Vol.9 Issue.1 2024

Review of Socio - Economic Perspectives
ISSN: 2149 - 9276
E-ISSN: 2547-9385

A Comparative Study of ARIMA, RBFNN, and Hybrid RBFNN-ARIMA Models for Electricity Net Consumption Forecasting in Algeria

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DOI: https://doi.org/10.19275/RSEP185

Article Type: Original/Research Paper

Article History
Received: 18 March 2024 Revised: 14 May 2024 Accepted: 19 May 2024 Available Online: 30 June 2024

Keywords: Electricity Net consumption forecasting, ARIMA, RBFNN, hybrid RBFNN-ARIMA, Algeria
JEL classification: C13, C53, Q40, Q47

Citation: Kahoui, H., Chekouri, S.M., Sahed, A. (2024). A Comparative Study of ARIMA, RBFNN, and Hybrid RBFNN-ARIMA Models for Electricity Net Consumption Forecasting in Algeria., *Review of Socio-Economic Perspectives,* 9(1), 189-198.

Abstract

This study aims to compare the performance of three different forecasting methods for electricity consumption such as ARIMA, RBFNN, and hybrid RBFNN-ARIMA in Algeria over the period from 1990 to 2030. The results show that the RBFNN model outperforms the other two models in terms of accuracy. The RBFNN model is able to capture the nonlinear relationships in the data and is more robust to noise than the other models. The findings of this study have important implications for energy planning and management in Algeria. The RBFNN model can be used to develop more accurate and reliable forecasts of electricity net consumption, which can help to improve the efficiency of energy planning and management.

1. Introduction

Electricity is a crucial resource for social and economic development (Mahia et al., 2019) and serves as a key energy source in every country (Ozoh et al., 2014). The growth and development of any nation are closely linked to its energy utilization rate (Şişman, 2017). Due to the robust and continuous increase in electricity consumption, it is essential to develop accurate predictive models to anticipate future consumption patterns. Thus, precise electricity consumption forecasts are of primary importance in the energy planning of developing countries and serve as vital tools for decision-makers in devising future policies (Jain et al., 2018). Minimizing forecasting errors is crucial since they may result in substantial financial losses; therefore, achieving a high degree of accuracy in electricity consumption forecasting is necessary to avoid such losses (Kavaklioglu, 2011).

Numerous methods have been proposed in the literature for forecasting, with various techniques gaining popularity in recent years. The autoregressive integrated moving average (ARIMA) model is one of the most common approaches for this purpose (Lee et al., 2022) and has been extensively applied to time series data (Guha & Bandyopadhyay, 2016; Fattah et al., 2018; Salman & Kanigoro, 2012). However, a significant limitation of these models is their linearity (Aslanargun et al., 2007).

In contrast, artificial neural networks (ANNs) are machine learning techniques that mimic the human neurological system (Camara et al., 2016). They consist of basic computing elements called neurons, which are interconnected to form networks. The parallel distributed processing architecture of ANNs has proven to be an effective computational tool (Fashae et al., 2019). The main advantage of neural networks is their ability to recognize nonlinear patterns without any prior information about the relationships present in the data (Khashei & Hajirahimi, 2019). ANNs are now employed in various fields to model nonlinear relationships (Dumitru & Gligor, 2019; Zou et al., 2010; Fernandes et al., 2008; Somvanshi et al., 2006).

Recent studies have provided comprehensive descriptions of hybrid ARIMA–ANN models (Díaz-Robles et al., 2008). Research has progressed towards combining the benefits of both ARIMA and ANN models to develop hybrid ARIMA-ANN models (Babu & Reddy, 2015), which have demonstrated superior prediction accuracy compared to individual models (Devi et al., 2021; Faruk, 2010; Cadenas & Rivera, 2010; Alam & AlArjani, 2021).

In this study, we will focus on forecasting electricity consumption in Algeria using the autoregressive integrated moving average (ARIMA), radial basis function neural network (RBFNN), and hybrid RBFNN-ARIMA models (Khashei and Bijari's Hybrid Model, 2011). We will compare these forecasting techniques based on their accuracy using mean square error (MSE) and root mean square error (RMSE).

