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DRAGONFLY OPTIMIZATION BASED LONG-TERM FORECASTING OF ELECTRICAL ENERGY

J. Kumaran Kumar[1], G. Ravi[2] and J. Sasikala[3]
[1]Department of Computer Science and Engineering, Pondicherry Engineering College, Puducherry, India
[2]Department of Electrical and Electronics Engineering, Pondicherry Engineering College, Puducherry, India
[3]Department of Computer Science and Engineering, Annamalai University, Tamil Nadu, India
E-Mail: kumaran@pec.edu

ABSTRACT

Long-term load forecasting plays a significant role in the operation and management of power systems. Accurate estimation of future energy demands for various lead times facilitates the task of generating power reliably and economically. The energy demand depends so many factors such as weather, average temperature, time, number of households, number of air conditioners, amount of CO_2 pollution, oil price, economy, population, etc. This paper attempts to suggest a hybrid model based on Artificial Neural Network (ANN) and Dragonfly Optimization (DFO) for predicting the electrical energy demand of India for the future years up to 2025. The model requires the year of the forecast as input, and predicts the net electrical energy demand. The comparison of the results with that of the regression model demonstrates the effectiveness of the proposed model.

Keywords: load forecasting, artificial neural network, dragonfly optimization.

1. INTRODUCTION

The Load forecasting (LF) is an important study for effective planning of production, transmission and distribution capacities in many countries all over the world, especially in fast developing countries like India with higher load growth rate in recent decades. The electric utilities make investments and take decisions on planning, maintenance and expansion. Accurate prediction of future load demand is difficult, as it depends large number of parameters that involve uncertainty [1].

LF has become an emerging research area due to the fast depletion of fossil fuels, the escalation in the population and the increase of the per capita power consumption. The growth in energy consumption is essentially linked with the growth in economy, the population growth, rapid development of industrial and commercial growth and structural changes in the economy [1].

LF can be generally classified into long, medium, short and very short, based on the forecasting period. Each term of forecast has its own merits to the utilities. The long term forecast is necessary for system expansion planning and financial analysis; medium term forecast is required for maintenance scheduling and diversity interchanges; whereas the short term and very short forecast represents a great saving potential for economic and secure operation of power systems [2, 3].

Several strategies such as auto regressive integrated moving average [2] and regression analysis (RA) [3] have been developed for forecasting the future electrical energy demand in the recent decades. Artificial neural networks (ANN) have been applied for LF due to their ability to extract the relationship among input variables and output through learning from the available database [4, 5]. ANNs combined with RA [6, 7] as well with fuzzy logic [8] for LF has been outlined. The other hybrid versions for LF have also been notified in [9, 10]. Though most of the studies discussing short-term LF are in vogue, relatively a little contribution is reported for medium and long term LF.

More recently, a Dragonfly Optimization (DFO), inspired from the static and dynamic swarming behaviors of dragonflies, has been suggested for solving optimization problems in [11]. Since its introduction, it has been applied to several real world optimization problems [12, 13] and found to yield satisfactory results.

In this paper, a hybrid model based on ANN and DFO for forecasting India's electrical energy demand for future years involving Per capita GDP and Population has been developed. The paper is organized as follows: section 2 suggests the proposed model (PM), section 3 provides the simulation results and section 4 concludes.

2. PROPOSED MODEL

The goal of the PM is to forecast the 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. 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. 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 [4]. Though the per capita GDP and population establish a good relationship with the electrical energy demand in the long-term forecasting model, they are not readily available for the future years. However, they can be predicted through trend analysis. The ANN model suggested in [4] uses population and per capita GDP as inputs in the long term forecasting model but does not comprise a tool for obtaining the required inputs for the

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future years, thereby making the model incomplete. The focus of this paper is thus to develop a complete model with minimum input for forecasting the future energy demand unlike the existing models using guessed input values.

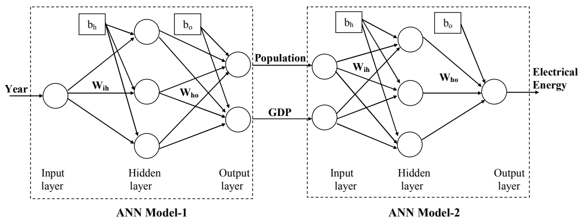

Figure-1. Proposed forecasting model.

