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Analysis and Forecasting of Electricity Demand in MOELCI-II Using ARIMA Model

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ABSTRACT

The research addresses the critical challenge of analyzing and forecasting electricity demand within the service area of the Misamis Occidental II Electric Cooperative, Inc. (MOELCI-II) in the Philippines. The study employs advanced time series analysis techniques, specifically the ARIMA model, to unravel historical trends, patterns, and nonstationary characteristics in electricity demand. The goal of the study is to present a comprehensive analysis and forecast of the energy consumption in the MOELCI-II service area. The researchers obtained electricity consumption information for MOELCI-II through the Department of Energy website. The ARIMA (2,1,0) model is meticulously selected based on the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, showcasing the necessity of differencing and autoregressive components. The researchers also assess the goodness of fit of the ARIMA model. The forecast for electricity shows a persistent upward trend in electricity demand for (MOELCI-II) is evident in the coming years. Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) analysis are used to determine how accurate a prediction is. The values that our ARIMA model produced are considered acceptable.

Keywords: ARIMA, Coincident Peak, Electricity Demand, Forecasting, Time series

INTRODUCTION

Electricity, the lifeblood of modern society, fuels the intricate machinery that powers our homes, businesses, and technological advancements. In the dynamic landscape of Misamis Occidental, specifically within the purview of the Misamis Occidental II Electric Cooperative, Inc. (MOELCI-II), the demand for a consistent and reliable power supply becomes increasingly critical for the sustained growth and development of the region.

Established on June 2, 1976, MOELCI-II holds the distinction of being the 77th electric cooperative in the Philippines. It plays a pivotal role in providing electricity to two cities and six municipalities, namely Ozamiz City, Tangub City, Bonifacio, Clarin, Tudela, Sinacaban, Jimenez, and Panaon. The cooperative's expansive coverage area amplifies the challenges of meeting the escalating electricity demands driven by rapid urbanization, population growth, and technological evolution.

This study aims to provide a comprehensive analysis and projection of energy demand in the MOELCI-II service region. Beyond a simple historical data analysis, the research employs advanced time series analysis methods, most notably the ARIMA model. The researchers aim to understand the complex dynamics of energy consumption and its evolving nature by analyzing past trends and patterns.

The research extends its scope by not only forecasting future electricity demand for the coming decade (2021-2030) but also by delving into actionable insights for efficient resource allocation and sustainable energy practices. The application of data preprocessing techniques, such as differencing, aims to enhance the model's predictive accuracy, ensuring that the forecasted values are not just projections but strategic tools for energy planners and decision-makers.

In the complex interplay of growth, technology, and energy consumption, this research aims to serve as a guiding beacon for MOELCI-II. By examining the past, forecasting the future, and providing pragmatic insights, the study aims to make a significant contribution to the cooperative's mission of delivering reliable, sustainable, and efficient electricity services to the communities it serves. As MOELCI-II navigates the challenges of a dynamic energy landscape, this research aims to provide a roadmap for informed decision-making, ensuring a resilient and responsive approach to the evolving demands of the region's power needs.

MATERIALS, METHODOLOGY, AND LITERATURE REVIEW

Materials of the Study

The study utilized MATLAB, which provides a comprehensive environment for time series analysis and forecasting, including tools for data manipulation, model identification, parameter estimation, forecasting, and evaluation. It simplifies the implementation of ARIMA models, allowing researchers and analysts to focus on the interpretation and application of results rather than the details of coding.

Methodology

During the data gathering process, the researchers obtained the electrical consumption data of Ozamiz City from the Department of Energy website. The collected data was processed using the selected forecasting model, ARIMA (Autoregressive Integrated Moving Average).

After gathering the data, the researchers developed a working code by programming it in MATLAB, an application that incorporated the ARIMA model. Once the required code was created, the researchers proceeded to plot the results for analysis.

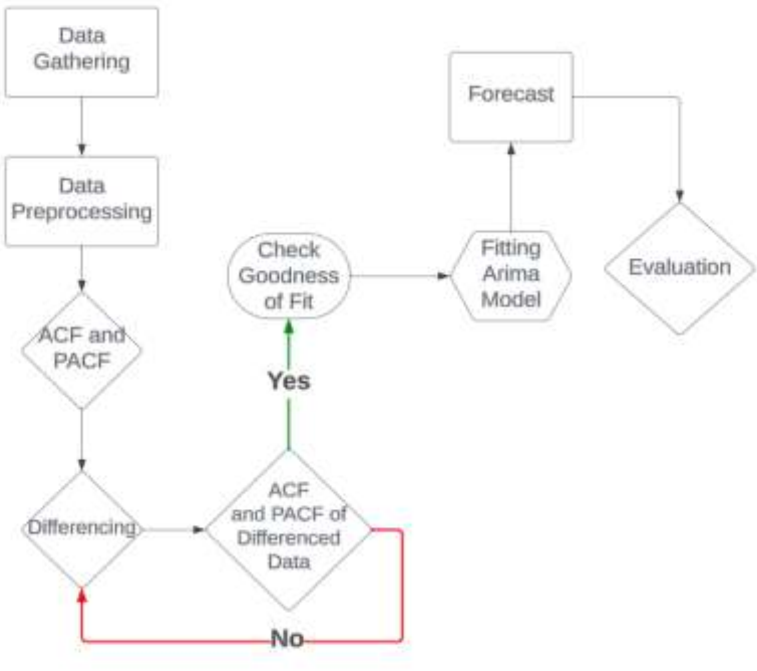

Figure1. Diagrammatic Representation of the Procedure for Analyzing and Forecasting

The diagram in Figure 1 illustrates the step-by-step procedure used for analyzing and forecasting the provided data.

