ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)

Vol 10, Issue 11, November 2023

Forecasting Electric Consumption of Cotelco in the Philippines Using Arima-Anfis Algorithm

[1] Juffrey Pascua Calimpitan, [2] Christhoffer Paran Lelis

[1] [2] University of Mindanao

Corresponding Author Email: [1] calimpitan.juffrey@gmail.com, [2] lelischristhoffer@gmail.com

***Abstract*— The study aimed to forecast daily electric consumption for the Cotabato Electric Cooperative (COTELCO) using ARIMA-ANFIS Algorithm. Spanning the years 2017 to 2022, the study examined data patterns from various components of electric consumption, including commercial and residential establishments, industrial facilities, streetlights, and public buildings. By employing a non-experimental quantitative approach, the research employed mathematical modeling to predict future consumption trends.**

The study developed and refined an ARIMA-ANFIS hybrid model, leveraging historical data to enhance predictive accuracy. An array of metric criteria, such as R^2, AIC, BIC, & MAPE, is utilized to assess the model's accuracy and goodness of fit. The results indicated that the proposed ARIMA-ANFIS model outperforms prior iterations with significantly lower evaluation metric values. The ARIMA-ANFIS hybrid model's forecasting for the next 36 months offers a valuable glimpse into the expected trends and patterns in COTELCO's electric consumption. By considering the forecasted values and their associated prediction intervals, stakeholders can make informed decisions and develop strategies aligned with the projected energy consumption trajectory. The policy recommendation is proposed based on the findings of the study. Furthermore, future researchers may utilize the proposed model by using the data in another setting to confirm its predictive ability.

***Index Terms*— Algorithm, ANFIS, ANN, Applied Mathematics, ARIMA, ARIMA-ANFIS, COTELCO, Electric Consumption, Energy Sector, Forecasting.**

I. INTRODUCTION

Electric Consumption is on the rise globally, especially in developed countries like the United States, where electric consumption is tripled over the past 60 years. In the latest study of USEIA, the average household in the United States consumes over 10,000 kWh of electricity per year – three times the amount consumed in the average household only 30 years ago. According to projections, the worldwide electricity demand is anticipated to witness a growth of almost 50% by the year 2040. This surge may be mainly attributed to the escalating power consumption observed in growing nations such as China and India. According to a US Energy Information Administration study, global electricity consumption is increasing. The study found that global electricity consumption increased by 1.1% in 2016, reaching 10,473 TWh (terawatt hours). This is a significant increase over 2015, when global electric consumption was 10,083 TWh. The electricity consumption in China accounted for the largest share of global consumption in 2016, with 4,870 TWh (about 43% of the total). The United States ranked second, with 1,651 TWh (about 13% of the total). The United States and China are the only countries that accounted for more than 10% of global electric consumption in 2016. Global electric consumption is expected to grow by 1.2% in 2017, reaching 10,735 TWh.

Electric consumption in the Philippines is also rising, which will continue. In 2013, the Philippines ranked as the 8th highest in terms of electric consumption. This is according to the 2014 World Energy Outlook report by the International Energy Agency. The Philippines accounts for 2% of the total energy consumption and is expected to increase by 4% in 2040. According to data from the Philippines Energy Regulatory Commission (PERC), electric demand in the country is expected to grow by 4.7 percent in 2018. This increase is driven mainly by the country's growing economy, which expanded by 6.8 percent in 2017. As the economy grows, so too does the electricity demand. This increased demand puts pressure on the country's electricity grid, which is already under strain from an aging infrastructure.

Based on a report from Inquirer.net, the frequency and duration of power outages in North Cotabato have escalated, with daily interruptions now lasting between six to eight hours. This situation has arisen as a result of the ongoing restoration efforts being carried out on two significant power generators located in Lanao del Norte and Misamis Oriental. According to Fernandez (2013), Godofredo Homez, the general manager of the Cotabato Electric Cooperative (Cotelco), has stated that the cooperative is currently implementing a strategy of rotating brownouts per feeder in the towns it serves. This is being done in response to the need for repairs and maintenance shutdowns of power plants, including the hydropower facilities, which are the primary sources of electricity in the Mindanao region. On August 18, 2014, Cotabato Electric Cooperative, Inc. (COTELCO) and Sarangani Energy Corporation (SEC) submitted an application for the approval of their Power Sales Agreement (PSA) for provisional authority. The rationale behind this application is twofold. Firstly, COTELCO anticipates a steady increase in its projected demand over the forthcoming years. Secondly, the National Power Corporation/Power

Sector Assets and Liabilities Management Corporation (NPC/PSALM), which currently serves as the primary supplier of power to COTELCO, has recently diminished its firm supply commitments to COTELCO by approximately one-third (1/3). The insufficiency of the overall power supply of COTELCO has led to occurrences of power outages. COTELCO is no longer able to obtain additional power from NPC/PSALM due to legal obligations that require the privatization of its generation facilities and prohibit investments in new generation capacity. Therefore, it is crucial for COTELCO to secure contracts for additional power supply in order to effectively meet its long-term power demands.

In addition to the expansion of the economy and the interplay between supply and demand in the electricity market, the price of electricity is influenced by speculative factors that have gained significant prominence. This is particularly evident since the onset of the pandemic last year, when there was widespread adoption of a stay-at-home approach among the general population (Dritsaki, C., Niklis, D., & Stamatiou, P., 2021). The prediction of electricity consumption is of utmost importance in the development of energy strategies, both in the short and long term, for nations worldwide. This holds true for both governmental decision-makers and various companies operating inside each country. The significance of precise forecasting is paramount within the realm of economics. In recent years, there has been a significant amount of study conducted in the field of forecasting. The literature has proposed numerous influential models aimed at enhancing the accuracy of time series modeling and forecasting. The Autoregressive Integrated Moving Average (ARIMA) model is widely acknowledged and frequently utilized as a stochastic time series model. It is commonly implemented using the Box-Jenkins Methodology, which involves considering numerous models.

The execution of the Model is predicated on the assumption of linearity and normal distribution within the time series. The ARIMA model is composed of three separate subclasses, which are Autoregressive (AR), Moving Average (MA), and Autoregressive Moving Average (ARMA) (Box & Jenkins, 1970; Hipel & McLeod, 1994). Moreover, the Seasonal Autoregressive Integrated Moving Average (SARIMA) technique, initially proposed by Box and Jenkins (1970), can be regarded as an adapted variant of the ARIMA model. The ARIMA model has gained prominence in the field of time series analysis due to its ability to successfully handle many forms of time series data and its strong association with the Box-Jenkins technique.

However, in many practical situations, the presumptive linear form with time series is these models' weakness. Numerous non-linear stochastic models are utilized in the literature to circumvent this issue (Zhang, 2003; Altavilla & De Grauwe, 2010).

In contemporary times, the practice of employing a blend of models has become prevalent in the realm of exchange rate forecasting. In their study, Khashei and Sharif (2020) employed autoregressive integrated moving average (ARIMA) and artificial neural network (ANN) models for the purpose of forecasting. It was observed that the collective models exhibit superior predicting performance compared to the individual models. In general, the combination of models tends to result in enhanced predictive performance in comparison to individual models. In addition, Matroushi (2011) employs two interconnected models, namely ARIMA-ANN and ARIMA-MLP, for the purpose of forecasting exchange rates. Based on the findings of Dunis et al. (2010), it has been indicated that ARIMAMLP exhibited superior performance in terms of forecast accuracy when compared to other combined and individual models.

