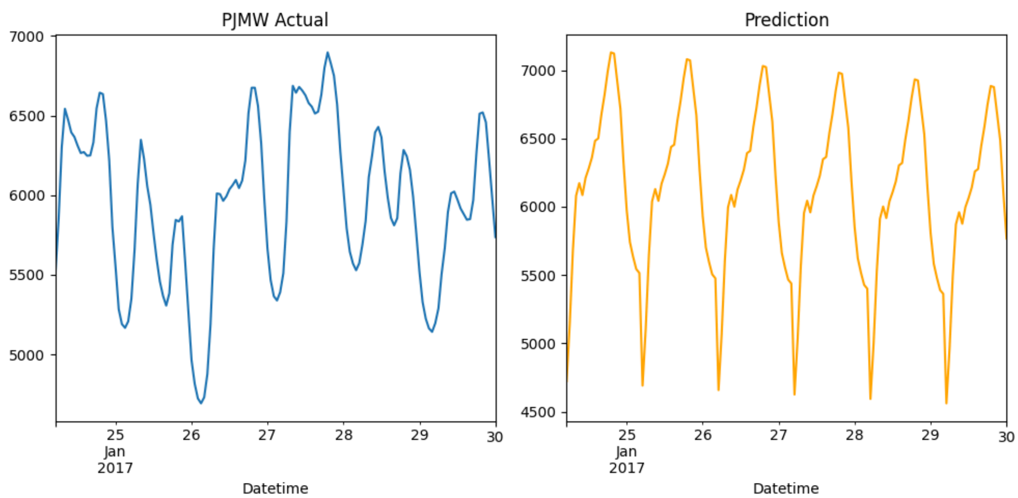
`Mean Absolute Percent Error: 0.0717` `Root Mean Squared Error: 521.24`

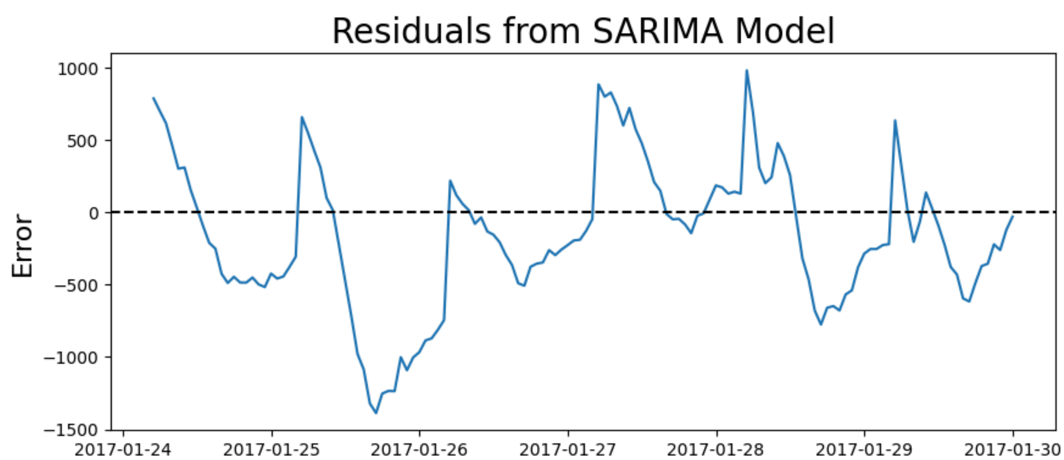
However, the foremost problem with our current SARIMA model as of this writing is that it failed to capture long-term fluctuations and their seasonal patterns. In other words, the model performed relatively well up to about 3 months of the predictive window, and then its predictive power dramatically collapsed. We believe this is not a shortcoming of the SARIMA model in general, but it is rather a result of our failure in properly parameterizing our current SARIMA model because it does not exhibit any attempt to model or incorporate long-term fluctuations as much as it does short-term fluctuations. In other words, the model behaves as if it is blind to the apparent long-term fluctuations, which are also seasonal.

This is a frustrating result even after we consider the fact that our dataset consists of hourly data points and therefore the approximate 3 months of predictive window translates to a rather large number of data points for the model to predict. Once a better combination of parameters is settled, we expect our current SARIMA model to perform much better beyond the current short-term predictive window.

4. Visualizations







5. Strengths and Limitations

The SARIMA model offers notable strengths and limitations when applied to energy consumption forecasting. It is particularly well-suited for datasets with consistent seasonal patterns, such as daily or monthly energy usage trends, and provides interpretable coefficients that offer valuable insights into the relationships between time lags and consumption patterns. When restricted to a short-term prediction window, our current SARIMA model shows some level of potential.

However, the model's reliance on stationarity necessitates extensive preprocessing for non-stationary data, which can be time-intensive. Additionally, datasets with high variability, such as those from our COMED dataset, posed challenges for the SARIMA model, resulting in significant deviations in predictions.

