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Research Article

Neuro-Fuzzy Logic Approach for Electric Load Forecasting of CSPGCL Thermal Units

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Abstract

The demand of electricity in India is increasing exponentially at the rate of 8-9% per annum. However, the installed power generation capacity of India as on 31st October 2012 was 209276 MW with a peak power shortage of more than 12%. In addition, the demand of electricity is increasing due to increased population, urbanization and comfort level of the peoples. These indicate that India's future energy requirements are going to be very high. In this paper an attempt has been made for generation forecasting by using a hybrid model of neural networks and fuzzy logic, for the hybrid model input monthly generation of CSPGCL Thermal Unit of CG has been collected from Chhattisgarh State Electricity Board , India .The results obtained from hybrid model has been validated with the actual value and found accurate. The average testing error in the forecasted value is 0.064 in comparison with the desired value.

Keywords: *Neuro-Fuzzy Logic; generation Forecasting; Energy Management, neuro-fuzzy*

1. Introduction

The demand of electricity is increasing drastically day by day. This increase in demand of electrical energy has drawn the attention of power system engineers towards the reliable operation of power system. For reliable operation of integrated power supply systems, a close tracking of electrical generation is required. Generation forecasting predicts the generation which is going to be required at a particular month of year. Generation forecasting plays an important role in the smooth operation of any power system. There are many techniques that could be employed for generation forecasting like linear regression, neural network, fuzzy logic, Neuro-fuzzy approach, etc. Among these neural networks is widely used when there is no fluctuation in condition. In case of sudden fluctuation Neuro fuzzy logic based approach is used. It has advantage over neural network that it leads with non-linear part of the forecasted generation curve as well as it has ability to deal with sudden variation. In addition, Neuro fuzzy logic approach is easy and robust. Keeping in view of the aforesaid variation in the inputs, an attempt has been made to develop the Neuro fuzzy logic based model for generation forecasting. The proposed model is simple, accurate and incorporates the uncertainties in the input variables. This paper is organized as follows: Brief idea about the Neural network is given in Section 2.Section 3 presents the Fuzzy Logic. Section 4 present Neuro-Fuzzy model. Section 5 present data collection and normalization of input and output data. Simulation and results are discussed in Section 6.

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2. Neural Networks

An artificial neural network is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform ''intelligent'' tasks similar to those performed by human brain.

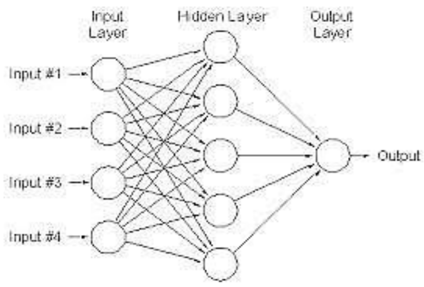

Fig1: Artificial neural Network

When load forecasting is dealt by using neural networks, we must select one of the number of the available architectures (such as Hopfield, back propagation, Boltzmann, etc), the number of layers and elements, the connectivity between them, usage of unilateral or bilateral links and the number format to be used by inputs and outputs. There will be differences in the estimation of performance depending on the different models. Generally back propagation is used. A back propagation network topology includes 3 layers or 4 layers, the transfer function may be linear or non linear or a combination of both. The network may be fully connected or non-fully connected. The application of neural networks in power utilities has been growing in acceptance over the years. The main reason behind this is because the capability of the artificial neural networks in capturing process Information in a black box manner.

3. Fuzzy Logic

The concept of Fuzzy Logic was introduced by Professor Lotfi A. Zadeh at the University of California, Berkeley in the 1960's. His goal was to develop a model that could more closely describe the natural language process. This model was intended to be used in situations when deterministic and/or probabilistic models do not provide a realistic description of the phenomenon under study. The fuzzy sets and fuzzy operators are the subjects and verbs of fuzzy logic. But in order to say something useful, we need to make complete sentences. The condition statements, IF-THEN rules, are things that make fuzzy logic useful. The fuzzy logic IF-THEN statements are used to characterize the state of a system and truth value of the proposition is a measure for how well the description matches the state of the system. The fuzzy set can be defined as follows:

Let X, be a universal set. The characteristic function μA of a subset of X takes its values in the two element set {0, 1} and μA (x) = 1, if x ϵ A and zero otherwise. A fuzzy set A has a characteristic function taking its values in the interval {0, 1}. μA is also called a membership function and μA (x) is the grade of membership of x ϵ X in A. In fuzzy set, the transition between membership and non membership is gradual rather than abrupt. The union and intersection of two fuzzy subsets A and B of X having membership function μA and μB respectively is defined as

Union: $\mu A \cup B\ (x) = \max\ [\mu A\ (x), \mu B(x)]$ (1)

Intersection: $\mu A \cap B\ (x) = \min\ [\mu A\ (x), \mu B(x)]$ (2)

Fuzzy logic usage has got several advantages. There is no need of a mathematical model mapping inputs to outputs and the absence of a need for precise inputs. Properly designed fuzzy logic systems can be very robust when used for forecasting with such generic conditioning rules. An exact output is needed in many situations. The logical processing fuzzy inputs is followed by ''defuzzification'' to produce precise outputs.

