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ORIGINAL ARTICLE

Modelling and forecasting India's electricity consumption using artificial neural networks

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Abstract
Precise electricity forecasting is a pertinent challenge in effectively controlling the supply and demand of power. This is due to the inherent volatility of electricity, which cannot be stored and must be utilised promptly. Thus, this study develops a framework integrating canonical cointegrating regressions (CCR), time series artificial neural network (ANN) and a multilayer perceptron ANN model for analysing and projecting India's gross electricity consumption to 2030. Annual data for the years 1961–2020 have been collected for variables like gross domestic product (GDP), population, inflation GDP deflator (annual %), annual average temperature and electricity consumption. The study was conducted in three phases. In the first phase of the study, the CCR method was used to check the significance of the selected variables. In the second phase, the projected values of independent variables (GDP, population, inflation GDP deflator [annual %] and annual average temperature) were predicted using the time series ANN model. Finally, a multilayer perceptron ANN model with independent variables was used to forecast the gross electricity consumption in India by 2030. The result shows that the electricity consumption in India will increase by around 50% in the next 10 years, reaching over 1800 TWh in 2030. The proposed approach can be utilised to effectively implement energy policies, as an accurate prediction of energy consumption can help capture future demand.

1 | INTRODUCTION

The most crucial element fostering living standards and nurturing social and economic advancement is energy (Oyedepo, 2012; Yang et al., 2016). In recent times, there has been a significant surge in energy consumption due to the growing global population and the widespread use of power-intensive technology and equipment in individuals' daily routines (Mir et al., 2020). However, the upsurge in global electricity consumption is steady and will likely continue to increase at a pace that is greater than double that of the increase in global energy consumption (IEA, 2019). Therefore, a nation needs to be able to deliver power in precise proportion to demand. However, power outages happen, and industries reliant on electricity are negatively impacted when a nation's electricity generation capacity is less than its total demand. On the flip side, when a nation's electricity generation potential is higher than its overall demand, power plants operate at idle capacity, wasting money (Günay, 2016). However, governments are becoming more worried about the security of their energy supply due to several factors. These include the escalating energy costs, the growing global need for energy, the rapid depletion of fossil fuel reserves and the economic limitations of emerging energy technologies in meeting the expanding energy requirements (Kucukali & Baris, 2010). Therefore, it is crucial to accurately forecast future power demand to create new electricity-generating investments and maintain the balance between supply and demand.

India ranks third among the electricity consumers in the world as a result of growing income and improved living standards (IEA, 2021). Thus, it is anticipated that India will make a contribution more than any other nation to rising world electricity consumption by 2030 (Hossain et al., 2022; UNFCCC, 2020). The smooth production operation of various industries by providing uninterrupted electricity supply is crucial for Indian economic growth to accomplish 'Vision 2047', a vision to make India one of the three largest economies globally as well as move closer to a developed country by the 100th year of its liberation (Narayan & Prasad, 2022). This makes it necessary to accurately estimate the amount of electricity required to meet the needs of the country's roughly 1.4 billion people. Strong networks and other forms of flexibility are extremely important given the speed of transformation in the electricity sector in India. Over the next 20 years, India's construction space is expected to be doubled, with metropolitan regions hosting 70% of the new development. Additionally, during the coming decades, the need for energy will be under tremendous pressure from automobiles, new industries and the 'Make in India' initiative. In several key markets, the sharp rise in demand exceeded the capacity of energy supply, leading to scarcities of gas and coal and adverse consequences on power producers, distributors and end consumers, particularly in China and India (IEA, 2021).

For government officials and related institutions in both industrialised and developing nations, modelling and projecting electricity consumption is crucial. However, it is particularly crucial for developing nations, as they rely significantly on imported electricity due to a lack of resources and capital investment in electricity production. As a result, both underestimating and overestimating the need for power is expensive in terms of lowering people's standard of life and wasting their resources' potential (Kavaklioglu, 2011). However, there are a lot of uncertainties that might affect the accuracy of long-term forecasts, so the unwavering attention of researchers in this specific sector and the ongoing emergence of new ways for more precise and consistent predictions are a concern now (Ekonomou, 2010). Therefore, it would be preferable to accurately predict electricity use to prevent costly errors. Additionally, as the pattern of the power consumption data typically is not linear, it is preferable to utilise frameworks that can accommodate nonlinearities across variables (Kavaklioglu, 2011). It is common knowledge that artificial neural networks (ANN) can accurately mimic any nonlinear connection by varying the network configuration (Gallo et al., 2014; Mutascu, 2022; Sarkar, Shankar, & Chaurasiya, 2015; Sarkar, Shankar, Thakur, et al., 2015). Thus, the multilayer perceptron ANN approach is the main instrument in this study and is utilised to get reliable forecast results. Nevertheless, similar to other concerns in modelling, it is imperative that a model incorporates all conceivable variables that may influence the desired outcome. To address this problem, population and gross domestic product (GDP) per capita as a proxy for economic growth, temperature and inflation rate are used as inputs to predict India's total electricity consumption, which is based on long-term data from 1961 to 2020.

Several social and economic factors that influence electricity consumption, whether directly or indirectly, should be taken into account in the model to improve prediction. The economic profile of a country has a considerable impact on the electricity demand (Mir et al., 2020). For instance, the patterns of power demand vary for advanced and emerging nations. While demand is growing at a pace of 0.7% yearly in wealthy nations, it is now growing at a rate of 3% annually in emerging nations (IEA, 2019). The electricity demand tends to increase as economic activity grows (Son & Kim, 2020). One economic proxy that measures a nation's population's wealth is its GDP per capita (Kucukali & Baris, 2010). People's living conditions improve and their reliance on electricity-intensive equipment and devices grows as the GDP per capita rises. The inflation rate is yet another economic aspect that may have an impact on the electricity demand (Zahedi et al., 2013). It is essential to include these economic drivers in the prediction model to more accurately forecast (Liu et al., 2018).