Through ongoing research efforts, a plethora of other neural network architectures have been documented in the existing body of literature. The Adaptive Neuro-Fuzzy Inference System (ANFIS) emerges. There are also numerous studies in forecasting that ARIMA combined with ANFIS has greater accuracy than ARIMA-ANN or ARIMA-MLP. ANFIS is the integration of ANN and Fuzzy Inference systems.

With this new and emerging Model, the researcher will develop ARIMA-ANFIS Algorithm to shed light on forecasting electric consumption in the province of North Cotabato. Also, the researcher will factor in different factors involving electric consumption, resulting in more accurate and better forecasting values.

II. RESEARCH OBJECTIVES

This study aimed to identify the best fit ARIMA-ANFIS Model in forecasting monthly electric consumption using time series data.

Specifically, it aimed to;

1. determine the electric consumption of COTELCO Consumption by Category:
   1.1. Commercial Establishments.
   1.2. Residential Spaces.
   1.3. Industrial Establishments.
   1.4. Street Lights.
   1.5. Public Buildings.
2. determine the best fit ARIMA (Autoregressive Integrated Moving Average) Model for the monthly electric consumption of COTELCO Consumers from 2017-2022.
3. develop an ARIMA-ANFIS algorithm based on four different patterns, ARIMA (Autoregressive Integrated Moving Average), ANN (Artificial Neural Network), ANFIS (Adaptive Neuro-Fuzzy Inference System), and ARIMA-ANFIS Hyrid Model.
4. compare all forecasts with 4 different prediction models and determine the most parsimonious model.
5. forecast the monthly electric consumption of

COTELCO Consumers for the next 3 years using the most parsimonious model.

III. LITERATURE REVIEW

Auto-Regressive Integrated Moving Average (ARIMA)

The ARIMA model is a category of statistical models that are utilized for the analysis and prediction of time series data. ARIMA, short for Autoregressive Integrated Moving Average, is an acronym used to denote a widely employed statistical model. The aforementioned model is an extension of the Autoregressive Moving Average (ARMA) model, incorporating the concept of integration.

Autoregression (AR) is a model that uses the dependent relationship between an observation and some lagged observations. Integrated (I) is the use of differencing of raw observations (i.e., subtracting an observation from an observation at the previous time step) makes the time series stationary. Moving Average (MA) is a model that uses the dependency between observation and residual errors from a moving average model applied to lagged observations.

A standard notation is used for ARIMA(p,d,q), where the parameters are substituted with integer values to indicate the specific ARIMA model being used quickly. The parameters of the ARIMA model are specified as follows: p is lag order, also known as the number of lag observations incorporated in the model, is a key parameter, q is the degree of difference, also known as the number of times the raw observations are differenced and q is the parameter that determines the size of the moving average window, which is sometimes referred to as the order of the moving average.

Adaptiive Neuro-Fuzzy Inference Systems (ANFIS)

The ANFIS (Adaptive Neuro-Fuzzy Inference System) model is well recognized as a prominent artificial intelligence model that combines the strengths of both neural networks and fuzzy models. Jang's work stands as the initial instance of ANFIS implementation in the domain of time-series prediction. The ANFIS (Adaptive Neuro-Fuzzy Inference System) model represents the relationships between variables through the utilization of fuzzy If-Then rules. Hence, the acquired outcomes may be interpreted, a task that is unattainable with frameworks such as neural networks. The model in question is considered to be one of the most exemplary estimate function models within the realm of neuro-fuzzy models. The ANFIS model was utilized by Ying and Pan to predict the annual regional electricity usage in Taiwan using data spanning from 1981 to 2000. Based on the evaluation criteria of Mean Absolute Percentage Error (MAPE) and statistical analysis, it can be concluded that the Adaptive Neuro-Fuzzy Inference System (ANFIS) model exhibited superior performance compared to regression, neural networks, support vector machines, genetic models, and fuzzy hybrid systems. In their study, Önüt (year) conducted a comparative analysis between neural networks and the ANFIS model in the context of demand forecasting with partial data. The findings of the study indicate that the utilization of ANFIS (Adaptive Neuro-Fuzzy Inference System) is viable for demand forecasting, even when confronted with a scarcity of available data. In their study, Akdemir and Çetinkaya (year) put out an ANFIS model as a means to predict the annual energy demand in Turkey. This model was constructed based on a dataset encompassing 27 years of population, income level, peak load, and energy demand information. Despite the limited quantity of data, favorable outcomes were achieved. The energy consumption in Jordan's transportation was projected using two models, namely Adaptive Neuro-Fuzzy Inference System (ANFIS) and quadratic exponential smoothing. The ANFIS model's efficiency in forecasting energy consumption was evaluated using annual data spanning from 1985 to 2009, with projections made for the years 2010 to 2030. Therefore, the majority of findings indicated that ANFIS exhibited favorable performance in modeling and forecasting energy demand.

Forecasting Electric Consumption

According to Lee (2022), certain models demonstrated superior performance compared to others over specific forecasting periods across multiple countries. The artificial neural network (ANN) model demonstrated the highest level of accuracy in forecasting Egypt's electricity consumption for both one-month and two-month periods, as well as Malaysia's short-term electricity consumption. The ANFIS model demonstrated the highest level of reliability in Switzerland when it came to forecasting electricity use in the near future. On the contrary, the Least Squares Support Vector Machine (LSSVM) model exhibited the highest level of accuracy when employed to forecast Egypt's electricity consumption over a period of three months. The FTS model demonstrated the highest level of accuracy in predicting short-term electricity usage in Norway, Algeria, Bulgaria, and Kenya. Furthermore, the FTS model had the highest level of reliability among the seven nations analyzed in this research when it came to long-term electricity consumption prediction, namely for forecasting periods of 6, 9, and 12 months. The FTS model demonstrated commendable performance by producing AFEs below 6% for all seven nations. The FTS model's ability to perform effectively with a limited amount of data and its incorporation of a fuzzy component, which enables it to reflect the inherent uncertainty in the data, may explain this phenomenon (Ser, 2022). Due to the requirement of a substantial amount of time series data for training purposes, the artificial neural network (ANN) model may have exhibited superior performance compared to the fuzzy time series (FTS) model. Given the propensity of the ANFIS model to exhibit superior performance in handling volatile data, it is noteworthy to mention that its performance fell short when compared to the FTS model.

In contrast, empirical evidence has shown that the LSSVM model consistently produced the highest accuracy forecasting errors (AFEs) across different prediction timeframes and countries. The sparse nature of the model may require more improvements in terms of accuracy. The proper training of the LSSVM model was found to be hard due to the influence of the kernel function's parameters (Selvachandra, 2022).

Electricity Consumption in the Philippines

The data from ourworldindata.org about energy consumption in the Philippines. The development of Our World in Data is a collaborative endeavor among researchers affiliated with the University of Oxford, the scientific contributors responsible for the website's content, and the non-profit organization Global Change Data Lab, which possesses ownership, publication, and maintenance responsibilities for both the website and its associated data tools. The research team at the University of Oxford is associated with the Oxford Martin Programme on Global Development, which is dedicated to generating scholarly study on the most crucial global issues through the empirical examination of worldwide data.

The data table and graphs provided indicate a notable rise in electric consumption in the Philippines, as well as an increase in energy consumption derived from various energy sources.

COTELCO

Cotabato Electric Cooperative, Inc. (COTELCO) was founded in May 1972 with the primary aim of spearheading the rural electrification endeavor in the Province of Cotabato, as stipulated by Republic Act No. 6038. The institutionalization of this cooperative was significantly influenced by the board of incorporators, under the leadership of Mr. Eduardo Alparaque. On June 15, 1978, COTELCO took over the previously owned infrastructure of Kidapawan Electric Light and Pres Roxas, with the aim of officially petitioning the National Electrification Administration (NEA) to include these assets within the cooperative's franchise jurisdiction. COTELCO, a non-stock and non-profit electric distribution utility, is committed to effectively and reliably providing power to its member-consumers in a cost-effective and adequate manner, in alignment with its organizational goal. The main aim of this initiative is to utilize the economic capabilities of rural regions as a driving force for overall national progress and advancement.