Dataset

The researchers obtained the electricity consumption information for MOELCI-II through the Freedom of Information on the Department of Energy website. The dataset comprises historical consumption data spanning from 2005 to 2022, measured in megawatts. The data that has been gathered will be used for our chosen forecasting model, which is ARIMA or Autoregressive Integrated Moving Average.

Data Preprocessing

Autoregressive Moving Average (ARIMA) Model

The ARIMA model was used to forecast electricity demand at MOELCI–II from 2020 to 2030. The generic ARIMA model may be found using:

$$\Phi(\mathrm{B}) = (1-B)^d\, y_t = \delta + \theta B_{\epsilon t}$$

$$\Theta(\mathrm{B}) = 1 - \Phi B - \Phi_2 B^2 - \cdots - \Phi_p B^p \text{and } \Theta\ \Theta(\mathrm{B}) = 1 - \theta B - \Phi_2 B^2 - \cdots - \Phi_3 B^3$$

where:

B the backshift operator, which represents a one-time-step lag in the data, **p** the order of the autoregressive (AR) part, indicating the number of lagged values used in the model, **b** the order of differencing, representing how many times the data has been differenced to achieve stationarity, **q** the order of the moving average (MA) part, signifying the number of past error terms included in the model, **δ,** the constant term (intercept), **Θ(B)** the polynomial in the backshift operator representing the MA terms, **ϵt** the error term at time t, assumed to be white noise. (Montgomery. et al.,2015).

Autocorrelation Function

To display the sample autocorrelation function (ACF) and confidence limits for the stochastic time series y, the MATLAB code used *autocorr(y)*. In pairs of values within the variable, separated by k periods or delays, this function computes correlation coefficients. The order of the moving average (MA) component can be determined with its help. This is the expression for the autocorrelation coefficient at lag k:

$$\boldsymbol{ACF(Lk)} = \frac{\frac{\mathbf{1}}{\boldsymbol{n-1}}\sum_{\boldsymbol{i=1}}^{\boldsymbol{n-k}}(x_{i+1}-\bar{x})(\mathrm{L}k_i-\bar{x})}{\sigma_x\,\sigma_x}$$

Where:

Lk= Lag, representing the number of periods by which the series is shifted.

σ_x= standard deviation of the time series.

x_{i+1}= Value of the time series at time *i*+1.

$\bar{x}$ = Mean of the time series.

n: The number of observations in the time series.

Partial Autocorrelation Function

In MATLAB, the *parcorr* function is used to generate the Partial Autocorrelation Function (PACF) plot for a given time series data. The partial autocorrelation calculates the correlation between the current observation and the previous observation, given that both observations are correlated to observations at other times. It also helps determine the order of the autoregressive (AR) component. The *k*th partial autocorrelation ofy_t and y_{t-k} is given by:

$$PACF = (Y_t, Y_{t-k}) = \frac{Cov(Y_t, Y_{t-k}|Y_{t-1,\ldots,}Y_{t-k+1})}{\sigma_{y_{t|y_{t-1,\ldots,}Y_{t-k+1}}}\,\sigma_{y_{t|Y_{t-1,\ldots,}Y_{t-k+1}}}}$$

Where:

$Y_{t=}$ The value of the time series at time t.

Y_{t-k} = The value of the time series at time $t-k$ (lagged by k periods).

$Cov(Y_{t,} Y_{t-k}|Y_{t-1,\ldots,} Y_{t-k+1})$ = Conditional covariance between $Y_{t,}$ and Y_{t-k} given the values at the intermediate lags $Y_{t-1}, \ldots, Y_{t-k+1}$.

$\sigma_{y_{t|y_{t-1,\ldots,} Y_{t-k+1}}}$ = Conditional standard deviation of Y_t given the values at the intermediate lag $Y_{t-1}, \ldots, Y_{t-k+1}$.

Differencing

Using the diff function, the code calculates the initial difference of the time series data and displays the resultant data. The variable (dY) contains the result of the diff function's computation of the variable Y's first-order differences. In time series analysis, differencing is frequently used to increase the stationary nature of a nonstationary series. To improve stationarity and eliminate the linear trend, this will be necessary.

ACF and PACF Plots for Differenced Data:

To determine the order of the ARIMA model, ACF and PACF displays are created for the differenced data.

Check the Goodness of Fit

The infer function is used to compute residuals. Based on the estimated ARIMA model (EstMdl) and the historical data (Y), the code uses the inferred function to produce conclusions. Typically, the infer function computes standardized residuals, which are then utilized for further analysis and diagnostic charts to evaluate the model's goodness of fit. To assess the ARIMA model's goodness of fit, several plots are created, including the standardized residuals, QQ plot, ACF, and PACF of residuals.

Fitting Arima Model

The Arima and estimate functions are used to define and estimate the ARIMA (2,1,0) model, respectively. For use with constant or unit root irregular linear time series models, these functions generate model objects. Moving averages (MA), autoregressive (AR), mixed autoregressive and moving average (ARMA), integrated models (ARIMA), multiplicative seasonal models, and linear time series models with a regression component (ARIMAX) are among the available models. The completely defined VAR(p) model is generated upon utilizing the estimate function, which is represented by EstMdl = estimate (Mdl, Y). The calculated parameter values from fitting the VAR(p) model Mdl to the observed multivariate response series Y using maximum likelihood estimation are retained in this model.

Forecast

The ARIMA model is applied to predict the upcoming values for the subsequent 10 periods. Forecasting is achieved by utilizing the forecast function, which produces forecasts (yF) and forecast errors (yMSE) for the designated number of periods (num_periods).

