# Smart Home Energy Management through ARIMA Model Forecasting: Leveraging Weather Data for Improved Efficiency

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**Abstract**

This study pursues machine learning models for the task of smart homes' energy management with the use of a dataset that combines smart meter readings and weather conditions at the same time. The assessment of the Baseline Qualification and ARIMA models is done using various criteria, such as MSE, RMSE, and others. Most telling, the best performance is shown by ARIMA, which gets the lowest MSE score, 0.0693, in this instance. They show that such a model is optimal in forecasting energy consumption dynamics, and while they could be better, weather information helps improve the accuracy of the forecasts. The conduct helps uncover priceless information, allowing for the development of new smart home operating systems with a prospect of energy efficiency enhancement as well as a sustainable environment.

**Keywords:** Smart homes; Home energy management; ARIMA models; Smart home operating systems

## 1. Introduction

The rise of smart homes, fueled by advancements in AI and IoT technologies, signifies a transformative shift in our approach to living spaces, promising heightened efficiency, comfort, and security [1]. However, this technological evolution introduces intricate challenges, including issues of privacy, security, interoperability, and user experience. As smart homes gain prevalence, concerns like consumer acceptance, device integration, and cybersecurity become prominent hurdles, necessitating comprehensive examination. The central research problem revolves around unraveling the complexities of smart home systems, particularly focusing on investigating and addressing interoperability issues. Without a thorough understanding of these challenges, the development of sustainable and resilient smart home systems remains challenging [2,3]. Positioned as a pioneering exploration, this article aims to bridge the gap between theory and practice. Through a synthesis of existing literature and empirical data, it provides tangible insights and recommendations for developers, decision-makers, and academia, facilitating effective adaptation and integration of smart home technology. Structured around four fundamental research topics, the study systematically addresses the complexities of smart homes [4]. The first topic explores optimizing smart home technologies for robust privacy and security, delving into implications and precautions for safeguarding user data. The second focuses on interoperability challenges, examining characteristics determining compatibility among gadgets and aiming for seamless integration. The third investigates user views and experiences, seeking to enhance satisfaction, engagement, and adoption of smart home technologies. Lastly, the study explores AI integration for enhanced intelligence, assessing how artificial intelligence contributes to more intuitive and responsive ecosystems [5,6]. In conclusion, the research aims to thoroughly examine the opportunities and obstacles within the smart home domain, contributing to academic knowledge and providing practical recommendations for creating safer, intelligible, and user-friendly smart homes [7]. Envisioning a future where



DOI: https://doi.org/10.54216/JAIM.080202
Received: March 26, 2024 Revised: May 28, 2024 Accepted: November 03 2024

technology seamlessly integrates into daily life, the study fosters collaboration across realms, promoting an intelligent, efficient, and economical management of homes [8].

## 2. Literature Review

Technical advancements have propelled the emergence of smart homes, integrating smart devices, IoT, and advanced technologies, revolutionizing our interactions with living spaces. The appeal of smart homes lies in their promise of time and energy savings, driving research and innovation across various fields. This literature review aims to evaluate the current state of knowledge on smart homes, examining their diverse applications, challenges, and advancements. By synthesizing information, it seeks to provide an overview of the multifaceted aspects of smart homes and underscore their potential societal impact in the future, addressing existing knowledge gaps.

The advent of the Internet of Things (IoT) presents new challenges, including effective device management, security vulnerabilities, and accurate device identification. A recent study [9] utilized logistic regression enhanced by supervised machine learning to classify 41 devices, achieving exceptional performance with 99.79% accuracy across four categories. Identified gaps in the literature include the integration of AI and IoT, the utilization of geospatial data in smart home development, and the absence of integrated systems for energy efficiency and aged care. The developed classification model holds promise as a valuable tool for managing solutions in diverse IoT environments. The Internet of Things (IoT) drives autonomous solutions in smart homes, aiming to reduce human intervention and enhance efficiency, sustainability, and diverse needs fulfillment. In [10], the Cognitive Assessment of Smart Home Resident (CA-SHR) model is introduced, employing supervised categorization to gauge residents' cognitive functioning. By utilizing cognitive impairment scores and temporal feature analysis, it identifies early signs of decline, categorizing residents into dementia, Mild Cognitive Impairment (MCI), and healthy groups using ensemble AdaBoost. This model improves reliability and accuracy compared to previous methods.