4. Neuro-Fuzzy Model

In the field of artificial intelligence, neuro-fuzzy refers to combinations of artificial neural networks and fuzzy logic. Neuro-fuzzy was proposed by J.S.R.Jang. Neuro-fuzzy hybridization results in a hybrid intelligent system that synergizes these two techniques by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks. Neuro-fuzzy hybridization is widely termed as Fuzzy Neural Network (FNN) or Neuro-Fuzzy System (NFS) in the literature. Neuro-fuzzy system incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. The main strength of Neuro-fuzzy systems is that they are universal approximates with the ability to solicit interpretable IF-THEN rules.

The basic structure of the type of fuzzy inference system is a model that maps input characteristics to input membership functions, input membership function to rules, rules to a set of output characteristics, output characteristics to output membership functions, and the output membership function to a single-valued output or a decision associated with the output.

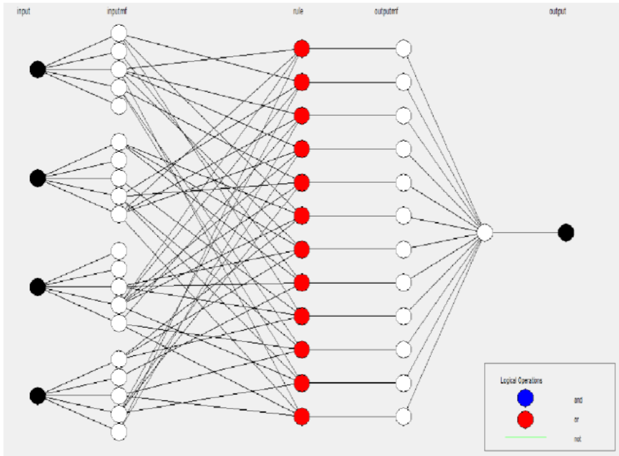

Fig 2: Neuro-Fuzzy Model

5. Data Collection

The monthly electricity generation of CSPGCL Thermal Units Chhattisgarh has been collected from Chhattisgarh Electricity Board India for the purpose of generation forecasting. The monthly electricity generation for the year of 2008, 2009, 2010, 2011 and 2012 in MW is presented in Table – 1. The input and output data is further normalized and scaled in the range of 0.100 to1.000 to avoid the convergence problem during the rules formation. Normalized input and output data shown in table 2.

6. Simulation and Results

For evaluating our proposed generation forecast, the model was implemented in MATLAB. FIS involves the operations between input fuzzy sets as illustrated graphically in figure 3 known as the Sugeno type. FIS derives output fuzzy sets from judging all the fuzzy rules by finding the memberships for the generation are represented by the 12 fuzzy output rules. Sugeno FIS represents each output membership function by a single spike rather than a distribution curve. The solution is

Table 1: Monthly Generation of CSPGCL Thermal Units during 2008, 2009, 2010, 2011 and 2012 in MW

	2008	**2009**	**2010**	**2011**	**2012**
Month	**Input -1**	**Input -2**	**Input -3**	**Input -4**	**Output**
January	1054.964	1219.858	1156.316	1291.957	1234.036
February	960.815	1148.968	1145.704	1155.487	1169.548
March	1067.012	1260.907	1219.99	1247.64	1234.773
April	1092.306	1191.538	1149.1	1131.692	1131.842
May	1134.04	1134.792	1176.815	1154.413	1112.085
June	927.831	918.979	1121.883	933.925	996.588
July	1064.859	944.68	1065.895	895.717	1047.843
August	992.409	950.597	1109.539	998.393	927.809
September	969.215	1081.922	1053.334	776.938	992.515
October	1170.794	1167.061	1186.593	1053.397	1082.84
November	1134.986	1172.02	1113.11	990.4	972.576
December	1094.268	1209.309	1204.469	1063.389	972.139

