ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 3, Issue 9, March 2014

Long Term Load Forecasting in Tamil Nadu Using Fuzzy-Neural Technology

C.P. Ronald Reagan, S.R. Sari

Abstract— ***The increasing of energy consumption is very important for all the government, particularly in Tamil Nadu. Precise energy consumption forecasting is of major importance to define the future energy consumption of a given region. A large verity of mathematical methods has been developed for energy forecasting. In order to effectively forecast the long-term energy consumption, a collaborative approach of fuzzy neural technology is proposed in this study. In this proposed methodology, the historical data set including Population(POP), Gross State Domestic Product(GSDP), Yearly Peak Demand(YPD), and Total Consumption(TC) of Tamil Nadu were considered from the year 1983 to 2012 for energy forecasting. The error obtained for this model will be compared with the errors produced by the other existing methodologies.***

Index Terms-**Energy consumption, Forecasting, Fuzzy-Neural Network (FNN), Collaborative approach, Long term forecasting.**

I. INTRODUCTION

Developing energy-forecasting models is known as one of the most important steps in long-term planning. In order to achieve sustainable energy supply toward economic development and social welfare, it is required to apply precise forecasting model. Applying different models for estimation of complex economic and social functions is growing up considerably in many researches recently. The present study has a focus on the future energy prediction of a state in India, facing electricity demand deficit problems every year due to increased demand for its energy use. So to predict the long term energy forecasting, Fuzzy neural networks (FNNs), being the product of fuzzy logic and neural networks, are computational machines with unique capabilities for dealing with both numerical data and linguistic knowledge (fuzzy) information is used. The input variables affecting the electricity consumption were analyzed by correlation coefficient analysis. The variables considered for the forecasting are population (POP), Gross State Domestic Product (GDSP), Yearly Peak Demand (YPD), and Total Consumption (TC). The Fig.1 gives the historical data of the variables form 30 years 1983 to 2012 for Tamil Nadu state. Energy consumption forecasting can be classified as short term (up to 1 day), mid-term (1 day to 1 year), or long-term (1-10 years). Mid- to long-term energy consumption forecasting is a vital tool for planning and forecasting future electricity network conditions. This study focuses on long-term energy consumption forecasting. The figure 1 clearly shows the clear parameters that have to be considered for electricity forecasting.

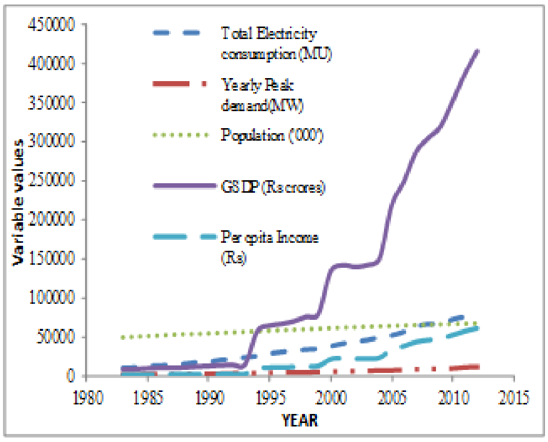

Fig.:1 Variables considered in the forecasting of Electricity for Tamil Nadu

II. RELATED WORKS

Energy consumption forecasting has attracted great attention in power system research. On the other hand, the energy consumption will lead to the increase of the global CO2 concentration, and therefore attracts the attention of many global worming research scholars. Alfares and Nazeerudin [4] divided the existing energy consumption forecasting methods into nine categories: multiple linear regression (MLR), exponential smoothing (ES), iterative reweighted least-squares, adaptive energy consumption forecasting, stochastic time series, autoregressive moving average with exogenous variable (ARMAX) models based on genetic algorithms (GAs), fuzzy logic, neural networks (NNs), and expert systems. Li et al. [5] combined principal component analysis (PCA) and support vector machine (SVM) for long-term energy consumption forecasting. Because the generalization and learning ability of single kernel function SVM is weak, Li et al. [6] combined rough set theory and SVM for the same purpose. Xia et al. [7] discussed the application of a radial basis function (RBF) network to the long-term energy consumption forecasting. They pointed out that, compared to a feed-forward neural network (FFNN) (or a back propagation network (BPN)), an RBF is more stable. Hong[8] and Hong[9] proposed some variants of support vector regression (SVR) for electric energy consumption forecasting by using different techniques to determine the values of the parameters. Pousinho et al. [10] combined particle swarm optimization and adaptive-network based fuzzy inference system (ANFIS) for the energy consumption forecasting in Spain. Particle swarm optimization (PSO) was used to tune the membership functions in ANFIS. Chen [13]

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 3, Issue 9, March 2014

broke down long term energy consumption into two sub-problems: annual electrical peak energy consumption estimation and annual energy consumption forecasting. Chang et al. [12] constructed a weighted evolving fuzzy neural network for monthly electricity demand forecasting in Taiwan.