In [11], a bibliometric analysis explores IoT-based applications for smart homes, classifying articles into knowledge engineering, AI-based detection processes, analysis tasks, and control processes. The study identifies pillars such as smart process management and the motivation for IoT use, offering guidance for future research. [12] conducts a bibliometric analysis of smart home-Internet of Things articles, highlighting significant improvements and developments in the domain. The findings underscore the growing impact of IoT in smart homes and related contexts, offering insights into trends, knowledge domains, and future directions.

Recent advancements in digital technology have popularized smart home monitoring systems. [13] targets machine learning (ML) methods to autonomously identify human behavior in smart homes. Various deep learning (DL) models, including autoregressive LSTM, are applied for human activity classification. The study showcases the superior performance of LSTM-based algorithms in human activity recognition compared to existing literature. In [14], ML models for predicting occupancy and window-opening behavior in smart buildings are reviewed, emphasizing CO2 concentration's significance for occupancy prediction. The study advocates integrating building and occupant information for enhanced accuracy and optimizing HVAC system control for energy savings.

The EU's Climate Action initiative focuses on enhancing energy efficiency and curbing greenhouse gas emissions in smart buildings. [15] compares ML techniques for predictive temperature control, identifying the Extra Trees regressor as the top-performing algorithm. Human Activity Recognition (HAR) is crucial for continuous monitoring in smart homes. [16] introduces an innovative HAR system using wearable devices and deep learning for recognizing daily activities, achieving a remarkable 97% accuracy.

In [17], explores the contribution of machine learning and big data analytics to smart building environments, addressing contemporary trends and challenges. The findings offer insights into the evolving scope of smart building services. In [18], provides a comprehensive review of IoT technology applications in homes, emphasizing the need to address gaps in smart home development and integration challenges. The study encourages researchers to develop strategies for creating energy-efficient smart homes.

In summary, this review explores the diverse dimensions of smart homes, combining technological evolution and evolving human needs. It underscores ongoing research and interdisciplinary collaboration's importance in overcoming challenges and realizing the potential of smart living.

## 3. Dataset

### 3.1 Dataset Description

The Smart Home Dataset [19] stands point by its Weather Information approach that perfectly matches the data to the household energetic consumption variations, going with a one-minute temporal granularity and deep curation. It demands that it collects a wealth of information from those supply and demand sources across the energy spectrum, which includes the total consumption as well as the renewable energy at the operation. This dataset involves a comprehensive study of source of energy and energy utilization concentrating on electrically-intensive appliances such as refrigerators, dishwashers, office spaces, heating system, and wine cellars thus enabling to know



DOI: https://doi.org/10.54216/JAIM.080202
Received: March 26, 2024 Revised: May 28, 2024 Accepted: November 03 2024

the periods of peak usage and patterns. Privileged with explanatory factors like temperature, humidity, and weather patterns, the dataset surpasses the temporal limits, providing to the full use of these important connections to allow the assessment of the intricate connections between external environments and energy dynamics on both a macro- and micro-levels. Researchers and practitioners can utilize this dataset for investigation, designing individual types of analyses, with the purpose to explore time-period dependencies, to predict future energy requirements, and to formulate time-efficient and energy-saving strategies adapted to smart homes. Under this concept, Smart Homes' Database with Weather Data evolves into one of a kind tools that opens up vast amounts of new information about smart homes' energy dynamics and this layer's effectivity, as well as about weather conditions that directly influence smart energy systems.

### 3.2 Dataset Preprocessing Steps

Comprehensive Data Preparation: A systematic preparation pipeline was implemented to ensure the Smart Home Dataset with Weather Information was reliable, consistent, and ready for analysis. The meticulous approach encompassed several key phases, each playing a pivotal role in enhancing the dataset's quality and utility. Addressing Missing Values: Initial dataset inspection revealed instances of missing values, prompting the use of imputation tactics, including statistical imputation techniques and interpolation, to ensure a seamless and continuous dataset suitable for in-depth analysis. Data Cleaning and Outlier Detection: A thorough data-cleaning technique was applied to identify and eliminate abnormalities or outliers that could distort findings. Statistical methods and visualizations were employed to detect extreme values, which were then meticulously analyzed to determine their impact on the overall dataset, leading to either adjustments or retention when deemed necessary.

