

ANN Based Long-Term Forecasting of Primary Fuels' Demand

J. Kumaran @ Kumar¹, J. Sasikala²Assistant Professor, Department of Computer Science and Engineering, Pondicherry Engineering College,
Puducherry, India¹Assistant Professor, Department of Computer Science and Engineering, Annamalai University, Annamalainagar,
Tamilnadu, India²

ABSTRACT: Long term forecasting of primary fuels' demand is an important study that predicts the future demand of a given region and plays significant role in financial planning. This article presents artificial neural network (ANN) based forecasting model that predicts the future demand of primary fuels of India. It involves two ANN models, the first model requires an input, the year of forecast, and predicts the corresponding per capita GDP and population, while the second one receives the output of former one as inputs and provides the forecast of primary fuels' demand. The forecasted results up to the year 2025 portray the superiority of the developed model.

KEYWORDS: primary fuels' demand; forecasting; artificial neural networks; back propagation technique.

I. INTRODUCTION

Fuel energy consumption that indicates social and economic growth of any nation, increases with the population growth and Gross Domestic Product (GDP). Fuel Energy, the most requirement of any country, is considered as a 'strategic commodity', whose shortage can affect the functioning of the economy of the country. The coal, lignite, crude oil and natural gas are considered as primary fuels, while wind, solar, small hydro, biomass, cogeneration bagasse etc. are considered as renewable energies [1].

It is well known that the consumption of primary fuel energies coal, lignite, crude oil and natural gas during the recent decades have been sharply increasing like anything. It is expected that the demand of these fuel demands reach the peaks in the forthcoming years. Among the primary fuels, coal is abundantly available in India, but the quality is inferior to those available in Australia or Canada. Besides coal washing facility is not sufficient to provide washed coal to steel industries. Because of these reasons, high quality coal is being imported from foreign countries, and such import is steadily increasing from year to year. Nearly 70% of crude oil requirements are met from imports from foreign countries and there is steady increase in the import level. However, India has the facilities to export processed petroleum products [2].

Fuel Energy forecasting is a prime problem of any country with a view of allocating funds for the import of fuels from foreign countries and mining from various regions of the country. Since 1950, various classical techniques such as exponential smoothing, decomposition methods, multiple regression, econometric models, Box-Jenkins method, and autoregressive integrated moving average method (ARIMA) have been applied to forecasting problems [3-7]. But recently, soft computing techniques such as artificial neural networks and fuzzy logic have been applied in forecasting problems. Besides hybrid forecasting methods, combining ANN, fuzzy logic and classical approaches, have been applied to forecasting problems.

This paper attempts to develop ANN based model forecasting primary fuel' requirements of India in future years. The model receives the year as input and forecasts the demand of coal, lignite, crude oil and natural gas.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

II. PROPOSED MODEL

The objective of the article is to build a forecasting model with reduced number of collected data for predicting the primary fuel' demand in future years. Recently ANNs have been popularly employed in forecasting problems as they mimic human brains and possess flexible structure of performing massive parallel computations. They are multi-layer feed forward networks possessing an input, an output and a hidden layer, each formed with a number of neurons. They are in general used in modeling problems that do not have mathematical equations relating the input and output variables [4]. As the forecasting problem does not possess mathematical modeling between the input and output, ANN is chosen to build the proposed model.

The factors like weather, temperature, number of households, number of air conditioners, oil price, economy, population, etc. are correlated with primary fuels' demand. The modeling of ANN for forecasting will be difficult with large number of input data. In addition, most of these factors are required only for short-term forecasting problems. It is therefore decided to select minimum number of factors that can be effectively related to the primary fuel energy requirement. Among these parameters, the population growth and the per capita GDP representing the revenue and living standards of public can be associated with primary fuels' consumption [7], and therefore these two factors are chosen as primary factors for forecasting, but these two factors are not available for future years. So, the proposed model involves two ANN model. The first model requires an input, the year of forecast, and predicts the corresponding per capita GDP and population, while the second one receives the output of former one as inputs and provides the forecast of primary fuels' demands for coal, lignite, crude oil and natural gas. The structure of the proposed ANN model is shown in Fig. 1. The input required for the first ANN model is just the year and the output of the second model is the forecasted primary fuels' demand. Thus the PM has one input, two intermediate predictions and four outputs.