Evaluation

The model's prediction accuracy is evaluated using the Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE). By comparing predicted and actual values, these metrics offer quantitative assessments of the model's performance. Here are RMSE and MAE: $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{Y}_i)^2}$

$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{Y}_i|$

Where:

$\backslash Y_i$ = Actual value at time i
$\hat{Y}_i$ = Actual value at time i
n = Number of observations

Literature Review

In the highly competitive manufacturing landscape, organizations are increasingly adopting demand-driven supply chains to swiftly respond to fluctuating customer demands. Accurate demand forecasting is pivotal for effective inventory management, as stock levels hinge on forecasted demand. Inaccurate estimations can result in substantial costs, leading to significant investments in inventories to prevent stockouts. Challenges arise with intermittent demands, complicating traditional statistical forecasting methods. While various approaches exist, this research focuses on comparing autoregressive integrated moving average (ARIMA) and artificial neural network (ANN) techniques in forecasting demand for a Moroccan food company. The study aims to develop an optimal production plan by evaluating ARIMA models using historical demand data from January 2010 to December 2015. The research highlights the importance of forecasting accuracy in enhancing inventory management performance and explores its implications for supply chain efficiency. The article concludes with a summary and outlines potential future research directions. (Fattah et al., 2018)

The study mentioned above examines how businesses in the competitive manufacturing sector can more accurately forecast what consumers will purchase and when. The story centers on the food industry in Morocco, where the perishable nature of the products necessitates precise forecasts. The purpose of the study is to determine the relative effectiveness of two forecasting techniques: artificial neural networks and ARIMA. Additionally, it utilizes historical demand data to help the organization better estimate the quantity of food to produce. For this purpose, the research utilizes historical data to assess the performance of the ARIMA model. This method could also be used to forecast electrical demand as precise estimates of the amount of electricity required to aid in resource management and planning.

China's vast population has long been a pivotal factor influencing its economic and social development. The demographic landscape significantly shapes a country's political, financial, and social trajectory, with population studies closely intertwined with societal issues. Predicting population data plays a crucial role in understanding future economic trends and optimizing resource allocation. Scholars globally have extensively researched population prediction models, employing methods such as time series modelling, data envelopment analysis, ARIMA models, and quadratic polynomials. This paper focuses on Zhejiang Province, a robust economic region with limited literature on population studies. Building on previous works, particularly those using autoregressive distribution lag and equal-dimensional grey number supplement models, this study employs an ARIMA model to predict Zhejiang Province's population and structure based on data from 1978 to 2017. The findings aim to contribute valuable insights into the demographic dynamics of this economically significant province in the coming years (Shield Square Captcha, n.d.).

Researchers frequently use models such as ARIMA in the context of electrical demand forecasting to project future trends in energy usage. The significance of population data prediction for resource allocation and economic planning is emphasized in the introduction. Analogously, forecasting electricity demand is essential for effective resource management and energy planning. Known for its efficiency in time series forecasting, the ARIMA model can be modified to examine past data on electrical consumption, spot trends, and predict future demand trends.

Time series analysis is used in both population and electricity demand forecasts. Therefore, methodological similarities can be found. Researchers examining the application of ARIMA models in electrical demand forecasting have a conceptual framework thanks to the introduction's mention of researchers utilizing ARIMA to anticipate population dynamics. Time series data, comprising ordered data points over time, is a fundamental aspect of various scientific, engineering, and business applications. Time series forecasting involves predicting future points based on observed data, with characteristics ranging from seasonal trends to varying levels of volatility. This study introduces a hybrid forecasting method, combining the linear ARIMA) with the nonlinear Artificial Neural Networks (ANNs). Unlike traditional hybrid approaches, our method avoids strong assumptions by characterizing nonlinearity using a moving-average filter, applying ARIMA to the linear component, and employing an artificial neural network (ANN) to combine the outputs. We further enhance our approach by integrating Empirical Mode Decomposition (EMD). Benchmarking on diverse datasets illustrates the effectiveness of our method, demonstrating improved accuracy with increasing linearity. The paper also proposes an enhancement to existing hybrid models by incorporating EMD, demonstrating consistently superior performance compared to linear, nonlinear, and hybrid methods. The subsequent sections detail existing forecasting methods, present our model, evaluate its performance, and discuss the positive impact of EMD on the proposed approach (Büyükşahin & Ertekin, 2019).

In this case, the researchers propose a novel hybrid forecasting technique that combines the nonlinear properties of artificial neural networks (ANNs) with the linear ARIMA model. This hybrid technique is motivated by the desire to characterize nonlinearity without making strong assumptions, hence overcoming the drawbacks of existing methods. The processes in the suggested method are described in depth in the introduction. These include combining the outputs using an artificial neural network (ANN), applying ARIMA to the linear component, and characterizing nonlinearity using a moving-average filter. Additionally, the researchers propose incorporating Empirical Mode Decomposition (EMD) into current hybrid models to enhance forecasting accuracy. The efficacy of the suggested approach in time series forecasting is demonstrated by evaluating it against benchmark datasets, including electrical demand data such as Turkey's Intraday Electricity Market Price data. Global warming, driven by escalating greenhouse gas emissions, particularly carbon dioxide (CO_2), poses a critical challenge to contemporary society. These emissions contribute to the greenhouse effect, wherein certain gases allow sunlight to penetrate but trap long-wave radiation, leading to the adverse impacts like climate change, glacial melting, rising sea levels, and biodiversity loss. China, as the largest global emitter of CO_2, is facing a significant surge in carbon emissions amid rapid economic growth, prompting the government's commitment to achieving carbon peak and neutrality in the Fourteenth Five-Year Plan. This study focuses on Beijing, Henan, Guangdong, and Zhejiang, analyzing their carbon emissions from 1997 to 2017. Utilizing Autoregressive Integrated Moving Average (ARIMA) models, the research seeks to forecast emissions trends over the next three years. The methodology involves addressing challenges in modelling, such as ensuring smoothness and addressing influential data points, to establish robust models for each region. Section 2 introduces the ARIMA model, while Sections 3-6 detail the specific models for the selected areas. Section 7 presents predictions and analyses of carbon emissions, and Section 8 concludes the paper, emphasizing the importance of informed policymaking for emission reduction (Ning et al., 2021).