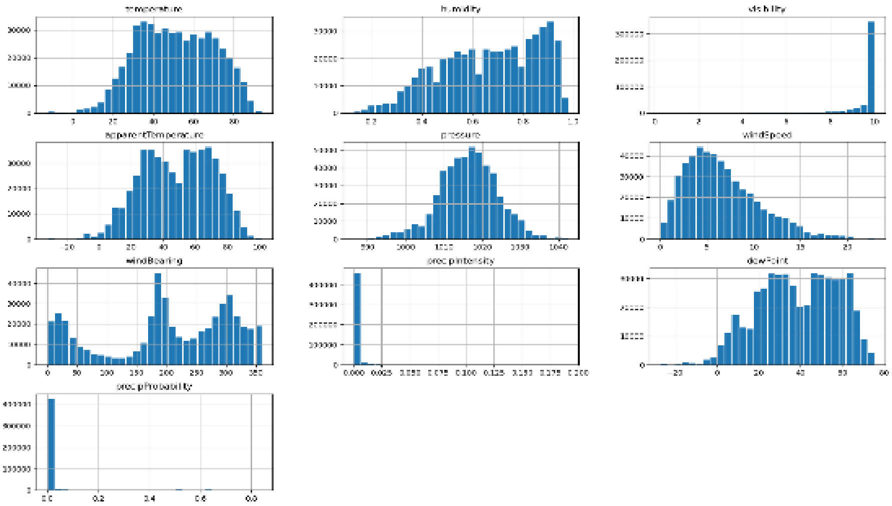


**Figure 1.** Energy Consumption Distribution Histogram

Normalization, Scaling, and Temporal Aggregation: Ensuring uniformity across numerical characteristics, normalization and scaling procedures were implemented, creating a consistent foundation crucial for algorithms sensitive to varying input data magnitudes. The temporal aspect was addressed through temporal aggregation, offering the dataset in window sizes, including hourly and daily averages. This approach facilitated a macroscopic view of energy usage patterns across different time periods.

Feature Engineering, Categorical Variable Encoding, and Correlation Analysis: We added additional features during enrichment increasing the dimensions for exaggeration: offline averages, weekend consumption moments, and efficiency indices. There was a process of encoding categorical variables into numerical formats, which was a pivotal object for machine identification. Correlation plots were created and then relevant variables were removed and the highly related variables were filtered in order to reduce the possibility of multicollinearity [20].

Quality Assurance: Stringent quality audits were introduced at each stage of the processing to include all statistic-sensitive assessments and redundant verifications. Thus, process of the looping around was a criterion ensured the presentation of the data's integrity and the consistency of the dataset with research objectives; such looping around was a constant value for the next step.



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The finally produced Smart Home Dataset Integrated with Weather Data skilled a refined, uniform, and deadline-ready condition, which could formulate a platform for an in-depth research study and also an intelligent mode of consumption of energy by smart homes.

### 3.3 Descriptive statistics

Descriptive statistics give a general view of the smart home data set with weather information, which shows how citizens deal with natural disasters and obtain accurate information that helps save lives. These key indicators, including range and standard deviation, in conjunction with frequently observed values, disclose such as the spread of energy consumption and the variation of energy consumption and the type of appliances utilized in they particular home and even the whole house. Features of distribution like prominent types of symmetrical, negatively skewed and a heavy tailed – is the most useful and it gives the general idea about the input data. Time series data mining deals with recognizing the general consumption patterns including the identifying the emerging trends on the basis of energy consuming as either a short term, a medium term or a long-term project. In this case, the correlation analysis precisely does the same, only clarifying possibly dependence both ways. This fundamental statistical analysis forms a basis for a comprehensive exploration of the smart homes energy use trends. It makes it possible for other scholars to perform data analysis using the insight gained here. Figure 1 shows a diagram of the energy consumption trends from the Smart Home Dataset with Weather Data represented with a histogram

Figure 2 provides a correlation heat map that can be used to visualize the outcomes of the correlation study, which is one of the significant visual aids intended for contributions to the understanding of the relationships between the variables in the Smart Home Dataset and Weather Information.