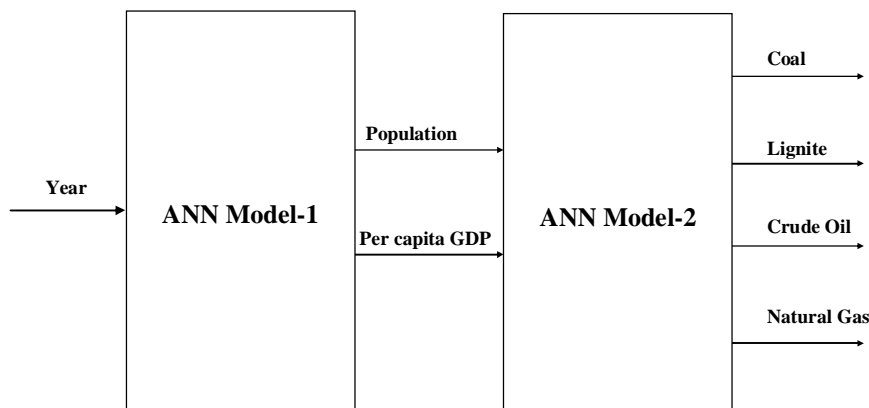


Fig. 1 Block Diagram of PM

The collected input-target data for each ANN model are divided into two sets: the former one, known as the training set, is employed for training the ANN, while the later one, known as testing data, is employed to assess how perfectly the ANN is modelled. Sometimes, the ANN may be poorly-modelled in such a way that it gives erroneous forecasting, which can be avoided by making the data set uniformly distributed and by changing the number of neurons in the hidden layer.

Wide range of values of input and output dataset may suppress the significance of the smaller valued data. Besides, the larger valued data may cause the activation functions of neurons to saturate. If a neuron is saturated, then it produces insignificant or no change in its output for a given change in the input. These effects influence badly the training performance and hence the collected data are normalized by Eq. (1) before using it in modeling the ANN.

$$data_n = \frac{(data - data_{min}) \times (U_R - L_R)}{data_{max} - data_{min}} + L_R \quad (1)$$

Where $data_n$ represents the normalized data

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

$data_{min}$ and $data_{max}$ denotes the smallest and largest values of the data variable respectively

L_r and U_r lower and upper limit for the normalized data respectively

Tangent hyperbolic and linear activation functions are used for modelling the neurons of hidden and output layers of ANN respectively. The weights connecting the neurons are altered in such a way to bring the mean square value (MSE) to negligibly smaller value by a training process involving back-propagation technique. Once the ANN models are effectively trained, then the model is ready for forecasting the primary fuels' demand.

Table 1 Results of PM

Year	Forecast by ANN model-1		Forecast by ANN model-2			
	Per Capita GDP	Population (Millions)	Coal	Lignite	Crude Oil	Natural Gas
2013	5120	1212	599	42	225	40
2014	5687	1234	610	45	244	41
2015	6291	1251	638	47	256	42
2016	6927	1268	665	50	269	45
2017	7623	1295	692	52	277	45
2018	8325	1326	711	53	290	46
2019	9042	1337	740	54	302	48
2020	9797	1360	749	56	316	50
2021	10554	1380	769	57	328	53
2022	11279	1386	812	60	340	55
2023	12026	1415	827	61	351	56
2024	12738	1423	846	62	362	58
2025	13394	1439	862	64	372	59

Table 2 Results of RM

Year	Forecast by RM-1		Forecast by RM-2			
	Per Capita GDP	Population (Millions)	Coal	Lignite	Crude Oil	Natural Gas
2013	5125	1209	605	49	234	44
2014	5690	1226	632	53	248	48
2015	6295	1248	659	58	263	51
2016	6938	1267	687	64	277	54
2017	7615	1287	716	68	292	58
2018	8321	1309	745	74	306	62
2019	9049	1330	774	79	320	65
2020	9792	1351	802	85	334	69
2021	10542	1372	828	91	348	72
2022	11287	1390	854	95	361	75
2023	12018	1406	878	99	372	78
2024	12721	1418	901	103	385	79
2025	13381	1431	919	104	394	80