The population is another main variable that strongly influences the demand for electricity since more population uses more power (Günay, 2016). However, the size of the population alone is insufficient to account for variations in the demand for power over time. The amount of power used may also be influenced by environmental factors, like typical temperatures. In the summer, more power is used for domestic cooling, refrigeration and irrigation; in the winter, more electricity is used for household heating systems as a result of the cooler temperatures outside (De Felice et al., 2013; Ekonomou, 2010). India has a wide range of simultaneous temperature patterns, making it challenging to collect separate measurements for summer and winter. As a result, we use the yearly average temperature.

In several researches, a variety of forecasting techniques based on data mining were used to estimate future power or energy consumption. Multiple linear regression approach (Bianco et al., 2013; Ekonomou, 2010; Kialashaki & Reisel, 2014; Panklib et al., 2015), fuzzy logic (Ali et al., 2016; Islas et al., 2021; Kucukali & Baris, 2010; Olaru et al., 2022; Zahedi et al., 2013), autoregressive forecasting methods (Guefano et al., 2021; Kaytez, 2020; Nawaz et al., 2014; Nepal et al., 2020; Ozturk & Ozturk, 2018), support vector regression methods (Ekonomou, 2010; Hong & Fan, 2019; Kavaklioglu, 2011; Kaytez, 2020; Shao et al., 2020) and ANN (Ekonomou, 2010; Elbeltagi & Wefki, 2021; Günay, 2016; Kialashaki & Reisel, 2014; Li et al., 2018; Sarkar, Shankar, & Chaurasiya, 2015; Sarkar, Shankar, Thakur, et al., 2015; Torabi et al., 2019; Zahedi et al., 2013) have been extensively employed for this purpose. Several studies have been published over the past 10 years using a variety of approaches to anticipate the demand for electricity in various nations. However, India, the third-largest power user worldwide, is still unexplored regarding such research. This is the central research void that this study seeks to fill. As a result, Indian policymakers would be better equipped to formulate policies linked to power generation and strike a balance between the production and use of electricity.

The current study offers four different contributions.

1. Predicting India's Electricity Consumption: The study is, to the author's knowledge, one of the very first research devoted to foretelling India's electricity consumption using a variety of approaches. Our study utilises a pioneering methodology that integrates the capabilities of a multilayer perceptron ANN with time series modelling. Data integration enables the comprehensive analysis of complex and evolving interconnections, encompassing historical patterns and nonlinear trends. Consequently, this approach facilitates a more precise estimation of electricity consumption.
2. Versatility and Comprehensive Analysis of Influencing Factors: This study is the inaugural thorough endeavour in India to examine and quantify the effects of multiple parameters, namely population size, temperature, inflation and gross GDP per capita, on gross electricity consumption. The comprehensive examination of these aspects is distinctive and crucial for comprehending the intricacy of energy consumption dynamics within the Indian setting. Additionally, we have validated the relevance of these parameters by utilising the canonical cointegrating regressions (CCR) approach.
3. Unique Prediction Scope and Dataset Expansion: Unlike prior research endeavours, our analysis offers projections for the total magnitude of power utilisation and provides targeted forecasts for the determinants of electricity use. The transition from making broad predictions to conducting a comprehensive analysis of the factors that influence the outcomes of our study enriches the depth and practicality of our results. In addition, our study uses an extended dataset encompassing a significant period of 60 years (1961–2020). The study's sizeable temporal scope is a distinctive and noteworthy characteristic, facilitating a thorough comprehension of long-term trends and patterns in energy usage.
4. Methodological Comparison and Real-World Application: This study compares the predictions of multilayer perceptron ANN and time series ANN models with official forecasts. The purpose of this comparative study is twofold: firstly, to authenticate our models, and secondly, to showcase the practical feasibility of our technique in forecasting scenarios that occur in real-world settings. In brief, the innovation of our approach stems from its distinctive amalgamation of state-of-the-art methodologies, exhaustive examination of many influential variables, enrichment of time series data and the pragmatic implementation of our discoveries. The combination of these factors collectively contributes to a notable progression in comprehending and forecasting energy consumption patterns in India.

The other sections of the article are structured as follows: 'Section 2' cover the data and technique, while 'Section 3' give the empirical findings and their interpretation. The study is concluded with some policy proposals in the 'Section 4'.

2 | COMPUTATIONAL DETAILS

2.1 | Data

Historical data for GDP (constant 2015 US$), population, inflation GDP deflator (annual %), annual average temp (input variables) and gross electricity consumption (output variable) were gathered from several sources from the years between 1961 and 2020. The GDP (constant 2015 US$) was extracted from World Bank Open Data (*World Bank Open Data – GDP*, 2022). The historical annual average temperature data were mined from the Climate Change Knowledge Portal and World Bank Database (*CCKP and World Bank Open Data*, 2022). The population data were compiled using Open Data from the World Bank (*World Bank Open Data – Population*, 2022). The dependent variable electricity consumption (in TWh) was sourced from the BP Statistical Review of World Energy (*BP Statistical Review of World Energy*, 2022). The annual percentage inflation GDP deflator was generated from the World Bank Database (*World Bank Open Data*