The remainder of this paper is structured as follows: Section 2 reviews the literature on forecasting electricity consumption. Section 3 discusses the methodology and data. Section 4 presents the results of applying the ARIMA, RBFNN, and Khashei and Bijari's Hybrid Model (2011) to forecast electricity consumption. Finally, Section 5 concludes the paper.

2. Literature Review

Electricity consumption forecasting has gained significant attention from researchers today, and different models have been used for this purpose. Several studies have applied statistical models, such as the ARIMA model. For instance, Mahia et al. (2019) applied the ARIMA model to forecast electricity consumption in Guangdong province in China, which demonstrated high precision, stable predictions, and suitability for predicting electricity consumption. Wang et al. (2012) used the PSO optimal Fourier method, seasonal ARIMA model, and combined models of PSO optimal Fourier method with seasonal ARIMA for electricity demand forecasting in China. The results revealed that the prediction accuracy of the three residual modification models is higher than the single seasonal ARIMA model, and the combined model is the most satisfactory of the three models. Additionally, de Assis Cabral et al. (2017) proposed a forecasting method of electricity consumption in Brazil that considers the spatiotemporal dynamics, which employs the Spatial ARIMA model (ARIMASp) showing better predictive performance compared to the ARIMA model. Furthermore, Hussain et al. (2016) applied the Holt-Winter and Autoregressive Integrated Moving Average (ARIMA) models to forecast electricity consumption in Pakistan, and the results revealed that Holt-Winter is the appropriate model for forecasting electricity consumption in Pakistan.

The studies mentioned above employ machine learning models to forecast electricity consumption. Hadjout et al. (2022) propose an ensemble learning approach that combines Long Short-Term Memory, Gated Recurrent Unit neural networks, and Temporal Convolutional Networks to forecast electricity consumption in the economic sector of Bejaia, Algeria. Their results show that the proposed ensemble models outperform traditional individual models and meet the company's requirements. Kavaklioglu et al. (2009) propose Artificial Neural Networks to model and predict electricity consumption in Turkey using a multi-layer perceptron with backpropagation training algorithm as the neural network topology. The authors demonstrate that electricity consumption can be modeled using Artificial Neural Networks and that these models can be used to predict future electricity consumption. Albuquerque et al. (2022) use regularized machine learning models to forecast Brazilian electricity consumption for short and medium terms and compare these models with benchmark specifications such as Random Walk and Autoregressive Integrated Moving Average. Their results show that machine learning methods, particularly Random Forest and Lasso Lars, provide more accurate forecasts for all horizons. Heghedus et al. (2019) propose four neural networks, including back propagation neural network, fully recurrent neural network, long short-term memory network, and gated recurrent unit, to forecast electricity consumption. The authors compare the predictive performance of these models and find that LSTM and GRU achieve lower errors than the other models, with GRU presenting better performance for the daily forecast and LSTM outperforming the rest for the monthly forecast. Finally, Kim et al. (2018) propose a short-term electricity consumption prediction method using the Long-Short-Term-Memory network, and their experimental results show that the proposed method achieves a prediction accuracy of about 82.5%, which can be improved with a longer period of training time and deliberate hyperparameter setting.

The following studies have utilized hybrid models that combine statistical and machine learning approaches for electricity consumption forecasting. Suksawang (2018) used different forecasting methods, including hybrid SARIMA-ANN and SARIMA-Gaussian Processes (GP) with a combined Kernel Function technique. Results showed that the SARIMA-GP hybrid model outperformed the SARIMA-ANN model. Guo et al. (2021) proposed an ARIMA-SVR hybrid model for electricity consumption prediction and compared it to other models such as ARIMA, ARIMA-GBR, LSTM, and GRU. The experiment demonstrated that the ARIMA-SVR model provided more accurate results than the other models. Fan et al. (2020) combined several machine learning approaches, thermal reaction dynamics theory, and the econometric model AR-GARCH to develop a novel hybrid forecasting model, the EMD-SVR-PSO-AR-GARCH, for electricity consumption forecasting in NSW, Australia. Zeng et al. (2017) applied a hybrid intelligent approach named ADE–BPNN, a BPNN model supported by an adaptive differential evolution algorithm, to estimate energy consumption. The proposed model provided more accurate predictions compared to traditional BPNN models and other popular existing models. Wang et al. (2020) proposed a hybrid model of empirical mode decomposition (EMD) and gated recurrent unit (GRU) to predict user electricity consumption. Experimental results demonstrated that the proposed model effectively reduced errors and improved training efficiency. Finally, Chandramitasari et al. (2018) proposed a deep learning neural network model with a combination of LSTM and Feed Forward Neural Network (FFNN) for electricity forecasting. Results showed that the proposed LSTM-FFNN model outperformed the LSTM and Moving Average (MA) models.