Further work requires insight into better parameterization of our current SARIMA model. Initially, we attempted to construct a matrix of parameters in order to perform hyperparameter tuning. However, any parameter beyond the most basic parameter of ARMA(1, 1) resulted in a failure in the solver function within the Python SARIMAX package on our local machine. We must investigate whether this behavior is due to a lack of computing power or due to incorrect or less-than-optimal parameters used in our current SARIMA model.

B. Holt-Winters Exponential Smoothing Method

1. Introduction

Holt-Winters Exponential Smoothing is a time-series forecasting method that extends simple exponential smoothing by incorporating trend and seasonality components into the model. This method is particularly effective for datasets that exhibit regular patterns over time, such as daily or monthly fluctuations in energy consumption. The model decomposes the time series into three key components:

- **Level (L):** The baseline value of the series.
- **Trend (T):** The direction of change in the data over time.
- **Seasonality (S):** Repeating patterns observed within specific periods.

There are 2 types of Holt-Winters model:

- **Additive Models:** Suitable when seasonal variations remain constant over time.
- **Multiplicative Models:** Appropriate when seasonal fluctuations scale proportionally with the data's magnitude.

For this study, the seasonal component was tuned to reflect daily patterns in the hourly energy consumption data, with a seasonal period of 24.

2. Application of Holt-Winters Exponential Smoothing

Holt-Winters Exponential Smoothing was applied to forecast energy consumption for multiple utilities in the PJM dataset. The methodology involved:

1. Model Selection: An additive seasonal component was initially tested, but multiplicative seasonality was chosen for some datasets to account for variations in seasonal amplitudes. The seasonal period was set to 24, corresponding to daily patterns.
2. Forecasting: The model was trained on historical energy usage data, and predictions were generated for a test period of one week (168 hours). Extreme forecast values were capped to avoid unrealistic predictions, such as negative or excessively high energy consumption.
3. Performance Evaluation: The accuracy of the forecasts was assessed using metrics like Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE).

3. Results

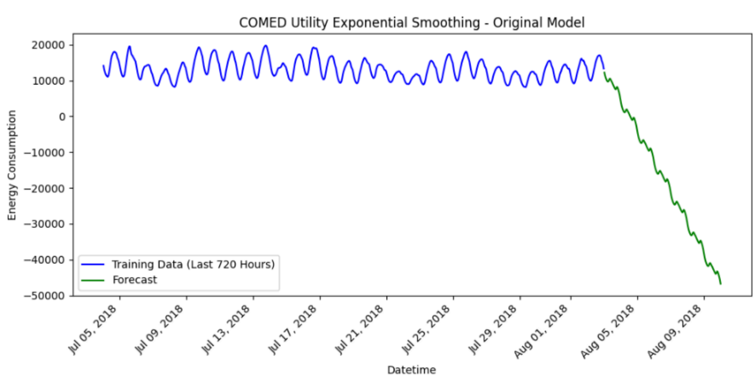
The Holt-Winters method performed exceptionally well for utilities with stable and predictable consumption patterns, such as AEP and DUQ (graph available in visualizations). These utilities exhibited consistent daily and seasonal trends, allowing the model to capture both short-term fluctuations and long-term patterns effectively. This alignment between the data characteristics and the assumptions of the Holt-Winters method resulted in:

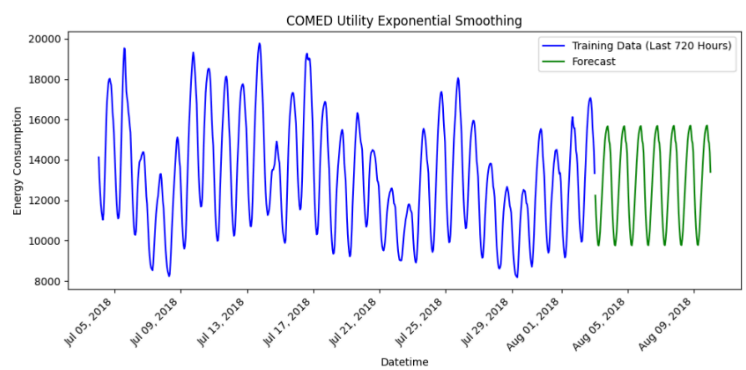
- High forecast accuracy: Predictions closely matched actual energy usage.
- Low RMSE values: Errors were minimal due to the regularity of the data.

- Reliable insights: The model provided clear indicators of peak usage times, aiding demand planning.

For utilities with volatile consumption patterns, such as COMED, the initial performance of the model was less effective due to the high variability and noise in the data. However, after tuning the hyperparameters, including transitioning from additive to multiplicative seasonality, the model achieved significant improvements. For instance:

- COMED RMSE improvement: Dropped from 34,207.74 to 1,602.09 (a 95.3% improvement).

