Australian Journal of Basic and Applied Sciences, 8(16) October 2014, Pages: 56-63

AENSI Journals

Australian Journal of Basic and Applied Sciences

ISSN:1991-8178

Journal home page: www.ajbasweb.com

Teaching Learning Based Optimization of ANN for Electrical Energy Forecasting

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ARTICLE INFO

Article history:
Received 8 August 2014
Received in revised form 12 September 2014
Accepted 25 September 2014
Available online 2 November 2014

Keywords:
load forecasting, artificial neural networks, teaching-learning based optimization

ABSTRACT

Long term load forecasting is an important study that predicts the future power consumption of a given region and plays significant role in power system planning and operation This paper presents a teaching-learning based optimization (TLO) for training of ANN models for forecasting the sector-wise electrical energy demand in India for the future years up to 2025. TLO mimics the behavior of the students in improving their performance through gaining the knowledge from the teacher and interacting with other students. The proposed model requires per capita GDP and population and offers the forecast of sector-wise electrical energy demand. The comparisons of the results with that of RM exhibit the effectiveness of the proposed model.

To Cite This Article: J. Kumaran @ Kumar and G.Ravi, Teaching Learning Based Optimization of ANN for Electrical Energy Forecasting. ***Aust. J. Basic & Appl. Sci.,*** *8(16): 56-63, 2014*

INTRODUCTION

Electrical Energy is one of the most important sources for social and economic development of all nations. The growth in energy consumption is essentially linked with the growth in economy. Electricity demand increases due to the population growth, higher per capita consumption, rapid development of industrial & commercial growth, higher Gross Domestic Product (GDP) growth and structural changes in the economy. Load forecasting problem has been receiving great and growing attention as being an important and primary tool in power system planning and operation. It has been an attractive research topic in many countries all over the world, especially in fast developing countries like India with higher load growth rate in recent decades. Load forecast can be generally classified into four categories based on the forecasting time, as shown in Table 1 (McSharry *et al*., 2005; Willis *et al*., 1984).

Table 1: Classification of Load forecast based on the forecasting time

Load Forecast	Period	Importance
Long	1-10 years	To calculate and allocate the required future capacity. To plan for new power stations to face customer requirements Plays an essential role to determine future budget
Medium	1-week to few months	Fuel allocation and maintenance schedules.
Short	1-hour to 1-week	Accurate for power system operation. To evaluate economic dispatch, hydrothermal coordination, unit commitment, transaction. To analysis system security among other mandatory function.
Very Short	1-minute to 1-hour	Energy Management Systems.

Each term of forecast has its own merits to the utilities. Long term forecasting is essential for system planning with a view of inflating the system capability in order to meet the long term growth in demand. Medium term LF is necessary for the scheduling of fuel supply and maintenance operations and planning for inter utility power transfer. Short-term LF is necessary in the daily operation such as unit commitment, energy transfer scheduling, fuel scheduling and demand side management. However, neither the accurate forecast nor the production of electrical energy is as easy as it looks, because (a) forecasting may be inaccurate (b) peak demand depends on temperature (c) data required for forecasting such as weather, economic data are not available and (d) construction of new power plants and transmission facilities require huge investment and take several years for completion.

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Many techniques such as auto regressive integrated moving average (Gonzales Chavez *et al*., 1999) and regression analysis (RA) (Arash Ghanabri *et al*., 2010; Hor *et al*., 2005; Asber *et al*., 2007; Geoffrey *et al*., 2007) have been investigated to solve the problem of LF in the last few decades. Recently, considerable interest appears to be focused on the application of artificial neural networks (ANN) for LF due to their ability to extract the relationship among input variables and output through learning from the available database (Henrique Steinherz Hippert *et al*., 2001; Kermanshahi *et al*., 2002; Madasu hanmandlu *et al*., 2011; Saravanan *et al*., 2012; Santosh Kulkarni *et al*., 2013). ANNs combined with RA (Ghanhari *et al*., 2009; Bong *et al*., 2008; Adem Akpinar, 2011; Sackdara, 2010) as well with fuzzy logic (Toly Chen. 2012; Toly Chen *et al*., 2012) for LF have been outlined. The other hybrid versions for LF have also been notified in (Jie Wu *et al*., 2013; Wei-Chiang Hong *et al*., 2013; Cheng-Ting Lin *et al*., 2014). Most of the studies focus on short-term LF. Only a few studies have been carried out for medium and long term LF.