The application of the Autoregressive Integrated Moving Average (ARIMA) model for carbon emission forecasting—discussed in the previous research introduction—is pertinent to scientists using comparable techniques to anticipate electrical consumption. ARIMA is a valuable method for time series forecasting in both scenarios, offering simplicity and effectiveness without requiring additional exogenous variables. The study of carbon emissions establishes a standard for using ARIMA to solve complex environmental problems and demonstrates its versatility across other fields.

ARIMA is particularly useful for electricity demand forecasting due to its ability to capture temporal patterns. Scientists studying energy and utilities often need to make accurate predictions about future electricity usage. Researchers in the field of electrical demand forecasting can utilize ARIMA to model and anticipate patterns of power consumption by drawing comparisons with the carbon emissions study, where ARIMA is employed to evaluate and forecast trends in emissions data for specific locations. Both situations may present similar difficulties, underscoring the need for reliable and knowledgeable modelling approaches. These difficulties include handling significant data points and guaranteeing model smoothness. Overall, the widespread use of ARIMA in energy and environmental research underscores its broad applicability in solving challenging forecasting problems, facilitating a more comprehensive understanding of trends and supporting the development of effective policies and initiatives.

The investigation focuses on predicting future meteorological conditions crucial for agrophysical modelling, given the sensitivity of crop production models to climate variations. Climate change's effects on the soil-plant-atmosphere system necessitate an understanding of shifts in weather patterns and extreme events. The escalating threats to food security due to global warming, such as increased temperature and limited precipitation leading to droughts, underscore the importance of forecasting these quantities. Leveraging historical data analysis, the study employs the widely used autoregressive integrated moving average (ARIMA) models for time series modelling. The paper also examines the application of SARIMA and regression models incorporating polynomial functions and Fourier series to predict daily mean air temperature and precipitation for four European locations up to six years in advance (Murat et al., 2018).

Researchers utilizing the ARIMA model to forecast electrical demands can benefit from the research covered in the introduction in multiple ways. Firstly, time series forecasting techniques are applied in both fields, and the ARIMA model is frequently chosen. The sensitivity of crop production models to climatic fluctuations is highlighted in the introduction, underscoring the significance of precise meteorological condition prediction. Analyzing and projecting future patterns and trends is also essential for efficient energy management and resource allocation in the context of electrical demand forecasting. The need to consider the temporal and geographical scaling aspects of weather time series is also emphasized in the introduction. It is essential to understand the temporal patterns and fluctuations in electricity use when forecasting electrical demand. The necessity to consider these elements in the contexts of both agriculture and energy consumption is in line with the ARIMA model's capacity to capture irregular, trend, and seasonal influences.

Addressing the challenge of attaining perceptual equivalence between free-field and virtual auditory sources in interactive virtual environments, the study explores the intricacies of achieving accurate spatial perception. The replication of intricate acoustic cues, particularly the individualized head-related transfer function (HRTF), is crucial for preserving localization performance in virtual environments. Despite previous successes in virtual source generation, differences persist, with increased front-back reversals being a notable concern. The absence of dynamic head-motion cues in static virtual systems necessitates reliance on spectral features for front-back judgments. The study examines the effect of real-time head tracking on localization performance, highlighting the importance of efficient processing to minimize latency. The use of truncated minimum-phase FIR representations of HRTFs is explored for faster processing, along with the challenges introduced by interpolation and cross-fading in rendering virtual sources. Existing head-tracked virtual audio implementations are critically evaluated, highlighting the scarcity of studies validating system performance in localization tasks. The overarching goal is to identify limitations in achieving free-field-equivalent localization in interactive virtual displays, paving the way for further investigations into modifying acoustic cues and understanding perceptual interpretations in dynamic environments. The first part of the study ensures the adequacy of HRTF measurement and headphone equalization procedures for static displays. In contrast, the second part examines the impact of lossy HRTF processing on localization performance in an interactive virtual auditory display (Forecasting Method of Stock Market Volatility in Time Series Data Based on Mixed Model of ARIMA and XGBoost, 2020).

Researchers are working with complex systems in both cases, where accurate modelling and prediction are crucial. The goal of the research on virtual auditory systems is to precisely simulate spatial perception by taking into account real-time head tracking and the customized head-related transfer function (HRTF). Similarly, researchers aim to precisely capture the patterns and dynamics of electricity consumption while forecasting electrical demand using the ARIMA approach and MATLAB software. Researchers in the field of electrical demand forecasting face similar challenges to those highlighted in the research on auditory systems, including the need for careful calibration, efficient processing, and consideration of dynamic factors. Both fields require a thorough understanding of the underlying processes and a commitment to minimizing errors, whether in predicting future electrical demand or replicating virtual auditory experiences. Essentially, although the research topics differ, they are all related to the complexity of the systems being studied and the mutual requirement for sophisticated modelling methods and software tools to handle the complexities and difficulties specific to each field.

Energy plays a pivotal role in shaping the trajectory of modern human life, influenced by factors such as population growth, urbanization, technological advancements, and industrialization. Global energy demand is met through various sources, including oil, coal, natural gas, renewable energy, and others. Concerns about climate change and global warming have led to a growing emphasis on renewable energy sources, such as solar, wind, biomass, and geothermal. This research focuses on Turkey, a key geographical and economic bridge, which is experiencing a significant rise in energy consumption due to its strategic position between energy-consuming Western nations and oil- and gas-producing Middle Eastern countries. As Turkey's energy consumption is intricately linked to its economic growth, population dynamics, and geopolitical factors, such as migration due to conflicts in neighbouring regions, forecasting becomes crucial for effective energy planning. The study employs univariate ARIMA models to forecast the next 25 years of coal, oil, natural gas, renewable, and total energy consumption in Turkey, contributing to the existing literature on this subject. The subsequent sections detail the data, methodology, application of ARIMA models, and discussions on the forecasted results (Ozturk & Ozturk, 2018).