Our comprehensive review of the literature has revealed that various models have been used to forecast electricity consumption with varying degrees of success. However, despite the abundance of studies, there is still a lack of consensus on which models perform best in different contexts. Therefore, in our study, we aim to contribute to the field by comparing the performance of three different methods for forecasting electricity consumption in Algeria.

3. Methodology

3.1. Data collection

This study focuses on comparing three methods of forecasting electricity consumption in Algeria using time series annual data from 1990 to 2021. The data was obtained from the International Energy Agency (IEA) website. The study only considers one variable, which is the annual electricity consumption in Algeria. The research aims to contribute to the development of accurate forecasting models that can assist in effective energy planning and management in Algeria. The results of the study will be relevant for policymakers, energy companies, and other stakeholders involved in the energy sector in Algeria. By comparing the different forecasting methods, the study seeks to identify the most accurate method for forecasting electricity consumption in Algeria.

3.2. ARIMA model

The ARIMA (Autoregressive Integrated Moving Average) model, which was proposed by Box and Jenkins in 1970, is one of the most popular linear models for time series analysis (Merh et al, 2010). The model assumes that the future value of a variable is a linear function of several past observations and random errors. Therefore, a time series can be modeled as a combination of past values and errors (Wang et al, 2013). The general form of ARIMA models is written as ARIMA(p,d,q), where p is the number of parameters in the autoregressive (AR) model, d is the degree of differencing, and q is the number of parameters in the moving average (MA) model (Al-Chalabi et al, 2018).

$$y_t = \theta + \sum_{i=1}^{p}(\emptyset_t y_{t-1}) + \sum_{i=1}^{q}(\varphi_t \varepsilon_{t-1}) + \varepsilon_t \quad (1)$$

Where:

θ: the mean value of the time series data.

$\emptyset$: autoregressive coefficients (AR).

φ: moving average coefficients (MA);

ε: the white noise of the time series data;

d: represents the number of differences calculated from equation (2)

$$\Delta y_t = y_t - y_{t-1} \quad (2)$$

ARIMA models are based on three steps: model identification, parameter estimation, and diagnostic checking (Khashei & Bijari, 2012).

Model identification step: The first step in ARIMA modeling is to identify a stationary time series. This is determined using methods such as autocorrelation function (ACF), partial autocorrelation function (PACF), Augmented Dickey Fuller (ADF) test, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, and Phillips-Perron (PP) test. non-stationary data can result in increased prediction errors. Based on the ACF and PACF graphs, the values of q and p are determined respectively (Barak & Sadegh, 2016).

Model estimation step: Once a stationary series is identified, the next step is to estimate the coefficients of the ARIMA model. The most common methods used for estimation are Maximum Likelihood Estimation (MLE) or linear least-squares estimation. In order to compare the estimated models, a minimal criterion is relied upon, such as Akaike's Information Criterion (AIC) and Bayesian Information Criteria (BIC) (Mondal et al, 2014).

Diagnostic checking step: After estimating the model, diagnostic checks are performed to assess the statistical adequacy of the estimated model. This involves checking whether the error terms are white noise, which means they are uncorrelated with zero mean and constant variance. If the estimated model is found to be inadequate, the three stages are repeated until a satisfactory ARIMA model is selected for the time-series under consideration (Ray et al, 2016).