Electric Shortage in Cotabato

Based on a report from Inquirer.net, the frequency and duration of power outages in North Cotabato have escalated, with daily interruptions now lasting between six to eight hours. This situation has arisen as a result of the ongoing restoration efforts being carried out on two significant power generators located in Lanao del Norte and Misamis Oriental. According to Fernandez (2013), Godofredo Homez, the general manager of the Cotabato Electric Cooperative (Cotelco), has stated that the cooperative is currently implementing a strategy of rotating brownouts per feeder in the towns it serves. This is being done in response to the need for repairs and maintenance shutdowns of power plants, including the hydropower facilities, which are the primary sources of electricity in the Mindanao region. On August 18, 2014, Cotabato Electric Cooperative, Inc. (COTELCO) and Sarangani Energy Corporation (SEC) submitted an application for the approval of their Power Sales Agreement (PSA) for provisional authority. The rationale behind this application includes the projected growth in COTELCO's demand in the upcoming years and the reduction in firm supply commitments by the National Power Corporation/Power Sector Assets and Liabilities Management Corporation (NPC/PSALM), which currently serves as the primary supplier of power to COTELCO, amounting to approximately one-third (1/3) of its total supply. The insufficiency of the overall power supply of COTELCO has led to power outages. COTELCO is unable to obtain additional power from NPC/PSALM due to legal obligations requiring the privatization of its generation facilities and prohibiting investments in new generation capacity. Consequently, it is crucial for COTELCO to secure contracts for additional power supply in order to effectively meet its long-term power needs. The expeditious provision of the supplementary power supply is likewise necessary.

Theoretical Framework

Various theoretical methods have been employed to forecast electricity consumption, such as growth curves, multiple linear regression models incorporating economic, social, geographic, and demographic factors, as well as Box-Jenkins autoregressive integrated moving average (ARIMA) techniques. Additionally, Adaptive Neuro Networks (ANN) and the more recent Adaptive Neuro-Fuzzy Inference System (ANFIS) have been utilized. In this study, we will utilize the ARIMA Outputs as the input for the ANFIS model.

ANFIS

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a data mining methodology based on a combination of fuzzy logic & neural networks by clustering values in fuzzy sets, membership functions are estimated during training, and using neural networks to estimate weights (Alnoukari, Alzoabi, and Hanna, 2008). Both Artificial Neural Networks (ANN) and fuzzy systems (FS) are utilized in Adaptive Neuro-Fuzzy Inference Systems (ANFIS). The combination of Artificial Neural Networks (ANN) and Fuzzy Systems (FS) has exhibited promising capabilities in expanding the respective technologies when utilized in isolation. There are two distinct systems that serve different purposes and do not collaborate with each other. The first system is the Artificial Neural Network (ANN), which aims to optimize the parameters of the Fuzzy System (FS) by reducing the error between the output of the FS and a given specification. The second system involves utilizing the learning capabilities of the ANN to make the FS more adaptable to a changing environment. The precision of the final system output is enhanced by correcting the output of a fuzzy system using the output of an artificial neural network.

Conceptual Framework

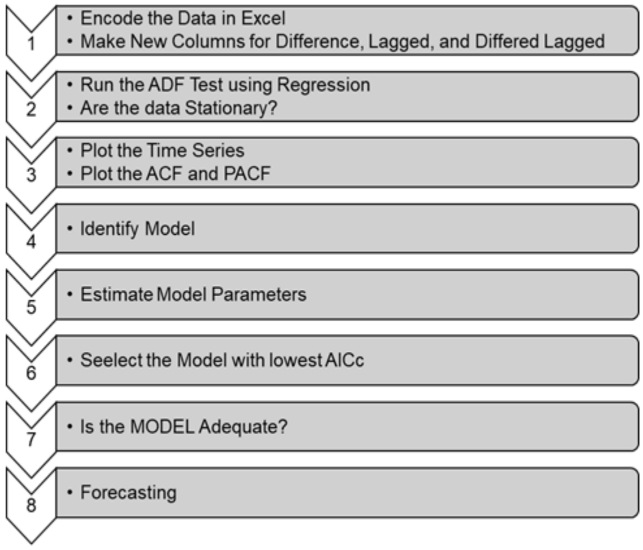

Figure 1. ARIMA Model

First, Encode the time series Data in Excel and then make New Columns for Difference, Lagged, and Differed Lagged. Run ADF Test using regression with Difference as Dependent Variable and Lagged and Differed Lagged as the Independent or Predictors. Use the standard critifcal value of t after running the ADF Test. It tells whether the time series is stationary or not. If not, using the next differencing. Take the first differences in the data until they are stationary if the data are not stationary. Plot the time series data for ARIMA modeling. Check volatility after that. If the data exhibit different fluctuations at various levels of the series, a transformation may be advantageous. To identify the optimum transformation method to stabilize the variance, use the box-Cox transformation. Check the data for seasonality as well. If so, you have the choice between fitting the seasonal ARIMA model or using seasonal differencing. Examine the ACF/PACF to determine the ordering of p, d, and q. Try out the models you've selected, then utilize the AICc/AIC/BIC to look for a better one. Try a modified model if they don't seem to be white noise. Verify if residuals have a mean of zero and a constant variance to see if they are regularly distributed. Thereafter, if the model is adequate, generate forecasts.

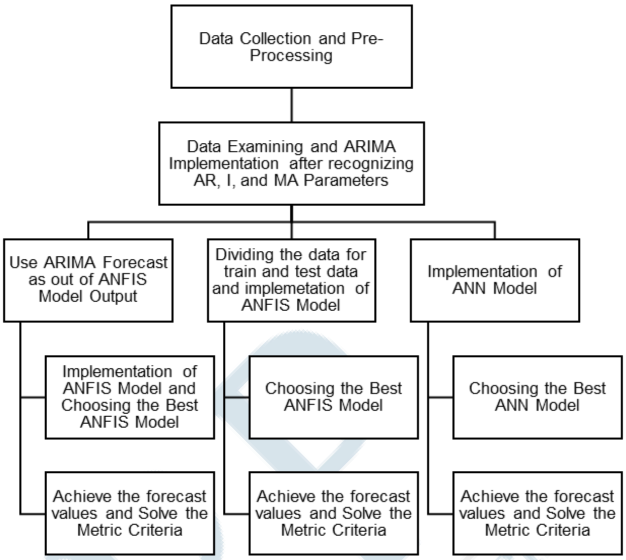

Figure 2. Model for ARIMA-ANFIS

In the proposed pattern, steps are as follows (see the right side of Figure 2):

The utilization of the ANFIS model is employed for the purpose of predicting ARIMA residuals due to the nonlinear nature exhibited. To facilitate the training and evaluation of the Adaptive Neuro-Fuzzy Inference System (ANFIS) models, the residuals are partitioned into separate sets for training and testing purposes. The process of selecting the most suitable model is determined by the objective of minimizing errors. The equation serves as a representation of the formula utilized in the model.