To predict Turkey's energy consumption, the researchers in this study use univariate ARIMA (Autoregressive Integrated Moving Average) models. They pay particular attention to coal, oil, natural gas, renewable energy, and the country's overall energy demand during the next 25 years. It is standard procedure in energy research to forecast energy consumption using ARIMA models. ARIMA models are beneficial for forecasting future energy consumption, as they are well-suited for analyzing time series.

Researchers can predict future energy consumption with confidence by using historical patterns, trends, and seasonality seen in the time series data, which the models account for. By utilizing ARIMA models, the researchers aim to contribute to the limited existing knowledge on Turkey's energy consumption and provide insightful analysis that will help energy-related organizations and policymakers better understand the opportunities and challenges presented by the nation's evolving energy landscape. Considering dynamic economic, demographic, and geopolitical considerations, the study highlights the importance of forecasting as a crucial tool for both short-term and long-term energy planning, emphasizing its relevance for informed decision-making.

The researchers conducted a study on long-term electricity demand forecasting in the Philippines, utilizing econometric models and considering various economic factors influencing electricity consumption (Madamba & Sanchez, 2015). The researchers delved into the challenges of short-term load forecasting in the Philippines. Their study employed a hybrid model combining ARIMA and artificial neural networks (ANNs) to enhance forecasting accuracy (Baltazar & de Luna, 2019). Explored the integration of weather variables in electricity demand forecasting for the Philippines. Their study incorporated meteorological data to enhance the accuracy of predictions (Lacap & Yñiguez, 2018). Researchers in the Philippines focused on load curve analysis, employing statistical methods to analyze load curves and identify patterns in electricity consumption (Castro & Cruz, 2017). The researchers investigated electricity demand forecasting in the context of renewable energy integration in the Philippines. Their study explored the challenges and opportunities presented by the increasing adoption of renewable energy sources (Gonzalez & Balili, 2016).

In their study, Buenavista and Mariano applied the ARIMA model to forecast electricity demand in a specific urban area in the Philippines. The research focused on the effectiveness of the ARIMA model in capturing the temporal patterns of electricity consumption, demonstrating its applicability to local forecasting scenarios (Buenavista & Mariano, 2016). Santos and Reyes conducted a study on short-term electricity demand forecasting for a regional power distribution system using the ARIMA model. The research emphasized the model's accuracy in predicting daily and weekly variations in electricity consumption, showcasing its utility in local contexts (Santos & Reyes, 2018). Exploring the efficacy of the ARIMA model in the context of climate-influenced electricity demand, Garcia and Lim's study integrated weather variables into the forecasting model. The results highlighted the model's capability to adapt to local environmental factors, making it a valuable tool for predicting electricity demand under varying weather conditions (Garcia & Lim, 2020).

Focusing on a province-level analysis, Torres and Cruz employed the ARIMA model to forecast electricity demand trends. The study examined the model's capacity to capture long-term variations in consumption, highlighting its significance for regional planning and resource allocation (Torres & Cruz, 2017). Mendoza and Ong conducted a comparative study of various forecasting models, including ARIMA, for electricity demand prediction in a suburban area. The results underscored the ARIMA model's competitive performance, particularly in scenarios with moderate fluctuations in consumption patterns (Mendoza & Ong, 2019).

RESULTS AND DISCUSSIONS

DATA GATHERING

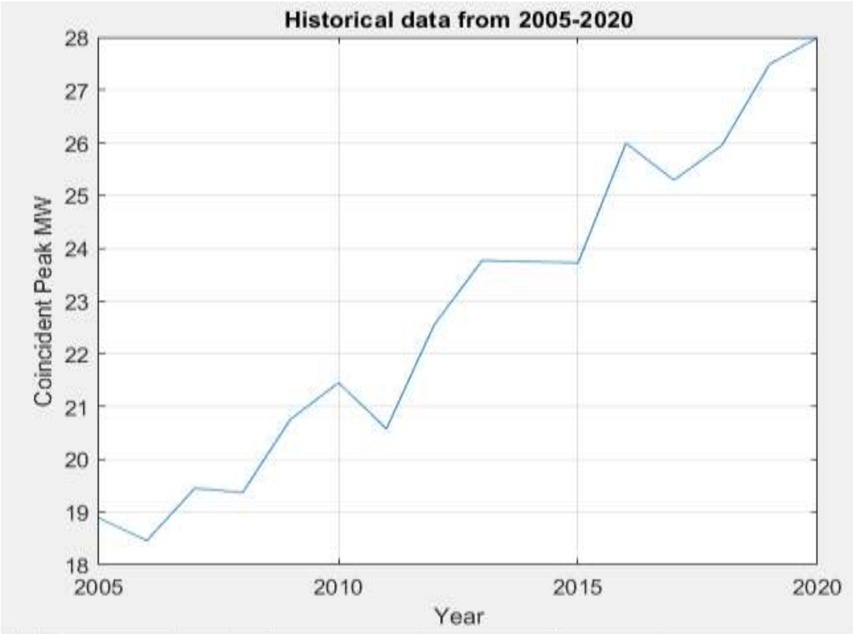

Figure 2. Electricity demand in MOELCI-II from 2005 to 2020.

Figure 2 shows the historical data of electricity demand in Misamis Occidental II Electric Cooperative, Inc. (MOELCI-II) from 2005 to 2020. The data shows alternate changes in coincident peak values over the years, with some years experiencing increases while others show decreases. The highest coincident peak occurred in 2020, with a value of 27.99 MW. This peak is the highest value in the entire dataset, indicating a significant coincident peak in that year. The series exhibits a lack of stationarity, characterized by a distinct upward trend.