3.3. Radial Basis Function Neural Network

The radial basis function neural network (RBFNN) is a type of feedforward network that has been used in various applications, including function approximation, classification, and time-series prediction (Heddam, 2016). The network consists of three layers, namely an input layer, a hidden layer, and an output layer (Chang & Chen, 2003). In RBFNN, the flow of data begins at the input layer, where the input signal is fed into the network. The signal then propagates through the hidden layer, where each neuron in the layer applies an activation function. The activation function used in the hidden layer is typically a radial basis function, which allows the network to learn complex nonlinear relationships between inputs and outputs (Singh et al., 2014).

The input and output layers of RBFNN employ linear activation functions, while the hidden layer uses a nonlinear activation function. The output of the hidden layer is a weighted sum of the input signals, which are then transformed by the activation function to produce an output signal. In the output layer, a linear activation function is used to combine the weighted outputs of the hidden layer neurons to produce the final network output. This output, denoted as $\hat{y}_k(x)$, can be calculated using the equation (3) (Yan & Ma, 2016).

$$\hat{y}_k(x) = \beta_0 + \sum_{i=1}^{n} \omega_i \rho_i(x) \qquad 1,2, \ldots\ldots, n \quad (3)$$

Where:

x is the input vector.

β_0 is the bias term.

ω_i is the connecting weight between the hidden unit and the layer output unit.

ρ_i is the activation function of radial basis function.

(x) denotes the Euclidean distance between the input vector and the vector of the centers of the basis function ρ_i.

Overall, RBFNN is a powerful neural network architecture that is capable of modeling complex relationships in high-dimensional data. Its ability to learn nonlinear relationships and its simple structure make it a popular choice in various fields, including finance, economics, and electricity.

There are various types of activation functions that can be used in the hidden units of a radial basis function neural network (RBFNN) to model the hidden output response. In this paper, the Gaussian activation function, as defined below in Equation (4), is commonly chosen for RBFNNs. (Chang et al., 2016).

The Gaussian activation function is a non-linear function that has a bell-shaped curve. It is often used in RBFNNs because it can model a wide range of data distributions.

$$\rho_i(x) = exp\left(-\frac{\|x - c_i\|^2}{2\delta_i^2}\right) \quad (4)$$

Where:

δ_i is the width of hidden neuron basis function (the width parameter).

$\|.\|$ is the Euclidean distance between the input vector and the vector of the centers of the basis function.

3.4. Khashei and Bijari's Hybrid Model

Time series data often exhibits both linear and nonlinear characteristics, making it challenging to model accurately. To address this, a hybrid methodology that combines ARIMA (AutoRegressive Integrated Moving Average) and ANN (Artificial Neural Network) models has been utilized. This approach, as reported by Aladag et al. in 2009, has shown to produce more accurate forecast results compared to using individual models. The combined strengths of ARIMA and ANN allow for capturing both linear and nonlinear patterns in the data, resulting in improved forecasting accuracy. Büyükşahin and Ertekin in 2019 also supported the effectiveness of the hybrid methodology in time series data analysis. This relationship can be expressed as a powerful tool in time series forecasting, benefiting various industries such as finance, economics, and electricity prediction.

This relationship can be formulated as:

$$y_t = f(L_t, N_t) \quad (5)$$

Where L_t and $N_t$is the linear and the nonlinear component, respectively.

The hybrid model for time series forecasting that consists of three steps, according to Pannakkong et al. (2019). In the first step, the model extracts the linear component $(\hat{L})$ from the time series using the ARIMA model. In the second step, the nonlinear components are defined as functions of lagged values of the ARIMA residuals (e_t) and lagged values of the time series (y_t). In the third step, the model applies the ANN model to determine the function representing the relationship between the time series and the linear and nonlinear components.

Additionally, the steps of the hybrid model can be described according to Khashei & Bijari (2011). In the first step, the linear modeling is applied using an autoregressive integrated moving average (ARIMA) model. In the second step, the nonlinear modeling is applied, where the authors assume that the nonlinear pattern still exists in the ARIMA residuals and the original data. Thus, the nonlinear components are defined as functions of the lagged values of the ARIMA residuals and the lagged values of the original data.

$$N_t^1 = f^1(e_{t-1}, \dots, e_{t-n}) \quad (6)$$

$$N_t^2 = f^2(e_{t-1}, \dots, e_{t-m}) \quad (7)$$

$$N_t = f(N_t^1, N_t^2) \quad (8)$$

Where f^1, f^2 are the nonlinear functions determined by the neural network, and (n, m) are integers representing the number of maximum previous periods included in the model, often referred to as orders of the model.

