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## Abstract

Accurate power load forecasting is essential for effective management and operations in critical infrastructure like Smart Grids. However, estimating electricity load remains problematic due to its nonlinear character. Recently, deep learning has emerged as a promising approach in the field of machine learning, displaying impressive performance across numerous tasks, ranging from image classification to machine translation. Consequently, interest in applying deep learning models to electric load forecasting has been developing among both scholars and industry personnel. Despite this interest, a full and robust comparison of several deep learning architectures for this job is still lacking in the literature. This work attempts to overcome this gap by conducting a detailed assessment and experimental evaluation of the latest trends in electric load forecasting. Specifically, we focus on short-term forecasting, particularly one-day ahead projections by using our energy usage statistics. By contrasting alternative deep learning architectures, we hope to provide insights into their effectiveness and identify the most viable ways for this key application in Smart Grid management.


# 1 In-depth Analysis and Foundation of Domestic Energy Utilization

## 1.1 System Examination

This analysis focuses on the complex dynamics of residential energy usage within suburban surroundings, encapsulating a spectrum of families each with individual energy consumption patterns driven by a blend of daily routines, meteorological fluctuations, and socioeconomic statuses.

## 1.2 Phenomenological Insights

- **Cyclical Energy Demand Patterns**: Characterized by pronounced increases in energy demand during early morning and evening hours, as well as during the climatic extremities of winter and summer. Mathematically, demand $D(t)$ varies with time $t$, showing peaks at specific intervals.

- **Weather-Dependent Energy Variability**: Includes the influence of temperature fluctuations, humidity levels, and wind velocities on energy consumption, modeled using multivariate regression to incorporate weather variables into energy usage predictions.

## 1.3 Problem Elucidation

Short-term electric load forecasting is increasingly becoming a linchpin in the management and operational dynamics of contemporary power systems, a significance magnified by the ongoing paradigm shift towards the integration of renewable energy resources and the evolution towards more sophisticated, interactive electrical grids. This form of forecasting, which aims to predict power usage over short intervals ranging from an hour up to a week ahead, is not only a procedural necessity but a basic factor that influences multiple parts of grid management. The quality of these forecasts is vital for insuring grid planning and dependability, as it enables grid operators to anticipate demand fluctuations precisely and make educated judgments regarding system setup and adjustments. Such preventative efforts are crucial for limiting potential overloads and the attendant risk of blackouts, thereby ensuring the grid's stability.

Beyond the criteria of reliability, the function of short-term electric load forecasting goes into enhancing operational efficiency. With accurate demand estimates, operators may fine-tune the scheduling and dispatch of power plants, aiming for an optimal balance that minimizes the need for costly, fast-acting reserve capacities. This element of forecasting becomes even more critical as the energy landscape evolves to integrate a growing percentage of renewable energy sources, typified by their inherent volatility and unpredictability. Efficiently integrating such sources into the grid necessitates a high degree of precision in demand forecasting to sustain grid stability and operational efficiency.

Moreover, the economic significance of short-term load forecasting cannot be understated, particularly in the context of economic dispatch—the process of determining the most cost-effective mix of power outputs from different producing units to supply the required load at the lowest cost. Accurate load forecasts are vital to this process, enabling grid operators to control electricity generation in a manner that matches with real-time demand, thereby minimizing operational costs. By guaranteeing that energy generation does not surpass demand, economic dispatch helped by precise short-term load forecasting avoids needless waste, supporting a more economically and environmentally sustainable approach to power system management.

## 1.4 Related Work

In our related work section, several current studies and their techniques are covered below:

The paper [1] presents a comprehensive review of research pertaining to electric energy consumption prediction, emphasizing the critical need for accurate forecasting methods amidst rapid population growth and technological advancements. Recognizing energy consumption as a multivariate time series prediction challenge, prior studies have explored various approaches to handle the complexities inherent in the data, including decomposition techniques to analyze different temporal patterns. Deep learning methodologies, particularly the combination of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) networks, have emerged as promising solutions for extracting spatial and temporal features from such data. While previous research has applied machine learning and deep learning techniques to energy consumption prediction, the proposed CNN-LSTM model represents a novel advancement tailored specifically for residential energy forecasting. By leveraging CNN layers for feature extraction and LSTM layers for modeling temporal information, the model demonstrates superior performance in handling high-resolution data and offers valuable insights into household energy consumption patterns. The study underscores the significance of accurate energy forecasting for ensuring stable power supply and optimizing energy management strategies in the face of growing demand and evolving consumption patterns.

The paper [2] addresses the emerging need for comprehensive analysis of electrical load data obtained from low voltage power distribution networks, emphasizing the importance of segmenting end users based on their daily energy consumption patterns or load profiles. While traditional analysis has been limited to single-day assessments, the advent of Advanced Metering Infrastructure (AMI) and Smart Grid technologies necessitates a broader examination of consumption patterns over extended time periods. The study aims to bridge this gap by introducing a novel framework for dynamic clustering, visualization, and identification of temporal patterns in load profile time series data. By extending the analysis beyond daily snapshots to encompass the evolution of consumption patterns over days, weeks, months, seasons, and years, the proposed framework offers a comprehensive approach to understanding energy consumption behaviors. The framework facilitates clustering and visualization of load profile time series using classical clustering algorithms while also introducing a dynamic clustering algorithm based on Hausdorff distance to compute similarity measures among segmented energy consumption time series data. The efficacy of the framework is demonstrated through experimentation on datasets comprising energy consumption load profiles from residential users in Spain and London, thereby providing valuable insights into consumer behavior and consumption trends.

The research [3] focuses on projecting monthly electricity load (MEL) using statistical methods. Accurate projections are vital for the operational planning and reliability of power systems, especially because electricity storage is limited. The research acknowledges the complexity of MEL forecasting due to its influence on different aspects like weather, economic events, and socio-economic variables.The study combines three statistical methods for forecasting: ARIMA (Autoregressive Integrated Moving Average), ETS (Exponential Smoothing), and Prophet. These strategies are chosen to address the non-linearity, annual seasonality, and random disturbances inherent in MEL time series. The novel technique of the study comprises the depiction of monthly load time series as annual cycle patterns, which simplifies the prediction procedure by unifying the data and filtering tendencies. The efficacy of these techniques is tested on MEL time series data from 35 European countries.

The literature review of the methodology described involves a multi-disciplinary approach drawing from various fields such as energy research, social science, and data analysis [4]. Authors utilize methods including modelling, sub-metering, load disaggregation, and non-intrusive appliance load monitoring (NILM) to understand household electricity consumption. They introduce an innovative methodology that integrates qualitative data about household activities with NILM data to characterize energy consumption. This approach leverages social science time use approaches, interviews, and ethnography data to understand how households spend their time at home. The methodology disaggregates electricity load to appliance level, providing detailed information on usage patterns. Authors also develop an ontology to formalize relationships between appliances and activities, facilitating inference about activities based on disaggregated data. They propose standardized metrics for quantifiable comparison of energy intensity and routine across households. The methodology is demonstrated through analysis of ten households, highlighting the accuracy of activity inference and potential applications in energy feedback and demand management.

The literature review [5] presented in this paragraph showcases the utilization of deep learning techniques for predicting residential energy consumption, which is akin to forecasting a complex multivariate time series. Authors address the challenges posed by irregular energy patterns and hidden correlations within power attributes by proposing a deep learning model combining multi-headed attention with a convolutional recurrent neural network. This approach aims to selectively learn spatiotemporal features to mitigate translational variance between energy attributes. Specifically, the model leverages attention mechanisms to capture transient and impulsive nature of energy demand. Experimentation conducted using the University of California, Irvine (UCI) household electric power consumption dataset, comprising over 2 million time-series, demonstrates significant reduction in prediction error compared to state-of-the-art deep learning models, with the multi-headed attention mechanism notably enhancing prediction performance.

The authors of this study [6] did a detailed literature analysis concentrating on energy consumption projections, given the growing demand for energy caused by population increase and globalization. They tested a range of machine learning models and classical time series forecasting techniques for predicting household energy usage, leveraging information obtained from the Kaggle data science community. Employing Weka as their initial tool, they employed models such as Multi-Layer Perceptron, K-Nearest Neighbor regression, Support Vector Regression, Linear Regression, and Gaussian Processes. Additionally, they deployed Python-based time series forecasting models, including Autoregressive Integrated Moving Average (ARIMA) and Vector Autoregression (VAR), to anticipate energy usage for selected South Korean households with and without meteorological data. Their investigation aimed to discern the most effective method for energy consumption prediction, leading them to conclude that Support Vector Regression produced the most accurate forecasts, followed by Multilayer Perceptron and Gaussian Process Regression, suggesting the superiority of more sophisticated machine learning approaches for capturing the complexities inherent in household energy consumption patterns.

In this study, the authors [7] address the difficulties of significant unpredictability and low latitude in short-term household electrical load data by providing a unique short-term load multi-step forecasting method based on the Long- and Short-Term Time Series Network (LSTNet). The process involves several critical steps. Firstly, the authors apply the time sliding window method to sample historical load data, creating feature maps as input. Next, they deploy Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) networks to record temporal short-term local information and long-term relevant information, respectively. Additionally, autoregressive (AR) models are introduced as linear components. The evaluation of the suggested models is accomplished using a walk-forward validation scheme, with the average absolute percentage error (MAPE) and root mean square error (RMSE) serving as accuracy evaluation indicators. To validate the effectiveness of the proposed method, the authors utilize four years of electric load data from a family in Paris, France, comparing it exhaustively with three popular load forecasting systems. The experimental findings demonstrate greater performance in predicting the next week's load, with less MAPE and RMSE compared to previous methods.

In this work, the authors [8] address the rising availability of data from sophisticated metering infrastructures, notably smart meters, which give highly disaggregated and high-frequency electricity consumption data. Recognizing the potential of this data to improve forecasting models and positively impact energy networks, the authors suggest a unique methodology for processing and forecasting smart-meter time series. Instead of standard univariate techniques, they build a single yet complicated recurrent neural-network model with long short-term memory (LSTM). This model seeks to capture individual consumption patterns and consumption habits across multiple households. Importantly, the model can accurately estimate future loads of individual consumers, even for individuals not included in the initial training set, indicating scalability and potential for large-scale applications. The authors undertake multiple numerical experiments utilizing real-world datasets containing thousands of disaggregated electricity usage time series to test the proposed approach. Additionally, they analyze how geo-demographic segmentation of consumers may influence the forecasting accuracy of the model, further enhancing the analysis. This research review highlights the application of LSTM-based recurrent neural networks in exploiting smart meter data for tailored load forecasting, highlighting the potential for scalability and the need of integrating consumer attributes for enhanced accuracy.

The study investigates [9] the prediction of electricity usage in smart grid environments, utilizing advanced metering infrastructure (AMI) data and time-series clustering approaches. Several forecasting models, such as ARIMA, Holt-

Winters, and neural networks, are assessed, and it is found that clustering methods outperform total demand approaches in terms of performance. In addition, using external factors such as cooling degree days, humidity, and power consumption from production improves the accuracy of the model. The research contributes to the development of effective demand forecast approaches for smart grid optimization by tackling issues given by dynamic residential power usage and using real-time communication capabilities.

The paper addresses [11] the difficulty of projecting individual household energy use by suggesting a two-phase strategy. Firstly, a long short-term memory (LSTM) model is applied to anticipate total generating active power for the following 500 hours. Subsequently, a hybrid deep learning model combining convolutional neural network (CNN) characteristics with LSTM is applied to anticipate weekly residential energy usage using Social IoT-based smart meter information. Experimental evaluation indicates the superiority of the proposed convolutional LSTM (ConvLSTM) architecture, achieving the lowest root mean square error of 367 kilowatts for weekly household power consumption prediction. This methodology mixes deep learning techniques with IoT-based data, enabling enhanced accuracy and aiding effective energy management in smart environments.

