



Power Consumption Analysis at Solar Power Grid

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Abstract-*This study examines the case study report on the application of regression analysis made at Kongu Engineering College campus. The Autoregressive (AR) and Autoregressive Integrated Moving Average (ARIMA) models in the time series analysis and forecasting of data, focusing on their effectiveness in capturing and predicting time series patterns. The AR model assumes a linear dependency between the present value and past values of a time series variable. By estimating autoregressive coefficients, this model captures underlying patterns and dynamics, making it suitable for stationary time series data. By applying differencing to non-stationary data, it is possible to convert it into a stationary series. This transformation subsequently gives rise to the ARIMA model, which amalgamates elements of autoregressive and moving average components. To achieve the research objective, appropriate model orders (p , d , q) are selected by analysing autocorrelation and partial autocorrelation plots, along with evaluating the stationarity properties of the series. Real-world datasets of Solar power data of KEC campus are employed to illustrate the practical application of AR and ARIMA models. The accuracy and performance of these models are assessed by comparing predicted values with actual observations using appropriate evaluation metrics. This study's results enhance our comprehension of and practical application for AR and ARIMA models in time series analysis. The research employs appropriate techniques for model selection and metric evaluation to assess the accuracy and efficiency of these models.*

I. Introduction

The global shift towards renewable energy sources, particularly solar power, has escalated in response to the pressing need for sustainable and clean energy solutions. Solar power grids play a pivotal role in harnessing and distributing solar energy efficiently. However, ensuring the optimal performance and reliability of solar power grids necessitates a detailed analysis of power consumption patterns within these grids. This paper presents a comprehensive exploration of power consumption within solar power grids, aiming to enhance the understanding of energy utilization, efficiency, and potential areas for improvement. By scrutinizing power consumption, load patterns, and energy management strategies within solar power grids, we aim to contribute to the sustainable development and effective integration of solar energy into the existing power infrastructure. The findings of this study can inform policy-makers, engineers, and stakeholders in making informed decisions to advance the efficiency and viability of solar power grids, thus fostering a sustainable energy landscape for the future.

Time series analysis is an analytical approach employed to examine and interpret data points gathered over a period of time. The key to making predictions or estimates about future values lies in comprehending the data's patterns, trends, and characteristics. To anticipate future values, time series forecasting needs to grasp and

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capture the substantive patterns and changes within the time series data. Its applications span various fields such as finance, economics, sales, weather forecasting, demand planning, and resource management. In these scenarios, historical data patterns offer invaluable insights to support informed decision-making. Time series forecasting methods utilize mathematical models, statistical strategies, and machine learning algorithms to comprehend the complexities and relationships inherent in time series data, enabling the presumption of future values. The choice of forecasting model depends on various aspects, involving the data's nature, the underlying trends, and the specific objectives of the research.

II. Literature Survey

The paper addresses the critical need for accurate solar power forecasting in incorporating the renewable energy sources effectively into power grid. The primary aim is to propose a methodology that utilizes autoregressive models with exogenous inputs, incorporating meteorological data, to enhance the accuracy of solar power forecasts. The approach leverages autoregressive models to capture time-dependent patterns in solar power production and augments these with external factors known to influence solar energy generation. The results demonstrate the effectiveness of this methodology, highlighting its potential in improving grid management and promoting optimal utilization of solar energy.

The research delves into the effect of the COVID-19 pandemic on the need for electricity and how this, in turn, affects load forecasting. It examines the substantial alterations in electricity consumption patterns brought about by changes in societal behaviours, economic activities, and the widespread adoption of remote work during the pandemic. Grasping these shifts is essential for accurate load forecasting as it assists in adapting strategies for power generation and distribution to accommodate the new demand dynamics. This study sheds light on how the pandemic has influenced energy consumption trends, offering valuable insights for optimizing energy resource planning and management in response to unforeseen events such as a global health crisis.