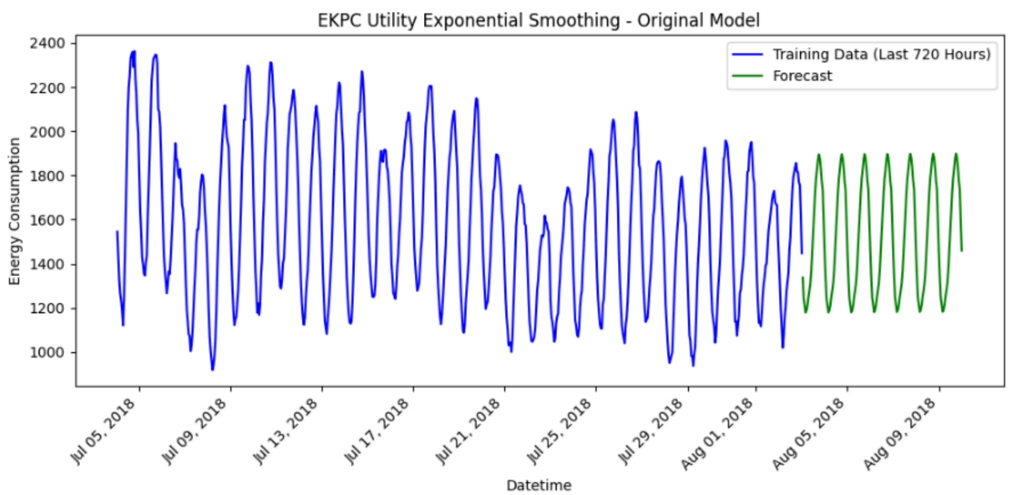




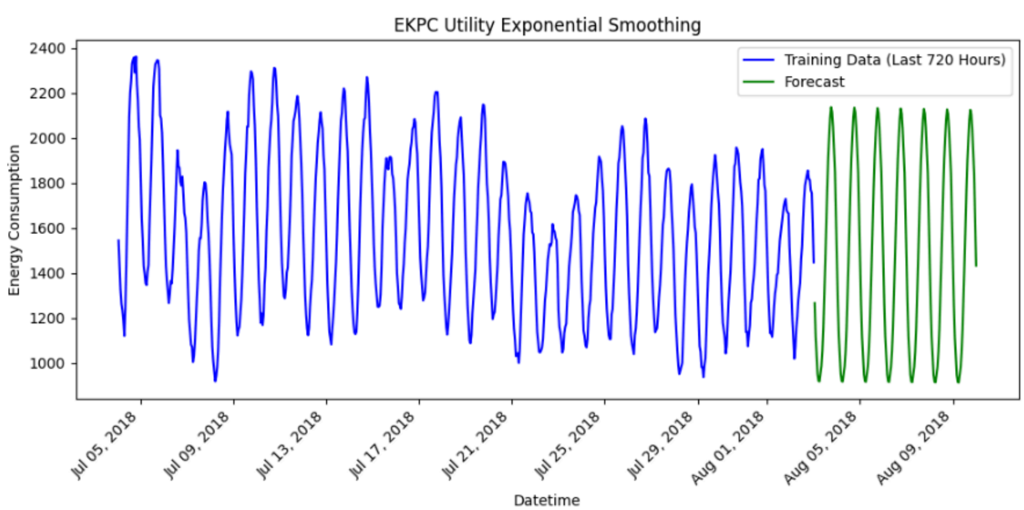
- Adaptability: The model demonstrated its capability to handle challenging datasets with proper tuning.
- Insights despite variability: Even for volatile utilities, the method revealed patterns in consumption behavior that could be useful for operational planning.

In some cases, such as EKPC, the model faced challenges after transitioning to multiplicative seasonality. The RMSE increased, indicating potential overfitting or sensitivity to noise in the data. These cases underscored the limitations of the method when:

- Seasonality is inconsistent: Multiplicative adjustments did not align well with the actual patterns in the data.
- Overfitting occurred: Tuning overly adapted the model to noise rather than meaningful patterns.