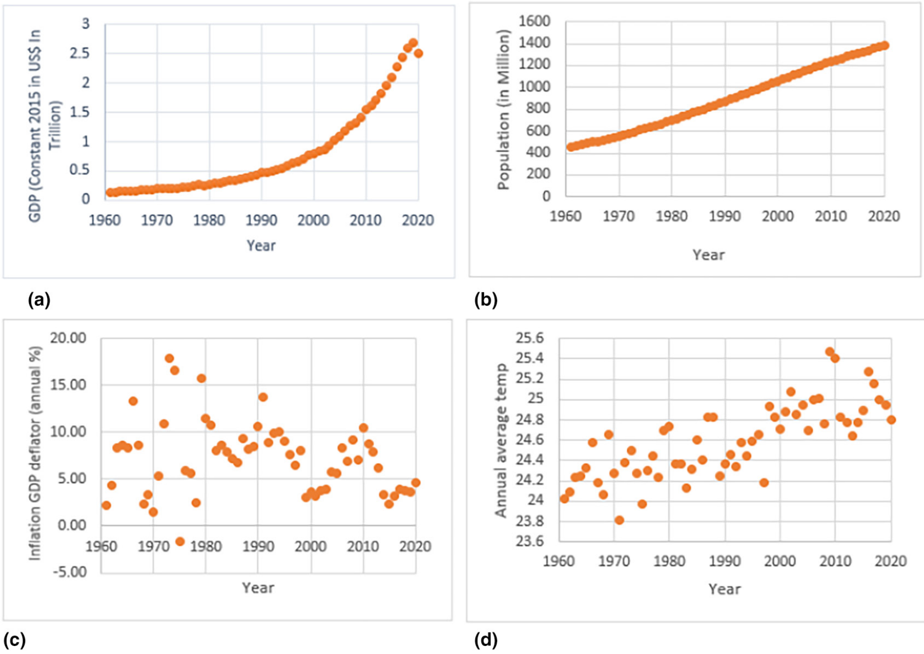

FIGURE 1 Input variables used in this study: (a) GDP (constant 2015 US$), (b) population, (c) inflation GDP deflator (annual %) and (d) annual average temperature.

– *Inflation*, 2022). The closest values were used to determine the missing data points in the dataset using linear interpolation or extrapolation.

The scatter diagram of all the input variables is shown in Figure 1. The figure shows us that the population reached 1.38 billion in 2020, while it was approx. 698 million in 1980, which indicates that it has (approx.) doubled in 40 years of span. The GDP value of India shows us an upward trend; for example, it has been multiplied by a factor of 9.22 from the year 1980 to 2020, reaching above $2.5 trillion. The inflation range averaged around 5%–10% between 1980 and 2010, while it came to around 15% in 1980 and 1990. As the graph shows, for the last 10 years, it has been below 5%. The annual average temperature shows an increasing trend in the graph. The average temperature increased around 1.4°C from 24.07°C to 25.41°C between 1970 and 2017.

2.2 | Methods

This study used the MATLAB (R2022a) environment to write the codes and develop the computational models. Descriptive variables like GDP (constant 2015 US$), total population, inflation GDP deflator (annual %) and annual average temperature were used to determine the total electricity consumption in India. The study was conducted in three phases. In the first phase of the study, the CCR method was used for the available data to check the significance of selected variables. Figure 2 illustrates the schematic flow of the study.

In the second phase, the time series ANN model (Model I) and the multilayer perceptron ANN model (Model II) were used to determine the values of the future years. To simulate the time series ANN models (Model I), a significant descriptive variable (e.g. GDP) at year '*t*' was considered a function of its past value to determine the future values, as shown in Figure 2. A similar procedure is applied to determine the future value of other significant descriptive variables. The multilayer perceptron ANN model (Model II) was used to forecast the total electricity consumption in India, as shown in Figure 3. In the final model, statistically significant variables are fed as an ANN input to determine future electricity consumption.

In MATLAB, the 'trainlm' function was used in both models to train the neural networks. The network training function updates bias values and weights according to Levenberg–Marquardt optimisation based on the Gauss–Newton and gradient descent methods. It is considered one of the fastest and most stable backpropagation algorithms. It is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms. While developing the neural network models, hidden layers were used to deal with data nonlinearity. For developing the

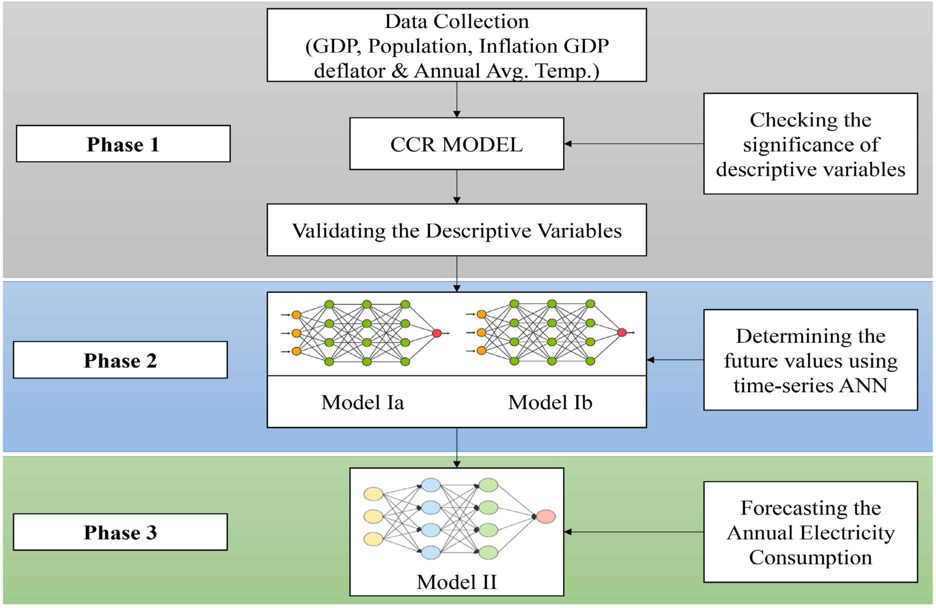

FIGURE 2 Schematic flow.

