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A Neuro-Fuzzy Method for Forecasting Electricity Consumption in the Agricultural Sector for India

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Abstract

The forecasting of electrical energy consumption (EEC) plays a key role in the planning, scheduling, and operation of the power system. Consequently, accurate and reliable prediction of electrical energy consumption is important and electrical energy is also very relevant for developing and developed countries. As the economy of these countries grow in the positive direction, their electric energy consumption increases rapidly. In this research study, ANFIS technique is applied to predict the long-term agriculture sector (AS) EEC in India. The empirical data inputs identified in this study are population, per capita GDP and permanent crop land (% of land area) and the AS-EEC is the predicted output variable. The time span considered for the historical data used in this study are between 1970 and 2021. The available 46 years data are randomly divided into two categories, such as 80% of data is used to train the network and the remaining 20% is used to assess network accuracy. Based on the percentage error calculation, the constructed model shows the very good predicting performance. According to the predicted results by the proposed model, the AS-EEC in the following years 2025 and 2030 will reach 223.465 Tera Watt hour (TWh) and 255.023 TWh respectively.

Keywords. Electrical energy consumption; India; agriculture sector; ANFIS.

1. INTRODUCTION

Electrical energy consumption forecasting (EEC) plays an essential role in planning, scheduling, distribution and power system operation. In general, EEC is linked with the growth of economy and the human population. Recent two to three decades the development of the electrical and electronics industry in the developed and developing country, the EEC is increasing significantly due to the reason behind that, almost in all the field, majority of the work doing with the help of electrical energy and also increasing the human population. Predicting electricity demand has become a very important task for electricity utilities in order to support GDP growth in a positive trend and meet the demand

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for electricity continuously in the coming years [1]. Because of India's economic growth, energy demand has increased by an average of 3.6% per year over the past three decades. In this contest, a good forecasting method is essential for exact investment planning for new power generating stations and their types, providing additional/upgrading the transmission and distribution lines and installation/upgrading of the new transformers. The installed capacity of India in the year March 2021 was 382.1 Giga Watts, among that two third of the electricity is produced with the help of the fossil fuels and the remaining one third produced from nonrenewable energy sources.

In India, AS-EC is the third biggest sector of the electric energy consumption. In the year 2015, AS of India consumed 18.36% of electrical energy. Figure 2 shows that the AS-EC has increased exponentially from the year 1947 to 2021. It has increased from 90.292 TWh in 2005 to 214.97 TWh in the year 2021. The growth rate of AS-EC was around 10.59% for the year 2013-14 over 2014-15 and the EEC of AS was reached 17.89 %, which is highest in the year 2015-16 among all countries. Therefore, the forecasting of AS-EEC is essential. The primary objective of this research study is to provide an AS-EEC forecast model taking into account India's population input factors, per capita GDP and permanent cropland (percentage of land area).

For the last four decades, the forecasting of electric energy consumption/demand is a research area of widespread current attentiveness among the researchers. Since 1980, much research was conducted on the conventional methods and the applications of soft computing techniques [2]. Vincenzo Bianco analyzed the EEC prediction in Italy using regression analysis. They used a historical data between 1970 and 2007.

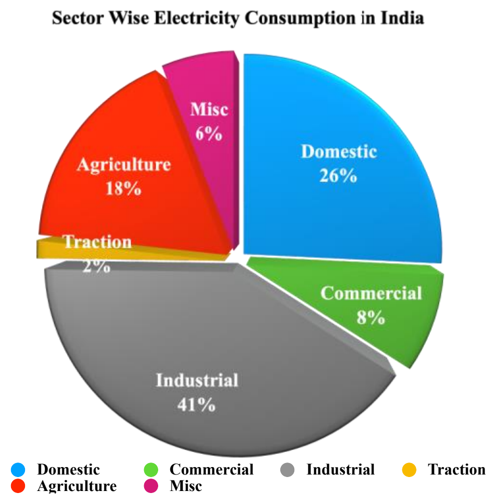

Figure 1. Sector wise electricity consumption in India as on 31 March 2021.

K. Panklib *et. al* [1] predicted Thailand's electricity consumption using multiple linear regression and Artificial Neural Network. It is used GDP, population,

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average ambient temperature and peak demand for electrical power input variables and stated that the output estimates of an ANN model were more reliable than the regression model. S. Saravanan et.al [3] predicted the demand for electricity in India using the Fuzzy logic method and compared the results with the 18th power survey report. They reported that the forecasted results are nearer to the actual value with minimum error. Suhono and Sarjiya [4] used the long-range alternate energy planning system to estimate the demand for electricity in the household and non-household industries. De Vita et al. [5] studied energy demand in Namibia for the time period between 1980 and 2002.