The publication discusses the integration of both quantitative and qualitative models to forecast instability, particularly in the realm of political and social contexts. It highlights the significance of employing a combination of numerical data-driven methods and qualitative assessments based on expert knowledge and insights. By blending these approaches, the aim is to achieve a more comprehensive understanding of factors contributing to instability and improve the accuracy of forecasts. The application of mixed-method modelling allows for a more nuanced analysis of complex dynamics, ultimately aiding in better anticipation and management of potential instability.

This paper focuses on short-term solar energy forecasting, presenting a methodology that utilizes

autoregressive models. Autoregressive models are statistical techniques that use past observations to predict future solar energy production accurately. By employing these models, the paper addresses the inherent challenge of solar energy's intermittent nature. The methodology outlined in the paper contributes to better energy planning and grid management, providing valuable insights for effective incorporation of solar energy into power system.

This study focuses on near-future load prediction within the framework of the Jordan power system. The authors suggest a hybrid forecasting method that merges the NARX-Elman neural network with the Autoregressive Integrated Moving Average (ARMA) model. By utilizing historical load data and external variables, the NARX-Elman neural network enhances the precision of load predictions. The research makes a valuable contribution to improving load forecasting within the Jordan power system, which, in turn, assists in optimizing energy resource planning and management for a sustainable and dependable power supply.

This research is centred on the utilization of the ARIMA (Autoregressive Integrated Moving Average) prediction model for forecasting the progression of the COVID-19 pandemic, with a specific focus on Saudi Arabia. The study integrates data regarding the ongoing health protection actions in order to enhance the precision of these forecasts. Through the application of the ARIMA model, the objective of this paper is to offer valuable perspectives on the potential path of the pandemic within Saudi Arabia, thereby contributing to informed decision-making and public health planning.

The paper focuses on short-term solar power forecasting in Greece and aims to compare the effectiveness of two forecasting models: ARIMA (Autoregressive Integrated Moving Average) and Artificial Neural Networks (ANN). It investigates which model, ARIMA or ANN, provides more accurate predictions for solar power generation in the short term. The study contributes valuable insights into the most suitable modeling approach for enhancing solar power forecasting, which is essential for efficient integration of solar energy into the power grid in Greece.

This paper focuses on short-term forecasting of solar irradiance, a crucial variable for solar power generation. The study specifically investigates the use of two popular models, Autoregressive (AR) and Autoregressive Moving Average (ARMA), to predict solar irradiance in the short term. The goal is to enhance the accuracy of solar irradiance forecasting, which is essential for optimizing the performance and efficiency of solar power systems. The research contributes to improving the reliability of solar energy production forecasts.

The paper addresses short-term solar power forecasting, proposing an enhanced methodology applying the ARIMA (Autoregressive Integrated Moving Average) model. The improvement involves incorporating seasonal decomposition techniques, recognizing the significance of seasonality in solar

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power generation. By refining the ARIMA model with this approach, the study aims to enhance the accuracy of short-term solar power forecasts. This research contributes to more precise predictions, enabling better integration and utilization of solar energy in the power grid.

This paper's primary emphasis is on employing time series analysis, particularly the ARIMA (Autoregressive Integrated Moving Average) model, to forecast the everyday and every month averages of worldwide solar ray emission. The research study is situated in Seoul, South Korea, highlighting the model's use in a specific, localized context. By using the ARIMA model, the study aims to provide accurate predictions for solar radiation, a critical factor in solar energy production. This research contributes to understanding and predicting solar radiation patterns, enabling efficient solar energy utilization and planning in the South Korean context.

III. Role of Time Series Analysis

Time series analysis is of vital importance in comprehending and overseeing electricity usage in solar power networks. It provides insights, predictions, and optimizations that are essential for effective energy management. Here's how time series analysis aids in addressing power consumption challenges.

A. Demand Forecasting and Planning:

Time series analysis helps forecast future power consumption patterns based on historical data. Accurate demand forecasting allows for better planning of energy generation, distribution, and storage. Solar power plants can adjust their production schedules and storage strategies to match anticipated demand, optimizing the overall energy system.