Root Mean Square Error (RMSE) for EKPC Utility - Original Model: 98.64



Root Mean Square Error (RMSE) for EKPC Utility: 188.66

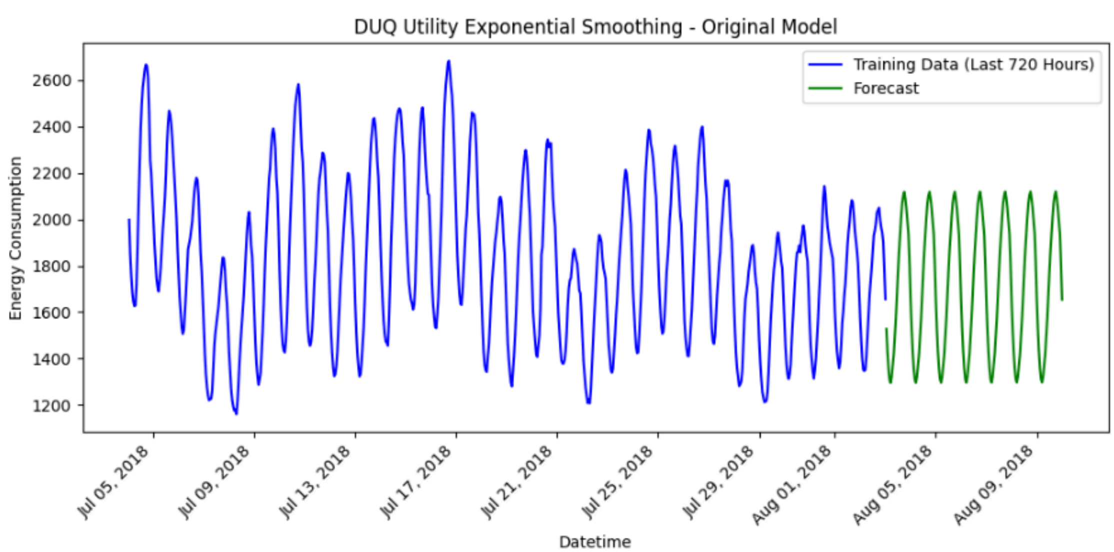
4. Observations

The visualizations of actual vs. predicted energy consumption highlighted the strengths and weaknesses of the Holt-Winters method. Graphs showed that:

- Strong alignment: Utilities with clear daily or seasonal patterns (e.g., AEP) displayed forecasts closely mirroring the actual usage.
- Room for improvement: Utilities with outliers or irregular consumption patterns (e.g., COMED) required additional preprocessing or tuning to achieve reliable forecasts.

5. Visualizations

Utility Name	Original RMSE	Tuned RMSE	Improvement (%)
AEP	1073.41	1235.24	-15.1%
COMED	34207.74	1602.09	95.3%
DAYTON	221.83	215.2	3.0%
DEOK	279.53	263.24	5.8%
DOM	1547.21	882.95	42.9%
DUQ	131.72	121.79	7.5%
EKPC	96.64	166.25	-72.0%
NI	2218.92	1922.67	13.4%
PJMW	375.18	422.32	-12.6%



6. Strengths and Limitations

The Holt-Winters Exponential Smoothing method demonstrated several strengths and limitations when applied to forecasting energy consumption. One of its key strengths lies in its ability to effectively capture both trend and seasonal components, making it particularly suitable for datasets with regular and predictable patterns. Its relatively simple implementation and interpretable components, such as level, trend, and seasonality, make it a practical choice for applications requiring quick adjustments and evaluation. Additionally, the flexibility to use either additive or multiplicative seasonality allows the model to handle varying types of seasonal fluctuations, which was particularly beneficial for utilities with changing seasonal amplitudes.

However, the method also exhibited notable limitations. It was sensitive to noise and outliers in the dataset, which necessitated extensive preprocessing to ensure reliable forecasts. Furthermore, in some cases, hyperparameter tuning led to overfitting, especially when transitioning from additive to multiplicative seasonality, resulting in less accurate predictions for certain utilities. These challenges highlight the importance of careful parameter selection and robust preprocessing to maximize the effectiveness of the Holt-Winters method.

C. Information Based Model

1. Introduction

Information-based models leverage features directly extracted from the dataset to drive predictions. These models focus on identifying meaningful patterns and relationships within the data to improve forecasting accuracy. For this study, we utilized a Random Forest model with time-based features to predict energy consumption. Random Forest, an ensemble learning method, combines the outputs of multiple decision trees to produce reliable and accurate predictions. Its flexibility and robustness make it well-suited for datasets with inherent variability, such as energy usage patterns, as it can capture complex, non-linear interactions between features while maintaining interpretability.

2. Application of Random Forest

The Random Forest model was tailored to the PJM energy consumption dataset by incorporating time-based features to capture the cyclical and seasonal nature of energy usage:

3. Results and Observations

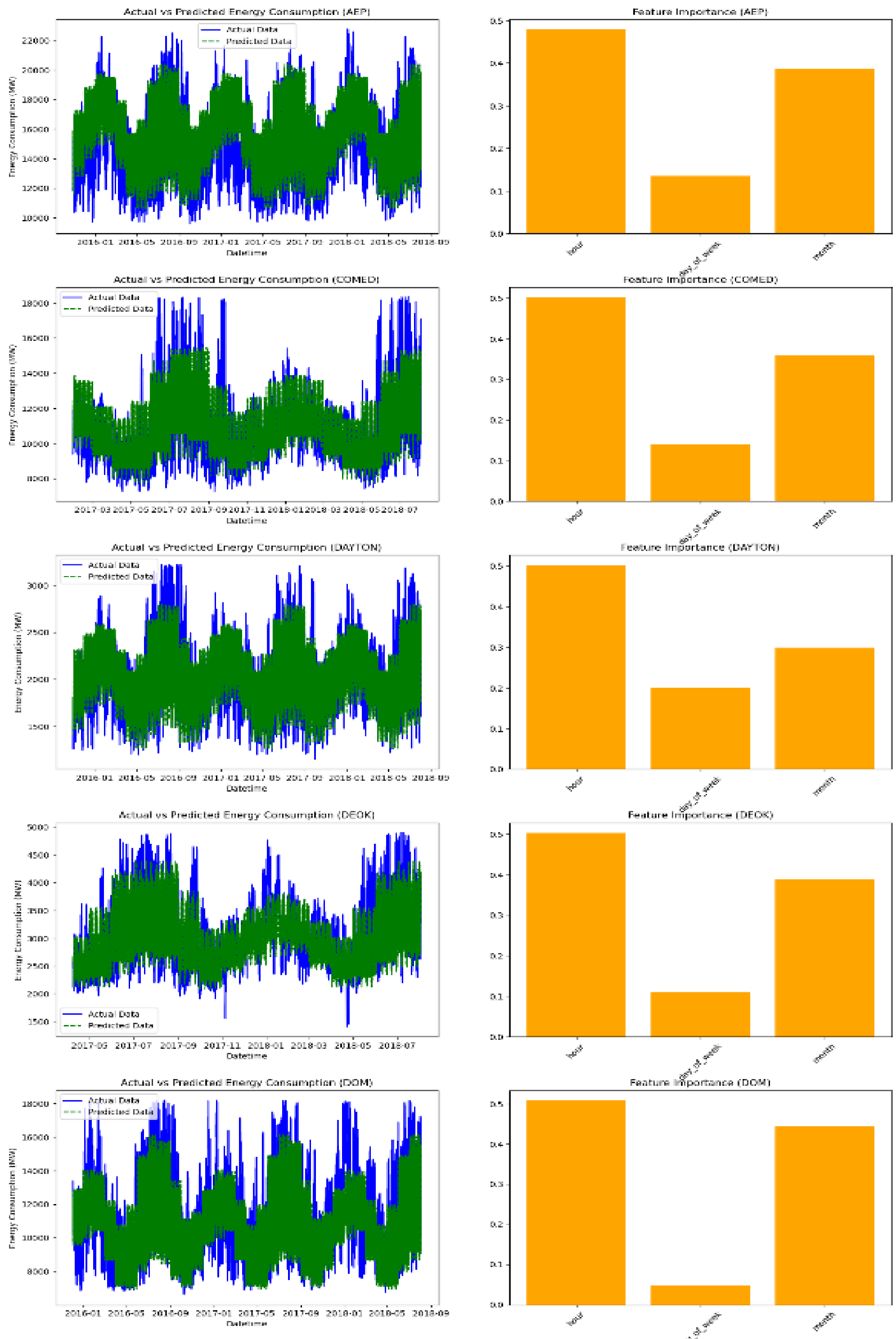
The random forest models performed well overall, demonstrating their effectiveness in predicting energy usage across multiple regions based on time-based features such as the hour of the day, day of the week, and month. Among the models, NI (Northern Indiana) emerged as the best-performing model, achieving the lowest normalized RMSE (9.72%) and MAPE (6.41%), indicating its strong accuracy and minimal prediction error.

Other high-performing models include DAYTON and DEOK, with normalized RMSE values close to 10% and MAPE values below 9%, showcasing their reliability in forecasting energy consumption with less complexity. These results suggest that the energy usage patterns in these regions are more consistent and less variable, making them easier to predict accurately. Regions such as AEP and DOM exhibited slightly higher errors (normalized RMSE > 13% and MAPE around 10%), reflecting more complex or variable energy demand patterns. These regions benefited from deeper trees and larger numbers of estimators to balance the trade-off between bias and variance.

The feature importance analysis consistently highlighted the hour of the day as the most influential factor in predicting energy consumption across the datasets. This underscores the critical role of diurnal patterns, as energy usage tends to fluctuate predictably within a 24-hour cycle due to daily human and industrial activity.

For some utilities, the month of the year also showed significant importance, indicating the presence of seasonal effects. Notably, in the EKPC dataset, the strong impact of the month feature reflects seasonal variations in energy demand, likely driven by temperature-dependent activities such as heating or cooling. These patterns reveal that certain regions experience pronounced seasonality, which utilities need to account for in their forecasting and resource allocation.

4. Visualization



5. Strengths and Limitations

The Random Forest model demonstrated both strengths and limitations when applied to energy consumption forecasting. One of its primary strengths was its ability to handle non-linear relationships effectively, making it particularly useful for capturing complex patterns in energy usage data. Additionally, the model's feature importance metrics provided valuable interpretability, enabling the identification of the most impactful factors driving energy consumption. This interpretability is especially beneficial for energy providers seeking actionable insights to optimize resource management. Furthermore, the ensemble nature of Random Forest reduced the risk of overfitting, enhancing its robustness to noise and improving its reliability when applied to diverse datasets.