Recently, teaching learning based optimization (TLO) has been suggested for solving optimization problems (Rao *et al*., 2011, 2012). It is inspired from teaching-learning process in class rooms. It mimics the behavior of the students in improving their performance through gaining the knowledge from the teacher and interacting with other students. It has been applied to a variety of power system problems (Provas Kumar Roy *et al*., 2014; Bouchekara *et al*., 2014) and found to yield satisfactory results.

In this paper, a TLO and ANN based model for forecasting India's sector-wise electrical energy demand for future years unlike the existing models. The paper is organized as follows: section II overviews the TLO, section III suggests the proposed model (PM), section IV presents the simulation results and section V concludes.

Teaching Learning Based Optimization:

TLO mimics the behavior of the students in improving their performance through gaining the knowledge from the teacher and interacting with other students. In this approach, each student represents a solution point and his performance is analogous to fitness value of the problem. The best student in the population is considered as the teacher. A group of students comprising a teacher forms the population and the solution process is governed by two basic operations, namely teaching and learning phases, which are briefed below:

Teaching Phase:

The teaching phase represents the global search property of the TLBO algorithm. During this phase, the students will gain knowledge according to the quality of the teaching delivered by a teacher and the quality of the students present in the class, the mean grade point of the subject increases and the difference between the grade point of the teacher and the mean grade point of the subject is expressed as

$$\Delta S^{j\,k} = rand(0,1) \times \left(S^{j\,k}_{teacher} - t_f \; S^{j\,k\,ave} \right) \tag{1}$$

Where

$S^{j\,k\;ave}$ is the mean grade of the j-th subject at k-th iteration and computed by

$$S^{j\,k\,ave} = \frac{1}{nS} \sum_{i=1}^{nS} S_i^{j\,k} \tag{2}$$

$S^{j\,k}_{teacher}$ is the grade point of the j-th subject of the teacher at k-th iteration

t_f is the teaching factor, which decides the value of mean to be changed and can be either 1 or 2, evaluated by

$$t_f = round([1 + rand\ (0,1)\{2-1\}] \tag{3}$$

The new grade point of the j-th subject of the i-th student, as a result of teaching, is mathematically modeled by

$$S_i^{j\,k+1} = S_i^{j\,k} + \Delta S^{j} \tag{4}$$

The grade points of all the students at the teachers phase are further improved by the learner phase.

Learning Phase:

The learner phase stands for the local search process of the TLBO algorithm. In this phase, the students enrich their knowledge by interaction among themselves, which helps in improving their performances. The influence on the grade points due to the interaction of p-th student with q-th student may be mathematically expressed as follows:

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$$S_p^{j\,k+1} = \begin{cases} S_p^{j\,k} + rand \times \left(S_p^{j\,k} - S_q^{j\,k}\right) & if\ F_p > F_q \\ S_p^{j\,k} + rand \times \left(S_q^{j\,k} - S_p^{j\,k}\right) & otherwise \end{cases} \quad (5)$$

Where F_p and F_q is the performance, indicating the fitness, of the p-th and q-th student respectively.

Proposed Model:

The goal of the PM is to forecast the sector-wise electrical energy demand in future years with minimum input data. Recently ANNs find extensive acceptance in many disciplines for modeling complex real-world problems that includes LF because of their clear and easy model implementation artifact. They are like human brains and massively parallel-distributed information processing systems with highly flexible configuration. Usually, they are multi-layer feed forward networks comprising of an input layer, an output layer and a hidden layer, each with a set of neurons and designed to perform a particular task. Solving undefined relationships between input and output variables, approximating complex nonlinear functions and implementing multiple training algorithms are the better-known advantages of these tools (Henrique Steinherz Hippert *et al*., 2001; Kermanshahi *et al*., 2002). The proposed forecasting model is thus based on ANNs.