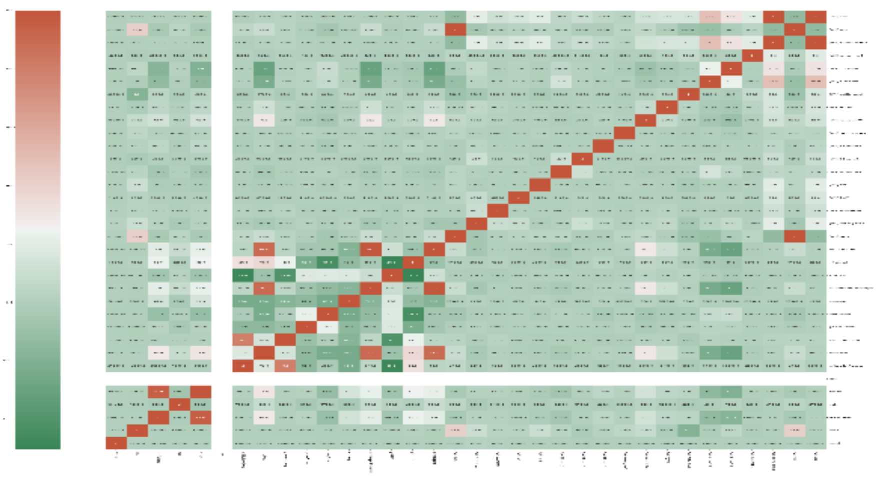

**Figure 2.** Heat Map of Variable Associations in Smart Home Energy Consumption

## 4. Results

This section extensively evaluates models that have demonstrated effective performance in predicting house appliance consumption, using a dataset combining smart meter readings and weather conditions. The study assesses the accuracy of various energy consumption models under weather-sensitive climate change conditions, including the Baseline Test and ARIMA. Metrics such as MSE, RMSE, MAE, R2, RRMSE, NSE, and WI are employed for comparison. Subsequent sections delve into the results of both DNN and ensemble models, unveiling their distinctive strengths in handling the intricacies of the smart home dataset compared to other models.

### 4.1 Machine Learning

This part of the article approaches assessing the performance of machine learning models in their predictive role of household appliance consumption. Machine learning solutions utilize computational algorithms to spot patterns in the smart home feed, which includes smart meter readings and weather conditions. What we want to find out is how good these models are at detecting the hidden relationships of these factors leading to energy use.

Machine learning models under question (the Baseline Test playing as the benchmark and the auto-regressive integrated Moving Average (ARIMA) used for time series forecasting) will be compared by the forecasting performance evaluation metric [21]. A set of metrics is then used for the evaluation of every model, which includes Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared (R2),



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Relative Root Mean Squared Error (RRMSE), Nash-Sutcliffe Efficiency (NSE), Weather Index (WI). In what follows, the outcome, together with the interpretation of how each machine learning model contributes to the overall prediction accuracy and reliability of the smart home system, is discussed from an application point of view.

ARIMA: ARIMA stands for Auto Regressive Integrated Moving Average and is a time series forecasting model. ARIMA, an auto-regressive integrated moving average time series model, is a popular statistical technique for forecasting that is instrumental in analyzing and forecasting sequential data points; therefore, it is commonly used in smart homes' energy consumption forecasting. The ARIMA function considers both trend and seasonal features of a time series by adding the AR model and differencing (I) and moving average (MA) models together.

Mathematical Foundation: AutoRegressive (AR) Component (p): The AR component represents the linear regression of the current observation on its past values. Mathematically, it is defined as:

$$X_t = c + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + \epsilon_t$$

where X_t is the current observation, c is a constant, ϕ_i are the autoregressive coefficients, and ϵ_t is the white noise error term.