The work [12] analyzes SVR, LSTM, GRU, CNN-LSTM, and CNN-GRU models for energy consumption prediction. Results demonstrate that as data amount increases, SVR performance deteriorates dramatically compared to deep learning techniques. The suggested CNN-GRU architecture beats others, with a 17.4% improvement in MAE over LSTM for daily granularity data. While LSTM significantly beats CNN-GRU for hourly data, the difference is minor. Additionally, CNN-LSTM and LSTM models accurately identify outliers. This research adds to developing predictive modeling methodologies for energy consumption in smart residential environments, underlining the advantages of deep learning techniques over typical machine learning approaches.

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This study investigates [12] the impact of dwelling and household factors on energy usage across different end-uses, including heating, cooling, DHW (domestic hot water), lighting, electric appliances, and cooking. Conducted in South Korea, data was obtained via a field survey of 154 households in sample apartment complexes. Energy usage was examined separately for each end-use during two periods: May 2017 to April 2018 and January to December 2019. Four models were created to assess the influence of features on energy consumption, with Model 1 focused on variables with the biggest impact and Models 2-4 analyzing physical building features, sociodemographic factors, and household appliance-use characteristics, respectively. Multiple regression analysis was performed to uncover relevant variables and their influence size. Findings reveal consistent influential variables between the two periods, except for DHW. Notably, area for exclusive usage, home size, and air conditioner operating hours were significant predictors across varied end-uses. Results also demonstrate varying consequences of dwelling and household features on different end-uses, with heating largely driven by building variables, cooling and electric appliances by household appliance-use characteristics, and DHW and cookery by sociodemographic factors. Lighting demonstrated a balanced influence from physical building components, sociodemographics, and appliance-use characteristics. This detailed analysis offers insights into sustainable options for energy consumption management in household settings

The research addresses [13] the very short-term load forecasting (VSTLF) problem, crucial for boosting smart grid and demand response systems. Effective VSTLF solutions allow real-time electricity deployment and quality optimization. The research provides a novel approach to mimic individual family loads based on context knowledge and daily scheduling patterns. By investigating time series of daily electricity consumption, several behavior pattern types are determined. Context features from multiple sources are collected to develop a rule system for anticipating behavior patterns for specific days. Additionally, power consumption volume prediction models are created for each behavior pattern type to forecast load at specified time periods. Focused on resolving VSTLF for individual households in Taiwan, the recommended technique offers promising results with an average mean absolute percentage error (MAPE) of 3.23% for forecasting individual household load and 2.44% for aggregating load 30 minutes ahead. These results surpass those of other methodologies, showing the utility of the suggested methodology. This work adds to enhancing VSTLF approaches, particularly suitable for individual home goods.

This study [14] explores the features of power consumption data based on different types of contracts and assesses the forecasting accuracy of deep learning models. Deep learning models have the potential to properly manage varied variables in real-world electricity consumption due to their complexity, especially when they are taught with a sufficient amount of data. The study attempts to evaluate potential differences in the learning performance of prediction models based on distinct contract types, as indicated by observed trends in experimental data that reflect diverse consumption patterns. The research analyzes the influence of model complexity and configuration on prediction performance for distinct contract sorts through experimental investigations. The outcomes of this inquiry are expected to provide insight into the applicability of deep learning models for predicting power demand in different contractual agreements. This work advances our grasp of the relationship between different forms of contracts and the efficacy of prediction models. It provides vital insights for the design of more exact and customizable algorithms for estimating power usage in varied contexts.

The suggested model's performance was proved by an experimental evaluation done on the massive Pecan Street dataset, which covers a period of roughly four years. The results reveal that HousEEC attains a noteworthy level of precision in load forecasting, as evidenced by a root-mean-square error of 0.44 kWh and a mean absolute error of 0.23 kWh for short-term load forecasting over a sample of 300 households. When compared to benchmark models, the suggested model displays superior performance [15]. It achieves 4 percentage points improved accuracy for hourly forecasting and much-reduced error rates for daily forecasting. The results underscore the effectiveness of employing deep learning to enhance the precision and dependability of short-term load forecasting for residential energy usage.

# 2 Part 2: Elaborate Analytical Framework for Residential Energy Consumption Modeling

## 2.1 Detailed Examination of State Variables

In modeling residential energy consumption, it is crucial to meticulously define and understand the variables that influence energy usage patterns. The *EnerForecast* model incorporates a set of key state variables that are central to the predictive accuracy of residential energy consumption:

- **Energy Consumption** ($E_t$): This is the primary dependent variable representing the total energy consumed by a household at time $t$, measured in kilowatt-hours (kWh). The variable $E_t$ is influenced by various factors, including environmental conditions, household characteristics, and temporal elements.

- **Temperature** ($T_t$): Temperature is a critical environmental variable that significantly impacts heating and cooling demands in residential settings. The model considers the ambient temperature at time $t$, measured in degrees Celsius (°C), to account for its direct influence on energy consumption. The relationship between temperature and energy usage is often nonlinear, especially at temperature extremes where energy usage for heating or cooling can spike.

- **Humidity** ($H_t$): Humidity levels affect the comfort and thus the energy consumption patterns within households, particularly through the efficiency and usage of air conditioning systems. The model incorporates humidity as a percentage value at time $t$, considering its interaction with temperature to influence cooling demands.

- **Household Income** ($I_t$): As a proxy for socioeconomic status, household income is included to capture the potential for investment in energy-efficient technologies and the adoption of energy-saving behaviors. Higher-income levels may correlate with reduced energy consumption through the use of more efficient appliances and systems.

## 2.2 Mathematical Representations and Interactions

The *EnerForecast* model includes a series of equations to describe the links between the state variables and energy consumption. These interactions are expressed through both linear and nonlinear mathematical formulations:

**Temperature-Energy Interaction:**

$$E_t = \alpha_1 + \beta_1 T_t + \gamma_1 T_t^2 + \epsilon_{1t} \tag{1}$$

This equation models the energy consumption $E_t$ as a function of temperature $T_t$, where $\alpha_1$ is the intercept, $\beta_1$ captures the linear impact of temperature, $\gamma_1$ represents the coefficient for the squared temperature term to account for nonlinearity, and $\epsilon_{1t}$ is the error term.

**Humidity-Energy Interaction:**

$$E_t = \alpha_2 + \beta_2 H_t + \gamma_2 H_t^2 + \epsilon_{2t} \tag{2}$$

Similar to the temperature model, this equation represents the nonlinear relationship between humidity $H_t$ and energy consumption $E_t$, with $\alpha_2$, $\beta_2$, and $\gamma_2$ denoting the intercept, linear, and nonlinear coefficients, respectively.

**Income-Energy Correlation:**

$$E_t = \alpha_3 + \beta_3 I_t + \epsilon_{3t} \tag{3}$$

This linear model explores the relationship between household income $I_t$ and energy consumption $E_t$, where $\alpha_3$ is the intercept and $\beta_3$ signifies the effect of income on energy usage.

## 2.3 Composite Model Formulation

Integrating the individual relationships, the *EnerForecast* model adopts a holistic approach to predict residential energy consumption, combining the effects of temperature, humidity, and household income alongside diurnal and seasonal variations:

$$E_t = \alpha + \sum_{i=1}^{3} (\beta_i X_{it} + \gamma_i X_{it}^2) + \Phi(D_t) + \Theta(S_t) + \epsilon_t \tag{4}$$

where $X_{it}$ represents the set of independent variables ($T_t$, $H_t$, $I_t$), $\Phi(D_t)$ and $\Theta(S_t)$ encapsulate daily and seasonal components, and $\epsilon_t$ is the overall error term. This comprehensive formulation allows the model to capture both the linear and nonlinear dynamics of energy consumption in response to a multitude of influencing factors.

## 2.4 Theoretical Underpinnings and Justifications

The incorporation of both linear and nonlinear components for temperature and humidity is based on the notion that energy usage for heating and cooling does not increase in a straight line with changes in temperature or humidity. During exceptionally hot days, the energy consumption for cooling can increase significantly. Likewise, the effect of humidity is not linear, particularly at elevated humidity levels where the perceived temperature can significantly surpass the actual temperature, resulting in increased energy requirements for cooling.

The household income variable is assumed to have a linear relationship with the capacity for energy-saving investments. It is believed that as income increases, there will be commensurate increases in this capacity. However, it is also recognized that the returns on these investments will diminish as income continues to climb.

## 2.5 Integration of Sub-Metering Variables into the Ener-Forecast Model

## 2.6 Data

The dataset includes important parameters, such as time, which is expressed in the hour:minute:second format, providing a precise temporal foundation for our research. The important factors analyzed include the global active power and global reactive power, measured in kilowatts, which represent the average power consumption of the household in terms of both active and reactive power. Furthermore, the dataset contains voltage data, measured in volts, which offers valuable information about the average voltage levels in the household on a minute-by-minute basis. In addition, the global intensity, measured in amperes, is another important factor that is taken into account to describe the average current intensity of the home throughout a minute. Our research seeks to analyze these parameters in a methodical manner in order to uncover patterns, trends, and potential connections in household electrical consumption. This will lead to a better understanding of energy usage dynamics and provide insights for improving efficiency and sustainability. We reduce unnecessary features that shows no co relation.

## 2.7 Definition of Sub-Metering Variables

**Global Active Power** ($G_t$): Represents the total energy consumption in the household at time $t$, measured in kilowatts (kW).

**Sub-Metering 1** ($SM1_t$): Measures the energy consumed by specific household appliances or systems (e.g., heating) at time $t$, recorded in watt-hours (Wh).

**Sub-Metering 2** ($SM2_t$): Accounts for the energy usage of other specific appliances or systems (e.g., cooling) at time $t$, also in Wh.

**Sub-Metering 3** ($SM3_t$): Tracks energy consumption by additional designated appliances or systems (e.g., water heating) at time $t$, in Wh.

## 2.8 Mathematical Representation of 'Other' Energy Consumption

The 'other' energy consumption ($E_{\text{other},t}$) at time $t$ can be calculated using the given formula, which accounts for the total active power minus the energy recorded by the three sub-meterings, converting the total active power from kW to Wh:

$$E_{\text{other},t} = \left(G_t \times \frac{1000}{60}\right) - SM1_t - SM2_t - SM3_t$$

This equation provides a measure of the energy consumed by electrical equipment not monitored by the sub-meterings, offering a more comprehensive view of household energy usage.

## 2.9 Incorporation into the EnerForecast Model

To integrate the 'other' energy consumption into the EnerForecast model, we consider $E_{\text{other},t}$ as an additional dependent variable influenced by temperature, humidity, household income, and possibly other factors not directly captured by the sub-meterings. The revised model, therefore, expands to include this variable in its predictive framework:

$$E_{\text{total},t} = \alpha + \beta_1 T_t + \beta_2 H_t + \beta_3 I_t + \beta_4 E_{\text{other},t} + \Phi(D_t) + \Theta(S_t) + \epsilon_t \tag{5}$$

where $E_{\text{total},t}$ represents the total energy consumption at time $t$, and $\beta_4$ is the coefficient for the 'other' energy consumption, encapsulating its impact on the total energy usage.

## 2.10 Theoretical Justification

The inclusion of $E_{\text{other},t}$ is crucial for a holistic analysis of household energy consumption. By accounting for energy usage not captured by the main sub-meterings, the model gains accuracy and depth in understanding the distribution and drivers of household energy consumption. This addition allows for a more nuanced analysis of energy-saving opportunities and efficiency interventions by highlighting areas of consumption that may not be immediately apparent from the main sub-meterings alone.

## 2.11 Temporal Change Pattern and Statistical Analysis

The dataset includes a wide range of important features that are essential for comprehending the dynamics of household energy usage. Measurements of global active power, global reactive power, voltage, global intensity, and appliance-specific sub-metering provide comprehensive and diverse information about energy consumption trends. Every feature has a distinct role in forecasting techniques designed to estimate future energy demand and optimize resource allocation tactics.