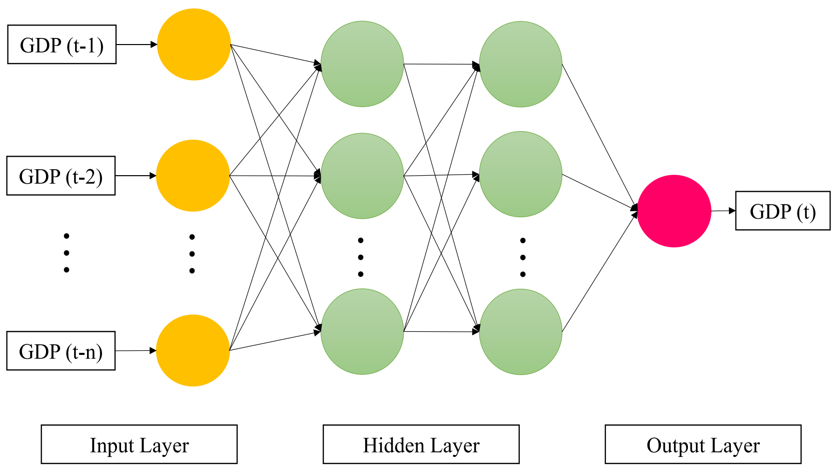

FIGURE 3 Time series ANN Model I to determine the GDP in the future from its past values.

time series ANN model for each statistically significant descriptive variable, the 'narnet' function of MATLAB was implemented. *Narnet* stands for 'Nonlinear autoregressive neural network'. In NAR prediction, the future values of a time series are predicted only from the past values of that series. For each descriptive variable, data from 1961 to 2010 are used in the time series ANN Model (Model Ia) to predict future data (2011–2020). The developed model was trained for eight iterations, with a learning rate of 0.9, and for 5000 epochs until a minimum value was reached.

Further, the predicted values for the years 2011–2020 for each descriptive variable were compared against the original available data to finalise the model parameters for Model Ib. Similar parameters were fed in Model Ib for each input (descriptive) variable. Future values of GDP (constant 2015 US$), total population, inflation GDP deflator (annual %), annual average temperature and total energy consumption were predicted.

In the third phase of the study, a multilayer perceptron ANN model (Model II) was developed to predict the total electricity consumption in India by 2030. ANN consists of three layers: the leftmost layer is the input layer, the middle portion is the hidden layer and the rightmost layer is the target/output layer, as shown in Figure 4. The developed Model II was loaded with descriptive variables in the input layer and total electricity consumption in the target layer. Further, 'trainlm' was used to train the Model II. The entire dataset (1961–2020) was divided into three parts. 70% of the data were used to train the network, 15% was used to test the network and the rest 15% was used to validate the model. Once training is

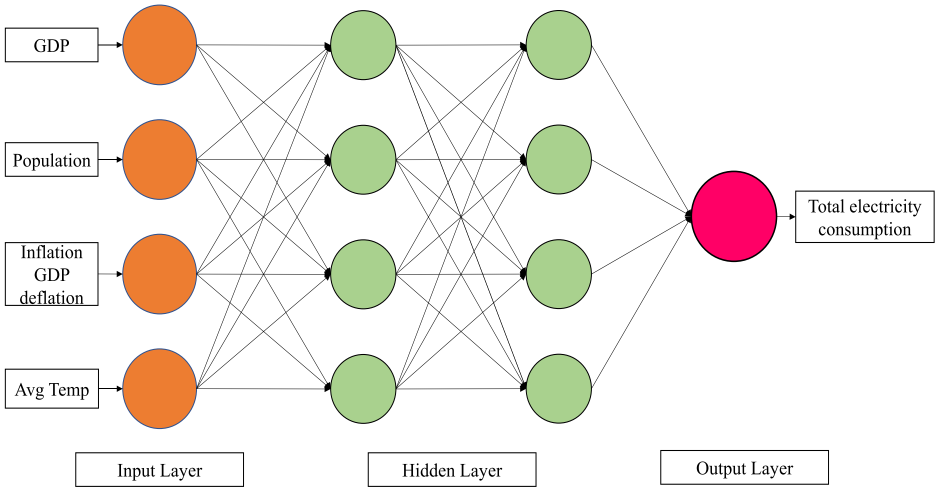

FIGURE 4 Multilayer perceptron ANN model (Model II) to determine the electricity consumption.

complete, the individual outputs from Model Ib (e.g. GDP from 2021 to 2030) for descriptive variables are fed as a sample input to Model II to forecast the total electricity consumption. Various combinations of neurons, transfer functions and performance criteria (MSE, RMSE and MAPE) were examined to attain the best feasible projected electricity consumption numbers.

3 | RESULTS AND DISCUSSION

The results and discussion section are shown in three parts: First, the statistically significant variables are identified using the CCR method for all the independent (descriptor) variables (GDP [constant 2015 US$], population, inflation GDP deflator [annual %] and annual average temp). Then a unit root test was applied to find the relative significance of the variables.