However, the model faced certain limitations. For utilities with highly volatile consumption patterns, prediction errors were more pronounced, as the model struggled to generalize effectively in the presence of significant noise. This highlights a challenge in addressing highly variable datasets where more specialized techniques may be needed. Another limitation was the computational cost of training the model, which increased with the size and complexity of the dataset. While this did not compromise accuracy, it posed challenges for scalability, particularly in large-scale implementations involving numerous utilities or extended forecasting horizons.

D. Linear Regression

1. Introduction

Linear regression is a foundational statistical and machine-learning method used to model the relationship between a dependent variable and one or more independent variables. It operates under the assumption that this relationship is linear, making it one of the simplest and most interpretable models available for predictive tasks. Despite its simplicity, linear regression is widely used due to its efficiency, ease of implementation, and ability to provide a baseline performance for comparison with more complex models.

In the context of this study, linear regression was applied to forecast energy consumption using time-based features. These features, such as hour of the day, day of the week, and month of the year, were engineered to capture cyclical and seasonal trends in the dataset. However, because energy consumption patterns often exhibit non-linear behavior, additional techniques, such as the incorporation of lag and cyclical features were attempted in order to create a model that can somewhat follow the trends exhibited in the data

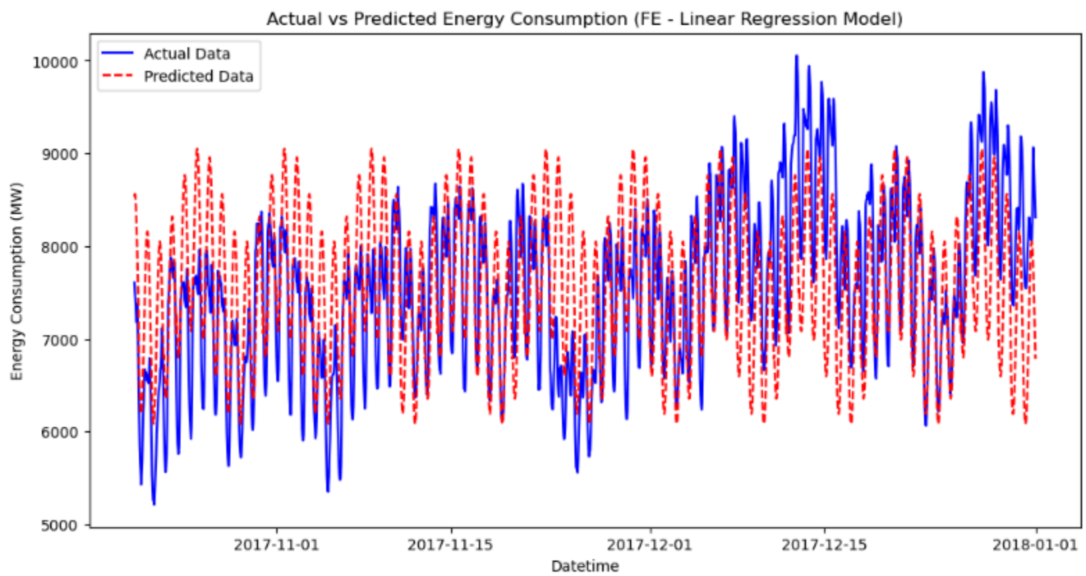
2. Application of Linear Regression Model

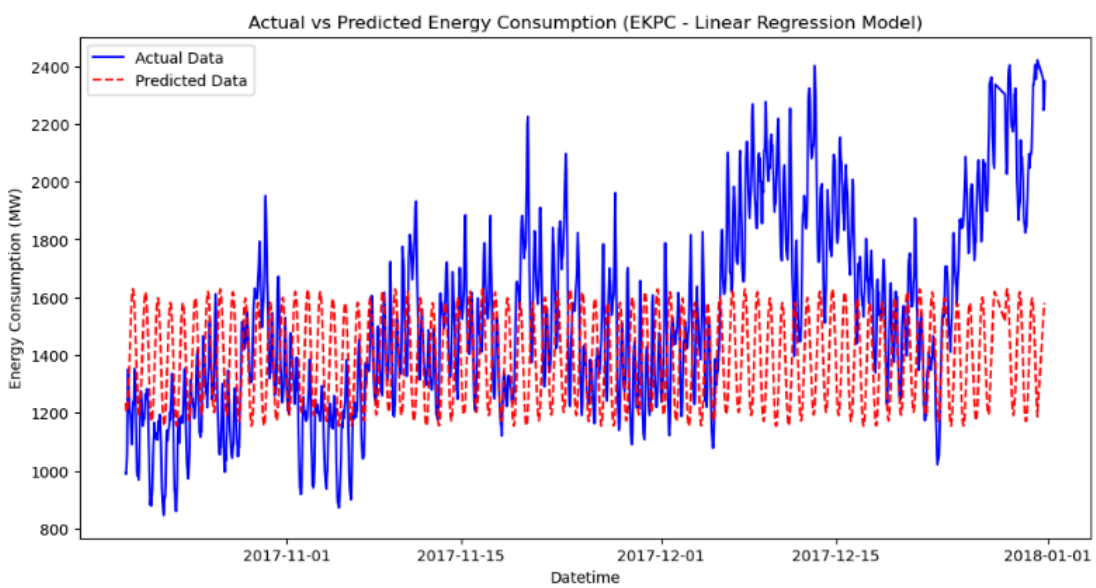
.Cos and Sin functions were utilized on hour and day in order to convey to the model the cyclical repeating nature of these two features, this means that the model will create repeating patterns when it comes to the same day a week later and the same hour a day later. The model works by predicting a new line every hour of where the trend of energy consumption is most likely to go. Surprisingly, this method proved to not be entirely hopeless.