Global active power and global intensity measures are essential markers of general energy consumption patterns. Their minute-averaged results offer a macroscopic view of household energy consumption, illustrating variations in demand throughout time. Simultaneously, worldwide measurements of reactive power and voltage provide additional and complementary data on the quality of power and the efficiency of distribution. Comprehending the fluctuations in these measurements allows forecasters to consider the elements that affect the stability of energy transmission and consumption.

The level of detail offered by sub-metering measurements that are individual to each device is extremely important for precisely adjusting forecasting models. Sub-metering data for appliances such as those found in the kitchen, laundry room, and water heater provide detailed information about energy use patterns in specific areas. These readings help determine the times when energy consumption is highest and evaluate the specific contributions of appliances to the overall energy demand. By combining sub-metering data into forecasting approaches, models can better capture nuanced consumption patterns and change projections accordingly. The figures are shown sequentially from Figure 1-26.

In utilizing these qualities for predicting, the study conducts a rigorous analysis of temporal trends across several scales. Exploration of year-long trends, monthly variations, and daily changes provides a full understanding of energy usage dynamics. Correlations between features and their temporal behaviors are thoroughly studied to find underlying patterns crucial for forecasting accuracy. Moreover, comparisons with mean values and trend analyses aid in finding abnormalities and deviations that may impair forecast dependability.

By integrating insights obtained from this in-depth investigation into forecasting approaches, stakeholders can construct more robust and precise predictive models. These analysis can estimate future energy consumption with increased precision, enabling proactive resource management and optimization measures. Ultimately, the complete evaluation of household energy consumption aspects strengthens forecasting methodologies, helping decision-makers to make informed choices regarding energy usage, efficiency programs, and sustainability activities.

# 3 Part 4: Advanced Implementation Post-Simulation Analysis [

## 3.1 Dickey-Fuller test

The Dickey-Fuller test is used to test the null hypothesis that a unit root is present in a time series, which suggests it is non-stationary and has some time-dependent structure. On the other hand, the alternative hypothesis is that the time series does not have a unit root, indicating it is stationary and does not have time-dependent structure.

In the Dickey-Fuller test, if the p-value is more than 0.05, it means we accept the null hypothesis and the data is regarded to be non-stationary. However, if