The PM uses two multi-layer feed forward networks, each possessing an input layer, an output layer and a hidden layer comprising of a set of neurons. The first ANN predicts the population and per capita GDP for a given future year and the second one forecast the future energy demand by considering the output of the former as input. The structure of PM is shown in Figure-1. The input required for the first ANN model is just the year of forecast and the output of the second model is the forecasted electrical energy demand. Thus the PM with one input and two intermediate predictions produces the future energy demand. The training and testing data set comprising the input (X) and the target (T) vectors for both the models are as follows.

$$\{X \leftrightarrow T\} = \{year \leftrightarrow Pop, \mathrm{GDP}\} \text{ for model-1}$$
$$\{X \leftrightarrow T\} = \{Pop, \mathrm{GDP} \leftrightarrow \mathrm{Energy}\} \text{ for model-2}$$

The connection weights are iteratively adjusted till the MSE reaches a value less than a small tolerance value with a view of correctly mapping the input-output training data set. The training of ANNs 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.

$$\text{Minimize} \quad MSE = \frac{1}{2N}\sum_{n=1}^{N}\left(O(n) - T(n)\right)^2 \tag{1}$$

The DFO works directly on decision variables through nature-inspired operators and enables the searching in multi-dimensional problem space with an objective of reaching the desired goal [11]. As there are no restrictions during search, it explores the entire problem space and offers the global best solution. It can be effectively used for training the ANNs of the proposed forecasting model with an objective of minimizing the MSE. Each dragonfly in the population is defined to represent the connection weights between input, hidden and output layers as

$$dragonfly = [W_{ih},\ b_h,\ W_{ho},\ b_o] \tag{2}$$

An initial swarm of dragonflies is obtained by generating random values within their respective limits. The cost function is calculated by considering the threshold values of each dragonfly; and the exploration and exploitation phases are performed for all the dragonflies in the swarm with a view of minimizing their costs. The above iterative procedure is continued until the number of iterations reaches the specified maximum number of iterations [11].

3. RESULTS AND DISCUSSIONS

Successful operation of ANN based load forecasters requires an appropriate training data set and training algorithm. The training data set should cover all ranges of the input patterns sufficiently to provide the network knowledge to recognize and generalize the relations among the variables in the problem. In this work, a historical data during the period of 1980-2012 have been used. The actual India's energy consumption, the per capita GDP and the population data have been taken from the references [14-16].

The results of the PM are compared with that of RA with a view to evaluate the performance of the PM. The average forecasting error for each forecast is evaluated using the following equation for assessing the goodness of the forecast.

$$\%\,Error = \left|\frac{Actual\ \ Load - Forecasted\ \ Load}{Actual\ \ Load}\right| \times 100$$

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Table-1. Results for Validation.

Year		Intermediate Results/Data		Forecasted Electrical Energy (BkWh)	% Error	
		Per Capita GDP	Population (Millions)		RM	PM
1989	Actual	821.48	817.49	160.20		
	RM	847.74	817.55	167.13	4.3258	
	PM	818.25	825.91	163.93		2.3283
1997	Actual	1285.94	962.38	280.15		
	RM	1298.55	958.70	272.26	2.8163	
	PM	1271.50	967.48	274.04		2.1810
2005	Actual	2190.27	1080.26	386.13		
	RM	2206.65	1086.40	400.92	3.8303	
	PM	2238.25	1089.55	396.21		2.6105
2009	Actual	3103.73	1166.08	554.00		
	RM	3138.71	1158.59	563.52	1.7184	
	PM	3090.00	1165.06	563.56		1.7256
Average % Error					3.1727	2.2114

Table-2. Results of the RM.

Year	Intermediate Results		Forecasted Electrical Energy (BkWh)
	Per Capita GDP	Population (Millions)	
2013	5125.28	1209.75	816.50
2014	5690.23	1226.25	889.63
2015	6295.78	1248.56	982.50
2016	6938.99	1267.88	1079.38
2017	7615.92	1287.75	1178.00
2018	8321.45	1309.94	1291.13
2019	9049.44	1330.69	1404.88
2020	9792.53	1351.38	1514.50
2021	10542.00	1372.50	1641.50
2022	11287.82	1390.13	1756.75
2023	12018.59	1406.69	1873.75
2024	12721.35	1418.81	2009.38
2025	13381.58	1431.25	2133.88

Table-3. Results of the PM.

Year	Intermediate Results		Forecasted Electrical Energy (BkWh)
	Per Capita GDP	Population (Millions)	
2013	5143.76	1213.11	828.50
2014	5653.80	1226.49	911.25
2015	6197.35	1239.55	1000.63
2016	6774.37	1252.29	1097.13
2017	7384.70	1264.71	1199.00
2018	8028.06	1276.82	1312.00
2019	8704.05	1288.63	1421.13
2020	9412.14	1300.14	1540.38
2021	10151.69	1311.36	1656.50
2022	10921.93	1322.32	1779.13
2023	11721.96	1333.01	1895.38
2024	12550.79	1343.46	2004.38
2025	13407.28	1353.69	2114.00

The results for the years 1989, 1997, 2005 and 2009 are given in Table-1 with a view of validating the trained network. It is clear from the results that the average of the PM is lower than that of RA. The lowered average error 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 2 and 3 respectively. It is to be noted from the results of these two tables that the demand given by the PM is slightly lower than that of RA, which indicates the policy makers to

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allocate lower funds for construction of new power plants and transmission systems just to meet the future energy demand.