3. Results and Observations

The Linear model was capable of predicting the increase and decrease of energy usage based on the time of day and day of the week, somewhat following the trends exhibited in the actual data. However, since this model heavily uses cyclical features, it is repetitive, and can not adjust to nonrepeating trends. In times when energy consumption would rise and not fall, The predictions failed to follow as seen in the visualization.

4. Visualization





The above graphs are the best and worst performances of the original linear regression model. The former is on average off by 8.31%, while the latter is on average off by 18.59%, over double the discrepancy. This difference can largely be attributed to the difference in explosiveness of the two data sets. While FE only slightly increases and stays within a modest range, EKPC varies wildly, creating new lows and new highs as time progresses. The relatively static behavior of the cyclical linear regression model fails to adjust to this type of variation in data, leading it to be ineffective when it matters.

5. Strengths and Limitations

The linear model was above all else fast and simple, it takes very little time to train and its logic is very straightforward, extrapolating the simplest of patterns and continuing them to generate the prediction. However these advantages pail in comparison to the weakness of the linear regression model, that being that it can only work well with linear data. Energy consumption relies on non-linear factors such as seasonal data and larger overarching trends, both of which are lost in the linear regression model. This means that the linear regression model is only serviceable when dealing with consumption that is already assumed to be stable, otherwise, a model that can properly handle the non-linear data is more apt.

E. Multiplication Chain

1. Introduction

The goal of this forecaster is to create a “model” which performs hour-to-hour forecasts for a given datetime range and which takes only two values as inputs - a year, and an average MW/h for the given year.

2. Approach

Simple visualizations of the data such as the yearly usage visualizations for each utility (an average from 2014 - 2017) show that the absolute magnitude of the power consumption for the utilities showed significant discrepancies by in some cases as much as a factor of 10. The relative trends and shapes within each dataset were visually extremely similar to the normalized scales of the y-axis. This indicates that it may be possible to extract trends on various scales of seasonality within a utility dataset, and have these trends be substantially accurate and applicable to the consumption dataset of a different utility. In considering trends, hourly (24 hours in a week), daily (7 days in a week), and monthly (12 months in a year) appeared as initially reasonable. Within a day, individuals tend to consume more energy during the daytime than at night when fewer lights and appliances are likely to be on which would repeat day to day. Within a week, fewer businesses or commercial properties are likely to be operating during the weekends leading to lower consumption during that time and this would repeat week to week. Within a monthly seasonality (12 months a year) certain hotter and colder months create significantly higher demand for indoor heating and cooling which greatly impact energy consumption across all properties and this (the seasons) repeats year to year. Another seasonality that could have possibly been included was weekly (roughly 4 weeks in a month) but this runs into the problem that most months do not contain exactly 4 weeks. More significantly, there didn't appear to be any meaningful weekly factors that would create trends within a month. The method of representing these seasonality trends was decided to be a series of 3 multiplier dictionaries - 24 entries in hourly, 7 in daily, and 12 in monthly) as well as a yearly multiplier. To make a prediction then, the user needs to only provide a base hourly consumption for a given year and a datetime range which they want to predict. For each hour within the datetime range, the base consumption is multiplied by its corresponding hourly, daily, and monthly multipliers and then the yearly multiplier and this value is the prediction for that hour.

3. Data Preparation

To extract the multiplier dictionaries from the dataset, the 10 individual datasets were first mean normalized, and then an average was taken over for each datetime with the range 2013-12-31 01:00:00 to 2018-01-02 00:00:00 to create a single normalized column which our multiplier dictionaries would be derived from. An approach that creates separate multiplier dictionaries derived on each utility would have likely yielded better performance on predictions on each given utility, but as the goal in this was to predict based on minimal information from generalized trends, this approach was decided against.