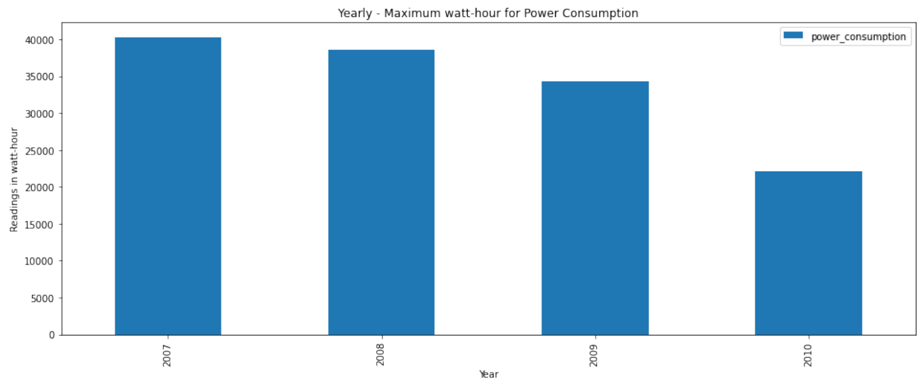


Figure 1: Power Consumption Yearly Obervation

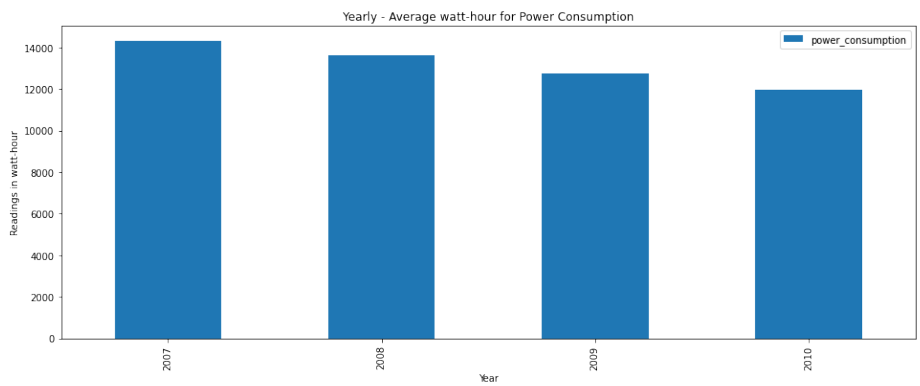


Figure 2: Average Power Consumption Yearly Obervation

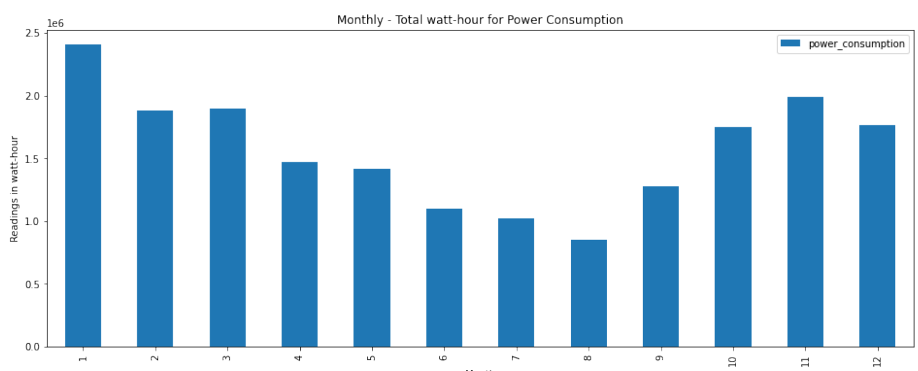


Figure 3: Monthly Total Power Consumption Yearly Obervation

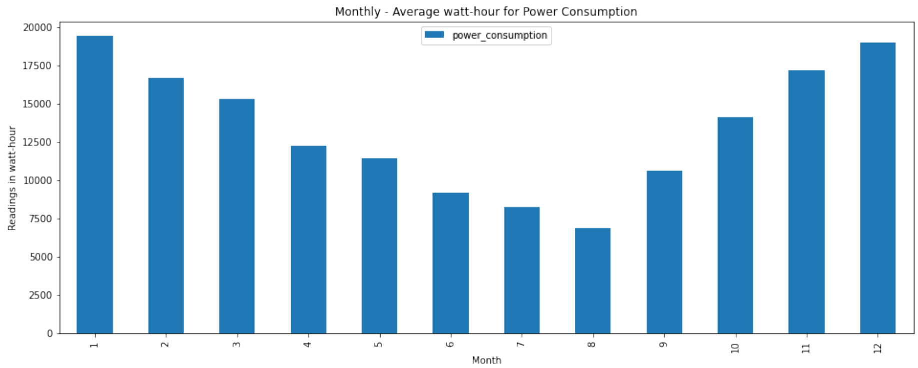


Figure 4: Monthly Average Power Consumption Yearly Obervation

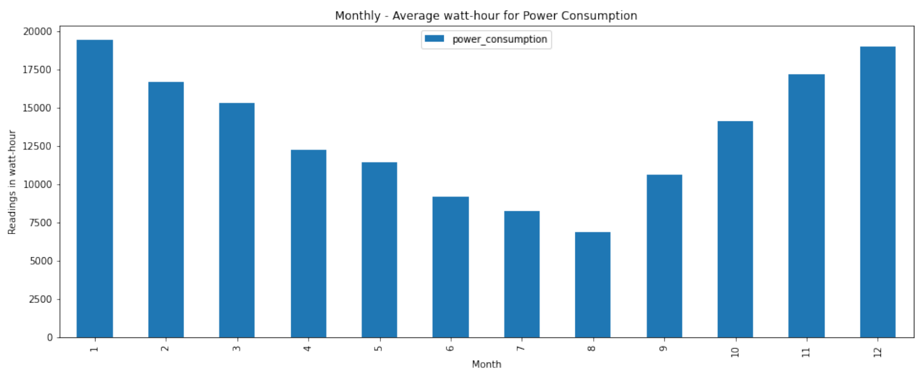


Figure 5: Monthly Average Power Consumption Yearly Obervation

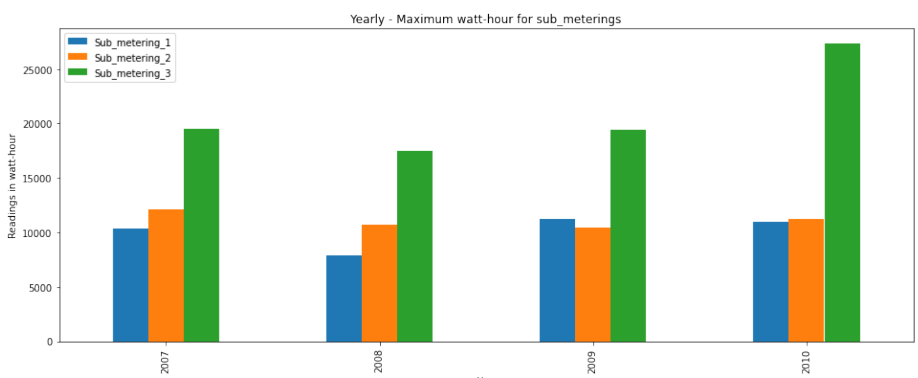


Figure 6: Maximum watt for sub meterings

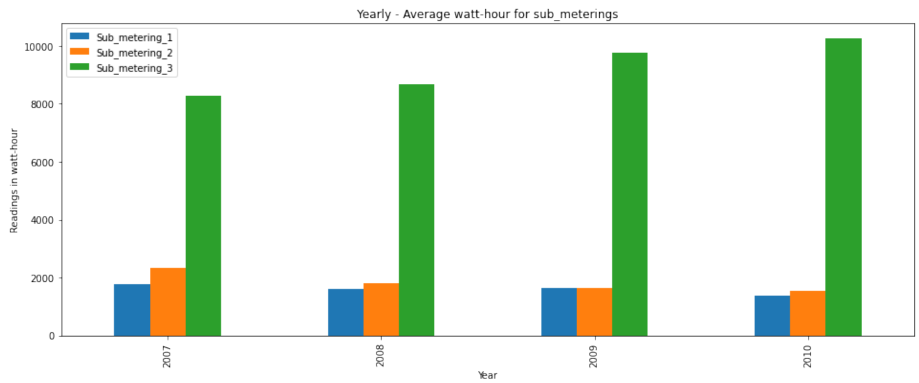


Figure 7: Average watt for sub meterings

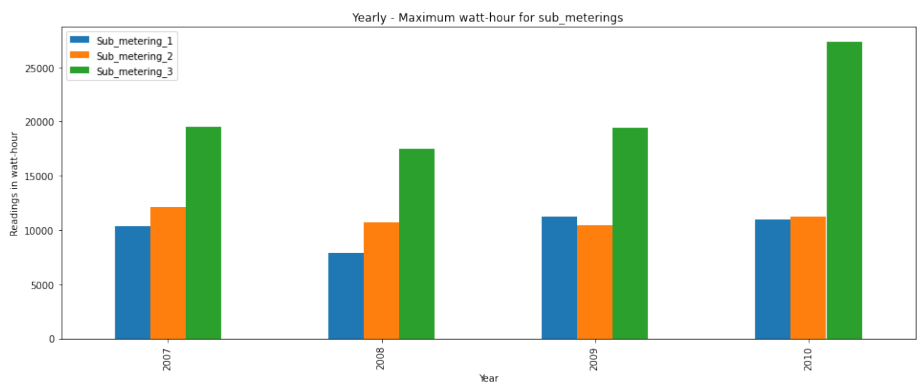


Figure 8: Maximum watt for sub meterings

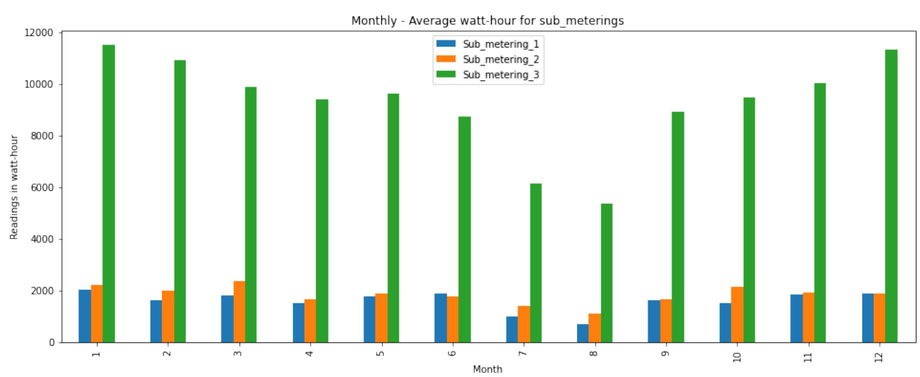


Figure 9: Monthly Avg watt hour for sub meterings

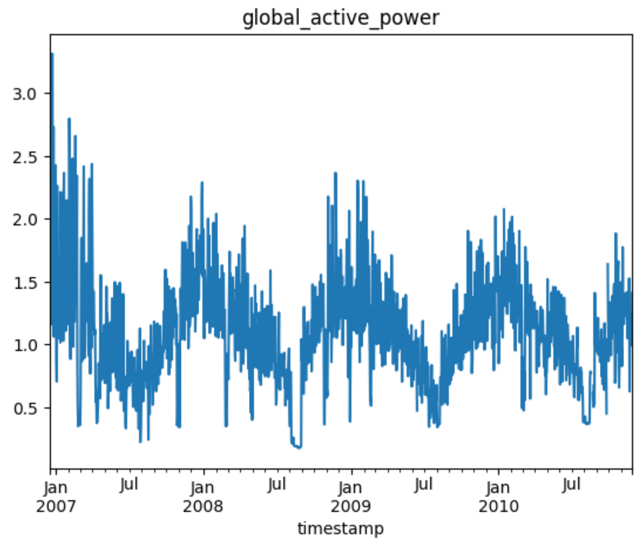


Figure 10: Monthly Avg watt hour for sub meterings

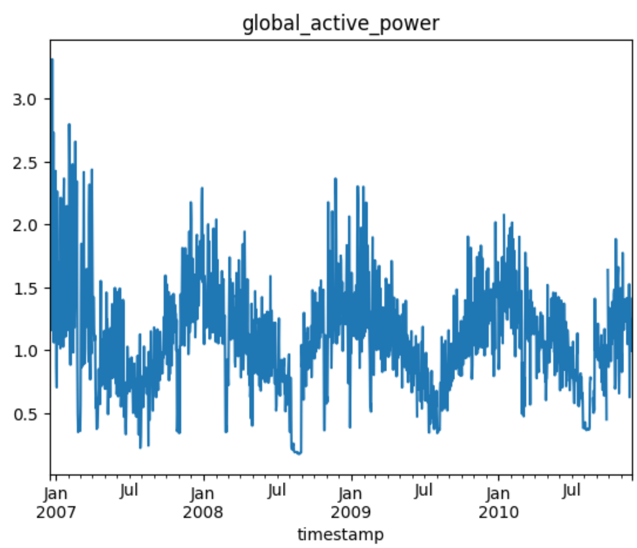


Figure 11: Monthly Global Active Power Observation in each day

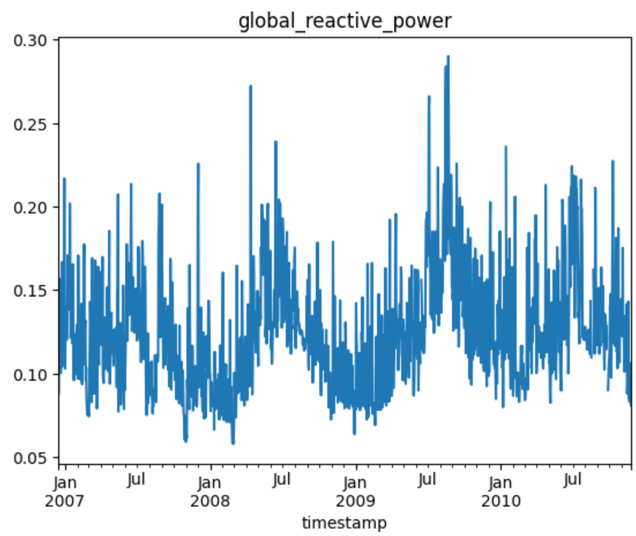


Figure 12: Monthly Global Active Power in each day

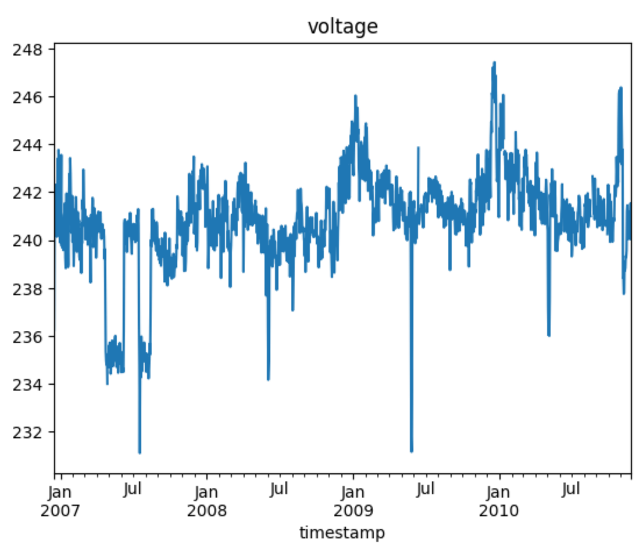


Figure 13: Monthly Voltage in each day

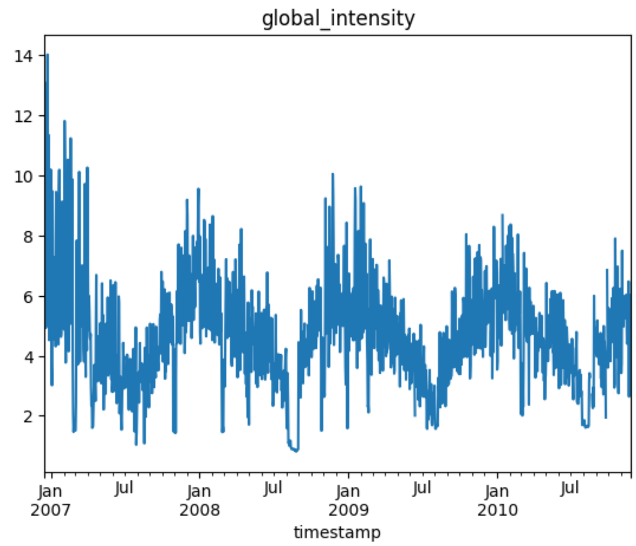


Figure 14: Monthly Global Intensity in each day

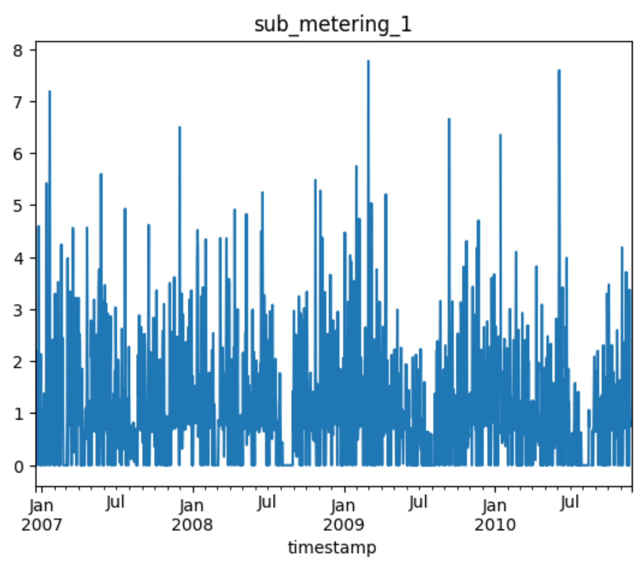


Figure 15: Monthly Sub Metering 1 in each day

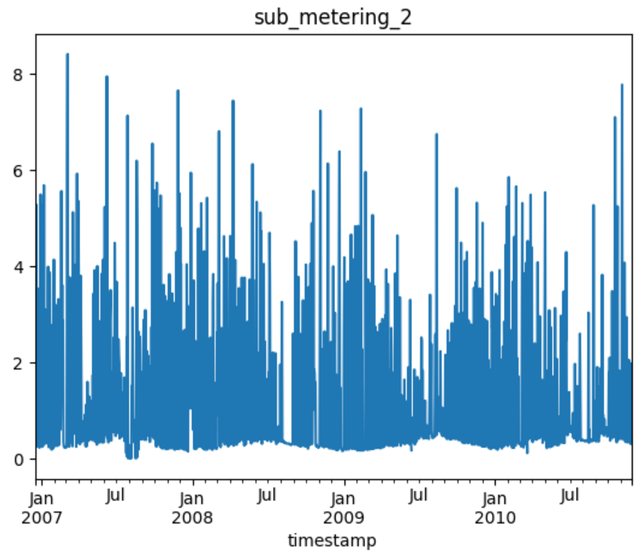


Figure 16: Monthly Sub Metering 2 in each day

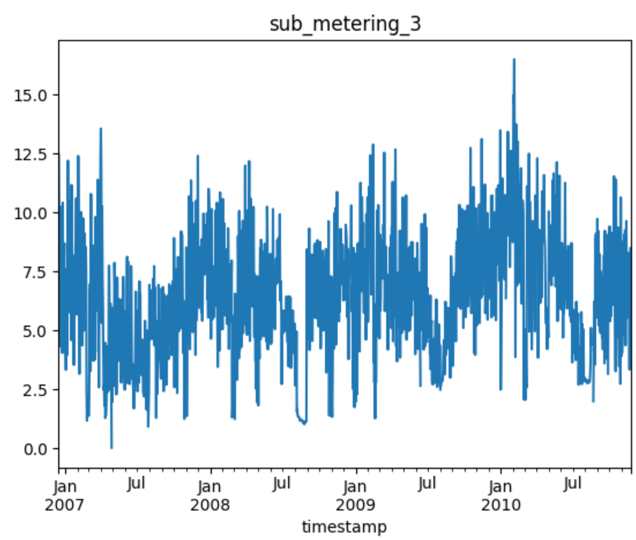


Figure 17: Monthly Metering 3 in each day


Figure 18: The average consumption of each month over a span of four years provides valuable insights into seasonal patterns and long-term trends in energy consumption. By calculating the average consumption for each month across multiple years, we can identify recurring patterns, peak consumption periods, and any significant variations in energy usage throughout the year.