DATA PREPROCESSING:

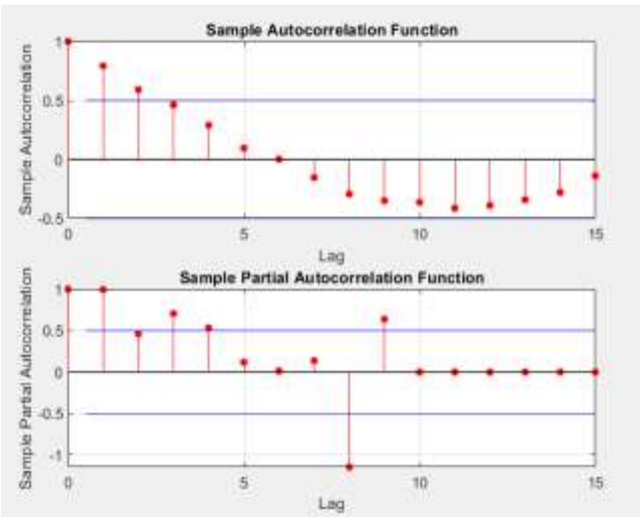

Figure 3. ACF and PACF plots of the series.

The dataset's Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are displayed in two subplots in Figure 3. A sinusoidal pattern appears alongside a slow decline in the ACF plot, indicating that this set of data is nonstationary. This means it would be challenging for the ARIMA model to replicate and forecast it, as the researchers require a stationary graph. It can be observed that at lags 1, 2, and 3, there is a spike, or it falls beyond the 95% confidence interval of 0.5. It shows that during that period, the peak demand for MOELCI–II is not behaving as usual and appears to be higher than expected. Lags 4 to 15 show that it is within the 95% confidence interval, which means that the peak demand of MOELCI – II is behaving like its usual rate, so there is no unusual pattern that can be observed here.

The PACF plot shows a spike at lag 1, indicating that the peak demand at that time was greatly influenced by past data. However, it can be observed that at lag 2, the spike was within the confidence interval, meaning the peak demand from last month did not affect the result of this month's peak demand. It can also be shown that in lag 8, the spike is beyond the -95% confidence interval, and it shows that the peak demand in this month was different and inversely related to the results from 8 months ago. The positive spike in lag 9 indicates the correlation between the results of this time series and those 9 months ago, and how it was affected. Lags 10 to 15 show no significant correlation, and therefore, it would have no impact on forecasting data.

The ACF and PACF graphs show significant spikes at various lags or a mix of positive and negative correlations, indicating the presence of trends, seasonality, or persistent patterns in the data. Differencing can be applied to address these issues and make the data more stationary, which is often a prerequisite for building accurate time series models.

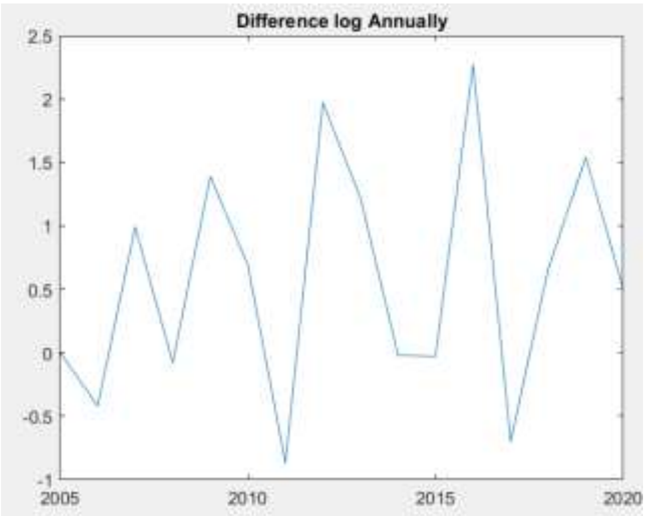

Figure 4. Demand for electricity in MOELCI-II after differencing.

In Figure 2, the researchers observed that the large upward and downward trends have disappeared, and the graph is more stationary, which means it would be easier for the ARIMA model to replicate and predict the future peak demand of MOELCI–II. Differencing helps remove those trends that are making our prediction inaccurate. Through differencing of the data, the sudden spikes and shifts of lag, as shown and explained in Figure 3, were removed, which would have altered the course of the prediction.

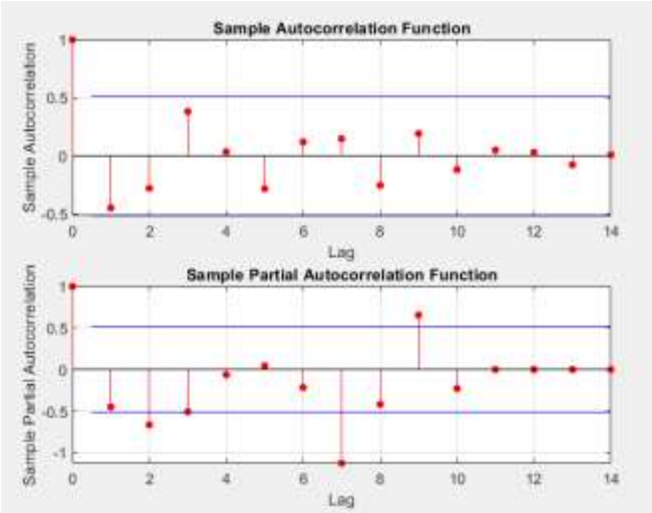

Figure 5. ACF and PACF plots of the transformed after the first-differenced series.