In the second part, the data from 2011 to 2020 were removed from the dataset. The statistically significant independent values were predicted using the time series ANN model, which was trained using the data between 1961 and 2010. In the next phase, the multilayer perceptron ANN model is used to forecast the dependent variable, electricity consumption, between 2011 and 2020 using earlier predicted values of the independent variables. Then the results were compared with actual electricity consumption values. The success and reliability of this advanced forecasting approach are tested using this approach.

In the final and third part, the data between 1961 and 2020 were used to forecast electricity consumption between 2021 and 2030. The method applied was similar to that of the second part. First, the future values of independent variables (GDP, population, inflation GDP deflator [annual %] and annual average temp) were predicted using the time series ANN model. Next, a multilayer perceptron ANN model with independent variables was used to forecast future electricity consumption values.

3.1 | Determining the statistically significant variables for future electricity consumption

The data from the years 1961–2020 were used to model the CCR method as shown in Equation (1), where electricity consumption is the dependent variable (modelled as an estimated value of $\hat{y}$), whereas GDP in constant 2015 US$ (x_1), inflation GDP deflator in annual percentage (x_2), total population (x_3) and the annual average temperature in Celsius (x_4) were the independent (input) variables.

$$\hat{y} = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \beta_3 \cdot x_3 + \beta_4 \cdot x_4. \tag{1}$$

Before conducting the CCR model, the unit root test is conducted to identify the stationarity property of the data series. Table 1 shows the unit root test result. As a rule of thumb, in order to avoid spurious regression, the time series variable should be integrated with I(0) or I(1). Further, we have also provided the Zivot–Andrews unit root test with a structural break following Ohlan (2018). As from Table 1, the results of all the variables conform to the above rule. Hence, all the variables were kept in the CCR model. Since all of the variables had a degree of contribution to forecasting the electricity consumption accurately; therefore, all four variables were used for the rest of the models.

The final equation of the CCR model is given in Equation (2). The coefficients of CCR, its corresponding t-statistics, standard errors of the coefficients and its corresponding p-value as well as the overall model's R-squared value, adjusted R-square value, standard error of the regression, long-run variance, mean dependent variables, the standard deviation of the dependent variable and sum squared residue, were calculated. Independent variables with a p-value smaller than 0.01 with a significant level of 99% confidence interval were considered statistically significant and presented in Table 2.

$$\hat{y} = -27.32 + 1.21x_1 + 0.07x_2 + 1.93x_3 + 6.32x_4. \tag{2}$$

Since all of the independent variables have a p-value lower than the 0.01 value, they were statistically significant. Next, the coefficient of the CCR model was investigated, and the result was consistent with our expectations. For example, temperature and population have the highest and second-highest positive coefficients, that is directly proportional to electricity consumption. It should be emphasised that the significant variables affecting demand may vary by country; for example, a variable that correlates with energy consumption in one country may not have a significant correlation in another. As a result, before making future estimates, it's good to figure out what statistically significant variables affect a country's electricity demand.

3.2 | Forecasting the electricity consumption for the years between 2012 and 2020

This paper's primary purpose is to forecast future electricity consumption. Before that, the predicting skills of both the time series ANN model and multilayer perceptron ANN models were evaluated for the years for which data were available, using a process that was quite similar to that used for future prediction. This way, the existing approach's success was assessed; if the model could accurately anticipate electricity consumption in this time frame, it may be used to forecast future electricity consumption with high reliability. As a result, the data for the years 2012–2020 were excluded from the dataset. The statistically significant input variables (GDP [constant 2015 US$], population, inflation GDP deflator [annual %] and annual average temp) were forecasted for the years 2012–2020 from their past values using multilayer perceptron ANN models. GDP in the year 't' was framework as a function of GDP in the years '$t-1$' to '$t-n$' (Equation 3). Similarly, population, inflation GDP deflator (annual %) and annual average temp were framework as a function of previous values themselves, as shown in Equations (4–6).

$$\mathrm{GDP}_t = f\left(\mathrm{GDP}_{t-1}, \mathrm{GDP}_{t-2}, \dots, \mathrm{GDP}_{t-n}\right), \tag{3}$$

$$\mathrm{population}_t = f\left(\mathrm{population}_{t-1}, \mathrm{population}_{t-2}, \dots, \mathrm{population}_{t-n}\right), \tag{4}$$

$$\mathrm{inflation}_t = f\left(\mathrm{inflation}_{t-1}, \mathrm{inflation}_{t-2}, \dots, \mathrm{inflation}_{t-n}\right), \tag{5}$$

$$\mathrm{avg\ temp}_t = f\left(\mathrm{avg\ temp}_{t-1}, \mathrm{avg\ temp}_{t-2}, \dots, \mathrm{avg\ temp}_{t-n}\right). \tag{6}$$

Figure 5 exhibits the perceptron ANN forecasted graph for GDP (constant 2015 US$ in Trillion) and population (in Million). As evidenced by the strong coefficient of determination (R^2) values, the ANN model accurately estimated previous values (1961–2011) and forecasted future values (2012–2020) for both the GDP (constant 2015 US$) and population (in Million). Then, using the time series model and multilayer perceptron ANN models, the expected GDP (constant 2015 US$), population, inflation GDP deflator (annual %) and annual average temp for the years 2012–2020 were used to forecast annual electricity consumption for the said years. It should be emphasised that the models developed in this section were trained using data from the 1961 to 2011 period, with no actual data being used in the modelled years. In Figure 6, the forecasts of the time series and perceptron ANN models were compared to the actual values, indicating that the perceptron ANN model's forecasting ability was superior to the time series models. Although the time series model

TABLE 1 Unit root test.