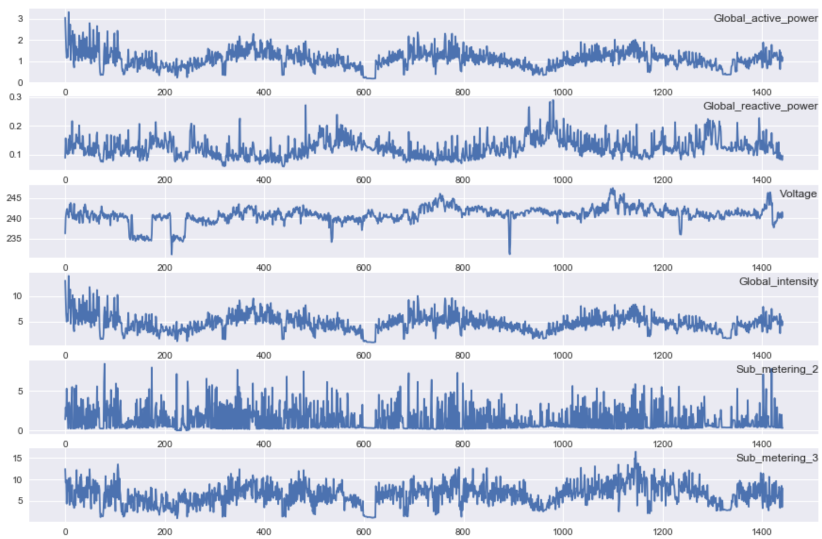


Figure 19: The mean value of different features resampled over a day provides a summarized view of the average behavior of each feature on a daily basis. By resampling the data at the daily level, we aggregate the observations within each day and compute the mean value for each feature, effectively smoothing out short-term fluctuations and highlighting longer-term trends

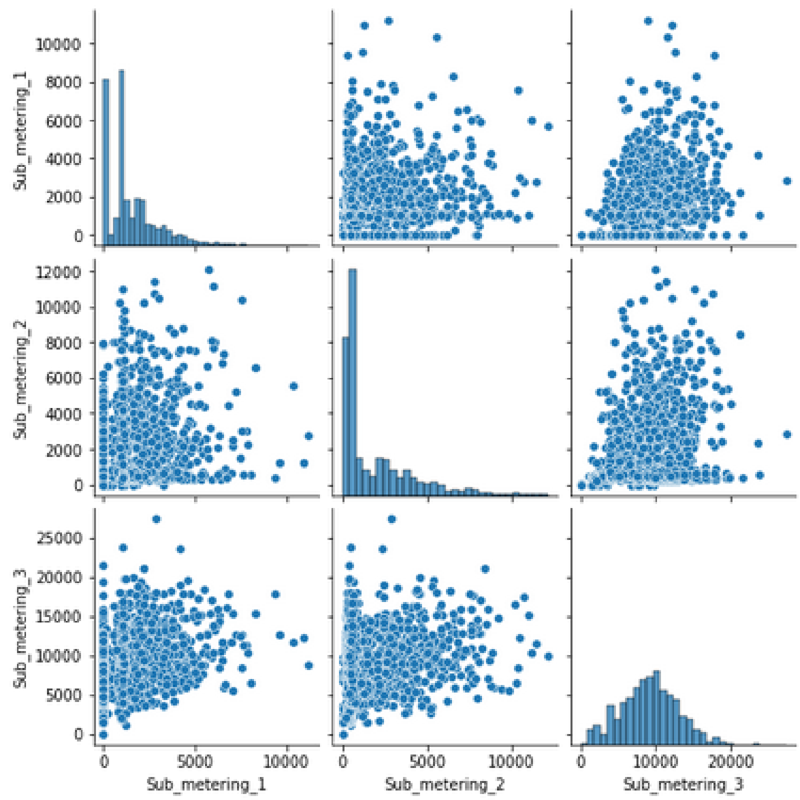


Figure 20: The figure depicts the distribution of data for Submeterings 1, 2, and 3. It is evident that Submeterings 1 and 2 exhibit left-skewed distributions, with most values clustered around the left tail and a longer right tail. In contrast, Submetering 3 displays a more symmetric, normally distributed pattern. Additionally, there appears to be a positive correlation between all three submeterings, indicating some level of relationship in the energy consumption patterns.

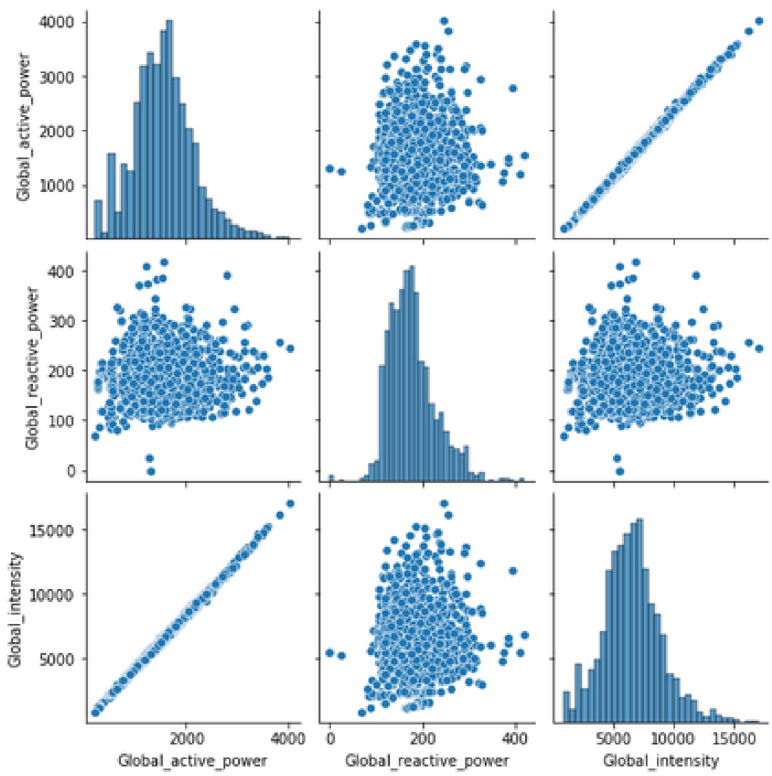


Figure 21: Global Active Power, Global Reactive Power, and Global Intensity display nearly normal distributions. There's a positive linear relationship between Global Active Power and Global Intensity, while Global Reactive Power shows little correlation with the other variables.

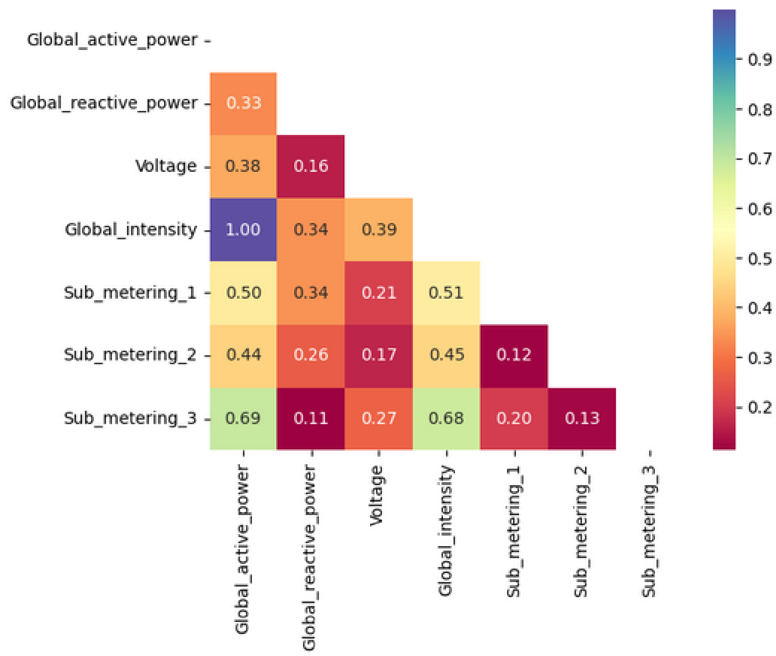


Figure 22: The high correlation observed between Global active power and Global intensity suggests a strong relationship between the overall active power consumption and the intensity of the current flowing through the electrical system. This correlation is expected, as higher levels of active power consumption typically result in increased current intensity. Consequently, variations in active power consumption are likely to be reflected in corresponding fluctuations in current intensity, leading to a high correlation between these two variables.

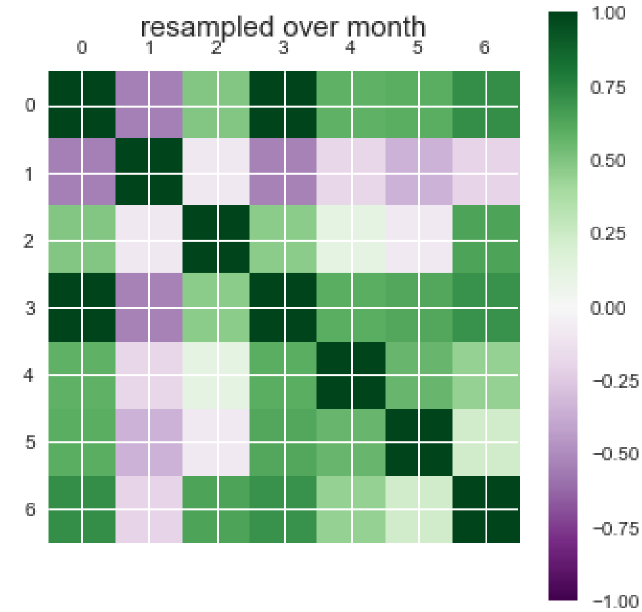


Figure 23: Correlations of Mean of Resampled All Features denoting as numerical 0-6 format over month

the p-value is less than or equal to 0.05, we reject the null hypothesis and the data is assumed to be stable. Our goal is to give this test for firstly predicting this p value state.

Figure 2 the graph depicts the implementation of the Dickey-Fuller test, a statistical tool used to evaluate the stationarity of a time series dataset. In this example, a simulated non-stationary time series dataset is presented together with a trend line derived by the Hodrick-Prescott filter. The blue line depicts the original data points, which exhibit variations and do not seem to have a stable mean or variance across time, showing non-stationarity. The red dashed line displays the trend retrieved from the data, demonstrating a distinct upward or downward pattern, suggesting the presence of a trend component in the series. Additionally, horizontal lines are painted to show crucial values corresponding to various confidence levels. These important values serve as benchmarks for understanding the relevance of the Dickey-Fuller test results. The p-value and test statistic of the Dickey-Fuller test are displayed on the graph, aiding in the evaluation of whether the null hypothesis of a unit root (showing non-stationarity) may be rejected or not. If the p-value is less than or equal to the selected significance level (usually 0.05), the null hypothesis is rejected, implying that the data is stationary. Conversely, a p-value greater than 0.05 shows acceptance of the null hypothesis and implies non-stationarity. Thus, this graph provides a visual depiction of the Dickey-Fuller test results, facilitating


Figure 24: Correlations of Mean of Resampled All Features denoting 0-6 over Year

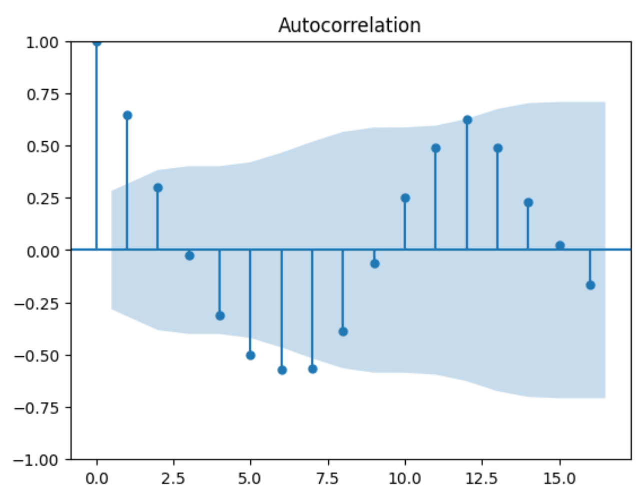


Figure 25: The Autocorrelation Function (ACF) analysis of monthly global active power consumption provides insights into the correlation structure of the time series data over different lag periods. The ACF plot visualizes the correlation between the global active power consumption at the current time point and its values at previous time points, up to a specified lag.