III. SIMULATION RESULTS

The PM involving ANN needs appropriate training and testing data set. In this regard, year wise India's per capita GDP and the population, and the corresponding primary fuel's demands over the years 1980-2012 were collected

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

[2,10,11]. 80% of collected data was considered as training data and the remaining 20% was treated as testing data. The number of neurons in the hidden layer is very important as it leads to poor-fitting or over-fitting or good-fitting. The number of neurons in the hidden layer varied from 2 to 8 and found that a hidden layer with 3 neurons for model-1 and a hidden layer with 7 neurons for model-2 give satisfactory results. The forecasted results were obtained by the PM and the classical RM. The forecasted results for the years 2013-2025 by the PM and RM are presented in Table 1 and 2 respectively. It can be observed from these tables that the primary fuels' demands, offered by PM, are in general lower than that of the RM. The PM indicates that the policy makers can allocate little lower funds for import of primary fuels' demand of future years.

IV. CONCLUSION AND FUTURE WORK

Long term load forecasting estimates the future energy demand of a country and signifies a major role in allocating funds by the government for newer power plants. The sector-wise electrical energy demands of India were forecasted for the future years through considering the year as the input. The proposed model involves two ANN models. The first model requires an input, the year of forecast, and predicts the corresponding per capita GDP and population, while the second one receives the output of former one as inputs and provides the forecast of primary fuels' demands for coal, lignite, crude oil and natural gas. The ANN models are trained back-propagation technique. The forecasting of the PM offers lower energy demands than that of RM, and helps the policy makers for allocating lower funds for constructing new generation plants to meet the future demands. The forecasted results up to the year 2025 exhibits the superiority of the developed model.

REFERENCES

1. P.E. McSharry, S. Bouwman, and G. Bloemhof, 'Probabilistic forecasts of the magnitude and timing of peak electricity demand', IEEE Transactions Power Systems, Vol. 20, pp. 1166-1172, 2005.
2. C.L. Hor, S.J. Watson, and S. Majithia, 'Analyzing the impact of weather variables on monthly electricity demands', IEEE Transactions on Power Systems, Vol. 20, pp. 2078-2085, 2005.
3. Geoffrey K.F. Tso, Kelvin K.W. Yau, 'Predicting electricity energy consumption: A comparison of regression analysis, decision tree and neural networks', Energy, Vol. 32, No. 9, pp. 1761-1768, 2007.
4. Henrique SteinherzHippert, Carlos Eduardo Pedreira, and Reinaldo Castro Souza, 'Neural networks for short-term load forecasting: a review and evaluation', IEEE Transactions on Power Systems, Vol. 16, No.1, pp. 44-55, 2001.
5. Madasuhanmandlu and Bhavesh Kumar Chauhan, 'Load forecasting using hybrid models', IEEE Trans. on Power Systems, Vol.26, No. 1, pp 20-29, 2011.
6. SantoshKulkarni, Sishaj P. Simon and K. Sundareswaran, 'A spiking neural network (SNN) forecast engine for short-term electrical load forecasting', Applied Soft Computing, Vol.13, pp. 3628-3635, 2013.
7. A. Ghanhari, A. Naghavi, S.F. Ghaderi, and M. Sabaghian, 'Artificial neural networks and regression approaches comparison for forecasting Iran's annual electricity load', Proceeding of International Conference on Power Engineering Energy and Electrical Drives, pp. 675-679, 2009.
8. AdemAkpinar, 'Modeling and forecasting of Turkey's energy consumption using socio-economic and demographic variables', Applied Energy, Vol. 88, No.5, pp. 1927-1939, 2011.
9. Toly Chen and Yu-Cheng Wang, 'Long-term load forecasting by a collaborative fuzzy-neural approach', Electrical Power and Energy Systems, Vol.43, No. 1, pp. 454-464, 2012.
10. Data for population available at <http://www.populstat.info/Asia/indiac.htm>
11. Data for per capita GDP available at [http://www.indexmundi.com/india/gdp_per_capita_\(ppt\).html](http://www.indexmundi.com/india/gdp_per_capita_(ppt).html)
12. India's sector wise energy demand available at http://www.iasri.res.in/agridata/08data%5Cchapter3%5Cdb2008tb3_57.pdf