Table 2: Normalized input and output data

Month	**2008**	**2009**	**2010**	**2011**	**2012**
	Input -1	**Input -2**	**Input -3**	**Input -4**	**Output**
January	0.816	0.944	0.895	1	0.955
February	0.744	0.889	0.886	0.894	0.905
March	0.826	0.975	0.944	0.965	0.955
April	0.845	0.922	0.889	0.875	0.876
May	0.877	0.878	0.91	0.893	0.86
June	0.718	0.711	0.868	0.722	0.771
July	0.824	0.732	0.825	0.693	0.811
August	0.768	0.736	0.858	0.772	0.718
September	0.75	0.837	0.815	0.601	0.768
October	0.906	0.903	0.918	0.815	0.838
November	0.878	0.907	0.861	0.766	0.752
December	0.864	0.936	0.932	0.823	0.752

arrived by taking the weighted average of these spikes (fuzzy output rules) as illustrated in figure4 The blue spikes arc the Sugeno outputs from each of the 12 fuzzy rules denoting probabilities (from 0 to 1) for belonging to the fault type denoted by each fuzzy rule.

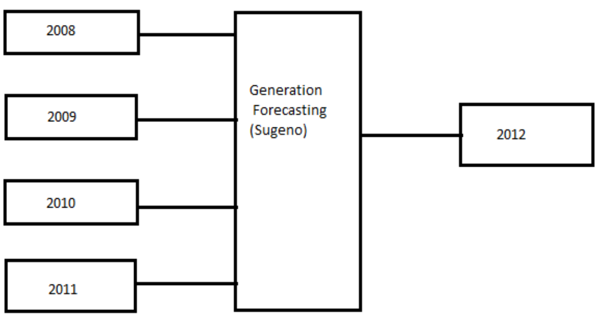

Fig3: Fuzzy logic based model for generation forecasting

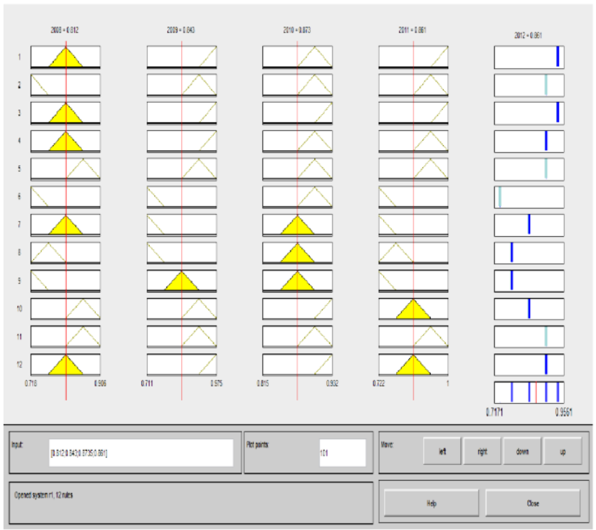

Fig4: Rule Viewer for Generation forecasting

Model is tested for 12 month. Figure 5 shows the output. Red dots denote the outputs calculated and blue dots denoted the actual (expected) values. For implementing the current system ANFIS is coded in MATLAB environment.

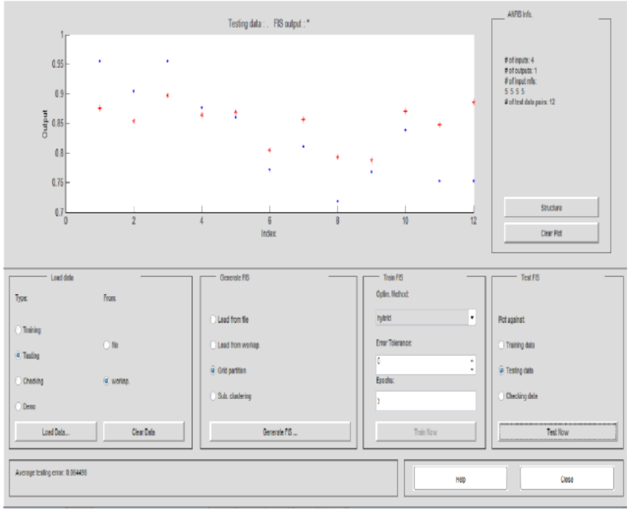

Fig 5: Graphical representation of expected outcome for tested data

Conclusions

The electrical generation forecasting is an essential component of any power system planner. Therefore, an attempt has been made for this, by using Neuro-Fuzzy logic. The average error in the forecasted generation data in comparison with the actual generation data is 0.064498 which is very close to the desired value. Hence, it is concluded that the developed model is accurate and effective for generation forecasting.

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