B. Load Profiling and Peak Demand Management:

Analysing time series data helps identify load profiles, showcasing periods of high and low power consumption. Understanding peak demand times allows for efficient resource allocation and load shedding strategies to avoid overloading the grid during high demand periods, thus ensuring system stability.

C. Efficient Energy Storage Management:

Time series analysis helps in modelling energy storage needs. By analysing historical patterns of solar energy generation and consumption, one can optimize the sizing and operation of energy storage systems. This ensures that excess energy is stored during peak solar generation times and efficiently utilized during low generation or high consumption periods.

D. Optimizing Renewable Integration:

Integrating solar power into the energy mix can be challenging due to its intermittent nature. Time series analysis allows for understanding solar generation patterns and their correlation with demand. This knowledge aids in developing strategies to integrate solar power effectively, minimizing reliance on non-renewable sources during peak solar production.

E. Load Shifting Strategies:

Time series analysis detects time-dependent trends in energy usage throughout the day. This knowledge is essential for implementing load-shifting tactics, encouraging consumers to move energy-intensive tasks to non-peak hours. This helps alleviate stress on the grid during peak demand times and supports energy conservation.

F. Fault Detection and Anomaly Identification:

By analysing time series data, abnormal consumption patterns or faults in the grid can be detected. Sudden spikes or drops in consumption may indicate malfunctions or anomalies, enabling quick response and efficient troubleshooting to maintain grid stability.

G. Policy and Investment Decisions:

Long-term time series analysis provides data for policy-makers and investors. They can use trends and patterns to make informed decisions regarding infrastructure investments, renewable energy targets, and policy adjustments to promote sustainable energy consumption.

IV. Methodologies Followed

In this research, we employed a variety of time series analysis methodologies, focusing on AR (Autoregressive), ARIMA (Autoregressive Integrated Moving Average), and SARIMA (Seasonal Autoregressive Integrated Moving Average) to analyse power consumption patterns within solar power grids. The following methodologies were implemented:

A. Data Acquisition and Manipulation

We collected past power consumption data from solar power grid monitoring systems. The data included hourly or daily records, capturing variations in power consumption over time. Preprocessing involved data cleaning, handling missing values, and ensuring data consistency for reliable analysis.

B. Exploratory Data Analysis (EDA)

We conducted EDA to understand the underlying patterns and characteristics of the power consumption time series data. This included plotting time series graphs, analysing trends, seasonality, and identifying any outliers or unusual patterns.

C. Autoregressive (AR) Modelling

We applied the Autoregressive (AR) model, a type of time series model that predicts future values based on past observations. The autoregressive (AR) model posits that the existing value of the time series results from a linear blend of its past values.

D. Autoregressive Integrated Moving Average (ARIMA) Modelling

We employed this model, an expanded version of the AR model that includes differencing to attain stationarity. The ARIMA model consists of autoregressive, differencing, and moving average

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elements, making it well-suited for time series data that is not stationary.

E. Model Evaluation and Validation

We evaluated the effectiveness of the AR and ARIMA models by employing relevant assessment measures like Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). To validate the models, we compared their predicted values to the real data, ensuring that they accurately represented the power consumption patterns.

F. Forecasting and Future Trend Analysis

We utilized the trained AR and ARIMA models to predict the future power consumption trends. The forecasts obtained from these models were analysed to identify potential future energy demand patterns and aid in proactive decision-making. Through the application of these approaches, our goal was to offer valuable understandings into the energy usage trends within solar power grids. This serves as a basis for efficient energy administration and well-informed choices to support a sustainable energy future.

V. Auto Regressive (AR) Model

In time series analysis, Auto Regressive (AR) models find extensive application for forecasting future values by relying on prior observations. This abstract provides an overview of AR models, including their underlying principles, applications, and key considerations.

A. Introduction:

AR, short for Autoregressive, is a time series model that anticipates forthcoming values by utilizing a linear combination of earlier observations of the same variable. Within an Autoregressive (AR) model, the variable's value at a specific time is projected as a linear relationship with its preceding values. The order of an AR model, represented as AR(p), determines the count of prior variable values used for predicting the current value. This parameter specifies the model's order, indicating the number of past observations were considered.