Integrated (I) Component (d): The differencing component aims to make the time series stationary by subtracting the previous observation from the current one. Mathematically, it is represented as:

$$Y_t = X_t - X_{t-1}$$

The value of d represents the order of differencing needed to achieve stationarity.

Moving Average (MA) Component (q): The MA component involves modeling the relationship between the current observation and a residual error from a moving average model applied to past observations. Mathematically, it is expressed as:

$$X_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \ldots + \theta_q \epsilon_{t-q}$$

where μ is the mean of the time series, ϵ_t is the white noise error term, and θ_i are the moving average coefficients.

The ARIMA model is presented as ARIMA(p,d,q), where the order of AR, I, and M components is denoted as p, d, and q, respectively. This type of training uses historical data and then produces coefficients that are utilized in forecasting future values in a time series. The power of the ARIMA model is verified based on different performance indicators, such as the outcomes revealed in the section above.

Baseline Model: The Baseline Model represents the necessary starting ground for models to be appraised against the performance of more complex ones. For the case when we discuss the issue of predicting house appliance consumption, the Baseline Model would not be the ultimate solution but rather the simple and basic tool that is put into the comparison of the efficacy of other models such as ARIMA. Sometimes, an easy-to-understand approach is taken, which is based on simple assumptions or heuristics that can be applied to different time series but not in a way similar to the one used in the creation of advanced algorithms.

Mathematical Foundation: In the Baseline Model approach, mostly uncomplicated methods like linear regression are utilized that are devoid of any complex mathematics equations. Two common types of baseline models are:

Mean Baseline:

Mathematical Representation: $y\hat{}_t = y^-$

Here, $y\hat{}_t$ represents the predicted value for time t, and $y^-$ is the mean of the historical data. The mean baseline assumes that future values will be similar to the average of past observations.

Naive Baseline:

Mathematical Representation: $y\hat{}_t = y_{t-1}$

In this case, the predicted value for time t is equal to the most recent observed value ($y_{t-1}$). The naive baseline assumes that the future value will be the same as the last observed value.

Although baseline models have higher simplicity, which makes them quite easy to compare with more complex models that help in measuring the improvement in predictive accuracy, the control models are very helpful.



DOI: https://doi.org/10.54216/JAIM.080202
Received: March 26, 2024 Revised: May 28, 2024 Accepted: November 03 2024

### 4.2 Performance Metrics

The next part of the chapter delivers an insightful overview of the types of metrics used to assess the precision and solidity of machine learning, as well as ARIMA approaches to predicting household appliance usage using the Smart Home Database with weather data.

Mean Squared Error (MSE):

Mathematical Formula $MSE = \frac{1}{n}\sum_{i=1}^{n} \quad (y_i - y\hat{}_i)^2$

Explanation: MSE calculates the average squared difference between the actual (y_i) and predicted (y ˆ_i) values. A lower MSE indicates better model performance.

Root Mean Squared Error (RMSE):

Mathematical Formula: $RMSE = \sqrt{MSE}$

Explanation: RMSE is the square root of MSE, providing a measure in the same unit as the target variable. It is sensitive to larger errors and helps in understanding the magnitude of prediction errors.

Mean Absolute Error (MAE):

Mathematical Formula: $MAE = \frac{1}{n}\sum_{i=1}^{n} \quad \vee y_i - y\hat{}_i \vee$

Explanation: MAE calculates the average absolute difference between actual and predicted values. It is less sensitive to outliers compared to MSE.

R-squared (R2):

Mathematical Formula: $R2 = 1 - \frac{\sum_{i=1}^{n} \quad (y_i - y\hat{}_i)^2}{\sum_{i=1}^{n} \quad (y_i - y^{-})^2}$

Explanation: R2 measures the proportion of the variance in the dependent variable (y) explained by the model. A higher R2 value indicates a better fit.

Relative Root Mean Squared Error (RRMSE):

Mathematical Formula: $RRMSE = \frac{RMSE}{y^{-}} \times 100$

Explanation: RRMSE normalizes RMSE by dividing it by the mean of the actual values $(y)^{-}$and expresses it as a percentage. It provides a relative measure of error.