As shown in Figure 4, ACF and PACF plots are generated using the differenced data. It can be observed in the ACF graph that, from lag 1 to lag 15, the spikes in the data are all within the confidence interval, indicating that the graph appears more stationary, as there is no significant data that can affect the prediction of the ARIMA model. The PACF graph indicates that persistent patterns exist, which can be utilized in forecasting, as these patterns are influenced by past values. This graph will not need differencing since, as it can be seen on the ACF plot, the lags are inside the confidence interval, so differencing it again would not be necessary and might even be counterproductive. If the ACF and PACF show no significant correlation, additional might eliminate any meaningful signals that can be used in forecasting. Over-differencing can influence the choice of the differencing parameter "d" when determining the orders (p, d, and q) for an ARIMA model. If "d" is set too high, the model may not be as accurate.

CHECK GOODNESS OF FIT

To assess the goodness of fit of the ARIMA model, several plots are made, namely the standardized residuals, QQ plot, ACF, and PACF of residuals.

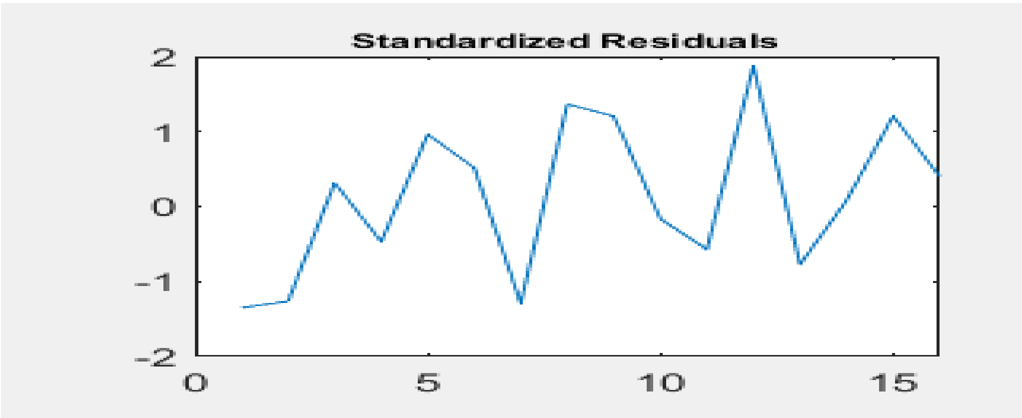

Figure 6: Standardized Residuals Plot

Figure 6 shows the standardized residuals over time. The examination of residuals is carried out, and the plots illustrating the residual analysis are presented in Fig.6. Notably, there are no discernible patterns observed in the residuals.

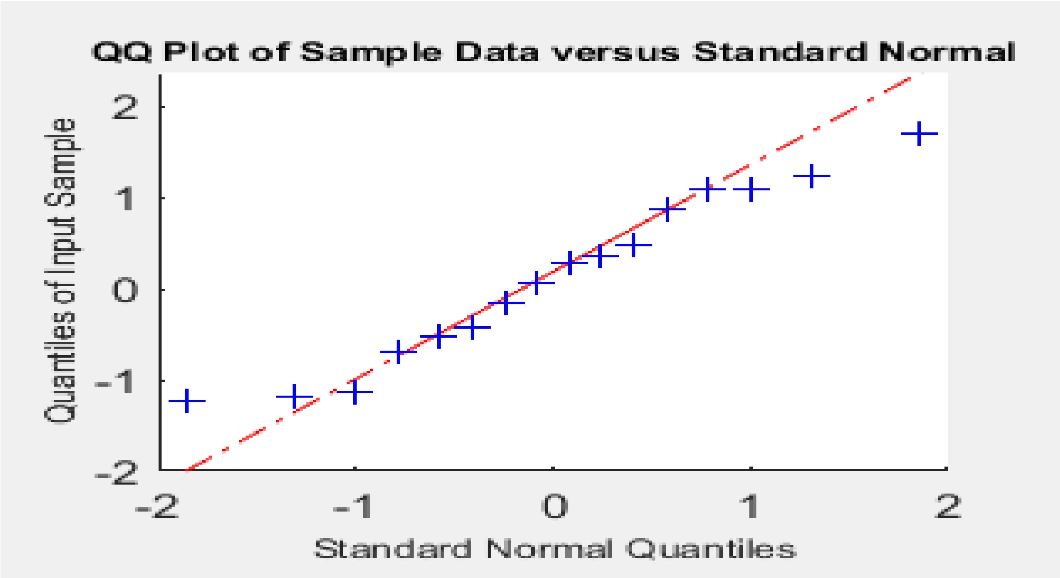

Figure 7: QQ Plot

A normal distribution is used to compare the residuals' distribution to the QQ plot. Plotting points make a straight line, as can be seen. Roughly drawn lines indicate deviations from the norm. It is possible that the residuals do not show a normal distribution if there are notable deviations from the mean.