B. Mathematical Representation:

$$X(t) = c + \phi(1)X(t-1) + \phi(2)X(t-2) + \dots + \phi(p)X(t-p) + \varepsilon(t) \quad \text{---(1)}$$

i. Parameters:

- c is intercept in the model.
- $\phi(1), \phi(2), \dots, \phi(p)$ are the coefficients that determine the influence of the lagged values.
- $X(t-1), X(t-2), \dots, X(t-p)$ are the values up to lag
- $\varepsilon(t)$ represents the residual, which captures the random and unexplained component of the model.

- The parameters $\phi(1), \phi(2), \dots, \phi(p)$ are usually calculated through techniques such as maximum likelihood estimation or least squares, which involve fitting the model to the existing historical data.

C. Finding the parameters of AR model:

Finding the attributes of an AR (Autoregressive) model involves several steps:

- **Verify Stationarity:** Verify the time series is stationary or not. Since stationary time series are preferred by AR models, stationarity may be achieved by transforming or diffusing the data.
- **Autocorrelation:** Check the autocorrelation plot of the time series to identify the values of p .
- **Fit the Model:** Use the identified value of p to fit the AR model to the time series. This can be done using software such as R or Python, which have built-in functions for fitting AR models.
- **Analyse the productivity of the Model:** Utilize statistical indicators such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) to assess the model's effectiveness.
- **Refine the Model:** If the model is not performing well, refine the parameter by repeating steps 2-4. This iterative process can be continued until an optimal model is achieved

D. key features of AR model

The key features of an Autoregressive (AR) model are as follows:

- **Auto-correlation:** In the AR model, it's assumed that the existing value of a time series is influenced by its previous values. This relationship is expressed in the model through autoregressive terms, which account for past values of the time series. The existence of auto-correlation is a fundamental characteristic of the AR model.
- **Stationarity:** The AR model presumes that the time series exhibits stationarity, signifying that its statistical characteristics remain consistent across time. In cases where the time series lacks stationarity, it might be required to perform data differencing before employing the AR model.
- **Parameter Estimation:** The AR model's parameters are determined through various methods, including utmost likelihood or least squares calculation. To

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identify the optimal value of 'p,' one can assess the autocorrelation and partial autocorrelation graphs of the time series.

- **Forecasting:** The AR model is usually used for time series forecasting, as it can provide accurate predictions of future values based on past observations. The order of the model, the standard of the data, and the precision of the parameter estimates all affect how accurate the forecast will be.

VI. Autoregressive Integrated Moving Average (ARIMA) Model

Autoregressive Integrated Moving Average (ARIMA) models are vastly employed in time series analysis to predict the values based on past observations. This abstract provides an overview of ARIMA models, including their underlying principles, applications, and key considerations.

A. Introduction:

ARIMA, an abbreviation for Autoregressive Integrated Moving Average, is a commonly applied model in time series analysis, used for both prediction and examination of time series data. It amalgamates autoregression (AR), moving average (MA), and differencing (I) concepts into a unified model. ARIMA is well-suited for time series data that are stationary or nearly stationary, meaning their mean, variance, and autocorrelation structure remain fairly consistent over time. It has the capacity to address both data trends and seasonality, rendering it a versatile and potent tool for time series analysis.

B. Mathematical Representation:

$$\Delta^d Y(t) = c + \phi(1) \Delta^d Y(t-1) + \phi(2) \Delta^d Y(t-2) + \dots + \phi(p) \Delta^d Y(t-p) + \theta(1) \varepsilon(t-1) + \theta(2) \varepsilon(t-2) + \dots + \theta(q) \varepsilon(t-q) + \varepsilon(t) \quad \text{---(2)}$$

i. Parameters:

- $Y(t)$ represents the value of time series at time 't'.
- Δ^d is the differencing operator applied 'd' times to make the data stationary.
- c is a constant term (intercept) in the model.
- $\phi(1), \phi(2), \dots, \phi(p)$ are the autoregressive attributes.
- $\theta(1), \theta(2), \dots, \theta(q)$ are moving average attributes.
- $\varepsilon(t)$ represents the error term or residual, which captures the random and unexplained component of the model.