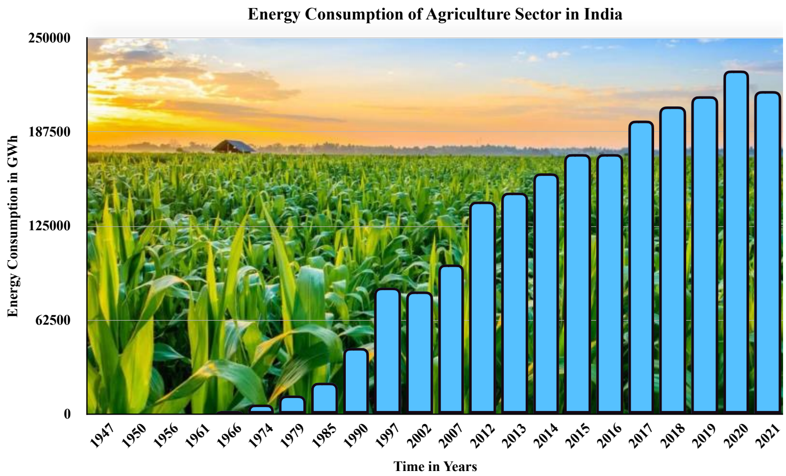

Figure 2. AS-EC between the year 1947 and 2021

They reported that the energy consumption going in negative direction to changes in price of energy and the air temperature and going in positive directions to changes in GDP. P. D. Sreekanth et al used for feed-forward neural network and ANFIS methods for predicting the ground water level in Maheshwaram. They concluded that the both models provided the better accuracy. Elham Pourazarm and Arusha Cooray studied that, residential sector EEC in Iran and also find the correlation between the output variables and its determinants. They estimated that the electricity price was negligible and that the profit elasticity was lower than the level, and that the EEC residential market would rise at an annual rate of 80% by 2020. Kavaklioglu used support vector regression approach for forecasting of EEC in Turkey considered the input variables population, imports, exports and Gross National Product.

2. Artificial Neuro Fuzzy Inference Systems

ANFIS is one of the Fuzzy Inference Systems (FIS) most commonly used. Roger Jang proposed in 1993 that ANFIS could correlate the relationship between the data input variables and the output variable(s) using a combination of multilayer feed forward network and FIS. ANN is capable to learn from the experience and generalized the model to produce

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the significant solutions. Fuzzy logic provides the thinking and reasoning capability. ANFIS can overcome the disadvantages of fuzzy logic and neural network. In fuzzy logic, identify the correct membership function, if-then rules and also poor generalization capability. For neural networks, problem to determine the size and function of the neural network and to establish the learning parameters. The ANFIS is the combination of the FL and the ANN and the preservation of the two strengths, the MF and, if so, the ANN determines and optimizes the laws of the fuzzy structures. A learning procedure has two steps: 1) The input data sets / parameters are propagated and the optimum resulting data is calculated using iterative method, while the training set, assuming the data sets are initially to be defined. 2) The patterns are circulated again; back propagation is used to alter the initially assumed data during this time, while the resulting data sets remain fixed. Then this process is iterated in [5].

To present the architecture of an ANFIS model, a FIS with three input variables, two rules, and one output variable is considered. ANFIS accepts the input parameters such as population, per capita GDP and permanent crop land (% of land area) in the format.

- The input parameters are given to the ANFIS.
- The network implements the forward pass, i.e., AS-EEC is computed.
- Next input parameters are given continuously to the network and the computing process until the input / output parameters of the network are trained.

3. Performance Measure And Testing

With the following performance criterion, the reliability of a qualified network can be measured: (i) Root Mean Square Error (RMSE).

$$\text{RMSE}=\sqrt{\frac{\sum_{i=0}^{n}(A_i-P_i)}{n}} \tag{1}$$

and (ii) MAPE or Mean Bias Error

$$\text{MAPE} = \left(\frac{1}{n}\sum_{i=0}^{n}\left|\frac{(A_i-P_i)}{A_i}\right|\right) \times 100 \tag{2}$$

Where, Pi, Ai are the expected and real data values for example i, and ' n ' is the total data set used for analysis. Lesser the value of MAPE and RMSE indicate that more accuracy in the prediction.