The ARIMA model's prediction is utilized as an input in the Adaptive Neuro-Fuzzy Inference System (ANFIS). Consequently, the linear forecasting outcomes are incorporated into the ANFIS model as additional inputs, with energy consumption serving as the model's output. An instance of this can be observed in the scenario when the ARIMA output (l_t) and the other inputs (m) are regarded as inputs for the Adaptive Neuro-Fuzzy Inference System (ANFIS). In this case, the model's formula can be represented as follows:

Where l_t is the output of ARIMA model.

In this stage, the data is partitioned into separate training and testing sets. Subsequently, the data is subjected to analysis utilizing six distinct structures of ANFIS models. The optimal hybrid model is determined based on predefined evaluation criteria and employed for the purpose of predicting energy consumption.

After the ANFIS findings have been obtained, the outputs are subjected to post-processing, where they are transformed back to their initial scale and subsequently presented as the results of the hybrid model.

Significance of the Study

This study's findings carry immense importance for COTELCO, as they pave the way for the establishment of well-defined and measurable objectives grounded in both historical and current data. By having access to accurate data and statistical insights, the energy provider can make informed decisions about the extent of change, growth, or enhancement necessary to achieve success. These goals play a pivotal role in tracking progress, enabling the company to fine-tune strategies as needed and ensure they remain on their desired trajectory.

As highlighted by Investopedia, the process of budgeting involves quantifying the anticipated revenue a business aims to attain in a future period, while financial forecasting estimates the potential revenue or income for that period. The study's insights not only provide a clear understanding of existing operational dynamics but also offer a glimpse into foreseeable trends. Integrating this comprehensive information equips COTELCO to allocate budgets more effectively and forecast more accurately, resulting in optimized resource allocation.

However, the significance of the study goes beyond just analyzing current data. It extends to projections and predictions about future developments. This enables the energy provider to adapt its strategies and operations in response to changing market dynamics. By recognizing emerging trends or shifts in consumer behavior, COTELCO can proactively realign its approach, stand out from competitors, and even alter its course if necessary.

The introduction of a forecast model through this study holds considerable value for COTELCO. The model empowers the company with the ability to make informed decisions and establish initiatives grounded in data. By meticulously analyzing historical data for patterns, the cooperative can predict forthcoming trends and alterations. This proactive approach allows COTELCO to anticipate potential shifts in consumer consumption patterns and prepare for them in advance.

In essence, the significance of this study is twofold: firstly, it arms COTELCO with the necessary insights to set well-defined goals and navigate their journey based on comprehensive data analysis; and secondly, it equips them with the tools to proactively respond to market changes and customer behavior, ensuring their continued relevance and success in the ever-evolving energy industry. Moreover, through the finding of this study, there will be Accurate electricity consumption predictions that can prevent power shortages, reduce social costs caused by unnecessary energy supply, and support stable and efficient power grid operation.

This study holds significance for professionals in the field of development, as well as energy policymakers, power utilities, and private investors. Accurate predictions of electricity demand play a crucial role in guiding investment choices related to power generation and the necessary network infrastructure. Forecasts hold significant importance in various domains. The occurrence of forecasting errors, regardless of whether they result in an overestimation or underestimation of demand, can lead to significant adverse consequences on both societal and economic levels.

The underestimation of demand leads to supply shortages and compelled power outages, hence yielding significant ramifications on productivity and economic growth. Overestimation of demand can lead to an overallocation of resources towards the development of generation capacity, hence causing financial challenges and ultimately resulting in escalated power costs. The electricity consumption prediction holds significant relevance in the energy planning of developing nations, like the Philippines. The act of forecasting usage offers clients the opportunity to establish a connection between their present usage patterns and the potential charges they may incur in the future. Hence, the utilization of forecasting systems can provide consumers with enhanced insights into their energy consumption patterns and future estimates, enabling them to effectively optimize the financial aspects associated with their energy usage. A deeper understanding of present energy consumption and its potential impact on future financial allocations will facilitate comprehension and assessment of energy usage patterns. While it is acknowledged that technology in isolation may not suffice to alter individuals' energy consumption patterns, it does provide a means to utilize energy in a deliberate and mindful approach.

Scope and Delimitation

The empirical results reported herein should be considered in light of some limitations.

- It limits only on the topics ARIMA Model combined with ANFIS.
- It will only explore best-fit models to forecast electricity consumption
- The data for simulation is limited to the dataset from COTELCO regarding Electricity Consumption
- Also, delimited to forecast the monthly, and annual electric consumption.

IV. METHODS

This section presents the discussions on research subjects, materials and instruments, research design, and ethical considerations.

Dataset

This study utilized 72 months (2017-2022) of information related to the electric consumption of COTELCO in the Philippines. These comprised cumulative data on electric consumption. The data covered a period of 72 consecutive months from January 2017 (Month 0) to December 2022 (Month 71); thus, the month as a unit of time t was considered. COTELCO provided the data. This study also used the ANFIS Model of which, we factored in the Increase of Connection, Number of Establishments, Residential Spaces, and Commercial Spaces, which the subject also provided. The data points undergone data cleaning to prepare for the proper data analysis process, and they were copied individually to the Microsoft Excel spreadsheet. It was organized according to the purpose of the study. The data undergone cleaning and organizing to omit entries capable of distorting the analysis process. The researcher developed an ARIMA model for forecasting electric consumption. The output of the ARIMA Model used with the ANFIS Model, along with the other factors that affect electric consumption. These models were candidate models for fitting the observed dataset. The data was encoded in the Microsoft Excel spreadsheet. The models were created by converting each Equation to its corresponding formula.

Research Subject

The subject matter of this study pertained to the Cotabato Electric Cooperative (COTELCO). COTELCO was founded in May 1972 in accordance with the stipulations of Republic Act No. 6038. Mr. Eduardo Alparaque, as a member of the board of incorporators, has the responsibility of leading the rural electrification initiative in the Province of Cotabato. On June 15, 1978, COTELCO assumed control of the previously owned Kidapawan Electric Light facilities. Subsequently, Pres Roxas submitted a formal request to the National Electrification Administration (NEA) to incorporate these facilities into the cooperative's jurisdiction. COTELCO is a non-stock, non-profit electric distribution utility that aims to deliver electricity to its member consumers in a cost-effective, dependable, and sufficient manner, covering a specific geographic area. Its main objective is to harness the economic potential of rural areas as a catalyst for national progress and advancement.

The cooperative encompasses the municipalities of Kabacan, Mlang, Matalam, Carmen, Banisilan, Tulunan, Makilala, Magpet, Kidapawan, Pres. Roxas, Antipas, and Arakan, as well as one city, inside Cotabato Province. The Board of Directors, comprising individuals elected within each town, assumes the role of a policy-making entity and represents the cooperative's member-consumers.

Research Materials and Instrument

SigmaXL Macro Addin for Micorsoft Excel was utilized in order to develop the ARIMA Models. The study also utilized MATLAB Software to develop the models for ANN, ANFIS and ARIMA ANFIS. After obtaining the forecasted values in those softwares, the observed values and forecasted values of those model were encoded to identify the metric criteria such as MAPE. The R2, AIC, BIC and RMSE was estimated using the Jamovi free program. Numerous scholarly investigations have employed Jamovi software (e.g., Arora et al., 2020) for the purpose of doing data analysis.