In the third step, the combined forecast of time series can be represented by the function of the linear and the nonlinear components as:

$$y_t = f\left(N_t^1, \hat{L}_t, N_t^2\right) = f\left(e_{t-1}, \dots, e_{t-n}, \hat{L}_t, e_{t-1}, \dots e_{t-m}\right) \quad (9)$$

where f are the nonlinear functions determined by the neural network; and are integers that are determined in the design process by varying them from one to twelve (Pannakkong et al,2019).

4. Empirical Results and Discussion

Descriptive statistics

Table 1 presents the descriptive statistics of net electricity consumption in Algeria, while Figure 1 shows the corresponding time-series graph.

Table 1. Descriptive statistics of Net Electricity Consumption in Algeria

ELC	35.20	29.25	74.40	13.70	19.919	0.714	2.104	3.796	0.14
Statistic	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability

Source: Author’s calculations

The range of net electricity consumption in Algeria is 74.35 - 13.7 = 60.65. This means that the highest net electricity consumption in Algeria is 60.65 greater than the lowest net electricity consumption. The mean net electricity consumption in Algeria is 35.20 billion kWh. This means that the average net electricity consumption in Algeria is 35.20. The median net electricity consumption in Algeria is 29.25 billion kWh. This means that half of the net electricity consumption values in Algeria are greater than or equal to 29.25 and half are less than or equal to 29.25. The standard deviation of net electricity consumption in Algeria is 19.91976. This means that the typical net electricity consumption in Algeria is 19.91976 away from the mean net electricity consumption. The kurtosis of net electricity consumption in Algeria is 2.104193. This means that the net electricity consumption values in Algeria are more peaked than a normal distribution. The skewness of net electricity consumption in Algeria is 0.714941. This means that the net electricity consumption values in Algeria are slightly right-skewed.

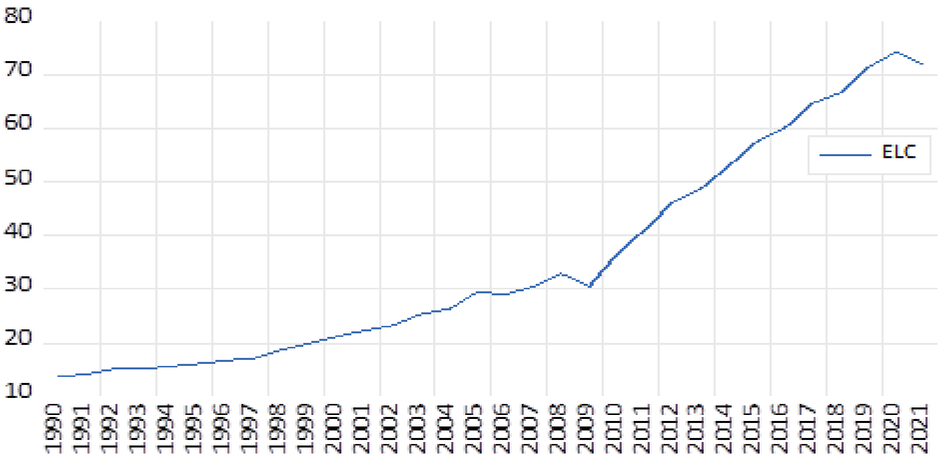

Figure 1. The time series plot of net electricity consumption in Algeria

Source: Prepared by the authors

4.2. ARIMA model

Upon examining the electricity consumption figure, it was observed that there was an increasing trend over time, indicating that the series was non-stationary. In order to confirm the non-stationarity of the series, an Augmented Dickey-Fuller (ADF) test was conducted. The p-value obtained from the ADF test was 0.9997, which was insignificant, thereby indicating that the series had a unit root and was non-stationary. To convert the non-stationary series to a stationary one, the lag differencing technique was used.

The ADF test was conducted again on the differenced data, and the p-value obtained was 0.0044, which was significant. Hence, it was concluded that the series was stationary at the first difference level.