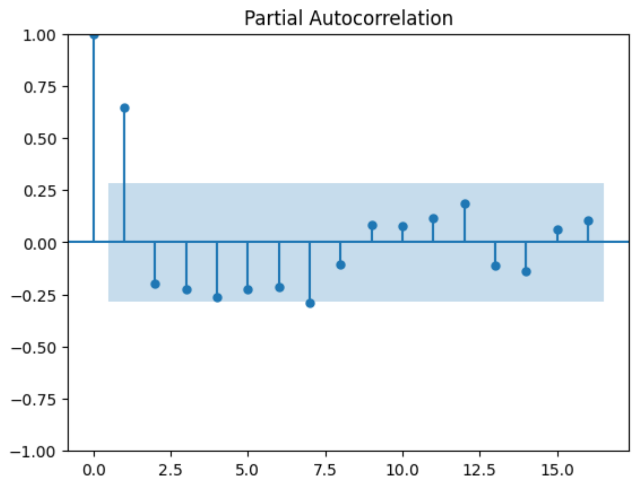


Figure 26: The Partial Autocorrelation Function (PACF) analysis of monthly global active power consumption delves deeper into the temporal dependencies within the time series data, specifically focusing on the direct relationship between the current observation and its lagged values, while controlling for the intervening observations

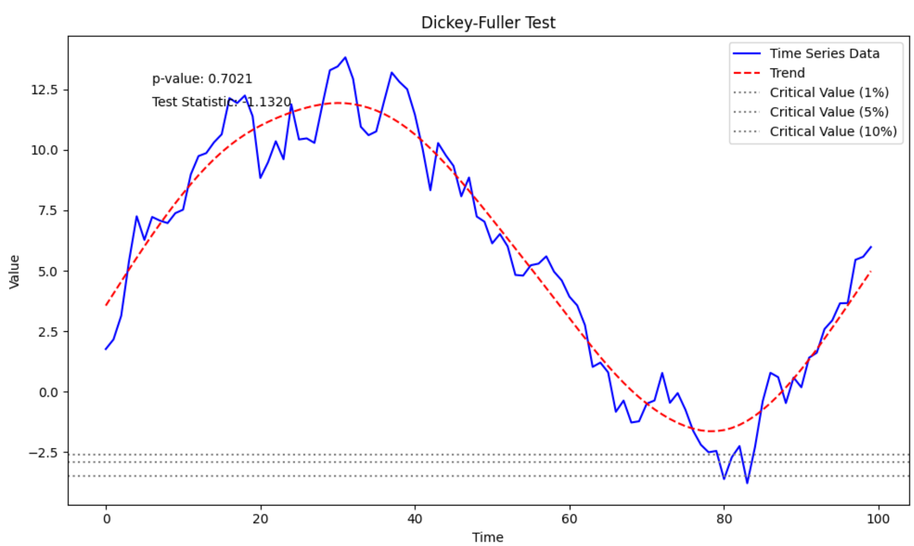


Figure 27: Dickey Fuller Test

in the assessment of the stationarity of the time series dataset.

Table 1: ADF Test Results

| Variable | Test Statistic | p-value | # Lags | # Observations |
|---|---|---|---|---|
| Global_active_power | -4.897270 | 0.000035 | 9.000000 | 38.000000 |
| Global_reactive_power | -3.951475 | 0.001687 | 3.000000 | 44.000000 |
| Voltage | -2.534397 | 0.107328 | 1.000000 | 46.000000 |
| Global_intensity | -6.054392 | $1.255 \times 10^{-7}$ | 7.000000 | 40.000000 |
| Sub_metering_1 | -5.385093 | $4 \times 10^{-6}$ | 0.000000 | 47.000000 |
| Sub_metering_2 | -4.583647 | 0.000138 | 0.000000 | 47.000000 |
| Sub_metering_3 | -3.354857 | 0.012598 | 0.000000 | 47.000000 |

The table 1presents the results of the Augmented Dickey-Fuller (ADF) tests conducted on various variables related to household energy consumption. The ADF test is commonly employed to assess the stationarity of time series data, a crucial assumption in many time series analysis techniques.

Across the examined variables, significant differences in stationarity are observed. Notably, the `Global_active_power` and `Global_intensity` variables exhibit strong evidence of stationarity, as indicated by their highly negative test statistics and extremely low p-values. This suggests that these variables are likely stationary, implying consistent statistical properties over time.

Similarly, the `Sub_metering_1` and `Sub_metering_2` variables also demonstrate significant evidence of stationarity, with both yielding substantially negative test statistics and very low p-values. Conversely, the `Sub_metering_3` variable exhibits weaker evidence of stationarity, with a less negative test statistic and a higher p-value compared to the other sub-metering variables.

However, it is important to note that the `Voltage` variable shows no significant evidence of stationarity, with a test statistic close to zero and a relatively high p-value. This implies that the voltage data may possess a unit root, indicating non-stationary behavior.

Overall, these ADF test results provide valuable insights into the stationarity of the examined variables, laying the groundwork for further time series analysis and forecasting techniques.

## 3.2 Model Implementation Strategy

The development of the EnerForecast model is a multidimensional process that combines state-of-the-art computational tools and algorithms to assess and anticipate home energy consumption. Figure 2 shows the initial prototype of our model implementation. The method involves several critical steps:

- **Data Preparation and Preprocessing:** This initial phase involves gathering and cleaning the dataset, including the global active power, sub-metering data, and variables reflecting temperature, humidity, household income, and 'other' energy usage. This stage guarantees the data quality and consistency necessary for accurate modeling.

### 3.3 ARIMA Modeling

Table 2: ARIMA Results

| | |
|---|---|
| **Dep. Variable:** | trend |
| **No. Observations:** | 48 |
| **Model:** | ARIMA(2, 0, 0) |
| **Log Likelihood:** | 263.293 |
| **Date:** | Fri, 10 May 2024 |
| **AIC:** | -518.585 |
| **Time:** | 17:21:59 |
| **BIC:** | -511.100 |
| **Sample:** | 12-31-2006 - 11-30-2010 |
| **HQIC:** | -515.756 |
| **Covariance Type:** | opg |

| | coef | std err | z | P¿—z— | [0.025, 0.975] |
|---|---|---|---|---|---|
| const | 1.0945 | 0.019 | 56.369 | 0.000 | 1.056, 1.133 |
| ar.L1 | 1.9089 | 0.029 | 64.742 | 0.000 | 1.851, 1.967 |
| ar.L2 | -0.9159 | 0.032 | -29.069 | 0.000 | -0.978, -0.854 |
| sigma2 | 8.364e-07 | 2.53e-07 | 3.300 | 0.001 | 3.4e-07, 1.33e-06 |

| | Ljung-Box (L1) (Q) | Jarque-Bera (JB) | Prob(Q) | Prob(JB) |
|---|---|---|---|---|
| | 3.97 | 6.20 | 0.05 | 0.04 |
| **Heteroskedasticity (H):** | 0.24 | **Skew:** | 0.65 | |
| **Prob(H) (two-sided):** | 0.01 | **Kurtosis:** | 4.19 | |

The table 2presents an overview of the ARIMA (Autoregressive Integrated Moving Average) model results applied to the dependent variable "trend." The model is defined as ARIMA(2, 0, 0), indicating two autoregressive terms and no differencing or moving average terms.

The model evaluation metrics show a satisfactory fit to the data. The Log Likelihood score of 263.293 shows that the model provides a good explanation of the observed data. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values are both negative, with lower values indicating a better fit. Additionally, the Hannan-Quinn Information Criterion (HQIC) is similarly negative, further proving the model's adequacy.

The calculated coefficients for the ARIMA model are shown in the second section of the table. The constant term (const) is predicted to be 1.0945, with a standard error of 0.019. The autoregressive coefficients (ar.L1 and ar.L2) are 1.9089 and -0.9159, respectively, reflecting the strength and direction of the link between the current observation and its historical

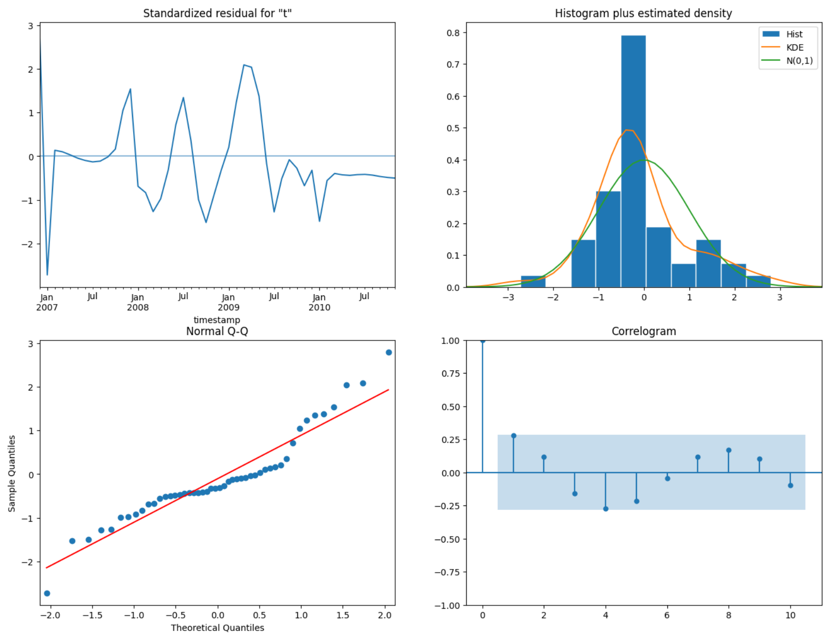


Figure 28: Arima Model Result Summary

values. The sigma2 term indicates the variance of the residuals, with an estimated value of 8.364e-07.

The last half of the table includes diagnostic tests for model adequacy. The Ljung-Box test statistic (Q) assesses the autocorrelation of the residuals, with a value of 3.97 indicating no significant autocorrelation at lag 1. The Jarque-Bera test statistic (JB) tests for normality of the residuals, with a score of 6.20 signifying minor departure from normality. The Heteroskedasticity test (H) reveals the presence of heteroskedasticity, with a probability of 0.01, while the skewness and kurtosis values provide additional insights into the distributional features of the residuals. Overall, these diagnostic tests indicate the suitability of the ARIMA model for forecasting the "trend" variable. Futhermore , Figure 31 and 29 depicts the predictions with different performance measurement of the ARIMA Model.

The ARIMA model is employed to represent the temporal characteristics of energy consumption, such as trends and seasonality [16]. This technique entails the subsequent procedures:

1. **Data Preprocessing:** The energy consumption data is examined to determine if it exhibits stationarity. Differencing is employed to attain stationarity when the data is non-stationary.

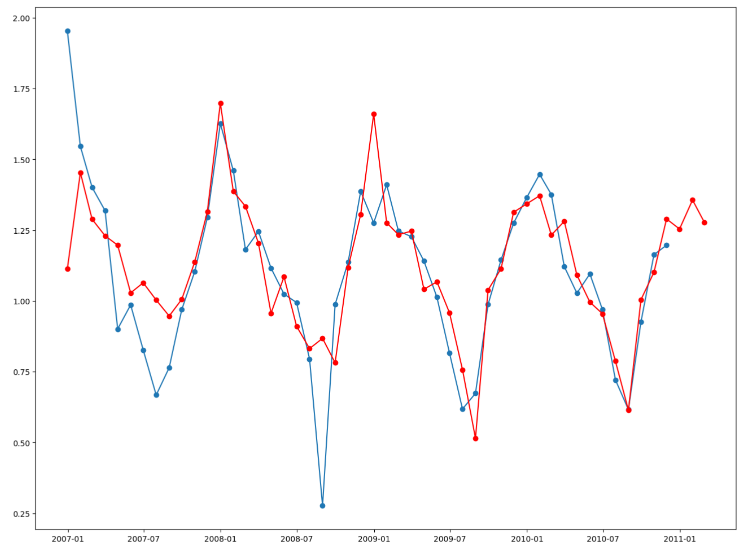


Figure 29: Arima Model Result Prediction for Yearly Analysis

2. **Model Selection:** The parameters $(p, d, q)$ of the Autoregressive Integrated Moving Average (ARIMA) model are found by analyzing the autocorrelation and partial autocorrelation functions.
3. **Model Fitting:** The ARIMA model is fitted to the preprocessed data using the given parameters.
4. **Model Evaluation:** The fitted ARIMA model is evaluated using relevant metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

The ARIMA$(p, d, q)$ model can be represented by the following equation:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{6}$$

where:

- $Y_t$ is the value of the time series at time $t$.
- $c$ is a constant.
- $\phi_1, \phi_2, \ldots, \phi_p$ are autoregressive coefficients.
- $\varepsilon_t$ is the error term at time $t$.
- $\theta_1, \theta_2, \ldots, \theta_q$ are moving average coefficients.
- $d$ is the degree of differencing applied to achieve stationarity.