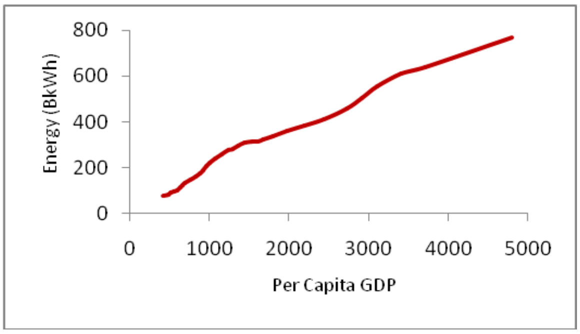

Fig. 1: Per Capita GDP versus Energy

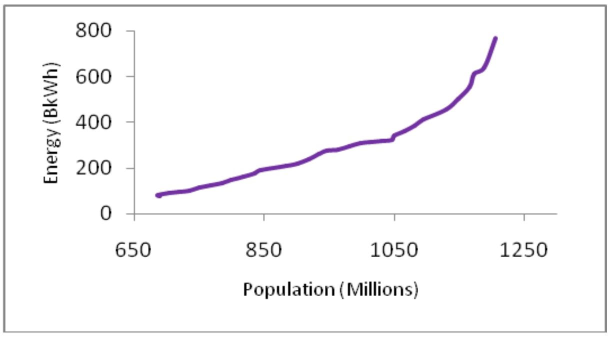

Fig. 2: Population versus Energy

There are a large number of input data such as such as weather, average temperature, time, number of households, number of air conditioners, amount of CO2 pollution, oil price, economy, population, etc., which are related to the electrical energy demand in any country. It would be difficult to train a neural network with all the available input data, as the number of connection weights and neurons would be large. Besides, many of these factors are usually used only for short term forecasting of energy demand. It is thus essential to reduce the number of inputs, which are mutually independent to one another and able to clearly establish the input-output relationship, to a neural network.

Among these factors, the population growth as well the continuous improvement in the public revenue and living standards, represented through per capita GDP, are related with the total energy consumption of any country (Saravanan *et al*., 2012; Ghanhari *et al*., 2009). The plots relating the energy consumed with per capita GDP and the population in India during the years 1980-2012, shown through Figs.1 and 2, clearly indicate that the energy consumed in India increases with both the per capita GDP and the population.

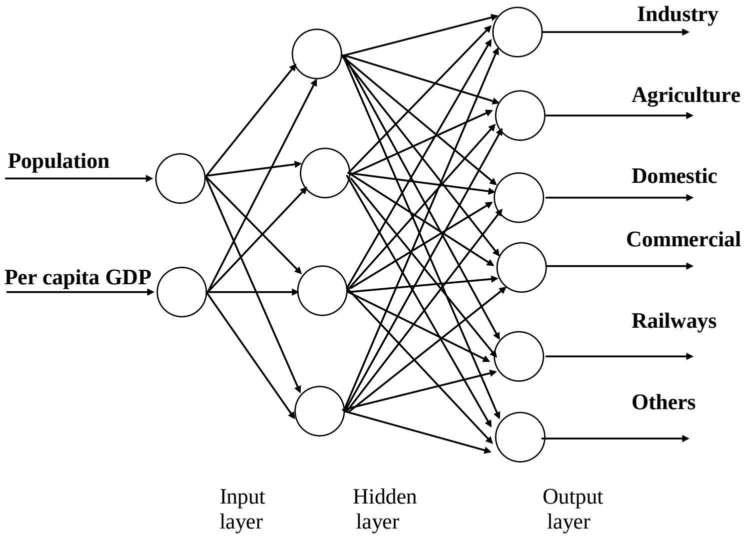

Fig. 3: Proposed forecasting model using TLO and ANN

In the light of the fact that the per capita GDP and population establish a good relationship with the electrical energy demand, they are considered as inputs in the PM. The structure of PM is shown in Fig. 3. The model requires two inputs and offers six outputs ($E_1 - E_6$), representing energy demand in the sectors of industrial, agricultural, domestic, commercial, railways and other areas. The historical data set comprising the input (X) and the target (T) vectors for the PM are as follows.