Variable	Form	ADF (*t*-statistics)		PP (*t*-statistics)		Zivot–Andrews unit root test		Order of integration
		Intercept	Trend + intercept	Intercept	Trend + intercept	Intercept	Break date	
lnEC	Level	−1.261 (0.636)	−2.983 (0.153)	−1.633 (0.456)	−1.629 (0.763)	−1.054* (0.063)	2009	I(1)
	First difference	−3.978*** (0.003)	−4.252*** (0.009)	−4.093*** (0.002)	−4.375*** (0.006)	−6.077* (0.060)	2006	
lnGDP	Level	−2.722 (0.233)	−1.28 (0.878)	−0.284 (0.918)	−2.189 (0.482)	−4.077 (0.160)	2006	I(1)
	First difference	−2.942** (0.05)	−6.04*** (0.000)	−2.968** (0.046)	−2.671 (0.253)	−5.980 (0.032)**	1999	
lnINF	Level	−2.204 (0.208)	−2.581 (0.290)	−2.144 (0.229)	−2.691 (0.245)	−6.548 (0.499)	1999	I(1)
	First difference	−3.968*** (0.003)	−7.195*** (0.000)	−7.280*** (0.000)	−7.184*** (0.000)	−5.981** (0.033)	1996	
lnPOP	Level	0.071 (0.994)	−1.428 (1.00)	−2.037 (0.290)	−2.098 (0.313)	−3.874*** (0.000)	1992	I(1)
	First difference	−3.569** (0.045)	−4.08*** (0.000)	−7.021*** (0.000)	−7.041*** (0.000)	−5.786** (0.018)	2007	
lnTEMP	Level	−3.116** (0.033)	−4.996*** (0.001)	−1.432 (0.732)	−1.93 (0.621)	−5.912*** (0.002)	1998	I(0)/I(1)
	First difference	−6.755*** (0.000)	−6.661*** (0.000)	−8.122*** (0.000)	−8.992*** (0.000)	−5.758* (0.090)	2011	

Note: Probability value is given in parenthesis. *** denotes a 1% level of significance, ** denotes a 5% level of significance and * denotes a 10% level of significance.

TABLE 2 Parameters of the CCR model for estimating annual electricity consumption (full model).

Canonical Cointegrating regressions				
Variable	**Coefficient**	**Std. error**	***t*-statistics**	**Prob.**
Constant	−27.32***	2.38	−11,48	0.000
lnGDP	1.21***	0.13	9.31	0.000
lnINF	0.07***	0.02	3.51	0.000
lnPOP	1.93***	0.15	12.87	0.000
lnTEMP	6.32***	1.26	5.02	0.000
R-squared		0.989	Mean dependent var	5.987
Adjusted *R*-squared		0.981	SD dependent var	0.767
SE of regression		0.098	Sum squared residual	0.374
Long-run variance		0.0002		

Note: *** indicates significance at 1% level.

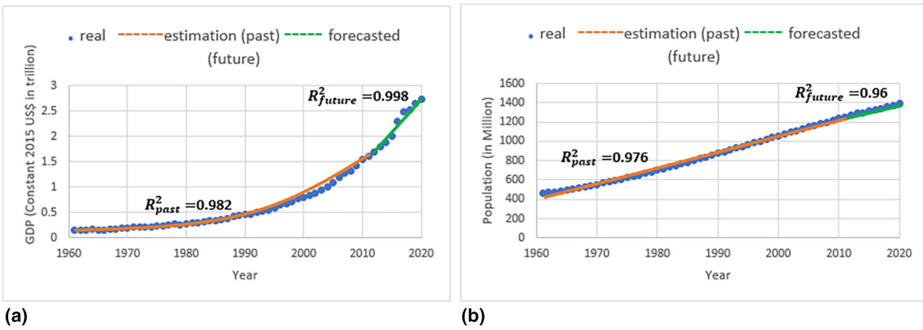

FIGURE 5 Forecasting (a) GDP (constant 2015 US$ in Trillion) and (b) population (in Million) using the perceptron ANN model for the years 2012–2020.

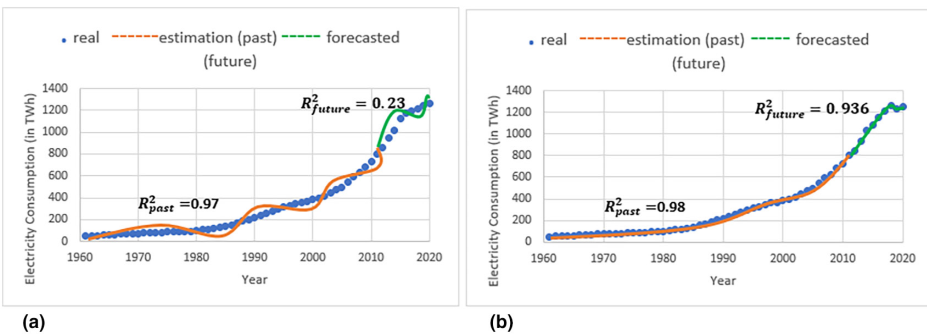

FIGURE 6 Forecasting the electricity consumption (in TWh) by (a) time series and (b) multilayer perceptron ANN model for the years 2012–2020.

estimated demand accurately in the past, it failed to forecast demand in the future (predicted results were greater than actual values). Consequently, the perceptron ANN model was better able to estimate future data; as a result, perceptron ANN modelling was used to complete the rest of the work.