Maximum likelihood estimation or least squares are used to estimate the parameters and the model is fitted to the historical data that is currently

available. After estimating the model's parameters, they can be employed for predicting future values by considering the past values and error terms.

ARIMA models provide a flexible framework for capturing complex patterns and dependencies in time series data. They are widely used for forecasting, anomaly detection, and understanding the underlying dynamics of various types of time series data, including economic data, stock prices, energy consumption, and more.

C. Finding the parameters of ARIMA model

Finding the parameters of an ARIMA (Autoregressive Integrated Moving Average) model involves several steps:

- **Stationarity:** Verify the time series stationary status. It might be necessary to alter or difference the data to attain stationarity because ARIMA models perform best with stationary time series.
- **Autocorrelation:** Check the autocorrelation and partial autocorrelation plots of the time series to identify the values of p, d, and q.
- **Fit the Model:** Use the identified values of p, d, and q to fit the ARIMA model to the time series. This can be done using software such as R or Python, which have built-in functions for fitting ARIMA models.
- **Analyse the productivity of the Model:** Utilize statistical indicators such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) to assess the model's effectiveness.

Overall, the process of finding the parameters of an ARIMA model requires careful analysis of the time series, including checking for stability and analysing the autocorrelation and partial autocorrelation plots, and fitting and evaluating the model. Check for Stationarity: Check whether the time series is stable or not. It could be necessary to alter or difference the data to achieve stationarity since AR models perform best with stationary time series.

D. key features of ARIMA model

The key features of an ARIMA (Autoregressive Integrated Moving Average) model are as follows:

- **Autocorrelation:** The ARIMA model, like the AR model, presupposes that a time series' present value depends on its past values. However, the ARIMA model also incorporates the concept of differencing to remove any trends or seasonality in the data, which can lead to more accurate forecasts.

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- Differencing: The differencing order, marked as 'd,' indicates how many times the time series must be varied to attain stationarity. Differencing is a technique employed to convert a non-stationary time series into a stationary one, simplifying the process of modelling and prediction.
- Parameter Estimation: The ARIMA model's parameters are determined through various methods, including maximum likelihood or least squares estimation. By analysing the autocorrelation and partial autocorrelation plots of the time series, one can identify the most suitable values for p, d, and q.
- Seasonality: The ARIMA model can be expanded to accommodate occasional patterns in the data, represented by the parameter 'S.' This leads to the creation of a seasonal ARIMA (SARIMA) model, which integrates seasonal differencing, seasonal autoregressive components, and seasonal moving average components.
- Forecasting: The ARIMA model is a vastly employed method for forecasting time series data because it can offer precise predictions of future values by considering past observations. The accuracy of the forecasts depends on factors such as the model's structure, data quality, and the accuracy of parameter estimates.
- Autocorrelation: The AR model operates on the assumption that the existing value of a time series is determined by its preceding values. This connection is established using autoregressive terms, which account for earlier values in the time series. The existence of autocorrelation is a fundamental characteristic of the AR model.

VII. Results Obtained

This chapter provides the result obtained from AR and ARIMA model in energy forecasting. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are statistical measures used for model choosing and comparison in AR and ARIMA models.

A. Akaike Information Criterion (AIC):

The AIC assesses how well a statistical model fits a specific dataset. It balances the model's goodness of fit with its level of complexity. In AR and ARIMA models, the AIC is calculated using the following formula:

$$AIC = -2 * \log\text{-likelihood} + 2 * k \quad \text{---(3)}$$

where log-likelihood represents the maximized log-likelihood of the model and k is the number of parameters estimated in the model. The lower the AIC value, the better the model is considered to fit the data. Therefore, when comparing different models, the model with the lowest AIC is typically preferred.