$$\{X \leftrightarrow T\} = \{Pop, \mathrm{GDP} \leftrightarrow E_1, E_2, E_3, E_4, E_5, E_6\} \tag{6}$$

The generated input-target data are split into two partitions: the first one is the training data, which is used to train the network and the second, the testing data, is used to assess how well the network is generalized. There is a possibility of obtaining good performance on the training data followed by much poor performance on the test data. This can be avoided by ensuring that the training data is uniformly distributed.

During training of the neural network, higher valued input variables may tend to suppress the influence of smaller ones. Besides, if the raw data is directly applied to the network, there is a risk of the simulated neurons reaching the saturated states. If the neuron becomes saturated, then the changes in the input value will produce a very small change or no change in the output value. This affects the network training to a great extent. The raw data is therefore normalized before it is applied to the neural network. One way to normalize the data x is by using the expression:

$$x_n = \frac{(x - x_{\min}) \times (U_R - L_R)}{x_{\max} - x_{\min}} + L_R \tag{7}$$

Where x_n is the normalized value

$x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the variable x respectively

L_R and U_R lower and upper range for normalization respectively

Tangent hyperbolic and linear activation functions are chosen for the hidden layer neurons and output neurons respectively for both ANN models. The connection weights are adjusted to correctly map the training set vectors at least to within a defined MSE limit during training. The ANNs are usually trained through back propagation algorithm, which involves a complicated training procedure and associates with problems such as long training time and local optimization, etc. Besides, the forecasting accuracy strongly depends on the training process, which determines the connection weights that minimize the following MSE.

Minimize $$MSE = \frac{1}{2N} \sum_{n=1}^{N} \sum_{i=1}^{no} \left(O_i(n) - T_i(n)\right)^2 \tag{8}$$

The proposed TLO based training model involves representation of problem variables and the formation of a performance function. Each student in the TLO is defined to represent the connection weights between input, hidden and output layers as

$$S = [W_{ih},\ b_h,\ W_{ho},\ b_o] \tag{9}$$

The TLO searches for optimal solution by maximizing a fitness function, denoted by F, which is formulated from the objective function of Eq. (8) and built as

$$Max \quad F = \frac{1}{1 + MSE} \tag{10}$$

An initial population of students is obtained by generating random values within their respective limits to every individual in the population. The fitness F is calculated by considering gp_s of each student; and the teaching and learning phases are performed for all the students in the population with a view of maximizing their performances. The iterative procedure is continued until the number of iterations reaches the specified maximum number of iterations. The ANN with the connection weights obtained from best student in the population is ready for forecasting the future energy demand. The TLO based training of ANN is summarized below:

1. ***Set*** *the algorithm parameters such as population size, maximum number of iterations for convergence check, etc*
2. ***Initialize*** *the population by generating* gp_s *within the respective range for each student as represented in Eq. (9).*
3. ***Compute*** *the performance function* F *for each student of the entire population by the following steps*
   - *Set the* gp_s *as the connection weights of the ANN*
   - *Actuate the ANN with the training data*
   - *Compute MSE and evaluate* F *using Eq. (10).*
4. ***Choose*** *the best student as the teacher*
5. ***Evaluate*** *the mean grade point for each subject*
6. ***Modify*** *the grade points of each student in the population according to teacher phase*
7. ***Update*** *the grade points of each student according to learners phase*
8. ***Repeat*** *steps 3-7 until the iteration number arrives at the maximum number of iterations.*
9. ***The best student*** *in the population represents the connection weights of the ANN.*

Simulations:

Successful operation of ANN based load forecasters requires an appropriate training data set that can adequately cover the entire solution space with a view to recognize and generalize the relations among the problem variables. In this work, a historical data during the period of 1980-2012 have been used. The actual India's sector-wise energy consumption, the per capita GDP and the population data have been taken from the references (Websites: http:/www…). The per capita GDP and population, calculated through RA during the years 2013-2025 and presented in Table 1, are considered as input data for actuating the PM, after training. The goodness of the forecast is evaluated through the following mean absolute percent error (MAPE).

$$\text{MAPE} = \frac{\sum_{i=1}^{nfo} |\Phi_i|}{no} \tag{11}$$

Where nfo is the number of forecasted outputs

$$\Phi_i = \frac{Actual\ Energy_i - Forecasted\ Energy_i}{Actual\ Energy_i} \times 100$$

One of the challenges in the design of ANN is the proper selection of the number of neurons in the hidden layer, which affects the learning capability and leads to the complexity of the problem. The fundamental rule is to select the minimum number of hidden neurons just enough to ensure the complexity of the problem, but too many may cause over fitting of the training set and losing the generalization ability. In this paper, a trial and error scheme has been adopted in determining the appropriate number of hidden neurons. The number of neurons in the hidden layer is varied from 2 to 10 and the resulting MAPEs are compared for the testing data. It is found that a hidden layer with 7 neurons gives satisfactory results. The results of the PM are compared with that of RM with a view to evaluate the performance of the PM.

Table 1: Data obtained by the RM

Year	Per Capita GDP	Population (Millions)
2013	5125.28	1209.75
2014	5690.23	1226.25
2015	6295.78	1248.56
2016	6938.99	1267.88
2017	7615.92	1287.75
2018	8321.45	1309.94
2019	9049.44	1330.69
2020	9792.53	1351.38
2021	10542.00	1372.50
2022	11287.82	1390.13
2023	12018.59	1406.69
2024	12721.35	1418.81
2025	13381.58	1431.25

Table 2: Comparison of Results for Yesteryears

Year	Per Capita GDP	Population (Millions)		Forecasted Electrical Energy (BkWh)						MAPE	
				Industry	Agriculture	Domestic	Commercial	Railways	Others	RM	PM
1989	821.48	817.49	Actual	76.82	38.85	24.61	10.06	4.04	5.82		
			RM	82.66	43.15	24.70	10.31	3.94	6.58	6.18	
			PM	78.17	44.26	25.11	10.82	3.98	6.31		5.86
1997	1285.94	962.38	Actual	104.17	84.02	55.27	17.52	6.53	12.64		
			RM	97.40	80.33	56.46	16.63	6.58	12.74	3.28	
			PM	102.02	84.51	55.03	17.50	6.55	12.73		0.70
2005	2190.27	1080.26PM	Actual	137.59	88.56	95.66	31.38	9.49	23.45		
			RM	148.18	95.38	97.21	34.09	9.56	24.23	4.95	
			PM	139.68	90.90	96.66	33.05	9.62	23.74		2.19
2009	3103.73	1166.08	Actual	209.47	109.61	131.72	54.19	11.43	37.58		
			RM	222.44	115.08	137.31	53.87	12.10	35.31	4.65	
			PM	211.32	109.55	130.35	54.05	11.60	33.95		2.23
Average MAPE										4.77	2.75

The results for the chosen yesteryears are given in Table-2. It clear from the results that the MAPE of the PM is lower than that of RM. The lowered MAPE validates the model and ensures the accuracy of the results for future years. The results of RA and PM during the years 2013-2025 are presented in Tables 3 and 4 respectively. It is seen from these tables that the sector wise energy demands, given by PM, are in general lower than that of the RM. This is graphically illustrated by comparing the net energy demand of all the methods over the forecasting period in Fig. 4. The PM predicts the energy demand in the future years to be lower than that of RM and indicates the policy makers to allocate little lower funds for construction of new power plants and transmission systems with a view to meet the future energy demand.