The model's accuracy was evaluated using several metric criteria, including R2, AIC, BIC, and Mean Absolute Percentage Error (MAPE)The accuracy of the model was assessed by previous researchers using MAPE as evaluation metrics (Li, Chen & Zhang, 2017; Jha & Saha, 2018; Jomnonkwao et al., 2020; Tao, 2020; Yang, 2020). Equation (3) and Table 2 present the Mean Absolute Percentage Error (MAPE) formula and its corresponding interpretation, as documented by Li et al. (2017). The researchers employed R2, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) to evaluate the adequacy of each model's fit. Relevant studies include Gholizadeh et al. (2018), Hsu and Wang (2008), Jha and Saha (2018), Jiang (2017), Larty (2020), Naseri and Elliot (2013), and Tao (2020). Preacher, K. J., and Yaremych, H. E. (2023) claim that the AIC and BIC criterion should be used as they place an emphasis on consistency and efficiency, respectively. Jiawei Zhang, Yuhong Yang, and Jie Ding (2023) also reiterated that if accurate prediction is the goal of the model selection process, they advise either (1) deciding between AIC-type and BIC-type methods based on parametricindex or cross-validation, or (2) using adaptive information criteria like BC to combine the strengths of AIC and BIC. Additionally, Ying Zhang and Gong Meng (2023) reaffirmed that the decisions should be based on relevant indicators, such as the AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion), in order to adequately balance the model's complexity and accuracy.

The R2, Akaike Information Criterion and Bayesian Information Criterion scores were computed using the open-source Jamovi program. A more favorable model fit is indicated by lower values of MAPE, BIC, and AIC, as well as greater R2 values approaching unity.

Design and Procedures

This study employed a non-experimental – quantitative, univariate - mathematical modeling method to predict the future based on those data patterns. The transformation of any problem situation into a mathematical model is known as mathematical modeling. However, this term has come to be widely used to describe the process of structuring, mathematizing, mathematical working, and interpretation/verification. Occasionally, the problem circumstance is nothing more than a pre-structured mathematical problem or a mathematical problem with real-world implications. According to Ali (2020), modeling analyzes current and past data and projects what it learns onto a developed model to estimate the most likely outcomes. The application of mathematics is defined as using mathematics to solve real-world problems. The application notion sometimes describes a link between real life and mathematics. In the last ten years, "application and modeling" notions have been utilized to explain any relationships between real life and mathematics. "Application and modeling" notions have been used to describe relationships between real life and mathematics in the previous ten years.

Ethical Considerations

By following the protocol assessments and standardized criteria, the researcher adhered to all ethical norms in the conduct of the study.

Risks. Also, the researcher ensured that the subject's participation in the study did not bring any foreseeable risks to the cooperatives' reputation. Also, the researcher ensured that if the subject becomes upset or distressed due to the processes that are part of the researcher's standard battery. Those subjects who withdraw their participation assured to be free from liabilities or responsibilities.

Benefits. Moreover, the researcher ensured that the benefits generated in this study will be shared with stakeholders. The benefits of this study include improving the forecast of the electric consumption to close up to 0% error or close to 100% accuracy by helping COTELCO develop an algorithm to forecast accurately. Likewise, the knowledge attained about this study can be extended to forecasting studies on electric consumption. For instance, the evidence gathered from this study will help develop the mathematical model. Further, the contribution of this study will lead to fewer power outages in the electric cooperative.

Plagiarism. Further, to avoid plagiarism, the researcher ensured that the resources being used in this study were cited appropriately. The authors' ideas are paraphrased and properly synthesized to abstained plagiarism. All ideas taken from the literature were presented with proper citations of the rightful author. Hence, to ensure quality, this paper was subjected to a plagiarism detector procedure to ensure that the manuscript is not plagiarized.

Fabrication. Furthermore, the researcher ensured that in the case that the fabrication of data occurs, it was unintentional. The data of this study was basically from the No fabrication or inclusion of data or enactment ever arises in data gathering. The researcher made only conclusions that are only found from the results of the study.

Falsification. In addition, the researcher avoided intentionally falsifying results. There is no overemphasis statement of the results to assure that the theory or proposition used in the study is justifiable. The researcher ethically stated the study's results in accordance exclusively with the underlying literature and propositions. There is no modification or alteration of the results to support the claims and hypotheses in the study. Moreover, no maneuver of the data, medium, or procedures existed in this study.

Conflict of Interest. The researcher also declared no conflict of interest. The subject in this subject is not under the researcher's supervision. The researcher cannot influence nor coerce the data. The researcher is only a consumer of the electric cooperative. Also, the researcher emphasized that the researcher's utmost interest is to finish the paper as a requirement to graduate with a Doctoral degree.

Deceit. Meanwhile, during the study, the researcher assured the subject that there was no deceit and that participating in this study did not cause any harm but to help. The researcher emailed and constantly communicated with the General Manager and talked through the process and the study's outcome. Before the title defense of this study, they were briefly informed on the purpose and content of the study. Their role and contribution to the study are promptly explained.

Technology Issues. The study used secondary data, which are available online. It does not gather information through online access panels. It does not view any information being transmitted in a digital environment.

Permission from Organization. Prior to the Title defense, the research secured permission from COTELCO to become the research subject. Then the reply from the said office allowed the researcher to conduct the study. Data were also given.

Authorship. The study identified the authors and gives them due credit for their contributions, whether they were significant in the study's conception, design, collection, data analysis, and interpretation. Additionally, the researcher prepared the article, critically edits it for significant intellectual substance, and gave final approval for the published edition. He also recognized the valuable contribution of his adviser, who painstakingly and scholarly critiqued this paper leading to several improvements.

V. DISCUSSION OF RESULTS

Presentation of Monthly Trend Electric Consumption of COTELCO from 2017 to 2022

The provided dataset represents the observed values of electric consumption for COTELCO in the Philippines from January 2017 to December 2022. These values provide crucial insights into the consumption patterns and trends over these six years.

Upon examining the data, several patterns and fluctuations are noticeable. Electric consumption exhibits both short-term variations and long-term trends. Within each year, there are months when consumption is higher and lower, suggesting a seasonal pattern. Additionally, a broader trend can be observed over the entire period, which might indicate changes in consumption habits or external factors affecting usage.

There is a clear seasonal cycle in the data, with electric consumption showing a pattern that repeats annually. Consumption tends to be specific in certain months and decreases during others. This may be attributed to weather conditions, holidays, or industrial activities that impact electricity demand.

Throughout the dataset, there are instances of months where electric consumption experiences significant spikes (peaks) followed by periods of lower consumption (valleys). These spikes could coincide with holidays, increased commercial or residential activities, or weather-related demands for cooling or heating.

The dataset also captures the impact of the COVID-19 pandemic, particularly evident in the early months of 2020. The months following the initial outbreak and subsequent lockdowns demonstrate a deviation from the usual consumption pattern. The decrease in electric consumption during these months is likely a result of lockdown measures, reduced economic activities, and changes in lifestyle due to remote work and restricted movement.

Despite the pandemic's influence, electric consumption has an overall upward trend. The consistent increase in consumption values suggests that factors are driving higher electricity demand, such as population growth, urbanization, and economic development.

In summary, the observed electric consumption values for COTELCO in the Philippines from January 2017 to December 2022 showcase a combination of seasonal patterns, short-term fluctuations, and an overall upward trend. The dataset reflects the interplay between various factors influencing electricity usage, including weather, economic activities, and societal changes. This information forms the foundation for deeper analysis and modeling, enabling stakeholders to make informed decisions regarding energy management, infrastructure planning, and sustainability.

Electric Consumption by Categories

The data presented here provides a detailed overview of COTELCO's electric consumption across five distinct categories: Residential, Commercial, Industrial, Public Building, and Streetlights. This information is invaluable for understanding consumption patterns, identifying trends, and making informed decisions regarding energy management and resource allocation. Let's discuss and interpret the data:

Residential Consumption

The residential sector consistently exhibits the highest electric consumption throughout the dataset. Consumption steadily increases from January 2017 to December 2019, peaking in May 2019 at 11,030,096 units. After December 2019, residential consumption shows a slight downward trend, possibly due to energy efficiency measures or seasonal variations.