B. Bayesian Information Criterion (BIC):

The BIC is another criterion used for model selection, similar to the AIC. Like the AIC, the BIC balances model fit and complexity, but it places a higher penalty on model complexity. The BIC can be found from the following formula:

$$BIC = -2 * \log\text{-likelihood} + \log(n) * k \quad \text{---(4)}$$

The log-likelihood stands for the highest attainable log-likelihood of the model, 'k' represents the count of parameters estimated within the model, and 'n' is the size of the sample. Similar to the AIC, a reduced BIC value suggests a model that fits better. Nevertheless, the BIC has a tendency to prefer simpler models compared to the AIC, as it imposes a more pronounced penalty for model complexity.

C. Effect of using AIC and BIC

Both the AIC and BIC serve as criteria for determining the most suitable model from a group of candidate models. They offer a compromise between model suitability and complexity, aiding in the avoidance of overfitting and in the selection of a model that strikes a balance between precision and simplicity. It's important to recognize that these criteria are not the sole considerations when choosing a model; additional factors like theoretical soundness and practical interpretability should also be taken into consideration. The AR and ARIMA model results are organized in a table, and by examining the AIC and BIC values, one can infer the model's accuracy. A lower AIC and BIC value corresponds to higher accuracy.

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VIII. Obtained Results

We had used the power consumption data for one month as raw data for Analysis. The Time series data is mentioned below

DATE	POWER
01/01/2023	92
02/01/2023	214
03/01/2023	403
04/01/2023	429
05/01/2023	356
06/01/2023	298
07/01/2023	348
08/01/2023	311
09/01/2023	422
10/01/2023	478
11/01/2023	490
12/01/2023	456
13/01/2023	407
14/01/2023	69
15/01/2023	48
16/01/2023	56
17/01/2023	69
18/01/2023	223
19/01/2023	472
20/01/2023	416
21/01/2023	354
22/01/2023	347
23/01/2023	228
24/01/2023	272
25/01/2023	268
26/01/2023	296
27/01/2023	434
28/01/2023	489
29/01/2023	322
30/01/2023	196
31/01/2023	367

In data prediction analysis, the power consumption data for every block is used as raw data. This raw data is arranged in a table format, where each row shows a specific block, and the columns represent different power consumed with block. The power consumption data captured for each block can then be used as input for various data prediction analyses, such as forecasting future power consumption, identifying trends or patterns in power usage.

A. Time series plot for raw data

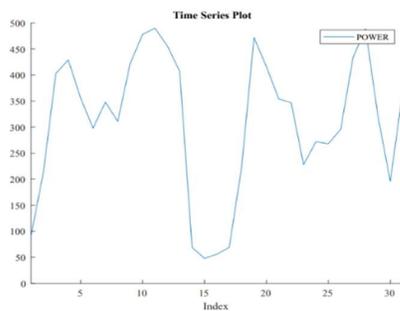


Fig 9.2.0 Time Series Plot for Raw Data

Fig 9.2.0.- plot depicts the power consumption data collected over the month. The x-axis shows the dates, while the y-axis represents the power consumption in an unspecified unit. The plot illustrates

the daily variations in power consumption over the course of the month, offering valuable understandings into consumption trends. Each data point on the plot represents the power consumption recorded for a specific day, allowing for a comprehensive analysis of the electricity demands over time. The plot showcases variations in power consumption, highlighting peaks and valleys that indicate periods of increased or reduced electricity usage. This visual representation enables the identification of recurring patterns or trends in power consumption, such as daily spikes during specific hours or consistent fluctuations across certain days of the week. By examining this time series plot, one can gain a deeper understanding of the power consumption dynamics, facilitating better resource management, demand forecasting, and optimization of energy usage. This data visualization serves as a valuable tool for energy analysts, utility providers, and researchers seeking to explore and make informed decisions regarding power consumption patterns.