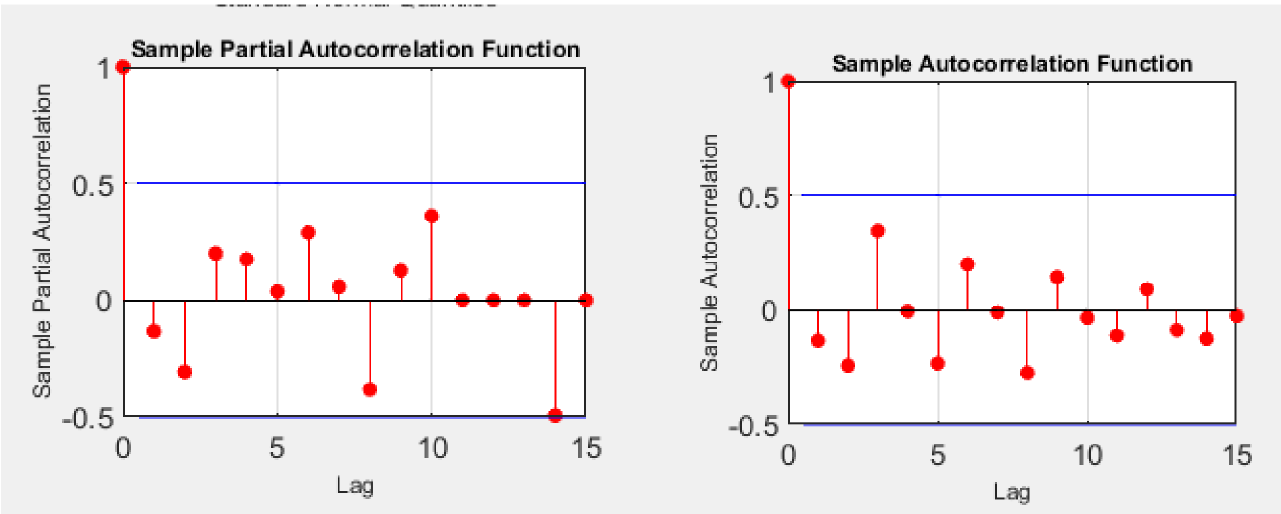

Figure 8: Autocorrelation and Partial Autocorrelation of Residuals

Figure 8 shows a display of the autocorrelation of the residuals at different lags. It can be observed that the autocorrelations and partial autocorrelation are within the confidence bounds, indicating no significant correlation between residuals at different lags. Any significant spikes outside the bounds suggest that there is still information in the data that the model has not captured. The plots depicted in Figure 8 show that all the data in the time series has been included in the model.

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FITTING ARIMA MODEL

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ARIMA(2,1,0) Model (Gaussian Distribution):

                  Value      StandardError    TStatistic      PValue
                __________   _____________    __________    __________

    Constant     0.010072      0.0032802        3.0707       0.0021356
    AR{1}         0.21206       0.095428        2.2222         0.02627
    AR{2}         0.33728        0.10378        3.2499       0.0011543
    Variance   9.2302e-05     1.1112e-05        8.3066      9.8491e-17
```

Both AR coefficients are significant at the 0.05 significance level.

Figure 9. FITTING ARIMA MODEL (2,1,0)

The ARIMA (2,1,0) model is designated and estimated through the use of ARIMA and estimate functions. Subsequently, the historical data is fitted to the specified order (2,1,0) of the ARIMA model, encompassing both autoregressive and differencing components.

FORECAST

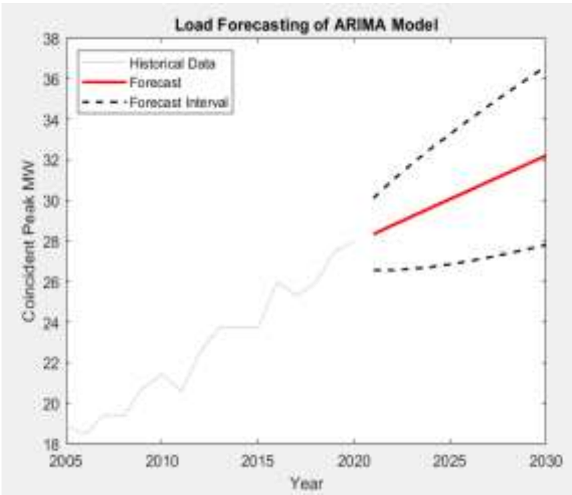

Figure 10. Forecasted electricity demand in MOELCI-II from 2021 to 2030

Year	Forecast (MW)	Lower 95% (MW)	Upper 95% (MW)
2021	28.3280	26.5540	30.1018
2022	28.7757	26.5574	30.9938
2023	29.2068	26.6235	31.7901
2024	29.6347	26.7175	32.5520
2025	30.0646	26.8510	33.2782
2026	30.4952	27.0034	33.9789
2027	30.9237	27.1872	34.6620
2028	31.3532	27.3809	35.3255

2029	31.7828	27.5879	35.9776
2030	32.2123	27.8062	36.6185

The ARIMA model is employed to predict electricity demand for the upcoming 10 periods (years) spanning from 2021 to 2030. The graph showcases the projected values and a 95% confidence interval. Furthermore, a corresponding table is included, providing a structured presentation of forecasted values. This table offers a detailed overview of the anticipated results for each year within the specified period. Notably, a persistent upward trend in electricity demand for (MOELCI-II) is evident in the coming years.

EVALUATION

Root Mean Square Error (RMSE) AND Mean Absolute Error (MAE).

In this scenario, the RMSE stands at approximately 5.6631, while the MAE hovers around 5.56996. These figures reflect the precision of the ARIMA (2,1,0) model in predicting the Coincident Peak MW. Generally, smaller RMSE and MAE values are indicative of superior model performance, as they signify minimized forecasting errors. The results of the RMSE and MAE are below 10%, which is the standard value to determine whether it is acceptable. The data and results of the RMSE and MAE indicate that the forecast is acceptable, demonstrating accuracy and precision.

CONCLUSION

In conclusion, the study successfully applied the ARIMA model to analyze and forecast electricity demand, contributing to a better understanding of the factors influencing energy consumption in MOELCI-II. The findings have practical implications for energy planning, resource allocation, and infrastructure development in the region. The RMSE and MAE results are acceptable since they are below 10, which is the standard in which a result is acceptable or not. Despite the challenges and uncertainties inherent in forecasting, the results provide a foundation for informed decision-making in the energy sector.

Based on the findings of this research, it is recommended that future investigations explore advanced time series models beyond ARIMA, such as SARIMA or machine learning approaches. These methodologies have the potential to provide deeper insights into the underlying factors influencing electricity demand in MOELCI-II. Additionally, researchers should consider investigating external factors, such as economic indicators, population growth, or environmental conditions, to further enhance the accuracy and robustness of forecasting models. If researchers team up with local utilities and authorities, it could make the models even more helpful in real-life situations. By obtaining more detailed and up-to-date data through these partnerships, the researchers can ensure that the forecasting models are accurate and helpful in addressing the ever-changing electricity demand in MOELCI-II.

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