Commercial Consumption

The commercial sector maintains a relatively stable level of electric consumption over the years. Consumption trends upward overall, with occasional fluctuations, reaching its highest point in August 2021 at 4,093,009 units. This category's stability suggests consistent demand for electricity from commercial establishments.

Industrial Consumption

The industrial sector demonstrates a notable variation in electric consumption. Consumption reaches its highest point in September 2019 at 4,738,437 units, indicating increased industrial activity during that period. Post-2019, industrial consumption decreases but remains relatively high, suggesting ongoing industrial operations.

Public Building Consumption

The public building category experiences moderate fluctuations in electric consumption. Consumption peaks in August 2020 at 1,682,274 units, possibly related to public infrastructure projects or weather-related factors. Despite fluctuations, consumption remains relatively consistent throughout the dataset.

Streetlights Consumption

Streetlights exhibit the lowest consumption levels among all categories. Consumption remains relatively stable with minor fluctuations. The data suggests efficient management and consistent usage of street lighting.

It's crucial to consider external factors such as seasonal variations, economic activities, and infrastructure development when interpreting these consumption patterns. Sustainable energy practices and efficiency initiatives could explain some of the observed trends, particularly in the residential sector. Industrial and commercial sectors might benefit from further analysis to understand the drivers behind consumption fluctuations. Public building consumption may correlate with government initiatives or events impacting energy use in these facilities. Streetlights exhibit stable consumption, potentially indicating well-maintained lighting infrastructure.

In summary, this data offers valuable insights into COTELCO's electric consumption by category, providing a foundation for informed decision-making, energy conservation efforts, and future planning to ensure a sustainable and reliable energy supply for the community.

Model Development

The development of the ARIMA-ANFIS model for predicting electric consumption of COTELCO involves a hybrid approach that combines the strengths of both the Autoregressive Integrated Moving Average (ARIMA) model and the Adaptive Neuro-Fuzzy Inference System (ANFIS) model. This hybridization aims to enhance the accuracy and robustness of predictions by leveraging the capabilities of both methodologies.

The ARIMA model is a time series forecasting technique that captures the temporal dependencies and trends present in the data. It involves three main components: Autoregressive (AR), Integrated (I), and Moving Average (MA). The AR component captures the relationship between the current value and its previous values, the I component deals with differencing to achieve stationarity, and the MA component models the relationship between the current value and its past forecast errors.

For the electric consumption data of COTELCO, the ARIMA component helps identify and model the underlying patterns and trends in consumption behavior. It considers the seasonality and autocorrelation present in the dataset, enabling the model to make short-term predictions based on historical patterns.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a machine learning technique that combines fuzzy logic and neural networks. It is designed to capture complex relationships between input variables and output predictions. ANFIS utilizes linguistic variables and membership functions to create a fuzzy logic system and then adapts the parameters of this system using a neural network framework. The ANFIS component of the hybrid model provides a mechanism for capturing non-linear relationships, uncertainties, and interactions between variables that may not be fully captured by the ARIMA model alone. This is particularly useful for accounting for external factors that influence electric consumption, such as changes in population, economic conditions, and policy shifts.

The hybrid ARIMA-ANFIS model combines the predictions of the ARIMA and ANFIS components in a weighted manner to generate a final forecast. The integration of these two models aims to capitalize on their complementary strengths: ARIMA's ability to capture temporal dependencies and ANFIS's capacity to handle non-linear relationships. The integration process involves training the ARIMA and ANFIS components on historical data and then using their predictions to develop a consensus forecast. Weighting factors can be established by analyzing the past performance of each component or by employing optimization techniques. The ultimate hybrid model seeks to enhance forecast accuracy and robustness by leveraging the respective characteristics of both approaches.

The performance of the ARIMA-ANFIS model is assessed using various metrics such as R^2, AIC, BIC, and Mean Absolute Percentage Error (MAPE). These metrics help quantify the accuracy of the model's predictions compared to the actual electric consumption values. If the hybrid model performs better than individual ARIMA or ANFIS models, it can be considered a successful outcome.

The development of the ARIMA-ANFIS model for predicting the electric consumption of COTELCO involves the integration of ARIMA's temporal modeling capabilities with ANFIS's ability to capture complex relationships. This hybrid approach aims to provide a more accurate and comprehensive forecasting tool that can contribute to effective energy management and planning for COTELCO.

Comparison of the four models

In the pursuit of enhancing the accuracy and reliability of predicting electric consumption, our research study delved into the application of four distinct modeling approaches: Autoregressive Integrated Moving Average (ARIMA), Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), and the hybrid ARIMA-ANFIS model. This section compares and contrasts the performance of these four models, shedding light on their respective strengths and limitations in forecasting electric consumption patterns. By comprehensively evaluating the predictive capabilities of each model, we aim to provide valuable insights into the efficacy of the ARIMA-ANFIS model as a robust and accurate tool for capturing the complex dynamics of electric consumption behavior.

Table 1. Summary of Forecast Accuracy Table

	MAPE	R^2	AIC	BIC
ARIMA	0.448740858	**0.830**	2159	2166
ANN	0.171045558	0.739	2166	2173
ANFIS	0.426673425	0.057	2282	2289
ARIMA-ANFIS	**0.035176594**	0.727	**2129**	**2135**

Let us compare and contrast the four models (ARIMA, ANN, ANFIS, and ARIMA-ANFIS) using the MAPE, R2, AIC, and BIC criteria:

The ARIMA-ANFIS model has the lowest MAPE value among the four models, suggesting that, on average, the percentage difference between forecasted and observed values is relatively lower. The ANFIS model also has a relatively high MAPE value, indicating more significant percentage errors. The ARIMA-ANFIS model shows the MAPE values among all the models, suggesting that it outperforms the others regarding forecast accuracy.

The ARIMA model relies on time series analysis and auto-regressive, integrated, and moving average components. It performs well in capturing temporal patterns and trends but may need help with more complex relationships in the data. As a deep learning technique, the ANN model can learn complex patterns from data but requires careful tuning and preprocessing to avoid overfitting. It shows higher errors in this case, possibly due to suboptimal hyperparameters or model complexity. The ANFIS model combines the strengths of fuzzy logic and neural networks to handle both numerical and linguistic data. However, it may struggle with non-linear and highly dynamic relationships. The ARIMA-ANFIS model is a hybrid approach, combining the advantages of ARIMA and ANFIS. It outperforms the other models in this study, as evidenced by lower errors and improved forecast accuracy.

The ARIMA-ANFIS model seems the most accurate and reliable for forecasting COTELCO's electric consumption based on the given metrics. It balances capturing time series patterns and handling complex relationships, resulting in lower errors and higher forecast accuracy. The ARIMA and ANN models have their strengths but show higher forecast errors in this context. Fine-tuning the ANN model and optimizing ARIMA hyperparameters might lead to better performance. The ANFIS model, while offering interpretability through fuzzy logic, does not perform as well as the ARIMA-ANFIS hybrid or the pure ARIMA models. This suggests that it may not be the most suitable approach for this specific dataset.

The R^2 value measures how well the model explains the variability in the dependent variable (electric consumption) relative to the total variability. A higher R^2 value indicates a better fit of the model to the data. In this comparison, the ARIMA model has the highest R^2 value of 0.830, which explains around 83.0% of the variability in the electric consumption data. This suggests that the ARIMA model fits the data relatively well and captures a significant portion of the variance. The ANN model follows with an R^2 value of 0.739, implying that it explains approximately 73.9% of the variability. The ARIMA-ANFIS model is also vital, with an R2 value of 0.727. The ANFIS model has the lowest R^2 value of 0.057, suggesting it explains only about 5.7% of the variability. This indicates that the ANFIS model might not be capturing the underlying patterns in the data as effectively as the other models.