B. ARIMA (2,2,1) Model (Gaussian Distribution) (ARIMA_POWER)

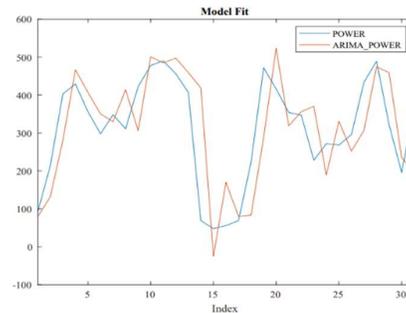


Fig 9.2.1

Fig 9.2.1 includes an autoregressive component of order 2. This indicates that the time series' present value is linearly reliant on its two most recent values. The plot will show how the existing value of the series is influenced by its preceding values, reflecting the trend or pattern captured by the autoregressive component. The ARIMA (2,2,1) model with a Gaussian distribution, also known as ARIMA_POWER, is a time series forecasting model that incorporates autoregressive (AR), differencing (I), and moving average (MA) components.

C. ARIMA (1,0,0) Model (Gaussian Distribution) (AR_POWER)

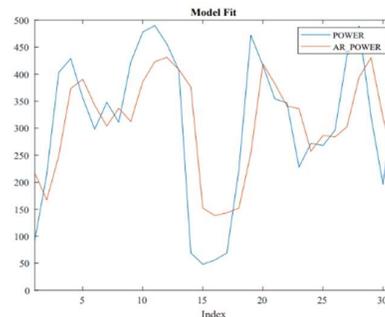


Fig 9.2.2

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The Fig 9.2.3 has an autoregressive component of order 1, denoted by the "1" in the (1,0,0) notation. This implies that the time series' present value is linearly reliant on its most recent value. The plot will show how the current value of the series is influenced by its most recent value, reflecting the trend or pattern captured by the autoregressive component. The AR_POWER model expects that the errors (residuals) follow a Gaussian (normal) distribution. This implies that the differences between the real values and the calculated values from the model are normally distributed. The plot may include a histogram or density plot of the residuals, allowing you to assess the goodness of fit to the Gaussian distribution assumption. The plot for the ARIMA (1,0,0) model (AR_POWER) with a Gaussian distribution will provide insights into the trend and noise present in the time series data. It aids in comprehending how the series' present value relates to its most recent value and evaluates how well the model fits the assumption of a Gaussian distribution.

D. Results from AR and ARIMA

Selecting the AR or ARIMA model with the lowest AIC or BIC value, as well as refining the model based on residual analysis, we can improve the accuracy of the predicted values. It's important to note that time series forecasting is a complex task, and there might be additional considerations based on the specific characteristics of our data.

Order	AR Model		ARIMA Model	
	AIC	BIC	AIC	BIC
1	381.4273	385.6309	382.954	389.615
5	378.3065	387.1132	382.9026	389.7391
10	354.2564	366.7907	379.0516	387.0448
15	400.4626	413.5967	388.3877	394.8668

Comparing the AIC and BIC values, the ARIMA model (ARIMA (1,0,0)) with AIC value 379.0516 and BIC value 387.0448 has the lowest AIC and BIC values among all the provided models. Therefore, based on these criteria, the ARIMA model (ARIMA (1,0,0)) is the best fitting model for the given data in terms of prediction. It's important to note that while AIC and BIC provide a measure of model fit, other factors such as the behaviour of residuals, interpretability of the model, and the underlying characteristics of the data should also be taken into consideration when selecting the best fitting model.

IX. Summary and Conclusion

To enhance grid management and effectiveness, real-time analysis of power consumption data from a solar power grid using AR, ARIMA, and SARIMA models offers significant benefits. These models provide dependable estimations of power demand, enabling informed decisions for energy distribution, storage, and generation by energy planners and grid operators. A comprehensive understanding of

power consumption patterns and trends empowers stakeholders to optimize resource allocation, ensure grid stability, and adjust energy production to match anticipated demand. Utilizing AR, ARIMA, and SARIMA models establishes a robust framework for examining power consumption trends and generating precise forecasts. To maintain ongoing accuracy and effectiveness, it is crucial to regularly assess and refine these models in light of new data. Moreover, the integration of other factors such as weather conditions, renewable energy availability, and demand-side management strategies can further amplify the precision of power consumption predictions and optimize the overall efficiency of the solar power grid.

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