### 3.4 SARIMAX Modeling

Table 3: SARIMAX Results Summary

| | |
|---|---|
| **Dep. Variable:** | y |
| **No. Observations:** | 48 |
| **Model:** | SARIMAX(1, 0, 0)x(2, 0, 0, 12) |
| **Log Likelihood:** | 15.516 |
| **Date:** | Fri, 10 May 2024 |
| **AIC:** | -21.031 |
| **Time:** | 17:22:21 |
| **BIC:** | -11.675 |
| **Sample:** | 12-31-2006 - 11-30-2010 |
| **HQIC:** | -17.496 |
| **Covariance Type:** | opg |

| | coef | std err | z | P¿—z— | [0.025, 0.975] |
|---|---|---|---|---|---|
| intercept | 0.1305 | 0.058 | 2.264 | 0.024 | 0.018, 0.244 |
| ar.L1 | 0.4044 | 0.168 | 2.414 | 0.016 | 0.076, 0.733 |
| ar.S.L12 | 0.4873 | 0.182 | 2.671 | 0.008 | 0.130, 0.845 |
| ar.S.L24 | 0.3158 | 0.164 | 1.928 | 0.054 | -0.005, 0.637 |
| sigma2 | 0.0243 | 0.004 | 6.587 | 0.000 | 0.017, 0.032 |

| | Ljung-Box (L1) (Q) | Jarque-Bera (JB) | Prob(Q) | Prob(JB) |
|---|---|---|---|---|
| | 0.73 | 32.63 | 0.39 | 0.00 |
| **Heteroskedasticity (H):** | 0.27 | **Skew:** | -0.33 | |
| **Prob(H) (two-sided):** | 0.01 | **Kurtosis:** | 6.99 | |

The table 3 presents a complete summary of the SARIMAX (Seasonal Autoregressive Integrated Moving Average with Exogenous Variables) model results applied to the dependent variable "y." The SARIMAX model is given as SARIMAX(1, 0, 0)x(2, 0, 0, 12), indicating one autoregressive term, no differencing, and no moving average terms, along with seasonal components.

The model evaluation metrics show a satisfactory fit to the data. The Log Likelihood value of 15.516 shows that the model provides a satisfactory explanation of the observed data. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values are both negative, with lower values indicating a better fit. Additionally, the Hannan-Quinn Information Criterion (HQIC) is similarly negative, further proving the model's adequacy.

The calculated coefficients for the SARIMAX model are shown in the second section of the table. The intercept term is predicted to be 0.1305, with a standard error of 0.058. The autoregressive coefficient (ar.L1) is predicted to be 0.4044, reflecting the intensity and direction of the link between the current observation and its prior values. The seasonal autore-

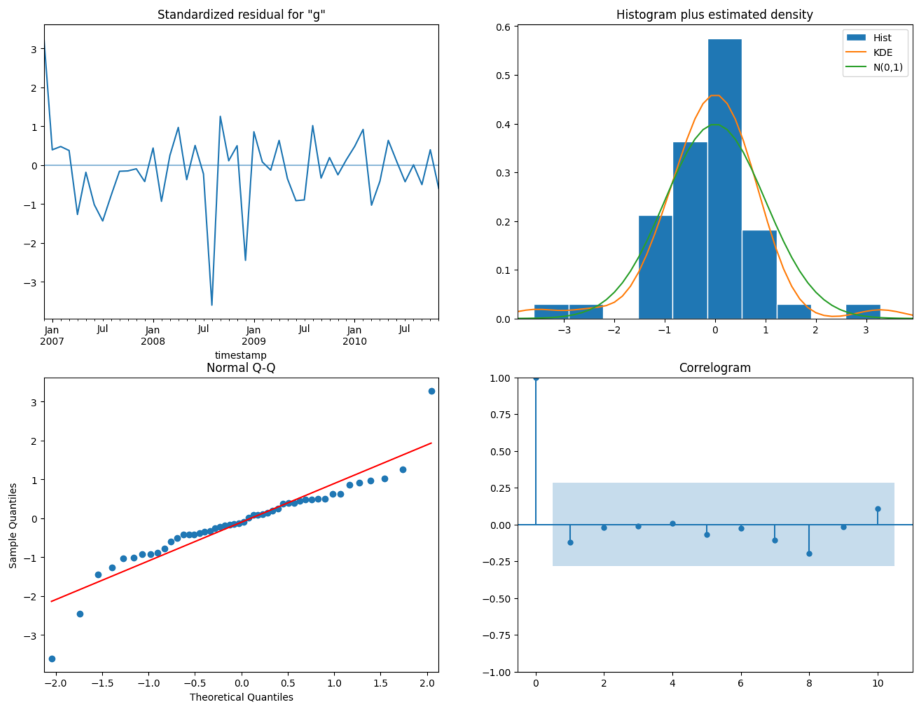


Figure 30: Sarimax Result Summary Result

gressive coefficients (ar.S.L12 and ar.S.L24) capture the seasonal patterns in the data.

The sigma2 term indicates the variance of the residuals, with an estimated value of 0.0243. This represents the level of variability in the observed data that is not explained by the model.

The last half of the table includes diagnostic tests for model adequacy. The Ljung-Box test statistic (Q) assesses the autocorrelation of the residuals, with a value of 0.73 indicating no significant autocorrelation at lag 1. The Jarque-Bera test statistic (JB) tests for normality of the residuals, with a result of 32.63 implying departure from normality. The Heteroskedasticity test (H) reveals the presence of heteroskedasticity, with a probability of 0.01.

Overall, these SARIMAX model results provide useful insights into the correlations between the variables and the suitability of the model for forecasting the dependent variable "y."

To account for seasonal fluctuations in energy demand, the Seasonal ARIMA (SARIMAX) model is introduced into the forecasting framework [17]. The methodology includes:

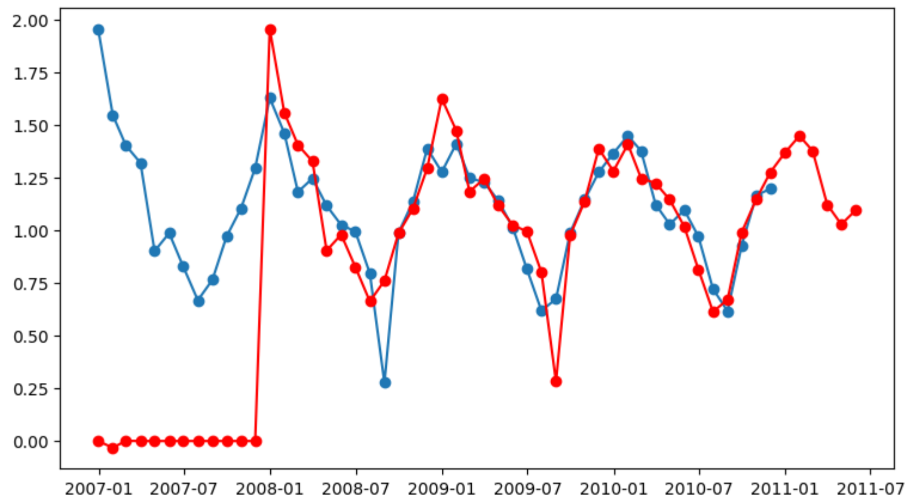


Figure 31: Sarimax Result Prediction for Yearly Analysis

1. **Seasonal Decomposition:** The energy usage data is decomposed into trend, seasonal, and residual components using techniques like seasonal decomposition of time series (STL).
2. **Model Parameter Selection:** Seasonal ARIMA parameters $(P, D, Q, s)$ are calculated based on examination of seasonal autocorrelation and partial autocorrelation functions.
3. **Model Training:** The SARIMAX model is trained using the deconstructed data, incorporating both the seasonal and non-seasonal components.
4. **Forecasting:** Future energy use is estimated using the trained SARIMAX model, incorporating both trend and seasonal changes.

The SARIMAX$(p, d, q)(P, D, Q, s)$ model with exogenous variables can be represented by the following equation:

$$Y_t = c+\phi_1 Y_{t-1}+\phi_2 Y_{t-2}+\ldots+\phi_p Y_{t-p}+\theta_1\varepsilon_{t-1}+\theta_2\varepsilon_{t-2}+\ldots+\theta_q\varepsilon_{t-q}+\beta X_t+\varepsilon_t \tag{7}$$

where:

- $X_t$ represents exogenous variables at time $t$.
- $\beta$ represents the coefficients associated with the exogenous variables.
- All other terms are similar to those in the ARIMA model.

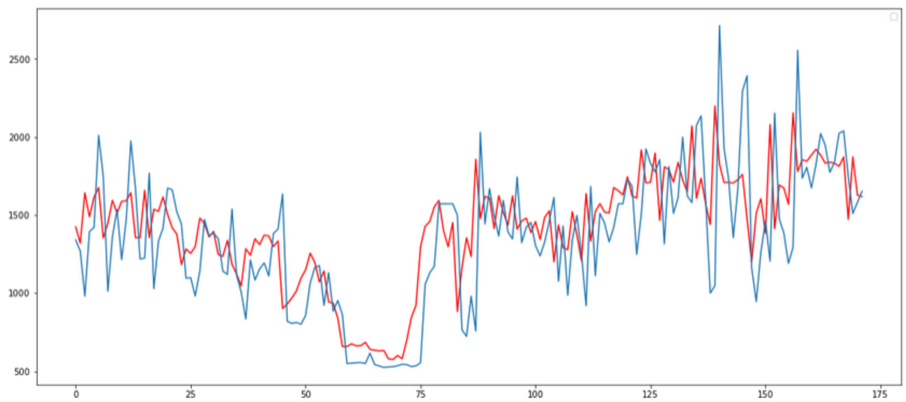


Figure 32: LSTM Result Prediction for Yearly Analysis

### 3.5 LSTM Modeling

Long Short-Term Memory (LSTM) networks are applied to capture complicated temporal dependencies in the energy use data [18]. The process involves:

1. **Data Sequencing:** The energy use data is sequenced into input-output pairs, treating a window of prior observations as input and the subsequent observation as output.
2. **Model Architecture:** An LSTM architecture is created, often consisting of numerous LSTM layers followed by fully connected layers for prediction.
3. **Model Training:** The LSTM model is trained using backpropagation through time (BPTT), optimizing model parameters to reduce predicting errors.
4. **Model Evaluation:** The trained LSTM model is tested using conventional evaluation metrics such as MAE, MSE, and RMSE on a validation dataset.
5. **Forecasting:** Future energy use is anticipated using the trained LSTM model, which can capture both short-term and long-term dependencies in the data.

The LSTM model involves the propagation of information through cells over time. However, expressing it in a single equation is not practicable due to its complicated architecture including numerous gates (input gate, forget gate, output gate) and memory cells. However, the essential activities within an LSTM cell can be expressed as follows:

$$f_t = \sigma_g(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{8}$$

$$i_t = \sigma_g(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{9}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{10}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{11}$$

$$o_t = \sigma_g(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{12}$$

$$h_t = o_t * \tanh(C_t) \tag{13}$$

where:

- $f_t$ is the forget gate output.
- $i_t$ is the input gate output.
- $\tilde{C}_t$ is the candidate cell state.
- $C_t$ is the cell state.
- $o_t$ is the output gate output.
- $h_t$ is the hidden state.
- $x_t$ is the input at time $t$.
- $\sigma_g$ represents the sigmoid activation function.
- $W_f, W_i, W_C, W_o$ are weight matrices.
- $b_f, b_i, b_C, b_o$ are bias vectors.