After verifying the stationarity of the series, the ACF and PACF correlograms were plotted to identify the most suitable model for the electricity consumption data. Based on careful examination of the ACF and PACF plots, several models were tested, and the best one was selected using the Bayesian Information Criterion (BIC) and Akaike's Information Criteria (AIC) techniques.

It was observed that the ARIMA (0,1,3) model had the least AIC (4.363) and BIC (4.595) values, indicating that it had the least performance error. Therefore, it was chosen as the best ARIMA model for electricity consumption.

4.3. RBFNN model

We experimented with several shapes of the Radial Basis Function (RBF) neural network architecture to fit our model. We then evaluated the performance of each model using the Mean Squared Error (MSE) measure, and after analyzing the results, we determined that the most appropriate network for our model was (1,9,1).

The chosen RBF neural network architecture consists of an input layer with one input node, a single hidden layer with nine nodes, and an output layer with one output node, which is represented as (1,9,1). We used the Normalized Gaussian Radial Basis Function activation function in the hidden layer and Linear activation function at the output layer.

Overall, our analysis led us to conclude that the (1,9,1) RBF neural network architecture with Normalized Gaussian Radial Basis Function in the hidden layer and Linear activation function at the output layer is the most suitable architecture for our model based on the performance metric of Mean Squared Error (MSE).

4.4. Hybrid ARIMA-RBFNN model (Kashei & Bijary, 2011)

Once we obtained the ARIMA (0,1,3) model, we used both the Estimated values and the Previous values and Previous residuals as inputs for this model to obtain the optimal RBF network structure. We experimented multiple times and evaluated the performance of each model using the Mean Squared Error (MSE) standard until we arrived at the most suitable network architecture.

The optimal RBF neural network architecture consists of a three-layer structure - an input layer, a hidden layer, and an output layer. The input layer contains three processing units that represent $\left(y_{t-1}, \hat{L}, e_{t-1}\right)$, and a single hidden layer with eight nodes, and an output layer with one node. This architecture is represented as (3,8,1).

The activation function used in the hidden layer is the Normalized Gaussian Radial Basis Function, and the activation function at the output layer is Linear.

To summarize, based on our analysis, the combined model will use the ARIMA (0,1,3) model with the optimal RBF network architecture of (3,8,1) using Normalized Gaussian Radial Basis Function in the hidden layer and Linear activation function at the output layer. This combined model is expected to provide more accurate and reliable predictions for the given data. Thus the hybrid model is given according to the following equation:

$$\hat{y}_t = f\left(y_{t-1}, \hat{L}_t, e_{t-1},\right) = ARIMA\_RBF(0,1,3)(3,8,1) \qquad (10)$$

4.5. Comparison of Models Performance

To determine the best model among ARIMA, RBFNN, and the hybrid ARIMA-RBFNN model, we compared their accuracy measures using the Root Mean Square Error (RMSE) on the training and testing datasets. RMSE is calculated as the square root of the Mean Squared Error (MSE) and is expressed as follows (Ma et al, 2020):

$$RMSE = \sqrt{MSE} \qquad (11)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(Y_i - \hat{Y}_i\right)^2 \qquad (12)$$

Table 2 presents the RMSE results for the training and testing datasets of electricity consumption from the three models. The RBFNN model had an RMSE value of 0.22668722, the ARIMA model had an RMSE value of 1.795780, and the hybrid model had an RMSE value of 0.35795116. Therefore, the RBFNN model had the best results, followed by the ARIMA model and the hybrid model.

Based on these results, we can conclude that the forecasting capacity of the RBFNN model is better than that of the ARIMA model and the hybrid model for the given dataset of electricity consumption. The RBFNN model can provide more accurate and reliable predictions for the future values of electricity consumption.

Table 2. Comparison of the ARIMA, RBFNN and hybrid ARIMA-RBFNN models: RMSE values.

Models	**MSE**	**RMSE**
ARIMA (0,1,3)	1.34006716	1.795780
RBF (1,9,1)	0.0513871	0.22668722
KHASHEI (3,8,1)	0.12812903	0.35795116

Source: Author's calculations

Figure 2 illustrates a comparison of electricity consumption between the original values and the forecasted values of the ARIMA, RBFNN, and hybrid models. The figure shows that the RBFNN model successfully simulated the time series of electricity consumption for Algeria, as indicated by the RMSE results. This suggests that the RBFNN model has a better predictive performance compared to the ARIMA and hybrid models for this particular dataset.