III. ARCHITECTURE

The proposed methodology is made up of several steps which will be described in the following sections. The flow chart of proposed methodology is shown in Figure 2.

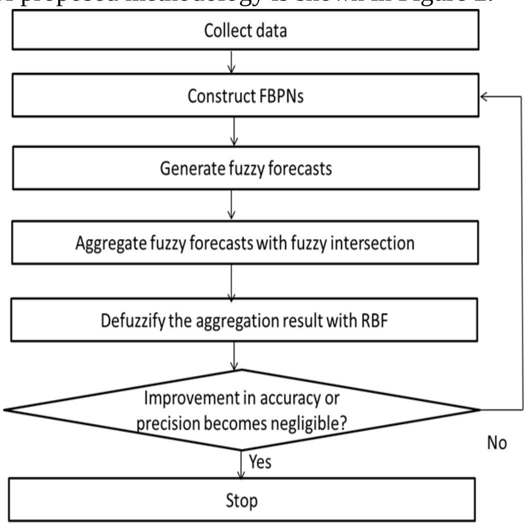

Fig 2: The procedure of the proposed methodology

In the proposed approach, multiple experts construct their own fuzzy back propagation networks from various viewpoints to forecast the long-term load in a country. To aggregate these long term load forecasts, fuzzy intersection is applied. After that, a radial basis function network is constructed to defuzzify the aggregation result and to generate a representative/crisp value. The practical case of Tamil Nadu is used to evaluate the effectiveness of the proposed methodology. In addition, the proposed methodology made it possible to accurately forecast the average and peak values of the annual energy consumption at the same time. To improve the effectiveness of the long-term energy consumption forecasting, a collaborative fuzzy-neural approach is presented in this study. The purpose of long-term load forecasting in this study includes:

(1) Generating an accurate annual energy consumption forecast so that long-term power planning can be based on it.

(2) Establishing a precise interval of annual energy consumption forecast so that it becomes less likely for the government to raise budget unreasonably.

(3) Reducing the risk of power shortage.

IV. PROPOSED SCHEME

The proposed methodology is made up of several steps (see Fig. 2) which will be described in the following sections:

(1) Constructed FBPNs to generate fuzzy annual energy consumption forecasts.

(2) Apply fuzzy intersection to aggregate fuzzy annual energy consumption forecasts into a polygon-shaped fuzzy number.

(3) Defuzzify the aggregation result with a Radial Basis Function (RBF).

(4) Stop if the improvement in the forecasting performance (either accuracy or precision) is negligible; otherwise, return step 3.

Step 1: Forecasting the annual energy consumption with a FBPN

Over the long term, Tamil Nadu's economy and population are expected to grow and, in turn, so are its electricity requirements. In planning to meet future electricity needs, a number of questions must be addressed to ensure Tamil Nadu government continues to provide reliable power, at low cost, for generations. How to accurately predict future demand for electricity is clearly one of the most critical issues. To this end, in the proposed methodology multiple experts construct their own FBPNs to forecast the future annual energy consumption of year. In the proposed methodology, each expert uses a fuzzy neural network to predict the annual energy consumption, based on the expert's opinion. The purpose is to generate an accurate annual energy consumption forecast so that long-term power planning can be based on it. Although here have been some more advanced artificial neural networks, such as the compositional pattern-producing network, cascading neural network, dynamic neural network, and others, a well-trained fuzzy neural network with an optimized structure can still produce very good results, which is why it is selected for this study. There are different types of fuzzy neural networks. Among them, Chen and Wang's fuzzy neural network is unique since it is aimed at optimizing precision. For this reason, it is chosen for this study. The configuration of fuzzy neural network is as follows:

- p inputs correspond to the historical data of the past p periods.
- The fuzzy neural network has only one hidden layer, which can approximate arbitrarily any function that contains a continuous mapping from one finite space to another. After trying each p input, the number of nodes in the hidden layer is chosen from 1 to 2p.
- The output from the fuzzy neural network is the normalized annual energy consumption forecast.
- The activation function represents the log sigmoid function.