## 3.6 GRU Modeling

In the realm of time series forecasting, Gated Recurrent Unit (GRU) models have emerged as powerful tools due to their ability to capture long-term dependencies and handle sequential data efficiently .

The GRU model formulation involves the use of recurrent units with gating mechanisms, which control the flow of information through the network and mitigate vanishing gradient problems. It can be expressed as follows:

$$h_t = \mathrm{GRU}(x_t, h_{t-1}) \tag{14}$$

where:

- $x_t$ represents the input at time $t$.
- $h_{t-1}$ represents the hidden state from the previous time step.

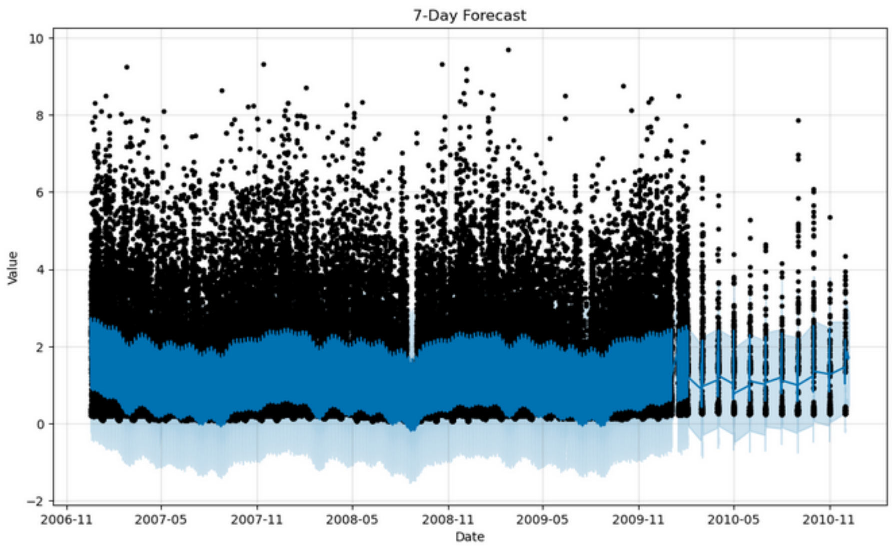


Figure 33: Prophet Result Prediction for Yearly Analysis

– $h_t$ represents the hidden state at time $t$.

The GRU model learns to adaptively update its hidden state based on the current input and the previous hidden state, allowing it to capture temporal dependencies effectively.

## 3.7 Prophet Modeling

Prophet, built by Facebook's Core Data Science team, offers a versatile framework for time series forecasting, particularly suitable for datasets with significant seasonal trends and abnormalities. The methodology comprises:

1. **Trend and Seasonality Modeling:** Prophet decomposes the time series into trend, seasonal, and holiday components using additive models, enabling flexible modeling of varied patterns.
2. **Changepoint Detection:** Prophet automatically recognizes changepoints in the time series, indicating alterations in trend and enabling the model to adapt to changes in the underlying data generating process.
3. **Uncertainty Estimation:** Prophet provides measures of forecast uncertainty, allowing decision-makers to assess the reliability of predictions and make informed decisions.

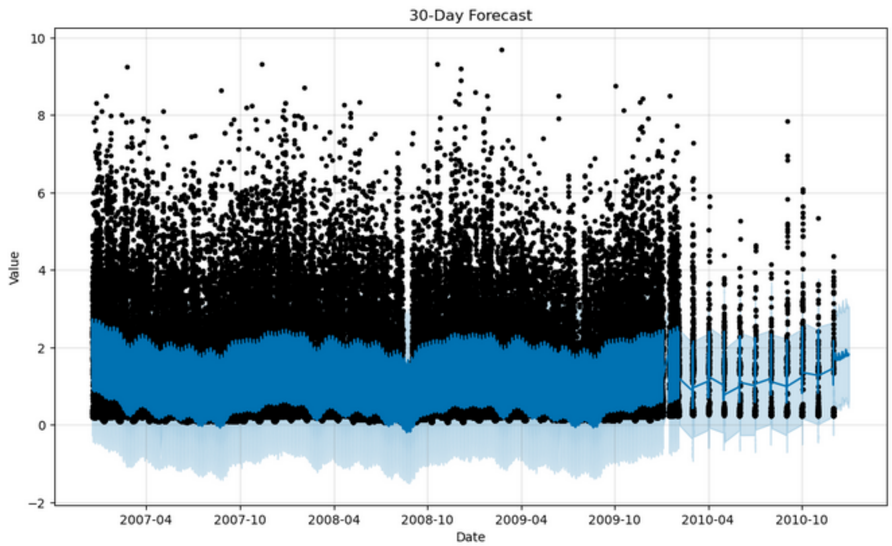


Figure 34: Prophet Result Prediction for Yearly Analysis

4. **Holiday Effects:** The framework incorporates holiday effects into the model, enabling it to account for the impact of holidays on the time series data.

The core equation of the Prophet model can be expressed as:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{15}$$

where:

- $g(t)$ represents the trend component.
- $s(t)$ represents the seasonal component.
- $h(t)$ represents the holiday component.
- $\epsilon_t$ represents the error term.

Prophet combines these components to generate forecasts, offering a flexible and intuitive approach to time series forecasting.The results in the Figure

In our result analysis, in Figure 34 and 33, it generates future dates for 7 and 30 days using the forecasting model. Predictions for these future time points are then computed and visualized in separate plots. The plots display the forecasted values overlaid on the original data, offering a concise view of the predicted trends over the specified time horizons. These visualizations facilitate quick insights into the expected future behavior of the time series data.

### 3.8 SARIMA Modeling

To account for seasonal fluctuations in energy demand, the Seasonal ARIMA (SARIMAX) model is introduced into the forecasting framework [**?**]. The methodology includes:

1. **Seasonal Decomposition:** The energy usage data is decomposed into trend, seasonal, and residual components using techniques like seasonal decomposition of time series (STL).
2. **Model Parameter Selection:** Seasonal ARIMA parameters $(P, D, Q, s)$ are calculated based on examination of seasonal autocorrelation and partial autocorrelation functions.
3. **Model Training:** The SARIMAX model is trained using the deconstructed data, incorporating both the seasonal and non-seasonal components.
4. **Forecasting:** Future energy use is estimated using the trained SARIMAX model, incorporating both trend and seasonal changes.

The SARIMAX$(p, d, q)(P, D, Q, s)$ model with exogenous variables can be represented by the following equation:

$$Y_t = c+\phi_1 Y_{t-1}+\phi_2 Y_{t-2}+\ldots+\phi_p Y_{t-p}+\theta_1 \varepsilon_{t-1}+\theta_2 \varepsilon_{t-2}+\ldots+\theta_q \varepsilon_{t-q}+\beta X_t+\varepsilon_t \tag{16}$$

where:

- $X_t$ represents exogenous variables at time $t$.
- $\beta$ represents the coefficients associated with the exogenous variables.
- All other terms are similar to those in the ARIMA model.

### 3.9 Model Comparison and Selection

The performance of each model (ARIMA, SARIMA, LSTM, GRU, Prophet, SARIMAX) is compared based on their forecasting accuracy and computational efficiency. The model that provides the most accurate and reliable forecasts for energy use is selected for deployment in practical applications.

- **Model Training:** It includes calibrating the models using a subset of the historical data set, allowing our implemented models to 'learn' the patterns and relationships within the data.

### 3.10 Validation Process

# 4 Results

Validating the accuracy and reliability of the EnerForecast model is crucial to ensure its effectiveness in real-world applications. The validation process includes:

**Accuracy Assessment:** Predictions are compared to real historical consumption data to measure the model's accuracy. Metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared ($R^2$) are used to quantify the each model's prediction ability.

**Cross-Validation with Existing Models:** Cross-validation techniques are applied to systematically compare the models over numerous data subsets, employing performance metrics like accuracy, precision, and recall to assess each model's prediction capabilities.

**Insight Generation:** This comparative research gives insights into the EnerForecast model's strengths and areas for improvement, demonstrating its comparative benefits and possibilities for boosting home energy consumption prediction.

## 4.1 Result Analysis

Table 4: Model Evaluation Metrics

| **Model** | **R_sq** | **RMSE** | **MAPE** | **MAE** |
|---|---|---|---|---|
| ARIMA | 97.82 | 74956.28 | 0.20 | 66931.53 |
| SARIMA | 97.82 | 74956.28 | 0.20 | 66931.53 |
| SARIMAX | 96.98 | 63809.47 | 0.12 | 42532.12 |
| LSTM | 44.54 | 327.93 | 0.20 | 242.08 |
| GRU | 44.13 | 329.153 | 0.21 | 244.28 |
| Prophet | 73.23 | 513.122 | 0.24 | 242.22 |

The table 4provides a brief summary of the effectiveness of numerous forecasting models when applied to the dataset being evaluated. Both ARIMA and SARIMA models indicate a large coefficient of determination (R-squared) of 97.82, which signifies a powerful explanatory capability. Nevertheless, they also exhibit significantly elevated Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) values, indicating large differences between the anticipated and observed values. Conversely, the SARIMAX model maintains a comparable R-squared value of 96.98 while achieving lower RMSE and MAE values, suggesting better accuracy in forecasting the target variable. In addition, the SARIMAX model has a Mean Absolute Percentage Error (MAPE) of 0.12, which shows that the percentage errors are relatively modest. However, when comparing LSTM and GRU models to SARIMAX, it is obvious that they have lower R-squared values and bigger RMSE, MAPE, and MAE values. This shows that their forecasts are less reliable, despite their capacity to capture sequential dependencies. Similarly, the Prophet model, despite getting a decent R-squared value of 73.23, displays greater error metrics compared to SARIMAX, indicating poorer accuracy in forecasting. Overall, the SARIMAX model shows as the most suited solution for accurate forecasting in this context, followed by ARIMA and SARIMA, while deep learning methods and Prophet demonstrate significantly fair accuracy in predicting the target. variable.

To determine the worldwide active power, we rely on the offered models. Thiese models serve as a significant tool for analyzing and quantifying power use worldwide. By assessing multiple criteria and data points, it improves informed decision-making processes. Global active power, an important measure, essentially reflects the entire use of electricity across different areas and sectors. Utilizing this approach boosts our capacity to make wise, strategic decisions around energy usage and allocation.

# 5 Conclusion

To summarize, this study emphasizes the crucial importance of accurate power demand forecasting in Smart Grid management. This need is further intensified by the complexities involved in anticipating electrical load patterns, which are defined by their non-linear nature. By utilizing the latest developments in deep learning techniques, we thoroughly examined different architectural strategies for predicting short-term electricity use, specifically focusing on creating forecasts for the upcoming day. Our thorough investigation has provided useful insights into the effectiveness of various deep learning models, revealing their potential uses in Smart Grid operations. In addition, our study aims to fill a significant gap in the current body of research by providing a thorough comparative examination of deep learning algorithms designed specifically for electric load forecasting. Our goal is to offer a strong framework that enables both academics and industry professionals to make better-informed decisions in the field of Smart Grid management. Furthermore, it is crucial to recognize the importance of taking into account different external factors, such as weather patterns, economic indicators, and the incorporation of emerging technologies, as essential elements in enhancing the precision and effectiveness of load forecasting models. By conducting thorough assessments and taking into account various factors, our goal is to propel the field towards Smart Grid solutions that are more efficient, durable, and adaptive.

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