Nash-Sutcliffe Efficiency (NSE):

Mathematical Formula: $NSE = 1 - \frac{\sum_{i=1}^{n} \quad (y_i - y\hat{}_i)^2}{\sum_{i=1}^{n} \quad (y_i - y^{-})^2}$

Explanation: NSE compares the model's performance to a simple mean model. A higher NSE indicates better predictive accuracy.

Weather Index (WI):

Mathematical Formula: $WI = 1 - \frac{RMSE_{model}}{RMSE_{baseline}}$

Explanation: WI compares the model's RMSE to that of the baseline model, providing insights into the model's improvement over the baseline.

The collectively interpreted meaning of these metrics provides a comprehensive diagnosis of the capacity of the models to accurately predict changing weather conditions for house appliances.

### 4.3 Machine Learning Results

In this part of the performance evaluation, we assess the outcomes of machine learning models, which are used to predict house appliance consumption after using the data set that merges weather information and the Smart Home Dataset. We take into consideration the three models, which are the Baseline Test and ARIMA, evaluated by the benchmark of different performance metrics. The tabulated numbers presented in Table 1 highlight the relative performance of the models in replicating the dynamics of energy use observed in smart homes.



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**Table 1:** The Models Performance

| Models | WI | NSE | RRMSE | R2 | r | mae | rmse | mse |
|---|---|---|---|---|---|---|---|---|
| **Baseline** | 0.485822 | -0.20312 | 38.84133 | 0.151154 | 0.388786 | 0.194436 | 0.303535 | 0.092134 |
| **ARIMA** | 0.539124 | 0.095053 | 33.6862 | 0.140368 | 0.374657 | 0.17428 | 0.263249 | 0.0693 |

Figure 3 log plots depict the performance results of various machine learning models (Baseline Test and ARIMA) used for predicting monthly household appliance consumption based on weather information from the Smart Home Dataset. The log scale allows a detailed examination of variations across metrics, providing a nuanced perspective on the models' strengths and weaknesses. The graphical outcome serves as a visual aid supporting the analysis of numerical data, contributing to a comprehensive understanding of the models' efficiency and forming the basis for their interpretation.

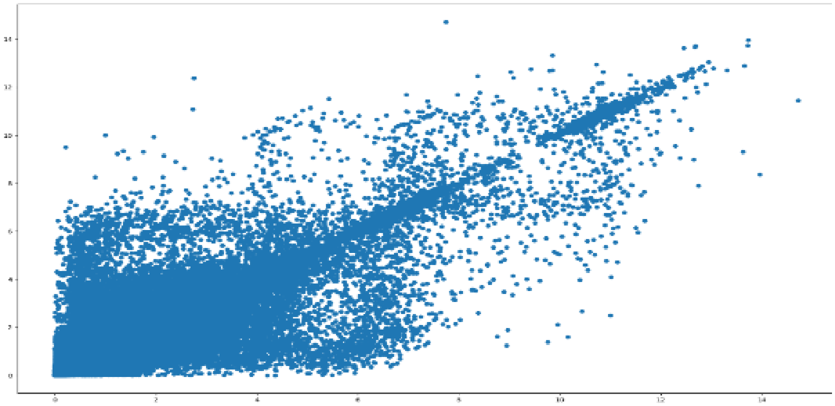

**Figure 3.** Log Plot of Model Performance Results

Figure 4 displays a correlation plot graph illustrating temporal autocorrelations within the performance results of ML models. This plot, unique among others, captures the forecasted and actual values from the past, offering valuable insights into the model's ability to predict sequences. The autocorrelation plot dynamically serves as a graphical representation, pinpointing residuals' symptoms and weaknesses in model improvement. It plays a crucial role in assessing how our models capture and preserve the sequential nature of the Smart Home Dataset with weather predictive data, focusing on a dissimilarity analysis of their accuracy.