Table 3: Results of RM

Year	Forecasted Electrical Energy (BkWh)					
	Industry	Agriculture	Domestic	Commercial	Railways	Others
2013	316.59	149.30	201.72	85.90	16.21	47.50
2014	348.98	163.18	225.37	96.65	17.29	52.67
2015	380.66	179.39	247.70	105.76	18.84	57.92
2016	417.05	197.25	279.28	117.44	20.39	63.88
2017	452.81	216.18	306.93	126.56	21.81	69.52
2018	489.81	234.45	344.48	140.50	23.33	75.95
2019	526.79	260.81	383.65	152.72	25.00	81.34
2020	558.12	287.67	422.26	164.58	26.89	89.44
2021	597.80	316.08	460.18	176.29	28.81	95.05
2022	621.94	347.88	502.34	191.56	30.67	101.78
2023	651.13	379.32	545.97	205.76	32.34	106.04
2024	672.23	417.67	594.35	218.98	34.41	111.39
2025	685.12	454.96	635.92	233.11	35.88	114.89

Table 4: Results of PM

Year	Forecasted Electrical Energy (BkWh)					
	Industry	Agriculture	Domestic	Commercial	Railways	Others
2013	315.09	151.48	205.32	82.22	16.17	48.00
2014	341.55	163.39	225.56	90.72	17.24	51.93
2015	368.94	176.98	247.71	99.86	18.37	56.07
2016	397.10	192.44	271.90	109.66	19.56	60.43
2017	425.86	209.97	298.27	120.13	20.81	65.01
2018	455.02	229.76	326.96	131.31	22.13	69.80
2019	484.36	252.01	358.10	143.20	23.51	74.81

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2020	513.65	276.95	391.84	155.82	24.95	80.03
2021	542.64	304.79	428.33	169.19	26.46	85.46
2022	571.06	335.77	467.73	183.32	28.04	91.10
2023	598.62	370.12	510.20	198.24	29.68	96.94
2024	625.04	408.10	555.90	213.95	31.38	102.98
2025	649.98	449.96	604.99	230.47	33.15	109.21

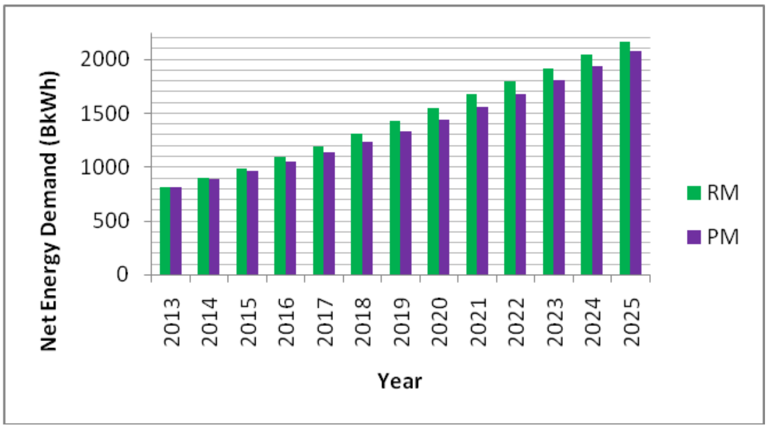

Fig. 4: Comparison of net energy demand

Conclusion:

Long term LF is a critical task for the policy makers as well as for the government. A precise upper bound for long term load avoids unnecessary power plant investment. The sector-wise electrical energy demand of India has been forecasted for the future years through the population and the socio-economic factors of per capita GDP by the developed ANN model. The standard back-propagation network training method often suffers from a number of inherent drawbacks such as the complex pattern of error surfaces, slow convergence rate, getting struck at local minima, etc. The ANN models thus trained through TLO predicts the sector-wise electrical energy demand. It has been found from the results that the PM offers more accurate predictions than that of RM, helps the policy makers for allocating appropriate funds for constructing new generation plants and transmission systems to meet the future demands and attempts to offer reliable service to the customers in the future years.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the authorities of SCSVMV and Pondicherry Engineering College for their continued support, encouragement and the facilities provided to carry out this work.

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