4. Training

The training methodology to derive the multipliers was to group our data by day, week, and year. For each day grouping, each of the normalized MW values for each of the 24 hours is divided into its day's average, and the resulting multipliers are saved as another column in the dataset. At the end, the dataset is grouped by hour (0-23), and a single multiplier is created from the average of the multipliers for that hour. The same process applies to days wherein each day in each weekly grouping is divided by its week's average, and a single daily multiplier for each day (0-6) is derived from the average of that day. And for monthly patterns, this logic remains the same. The yearly multiplier unlike the others is a single number as each year does not have a seasonality that we are considering and this is simply computed by taking the geometric mean of the year of year-over-year percentage changes across our training datetime range.

5. Results

The model(multipliers) was evaluated on all ten of the utility datasets used for training. The prediction datetime range from 2017-01-01 to 2017-12-31 was used and the base year was chosen as 2016 for all datasets with the base consumption being the average hourly consumption in that year. The results delivered by the “model” were quite surprising with MAPE scores of 10-17% across the ten utilities.

Discussion

The analysis of household hourly electricity consumption using various forecasting models provided valuable insights into the potential and limitations of these techniques. Each model exhibited unique strengths and weaknesses, underscoring the importance of choosing an approach tailored to the dataset's characteristics and specific forecasting objectives.

Key Summary

1. Effectiveness of SARIMA for Short-Term Seasonal Trends

   The SARIMA model excelled in capturing short-term seasonal fluctuations, such as daily and hourly patterns. Its performance highlighted the importance of understanding the cyclical nature of energy consumption, as demonstrated by its low MAPE for utilities with predictable usage. However, the model struggled with long-term predictions, suggesting a need for more robust parameterization or complementary models to address extended forecasting windows.

2. Holt-Winters Method's Adaptability

   The Holt-Winters Exponential Smoothing method showcased its strength in handling datasets with stable and predictable patterns, performing exceptionally well for utilities with consistent seasonal trends. Its ability to tune between additive and multiplicative seasonality allowed it to adapt to varying amplitudes. However, its sensitivity to outliers and potential for overfitting emphasized the importance of preprocessing and careful parameter tuning.

3. Random Forest's Flexibility with Feature-Based Predictions

   Random Forest models proved to be highly effective, particularly for utilities with moderate variability. The feature importance analysis revealed the critical role of time-based features, such as the hour of the day and month, in driving energy usage. While computationally intensive, the Random Forest approach demonstrated the potential to capture complex, non-linear patterns, making it suitable for applications requiring detailed interpretability and adaptability.

4. Limitations of Linear Regression for Non-Linear Trends

   Linear regression, while simple and computationally efficient, was largely limited by its inability to account for non-linear relationships inherent in energy consumption data. Its reliance on cyclical features, such as sine and cosine transformations, provided some utility for stable datasets but fell short in scenarios with significant variability or long-term trends.

5. Multiplication Chain for Generalized Forecasting

   The multiplication chain model offered an innovative approach to forecasting with minimal input requirements. Despite its simplicity, the method achieved reasonable accuracy, demonstrating the potential of leveraging generalized trends for resource-efficient predictions. Its performance across utilities with diverse consumption patterns highlighted its robustness but also suggested that further refinement could improve its alignment with volatile datasets.

Broader Implications and Applications

The findings from this study show the importance of using multiple approaches to energy forecasting. For utilities with steady, predictable energy use, simpler models like Holt-Winters or the multiplication chain method work well and are cost-efficient. On the other hand, regions with more unpredictable patterns benefit from advanced models like Random Forest or SARIMA, though these require more data cleaning and parameter adjustments. By combining these methods, utility providers can make better decisions about resource management, prepare for spikes in demand, and improve the reliability of the grid.

Additionally, the feature importance analysis shows how time-based patterns, like daily and seasonal cycles, play a big role in predicting energy use. These consistent diurnal and seasonal trends provide useful insights that can help with planning and managing energy systems.

Future Work and Recommendations

1. Enhanced Parameter Tuning

   Both SARIMA and Holt-Winters models could benefit from advanced hyperparameter optimization techniques, potentially leveraging grid or random search methods. Improved parameterization could extend the predictive horizon and enhance accuracy for long-term forecasts.

2. Hybrid Model Development

   Combining the strengths of different models could address their limitations. For example, integrating SARIMA's seasonal accuracy with Random Forest's adaptability to non-linear trends may yield a more reliable forecasting framework.

3. Incorporation of External Factors

   Future studies should explore the integration of external variables, such as weather conditions, economic indicators, and policy changes, to enhance model performance and capture various dimensions of variability in energy consumption.

4. Evaluation of Extended Timeframes and Diverse Datasets

   Expanding the evaluation to cover longer prediction windows and a wider variety of datasets can offer deeper insights into how the models perform under different conditions, improving their overall versatility. Additionally, comparing the models within specific timeframes can provide a clearer picture of their strengths and weaknesses.

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