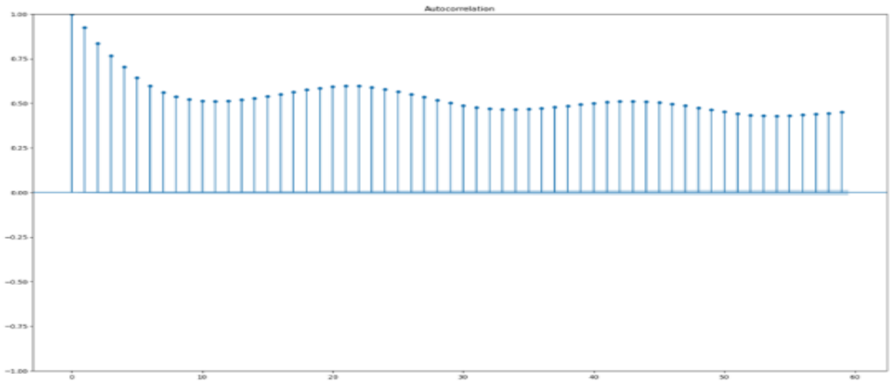


**Figure 4.** Autocorrelation Plot of Model Performance Results

**Key Findings**

Mean Squared Error (MSE): The ARIMA model has the upper hand over the Baseline Test as it features the lowest MSE. This implies that ARIMA is becoming more accurate as the range between predicted and actual values is sound.

Root Mean Squared Error (RMSE): Compared to the baseline, ARIMA makes smaller errors, as its predictive error is limited to a close range. Mean Absolute Error (MAE): ARIMA has a lower MAE value, which means that its



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predictions' trend is closer to the real values than the Baseline test's. R-squared (R2): Both models have relatively low R2 values, which means that even though a fair amount of the variation of the dependent variable is explained, there is still a large unexplained portion. Nevertheless, the model with an R2 bigger than that of ARIMA is considered more accurate by some. Relative Root Mean Squared Error (RRMSE): The relatively lower RRMSE it exhibits when normalized by the mean of actual values shows its dominance among various comparative metrics. Nash-Sutcliffe Efficiency (NSE): While the ARIMA outperforms the univariate SITM in terms of an increase in its NSE, the negative NSE for the no information at all reveals that it is not good at forecasting. Weather Index (WI): The presence of a positive WI in the case of ARIMA suggests that it is doing better than the Baseline Test, stressing its capability to have an accurate prediction in relation to the other model. These important observations, which emphasize the success of the ARIMA model relative to the Baseline Test in predicting house appliance consumption based on the assessed metrics, undoubtedly reveal it as the most effective. The findings also demonstrate the significance of having an ARIMA-based time-series technique in play within the context of developing smart home energy systems.

## 5. Conclusion

In summary, this work is oriented on smart home energy management by employing machine learning models to predict energy usage patterns under the dataset containing the smart meter reading and the weather condition as contextual factors. A comparison between the results for the Baseline Test and the Auto Regressive Integrated Moving Averages (ARIMA) models with performance metrics like Mean Squared Error (MSE) confers surprisingly interpretable outcomes. Firstly, the ARIMA model is the best one since it has the lowest MSE value, which is 0.0693, among others. Thus, its tremendous accuracy in energy prediction in the smart home environment is revealed. The results, thus, accentuate the importance of putting this sort of forecasting technique, such as ARIMA, into use in order to maximize the utility of smart homes and their energy management systems. The discovery that ARIMA outperforms other models in reflecting the intricacy of energy consumption, mainly when there are varying weather conditions, shows the chance of using ARIMA as a robust tool to enhance the efficiency and sustainability of household energy usage through the detection of anomalies. As witnessing the advancement in smart home technologies, the time comes to use in-depth modeling in forecasting. It feeds into the dynamic process that is the emerging horizon of ARIMA applications by presenting useful findings on the effectiveness of the method and by drawing attention to the highly significant aspect of weather information in improved accuracy. Beyond the fact that these findings give a new insight into the present understanding of smart home energy management, they allow policymakers, energy providers, and homeowners to work together to ensure that energy use is beneficial to both the environment and the human race.

**Funding:** "This research received no external funding"

**Conflicts of Interest:** "The authors declare no conflict of interest."

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DOI: https://doi.org/10.54216/JAIM.080202
Received: March 26, 2024 Revised: May 28, 2024 Accepted: November 03 2024