3.3 | Forecasting the electricity consumption for the years between 2021 and 2030

In this phase of the model, the future values of GDP, inflation GDP deflator in annual percentage, population and annual average temperature are forecasted using the perceptron ANN model for the year between 2021 and 2030 using

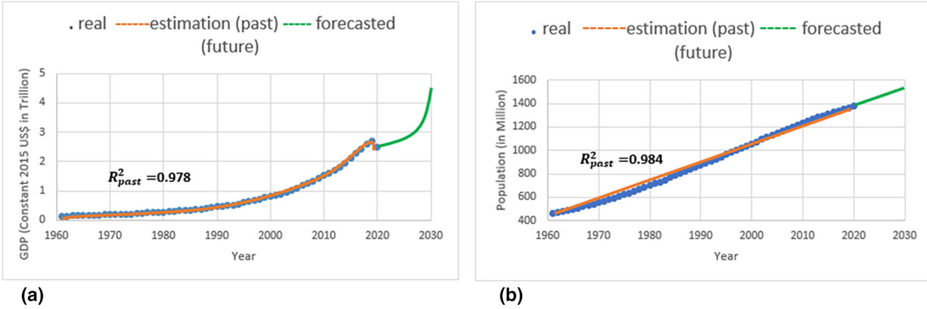

FIGURE 7 Forecasting (a) GDP (constant 2015 US$) and (b) population for the year between 2021 and 2030 using the perceptron ANN model.

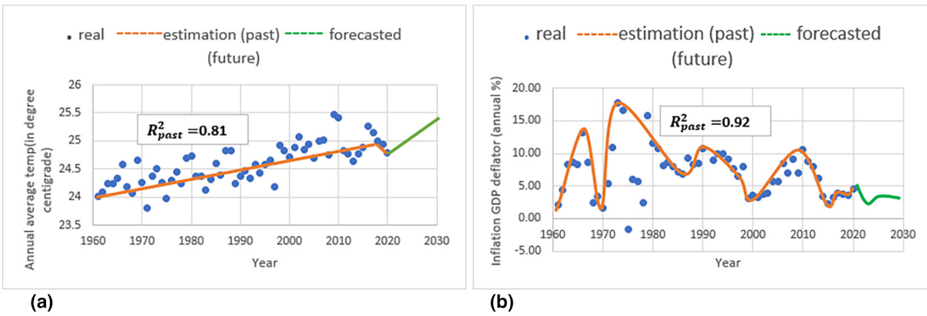

FIGURE 8 Forecasting (a) Annual average temperature (in degrees centigrade) and (b) inflation GDP deflator (annual %) for the year between 2021 and 2030 using the perceptron ANN model.

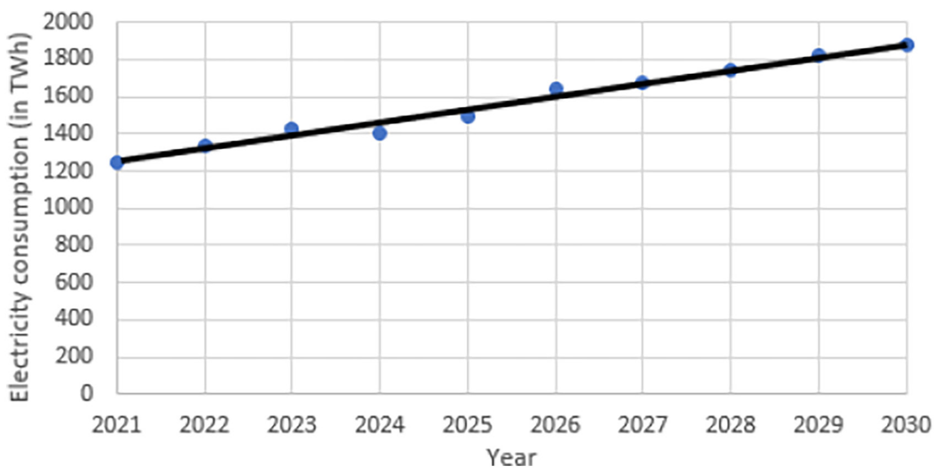

FIGURE 9 Forecasting the electricity consumption for the years between 2021 and 2030 using a multilayer perceptron ANN model.

the same ANN parameters that were modelled in Section 3.2. The change in GDP and population concerning different years is shown in Figure 7, whereas the values of inflation GDP deflator and annual average temperature are shown in Figure 8. The figures specify that the population will reach over 1.5 billion, while GDP (constant 2015 US $) is predicted to reach over $4.5 Trillion by 2030. The figure also captures the sudden drop in GDP in the years 2020 and 2021 because of COVID-19. Along with this, the inflation GDP deflator (in annual %) is expected to increase slightly to 6.3% in 2021 (which is precisely matching in 2022) and will decrease to around 4% in the year 2030. It also successfully captures the sudden increase in inflation in 2020 and 2021 because of COVID-19, as shown in Figure 8b. The average annual temperature is expected to increase by around 0.5°C in these years.