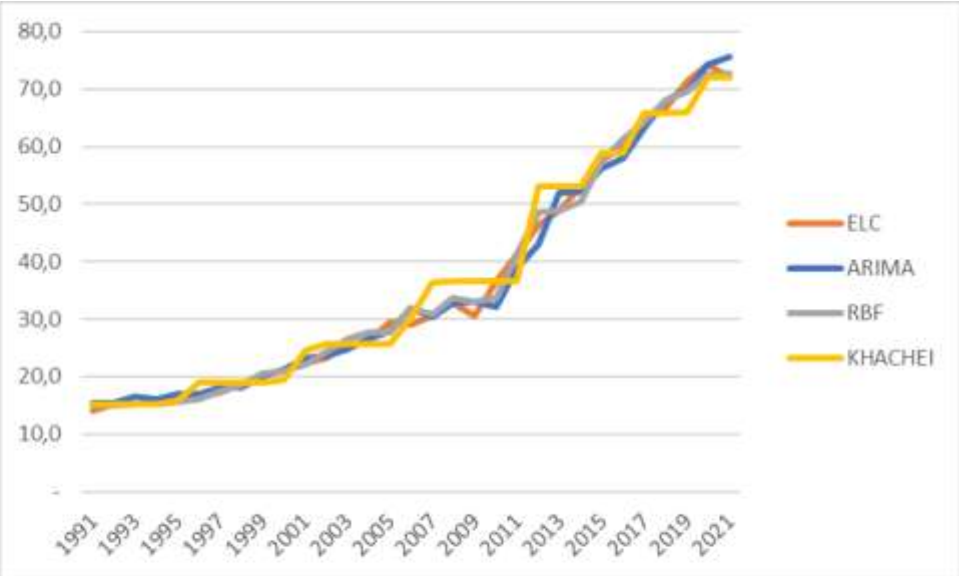

Figure 2: Comparison of Electricity Consumption between Original and Forecasted Values using ARIMA, RBFNN, and Hybrid Models

Source: Prepared by the authors

According to Table 3, there is a clear upward trend in electricity net consumption in Algeria from 2022 to 2030. The annual growth rate for the period is estimated to be around 2%, which indicates a significant increase in electricity demand. This trend is likely due to the country's population growth, urbanization, and economic development. The government of Algeria needs to take steps to ensure the sustainable supply of electricity to meet the growing demand.

Table 3. "Forecasted Electricity Net Consumption in Algeria by RBF (1,9,1) Model (2022-2030)

Years	Forecasting Electricity Net Consumption (billion kWh) RBF (1,9,1)
2022	72.1884
2023	72.1885
2024	72.2050
2025	73.0209
2026	76.3322
2027	77.7859
2028	81.0976
2029	81.9136
2030	81.9301

Source: Author's calculations

5. Conclusion

The aim of this study was to propose three models, namely ARIMA, RBFNN, and the hybrid ARIMA-RBFNN model, to increase the accuracy of time series forecasting. The dataset used for this study was obtained from the IEA website and contained annual electricity consumption data in Algeria from 1990 to 2021. The study results revealed that the optimized structures for the models were ARIMA (0,1,3), RBFNN (1,9,1), and the hybrid of ARIMA-RBFNN (0,1,3) (3,8,1). According to statistical measures such as MSE and RMSE, the RBFNN model was found to be the most effective in improving the forecasting accuracy compared to the ARIMA and hybrid models. These findings can be useful for decision-makers who require accurate time series forecasting for electricity consumption in Algeria. Moreover, the study identified a clear upward trend in electricity net consumption in Algeria from 2022 to 2030, with an estimated annual growth rate of around 2%, indicating a significant increase in electricity demand. This trend can be attributed to population growth, urbanization, and economic development. Therefore, the Algerian government needs to take appropriate measures to ensure the sustainable supply of electricity to meet the growing demand.

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