4. Results And Discussion

The identified input parameters used for this proposed model are population, per capita GDP and permanent crop land (% of land area) and AS-EEC is the predicted output variable. ANFIS modelling includes various parameter choices such as membership functions (MFs), types and MFs numbers relevant to each input parameter, selecting the output of the model being created. Further studies were performed in this research study in

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order to obtain the best results. The following seven different MFs are considered and the number of MFs varies from 2, 2, 2 to 4, 4, 4 and Table 1 shows the best results for each MF.

a) Built-in MF consisting of a two-sigmoid MF product ('psigmf')
b) Generalized bell MF ('gbellmf'),
c) Gaussian mixture of MF ('gauss2mf'),
d) Gaussian curve integrated in MF ('gaussmf'),
e) Built-in trapezoidal MF ('trapmf'),
f) Built-in MF consisting of two sigmoidal MF gap ('dsigmf')
g) Ttriangular MF ('trimf') and
h) Pie-shaped built-in MF ('pimf').

Table 1: Best results with different number MFs and their types

Types of MFs	**No. used in each MFs**	**MAPE**	**Types of MFs**	**No. used in each MFs**	**MAPE**
Psigmf	2,3,4	1.308	Trapmf	3,3,4	0.95
Gbellmf	3,4,3	1.292	Dsigmf	2,3,4	1.308
Gauss2mf	2,4,3	1.422	Trimf	3,4,4	1.29
Gaussmf	4,4,2	1.148	Pimf	3,4,4	1.145

From Table 1, it is examined that the 'Trapmf' MF with the numbers used in each MFs are 3, 3, 4 is establish to have a good accuracy in terms of MAPE with 0.95. Table 2 displays the other parameters and their values for the proposed implementation of the ANFIS model.

Table 2: Parameters for the ANFIS model and their values

Parameters	**Numbers**
Fuzzy rules	36
Epochs	100
Nodes	98
Linear parameters	144
Parameters that are not linear	40
Total parameter number	184
Training pairs of data	41
Testing pairs of data	09

The results for the proposed model are given in the Table 3 and it contains the actual and predicted AS EEC values (TWh), error variation, average MAPE and average RMSE.

Table 3: Comparison between actual and predicted AS-EEC

Year	**Actual (TWh)**	**Predicted (TWh)**	**Error variation**	**MAPE**	**RMSE**

1994	79.301	79.3256	-0.031	0.031	0.0006
1980	14.489	14.46923	0.136	0.136	0.0003
1991	58.557	58.54065	0.028	0.028	0.0002
1974	7.763	7.610207	1.968	1.968	0.0233
1992	63.328	64.41742	-1.720	1.72	1.1868
2013	152.744	157.0614	-2.826	2.827	18.639
2021	214.97	216.453	-1.483	1.483	1.1584
			Average	1.0031	2.4693

The actual value of AS-EEC in 1985 was 23.42 TWh from the findings in Table 2, and the same was 152.744 TWh in 2013. The AS-EEC was estimated using the proposed ANFIS model is 23.475 TWh for the year 1985, and 157.0614 TWh for the year 2013. The error deviations in the range of -2.826 to 1.596, according to the results obtained.

5. FUTURE PREDICTION

To predict the AS-EEC, the input parameters (population, per capita GDP and permanent crop land (% of land area)) should be examined and should be predicted first and the predict the future years from the year 2023 to 2030. Using the predicted input parameters, an AS-EEC has been predicted using developed ANFIS model. The predicted results are given in Table 4.

Table 4: Predicted values of input parameters and output parameter

Year	**Population (Million)**	**Per capita GDP (INR)**	**Permanent Crop land (% of land area)**	**AS_EC (TWh)**
2023	1791.531	118984.275	5.023	212.016
2024	1863.192	123743.646	5.108	217.639
2025	1937.720	128693.391	5.195	223.465
2026	2015.228	133841.127	5.283	229.484
2027	2095.838	139194.772	5.373	235.722
2028	2179.671	144762.563	5.464	242.167
2029	2266.858	150553.066	5.557	248.844
2030	2357.532	158234.270	5.764	255.023

6. CONCLUSION

The prediction of AS-EEC is the most important in developing the sustainable energy policies. In this research study, an application of ANFIS, model was designed to map three parameters as inputs and AS-EEC is the predicted output variable. The proposed ANIFS model has very good predicting capability with MAPE of 0.95%. It can be summarized based on the findings that the implementation of the ANFIS model can be used as a useful tool for predicting the AS-EEC. The found results showed that the application of the ANFIS model is reliable and apt for indeterminate data because it composed the futures of fuzzy logic and ANN. The estimated AS-EEC may reach 223.465 TWh and 255.023 for

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the years 2025 and 2030. The predicted results are useful to give a new way to the power system planners and power producers.

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