4. CONCLUSIONS

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 net electrical energy consumption of India is forecasted for the future years through predicting the socio-economic factors: per capita GDP and population growth. 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 DFO first predicts the population and per capita GDP and then forecasts the electrical energy demand. The forecasted results clearly indicate that the PM offers more accurate predictions than that of RA.

Nomenclature	
ANN	Artificial Neural Network
b_i	a constant representing bias
b_h and b_o	bias for hidden and output layers respectively
DFO	Dragonfly Optimization
GDP	Gross Domestic Product
LF	Load Forecasting
MSE	Mean Squared Error
N	number of training data
$O(n)$	output for n -th training data
PM	Proposed Model
RA	Regression Analysis
$T(n)$	targeted value for n -th training data
w_{ij}	connection weights between i -th neuron and j -th input
W_{ih}	weight matrix in between input and hidden layers
W_{ho}	weight matrix in between hidden and output layers
X and T	input and target vectors of the training data respectively

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REFERENCES

[1] P.E. McSharry, S. Bouwman and G. Bloemhof. 2005. Probabilistic forecasts of the magnitude and timing of peak electricity demand. IEEE Transactions Power Systems. 20: 1166-1172.

[2] S. Gonzales Chavez, J. Xiberta Bernal and H. Llaneza Coalla. 1999. Forecasting of energy production and consumption in Asturias (Northern Spain), Energy. 24(3): 183-198.

[3] Arash Ghanabri, S. Farid Ghaderi and M. Ali Azadeh. 2010. Adaptive neuronuzzy inference system vs. regression based approaches for annual electric load forecasting. 2nd International Conference on Computer and Automation Engineering (ICCAE), Singapore. 5: 26-30.

[4] S. Saravanan, S. Kannan and C. Thangaraj. 2012. Forecasting India's electricity demand using artificial neural network. IEEE- International Conference on Advances in Engineering, Science and Management (ICAESM -2012). pp. 79-83.

[5] Santosh Kulkarni, Sishaj P. Simon and K. Sundareswaran. 2013. A spiking neural network (SNN) forecast engine for short-term electrical load forecasting. Applied Soft Computing. 13: 3628-3635.

[6] Adem Akpinar. 2011. Modeling and forecasting of Turkey's energy consumption using socio-economic and demographic variables, Applied Energy. 88(5): 1927-1939.

[7] Sackdara S. Premrudeepreechacharn and Naamsanroaj K. 2010. Elecricity demand forecasting of Electricite DU Lao (EDL) using neural networks. TENCON-2010. pp. 640-644.

[8] Toly Chen and Yu-Cheng Wang. 2012. Long-term load forecasting by a collaborative fuzzy-neural approach. Electrical Power and Energy Systems. 43(1): 454-464.

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[9] Wei-Chiang Hong, Yucheng Dong, Wen Yu Zhang, Li-Yueh Chen and B. K. Panigrahi. 2013. Cyclic electric load forecasting by seasonal SVR with chaotic genetic algorithm. Electrical Power and Energy Systems. 44: 604-614.

[10] Cheng-Ting Lin, Li-Der Chou, Yi-Ming Chen and Li-Ming Tseng. 2014. A hybrid economic indices based short-term load forecasting system. Electrical Power and Energy Systems. 54: 293-305. 21.

[11] Seyedali Mirjalili., Dragonfly algorithm. 2015. A new meta-heuristic optimization technique for solving single-objective, discrete and multi-objective problems. Neural Comput and Applic. DOI. 10.1007/s00521-015-1920-1.

[12] Rakoth Kandan. S, Sasikala. J. 2016. Self-adaptive dragonfly based optimal thresholding for multilevel segmentation of digital images. Journal of King Saud University-Computer and Information Sciences. http://dx.doi.org/10.1016/j.jksuci.2016.11.002.

[13] Hamdy M., Nguyen AT. and Hensen J.L.M. 2016. A performance comparison of multi-objective optimization algorithms for solving nearly-zero-energy-building design problems. Energy and Buildings. http://dx.doi.org/10.1016/j.enbuild.2016.03.035.

[14] 2014. Data for per capita GDP available at http://www.indexmundi.com/india/gdp_per_capita_(ppt).html on 20 January.

[15] Data for population available at http://www.populstat.info/Asia/indiac.htm.

[16] India's sector wise energy demand available at http://www.iasri.res.in/agridata/08data%5Cchapter3%5Cdb2008tb3_57.pdf on 20 Jan 2014.