The procedure for determining the parameter values is now described. After pre-classification, a portion of the adopted examples is fed as "training examples" into the fuzzy neural network to determine the parameter values. In the forward phase, inputs are multiplied with weights, summated, and transferred to the hidden layer. Then, activated signals are outputted from the hidden layer as shown in equation 1:

$$\tilde{h}_1 = \frac{1}{1+e^{-n1^{\sim h}}}$$

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(1)

Where

$$\tilde{n}_1^{h} = \tilde{I}_l^{h} (-) \tilde{\theta}_l^{h}$$

$$\tilde{I}_1^{h} = \sum_{all\,k} \tilde{w}_{kl}^{h} . x_k$$

$\tilde{h}_1$ is the output from hidden-layer node l, l=1~L; $\tilde{\theta}_l^h$ is the threshold for screening out weak signals by hidden-layer node l; $\tilde{w}_{kl}^h$ is the weight of the connection between input node k and hidden-layer node l, k=1~p; l=1~L; x_{ij} is the k-th input, k= 1~p. The remaining parameters are transition variables. (-) and (x) denote fuzzy subtraction and multiplication, respectively. $\tilde{h}_1$ s are also transferred to the output layer with the same procedure. Finally, the output of the fuzzy neural network is generated as shown in equation 2:

$$\tilde{O}_t = \frac{1}{1+e^{-\tilde{n}^{o}}} \qquad (2)$$

Where

$$\tilde{n}^{o} = \tilde{I}^{o} (-) \tilde{\theta}^{o}$$

$$\tilde{I}^{o} = \sum_{all\,l} \tilde{w}_l^{o} (*) \tilde{h}_l$$

$\tilde{o}_t$ is the network output, which is the normalized value of the annual energy consumption forecast of period t; $\tilde{\theta}^o$ is the threshold for screening out weak signals by the output node; $\tilde{w}_l^o$ is the weight of the connection between hidden-layer node l and the output node; l=1~L.

Steps 2 and 3: Aggregating and Defuzzifing forecast

In the existing methods, deriving a representative value from a group of fuzzy forecasts consists of two tasks: aggregation and defuzzification. This process may be time-consuming in the absence of consensus, which requires a lot of time for them to adjust their settings to gradually close to each other. The collaboration process can be shortened. Subsequently, these final settings are fed into the corresponding fuzzy neural networks to generate fuzzy energy consumption forecasts. For each period, the three corners of the fuzzy forecast by each agent are recorded, and used to construct a multiple linear regression equation to derive the representative value that can be directly compared with the actual value.

V. IMPLEMENTATION

The fuzzy-neural network (FNN) is implemented with MATLAB 2011a.The objective of this technique is to minimize MAPE. Replacing the inputs to the fuzzy neural network is considered to be beneficial to the efficiency of training the fuzzy neural network. To this end, we standardized the inputs and obtained the correlation matrix, for which the eigenvalues and eigenvectors were calculated. The variance contribution rates were then derived. To meet the requirement that the accumulative percent variability explain: 85% ~ 90%, the number of new/independent variables (p) was chosen as 3. Subsequently, the component scores were calculated, which contain the coordinates of the original data in the new coordinate system defined by the principal components, and used as the new inputs to the fuzzy neural network. To make a comparison with some existing approaches Multiple Linear Regression Method (MLRM), Genetic Algorithm-MLRM (GA-MLRM) and Simulated Annealing-MLRM (SA-MLRM). The MAPE error is calculated using the following formula (3):

$$MAPE = \frac{\frac{\sum |Actual - Forecast|}{Actual} X100}{n}$$

(3)

Year	Actual data (MU)	MLRM	MAPE error (%)	GA-MLRM	MAPE error (%)	SA-MLRM	MAPE error (%)
2006	56726	57635	-1.60188	57602	-1.54513	57632	-1.59802
2007	63563	61910	2.60120	61846	2.70113	61919	2.58703
2008	66848	64391	3.67555	64294	3.82077	64384	3.68628
2009	66966	67079	-0.16851	66938	0.04197	66977	-0.01717
2010	72887	71179	2.34331	70990	2.60325	71027	2.55128
2011	76071	76497	-0.56000	76233	-0.21247	76121	-0.06605
2012	77819	80210	-3.07214	79890	-2.66125	79768	-2.50447
Average	-	-	2.00		1.94		1.86

Table 1: comparison of MAPE error for various models

The above table clearly indicates the MAPE error for various models and our model is having high accuracy

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VI. CONCLUSION

Much evidence also reveals that collaborative intelligence has potential applications in long-term energy consumption forecasting. In order to effectively predict the long-term energy consumption, an fuzzy-neural approach is proposed in this study. In the fuzzy-neural approach, uses a fuzzy neural network to predict the annual energy consumption based on the setting. After receiving this information, the experts may change the settings, in an automatic way.In Tamil Nadu, whether to build new nuclear power plants is a controversial issue. Undoubtedly, the whole community should pursue green manufacturing, services, and communication. After applying the fuzzy-neural approach to predict the annual energy consumption in Tamil Nadu, improves the efficiency of the prediction than other existing methods.

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AUTHOR'S PROFILE

Ronald Reagan C.P is working as Assistant professor in Apollo Engineering College, Chennai. He completed his M.E degree in Computer Science & Engineering. He has published a lot of papers in Artificial intelligence, Data mining and Network.

S.R.Sari is a student of master of engineering in computer science and engineering at Apollo Engineering College, Chennai. She has received her B.E degree in computer science and engineering at Bethlehem institute of engineering