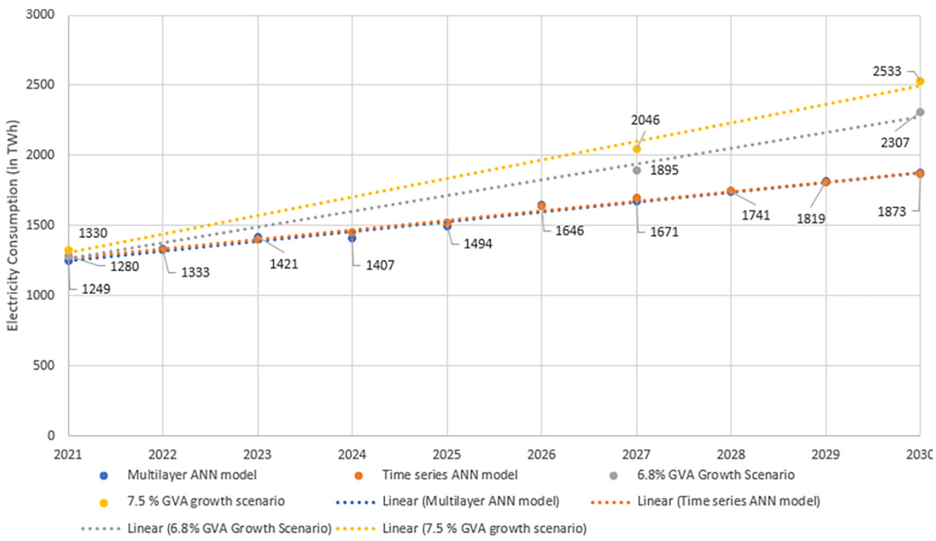

FIGURE 10 Comparison of multilayer perceptron ANN and time series ANN model prediction applied in this work with official prediction.

Lastly, the data from 1961 to 2020 were used to train the multilayer perceptron ANN model. The ANN model is simulated using the predicted values of input variables in the year between 2021 and 2030 to forecast the electricity consumption in the said period. Figure 9 reveals that electricity consumption will increase by around 50% in the next 10 years, attaining over 1800 TWh in 2030. The Energy and Resources Institute (TERI) & Energy Transitions Commission Of India's forecasts based on '6.8% GVA Growth' and '7.5% GVA Growth' scenarios for the 2021–2030 time period were compared to the forecasted results of the gross annual electricity consumption generated by the ANN models used in this study (Spencer & Awasthy, 2019). The official predicted values (approx. 2500 and 2300 TWh) were found to be much higher than the forecasted values (1800 TWh) of ANN models, as specified in Figure 10. Also, the exact figure revealed that the time series model's prediction is slightly higher than the perceptron ANN model's prediction.

4 | CONCLUSION AND POLICY IMPLICATIONS

The major source of carbon emission in any developing economy is electricity consumption from various sources, as most of the electricity is produced through burning fossil fuels. India being a fast-developing economy, the electricity consumption will keep increasing with further development. However, considering the burning issue of global warming and the COP26 pledge of India, the reduction of the ecological footprint is extremely essential. Various policy measures have been adopted by the Government of India to reduce carbon emissions; however, unless we have an estimate of the total energy consumption by 2030, it would be difficult to judge the efficacy of the policy measures in achieving the target. In this study, the total annual electricity consumption in India is forecasted using time series ANN and multilayer perceptron ANN models using independent variables like GDP, population, inflation and annual average temperature. The significance of the descriptive variables has been examined using the CCR method, and thereafter, the time series ANN model is used to forecast future values (2011–2020) using data from 1961 to 2010. Finally, the multilayer perceptron ANN model is used to forecast electricity consumption until 2030.

The results of the CCR model identified the significant contribution of all independent variables in predicting annual electricity consumption. The comparative analysis between the time series prediction model and the ANN model identifies that the ANN model performs better in forecasting future values. The future values of GDP, inflation GDP deflator in annual percentage, population and annual average temperature are forecasted using the time series ANN model for the year between 2021 and 2030 using the same ANN parameters. The results successfully capture the sudden drop in GDP as well as a sudden increase in inflation in the years 2020 and 2021 owing to the pandemic situation. Finally, the multilayer perceptron model of ANN forecasts that electricity consumption will increase by around 50% in the next 10 years, attaining over 1800 TWh in 2030.

The unique results obtained in this study provide important insights for the consideration of policymakers. The proposed approach can be utilised for the effective implementation of energy policies, as an accurate prediction of energy consumption can help in capturing future demand. Depending on future energy demand the policymakers can implement required directives for an effective energy transition from fossil fuel to renewable energy. Moreover, advance budget allocation for renewable energy projects can be prioritised depending on the forecasted consumption. Therefore, this approach can prove to be helpful in achieving the SDGs as well as fulfilling the COP26 pledge.

Considering the rapid rise in energy consumption, the government should increase investment in electricity infrastructure, which includes the expansion of power generation capacity, upgradation of transmission infrastructure and distribution networks. The infrastructure by only the government will not be efficient if private investment in the power sector is not facilitated; therefore, policies to encourage public–private partnerships are extremely important. Further, any supply or demand shock in the forecasted energy consumption can only be mitigated if energy efficiency programmes are properly implemented and promoted to optimise electricity usage. Investment is required in modernising the power grid to enhance reliability, resilience and the ability to integrate renewable energy sources. Smart grid technologies can improve the monitoring, control and efficiency of the electricity distribution system. These policy implications are general recommendations and should be tailored to the specific context and needs of the Indian economy. Policymakers should consider the social, economic and environmental aspects while formulating and implementing policies to address the forecasted increase in electricity consumption.

Future studies can use various other combinations of independent variables; for example, the price of electricity can be considered as a factor determining electricity consumption based on the choices available to the consumers. Moreover, future studies can focus on estimating the specific type of energy consumption, such as solar, hydropower etc., to help effective policy-making and budget allocation for specific energy sources. Finally, future studies can also improve the prediction models by implementing future developments in machine learning-based forecasting models, like deep learning, AI etc.

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