AIC is a measure of the model's goodness of fit while taking into account the number of parameters. Lower AIC values indicate a better fit. The ARIMA-ANFIS model has the lowest AIC value of 2129, suggesting a relatively better fit than the other models. The ARIMA model follows with an AIC value of 2159, indicating a relatively good fit. The ANN and ANFIS models have higher AIC values of 2166 and 2282, respectively. These higher AIC values suggest that these models are less suitable for explaining the data than ARIMA and ARIMA-ANFIS.

BIC is similar to AIC but applies a more substantial penalty for the number of parameters. Like AIC, lower BIC values indicate a better fit. The ARIMA-ANFIS model has the lowest BIC value of 2135, again suggesting a better fit than the other models. The ARIMA model has a BIC value 2166, slightly higher than the ARIMA-ANFIS model. The ANN and ANFIS models have higher BIC values of 2173 and 2289, respectively. These higher BIC values indicate that these models might have relatively worse fits than the others.

Based on the forecast accuracy results, the ARIMA-ANFIS model is recommended for future forecasting of COTELCO's electric consumption. Further research and analysis could focus on fine-tuning the ARIMA-ANFIS model's hyperparameters, exploring additional input features, and implementing model validation on out-of-sample data to assess its performance on unseen observations.

In conclusion, the ARIMA-ANFIS model shows improved forecast accuracy compared to previous versions, as evidenced by the lower AIC, BIC, and MAPE values. However, ongoing evaluation and refinement are necessary to maintain its effectiveness in accurately forecasting COTELCO's Electric Consumption.

Most Parsimonious Model

To determine the most parsimonious model among the four developed models, a checklist was constructed to score the models under MAPE, R2, AIC and BIC Criteria.

Table 14. Checklist for the most parsimonious model

	MAPE	R^2	AIC	BIC
ARIMA		/		
ANN				
ANFIS				
ARIMA-ANFIS	/		/	/

Based on the checklist constructed above, with favorable results on 3 criterions, namely, MAPE, AIC and BIC, we can further conclude that ARIMA-ANFIS Model is the most parsimonious model. Preacher, K. J., and Yaremych, H. E. (2023) claim that the AIC and BIC criterion should be used as they place an emphasis on consistency and efficiency, respectively. Jiawei Zhang, Yuhong Yang, and Jie Ding (2023) also reiterated that if accurate prediction is the goal of the model selection process, they advise either (1) deciding between AIC-type and BIC-type methods based on parametric index or cross-validation, or (2) using adaptive information criteria like BC to combine the strengths of AIC and BIC. Additionally, Ying Zhang and Gong Meng (2023) reaffirmed that the decisions should be based on relevant indicators, such as the AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion), in order to adequately balance the model's complexity and accuracy.

Forecasting the next 36 months using the most Parsimonious model (ARIMA-ANFIS Model)

Applying the ARIMA-ANFIS hybrid model to forecast the electric consumption of COTELCO for the next 36 months (January 2023 to December 2025) has yielded insightful predictions. These forecasts, detailed in the provided table, offer valuable insights into the anticipated trajectory of electric consumption, which is crucial for informed decision-making, resource allocation, and energy management strategies.

The forecasted values reveal that electric consumption is expected to continue its upward trend over the coming months, aligning with the historical growth observed in the dataset. This suggests that factors contributing to increased electricity demand, such as population growth, urbanization, and economic development, are projected to persist. The seasonal variations present in the data are also reflected in the forecasted values, as consumption is anticipated to follow a cyclical pattern, reaching peaks and valleys throughout the upcoming years.

It is important to note that the forecasted values are accompanied by lower and upper 95.0% prediction intervals (PI), representing the level of uncertainty associated with the predictions. These intervals provide a range within which the actual consumption values will likely fall with a certain degree of confidence. As the forecast table shows, the prediction intervals widen as we move further into the future, reflecting the increasing uncertainty associated with long-term predictions.

The ARIMA-ANFIS hybrid model's forecasting for the next 36 months offers a valuable glimpse into the expected trends and patterns in COTELCO's electric consumption. By considering the forecasted values and their associated prediction intervals, stakeholders can make informed decisions and develop strategies aligning with the projected energy consumption trajectory. Continuous validation and refinement of the model will enhance its effectiveness as a predictive tool for guiding energy management and resource

ISSN (Online) 2456 -1304
International Journal of Science, Engineering and Management (IJSEM)
Vol 10, Issue 11, November 2023

allocation efforts.

VI. CONCLUSION

The study's objective was to forecast the electric consumption of COTELCO by employing a combination of ARIMA and ANFIS modeling approaches. The ARIMA-ANFIS model was formulated and assessed using past data, yielding significant findings about its predictive precision. The study's findings revealed that the ARIMA-ANFIS model exhibited enhanced forecast accuracy compared to its prior iterations. This was substantiated by the observed lowered in various evaluation metrics, including the AIC, BIC, R^2, and MAPE values.

VII. RECOMMENDATIONS

Based on the study's findings, the following recommendations and ways forward are suggested:

1. Subsequent Model Refinement: Proceed with the ongoing refinement of the ARIMA-ANFIS model by investigating supplementary permutations of model parameters and time series data. To increase the forecasting capabilities of the model, consider including other exogenous variables that may impact energy consumption.
2. Ensemble Modeling: Construct an ensemble of forecasting models that amalgamates forecasts from many methodologies, encompassing ARIMA, ANFIS, and other machine learning techniques. Ensemble models have demonstrated efficacy in enhancing forecast accuracy and resilience.
3. Conduct a comprehensive out-of-sample validation to evaluate the model's efficacy on previously unseen data. This approach will yield a more precise assessment of the model's predictive accuracy and capacity to extrapolate to novel data points.
4. Enhancing Data Quality: Guarantee the acquisition and upkeep of historical data on superior quality and dependability energy consumption. It is advisable to allocate resources toward implementing data purification and preprocessing procedures to effectively manage missing or noisy data, hence safeguarding the model's performance.
5. Conducting Forecast Uncertainty Analysis: In order to assess the level of uncertainty associated with the forecasts, it is necessary to do a forecast uncertainty analysis. Gaining an understanding of the many possible forecast inaccuracies helps decision-makers in making more informed judgments.
6. Collaboration with Experts: Facilitate the involvement of domain experts and stakeholders from COTELCO in the forecasting process. The expertise possessed by individuals in a specific field can offer significant perspectives and contribute to the verification of model outcomes, so ensuring that predictions are consistent with established knowledge and anticipated outcomes in the actual world.

REFERENCES

[1] S. Chen, B. Mulgrew, and P. M. Grant, "A clustering technique for digital communications channel equalization using radial basis function networks," IEEE Trans. on Neural Networks, vol. 4, pp. 570-578, July 1993.

[2] J. U. Duncombe, "Infrared navigation—Part I: An assessment of feasibility," IEEE Trans. Electron Devices, vol. ED-11, pp. 34-39, Jan. 1959.

[3] C. Y. Lin, M. Wu, J. A. Bloom, I. J. Cox, and M. Miller, "Rotation, scale, and translation resilient public watermarking for images," IEEE Trans. Image Process., vol. 10, no. 5, pp. 767-782, May 2001.

[4] Al-Gounmeein, R.S., & Ismail, M.T. (2020). Forecasting the Exchange Rate of the Jordanian Dinar versus the US Dollar Using a Box-Jenkins Seasonal ARIMA Model. Computer Science, 75(1), 27-40.

[5] Altavilla, C., & De Grauwe, P. (2010). Forecasting and combining competing models of exchange rate determination. Applied Economics, 42(27), 3455-3480.

[6] Amat, C., Michalski, T., & Stoltz, G. (2018). Fundamentals and exchange rate forecastability with simple machine learning methods. Journal of International Money and Finance, 88, 1-24.

[7] Boaler, J. (2001). Mathematical Modelling and New Theories of Learning. Teaching Mathematics and its Applications. Vol. 20, No. 3, 121-128, 2001.

[8] Blum, W. (2002). ICMI Study 14: Applications and Modelling In Mathematics

[9] Education. Educational Studies in Mathematics No.51, 149-171, 2002.

[10] Box, G.E., Jenkins, G.M., & Bacon, D.W. (1967). Models for forecasting seasonal and non-seasonal time series. Wisconsin univ madison dept of statistics.

[11] Box, G.E., Jenkins, G.M., & Reinsel, G.C. (1994). Time series analysis, forecasting, and control. Englewood Cliffs.

[12] COTELCO (2020). Company Profile: Who We are. https://cotelco.com.ph/about-us-2/company-profile/

[13] Dritsaki, C., Niklis, D., & Stamatiou, P. (2021). Oil consumption forecasting using ARIMA models: An empirical study for Greece. International Journal of Energy Economics and Policy, 11(4), 214-224. https://www.proquest.com/scholarly-journals/oil-consumption-forecasting-using-arima-models/docview/2610031539/se-2

[14] Fernandez, E. (2013, Sep. 1), Power outages in North Cotabato worsen. Philippine Daily Inquirer. https://newsinfo.inquirer.net/479341/power-outages-in-north-cotabato-worsen

[15] Gajowniczek, K., & Ząbkowski, T. (2017). Electricity forecasting on the individual household level enhanced based on activity patterns. PloS one, 12(4), e0174098. https://doi.org/10.1371/journal.pone.0174098

[16] Grimm, S., Stevens, J., & Dixon, S. (2018). Estimating Future Health Technology Diffusion Using Expert Beliefs Calibrated to an Established Diffusion Model. Value in Health. https://doi.org/10.1016/j.jval.2018.01.010

[17] Hauben, M., & Hung, E. (2021). Effects of the COVID-19 pandemic on spontaneous reporting: Global and national time-series analyses. Clinical Therapeutics, 43(2), 360-368.e5. doi:http://dx.doi.org/10.1016/j.clinthera.2020.12.008

[18] Lee, M. H. L., Ser, Y. C., Selvachandran, G., Thong, P. H., Cuong, L., Son, L. H., & Gerogiannis, V. C. (2022). A comparative study of forecasting electricity consumption

using machine learning models. Mathematics, 10(8), 1329.

[19] Liu, Q., Charleston, M. A., Richards, S. A., & Holland, B. R. (2023). Performance of Akaike Information Criterion and Bayesian Information Criterion in Selecting Partition Models and Mixture Models. Systematic Biology, 72(1), 92-105.

[20] Mohammed Jamii, Mohamed Maaroufi, (2021). "The Forecasting of Electrical Energy Consumption in Morocco with an Autoregressive Integrated Moving Average Approach", Mathematical Problems in Engineering, vol. 2021, Article ID 6623570, 9 pages, 2021. https://doi.org/10.1155/2021/6623570

[21] Nasirov, S., Girard, A., Pena, C., Salazar, F., & Simon, F. (2021). Expansion of renewable energy in Chile: Analysis of the effects on employment. Energy, 226, 120410.

[22] Onu, C. E., Igbokwe, P. K., Nwabanne, J. T., & Ohale, P. E. (2022). ANFIS, ANN, and RSM modeling of moisture content reduction of cocoyam slices. Journal of Food Processing and Preservation, 46, e16032. https://doi.org/10.1111/jfpp.16032

[23] Ozturk, S., Ozturk, F. (2018). Forecasting energy consumption of Turkey by ARIMA model. Journal of Asian Scientific Research, 8(2), 52-60.

[24] Phillips, P.C.B., Perron, P. (1998). Testing for a unit root in time series regression. Biometrika, 75(2), 335-346.

[25] Preacher, K. J., & Yaremych, H. E. (2023). Model selection in structural equation modeling. Handbook of structural equation modeling, 206-222.

[26] Ramsey, J.B. (1969). Tests for specification errors in classical linear least-squares regression analysis. Journal of the Royal Statistical Society, Series B, 31(2), 350-371.

[27] Rebalde, BB., & Lelis, CL. (2022). Modified Bass Diffusion Model to Study Adoption of Covid–19 Vaccines in the Philippines: Input for Inoculation Rollout. American Journal of Multidisciplinary Research and Innovation, 1(4), 76-85.

[28] Ritchie, H. and Roser, M. (2020). "Energy". Published online at OurWorldInData.org. Retrieved from: 'https://ourworldindata.org/energy' [Online Resource]

[29] Szafranko, E., Srokosz, P. E., Jurczak, M., & Śmieja, M. (2022). Application of ANFIS in the preparation of expert opinions and evaluation of building design variants in the context of processing large amounts of data. Automation in Construction, 133, 104045.

[30] Steinbuks, Jevgenijs; de Wit, Joeri; Kochnakyan, Artur; Foster, Vivien. 2017. Forecasting Electricity Demand : An Aid for Practitioners. Live Wire;2017/73. World Bank, Washington, DC. © World Bank. https://openknowledge.worldbank.org/handle/10986/26189 License: CC BY 3.0 IGO.

[31] Suleiman, Shamsuddeen & Sani, Muhammad. (2020). Application of ARIMA and Artificial Neural Networks Models for Daily Cumulative Confirmed Covid-19 Prediction in Nigeria. 83-90.

[32] Theil, H. (1961). Economic Forecasts and Policy. Amsterdam: North-Holland Publishing Company.

[33] Ullah, M. A., Mujahid, H., Tabash, M. I., Ayubi, S., & Sabri, R. (2021). FORECASTING INDIAN RUPEE/US DOLLAR: ARIMA, EXPONENTIAL SMOOTHING, NAÏVE, NARDL, COMBINATION TECHNIQUES. Academy of Accounting and Financial Studies Journal, 25(3), 1-8. Retrieved from https://www.proquest.com/scholarly-journals/forecasting-indian-rupee-us-dollar-arima/docview/2543522119/se-2?accountid=31259

[34] Wei, Y., Wang, Z., Wang, H., Li, Y., & Jiang, Z. (2019). Predicting population age structures of China, India, and Vietnam by 2030 based on compositional data. PLoS One, 14(4), e0212772.

[35] Yadav, R.K., Balakrishnan, M. (2014). Comparative evaluation of ARIMA and ANFIS for modeling of wireless network traffic time series. J Wireless Com Network 2014, 15 https://doi.org/10.1186/1687-1499-2014-15

[36] Zhang, G., Patuwo, B.E., & Hu, M.Y. (1998). Forecasting with artificial neural networks: The state of the art. International Journal of Forecasting, 14(1), 35-62.

[37] Zhang, J., Yang, Y., & Ding, J. (2023). Information criteria for model selection. Wiley Interdisciplinary Reviews: Computational Statistics, e1607.

[38] Zhang, Y., & Meng, G. (2023). Simulation of an Adaptive Model Based on AIC and BIC ARIMA Predictions. In Journal of Physics: Conference Series (Vol. 2449, No. 1, p. 012027). IOP Publishing.

[39] Zhang, G.P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing, 50, 159-175.