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ANN and Firefly Optimization Based Long-Term Electrical Energy Forecasting

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ABSTRACT: Long term load forecasting estimates the future energy demand of a country and signifies a major role in allocating funds by the government for constructing newer power plants. This article suggests an artificial neural network (ANN) model that is trained by a firefly optimization algorithm (FOA),for forecasting electrical energy demand for future years. FOA mimics the flashing behavior of fireflies in solving optimization problems. The suggested ANN model receives per capita GDP and population as inputs and provides the forecast of electrical energy demand. The forecasted results up to the year 2025 portray the superiority of the developed model.

KEYWORDS: load forecasting; artificial neural networks; firefly optimization

I. INTRODUCTION

Electrical Energy consumption that represents social and economic growth of any nation, increases with the population growth and Gross Domestic Product (GDP). Energy forecasting is a prime problem in power system planning and operation, as it helps the government to allocate appropriate funds for newer power projects. Many researchers and system engineers in several countries are working to build newer tools for accurate forecasting of future electrical energy demand. Energy forecast problem is broadly portioned into long, medium, short and very short depending on the forecasting period [1,2].

Long term forecasting is required for planning to construct newer power plants with a view of meeting long term growth in energy demand. Medium term forecasting is required for fuel supply allocation and maintenance scheduling. Short-term forecasting is required to meet the day-to-day operations such as economic load dispatch, unit commitment, fuel scheduling and management of load demand. The accurate energy forecasting is not as simple as it looks due to the difficult in getting the weather and economic data.

Several methods that include regression analysis (RA) [2,3], auto regressive integrated moving average [1], and artificial neural networks (ANN) [4-6] were suggested to perform energy forecasting in recent years. Later, ANNs blended with regression analysis (RA) [7,8] and fuzzy logic [9] were suggested for energy forecasting. In general many of the articles focus only on short-term energy forecasting, but little significance is given to long-term energy forecasting.

Recently, Firefly Optimization Algorithm (FOA), a nature-inspired meta-heuristic algorithm mimicking the flashing behaviour of fireflies, was outlined for solving optimization problems by Xin She Yang[10]. This article attempts to build a new energy forecasting model employing ANN and FOA. The model attempts to forecast the sector wise energy demand unlike the traditional forecasting models of estimating the net energy demand.

II. PROPOSED MODEL

The objective of the article is to build a forecasting model with reduced number of collected data for predicting the sector-wise electrical energy 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

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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 electrical energy 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 energy demand. Among these parameters, the population growth and the per capita GDP representing the revenue and living standards of public can be associated with energy consumption [7], and therefore these two factors are chosen as inputs in the PM. The forecasted outputs are chosen as sector-wise energy demands at Industry, Agriculture, Domestic, Commercial, Railways and Others.

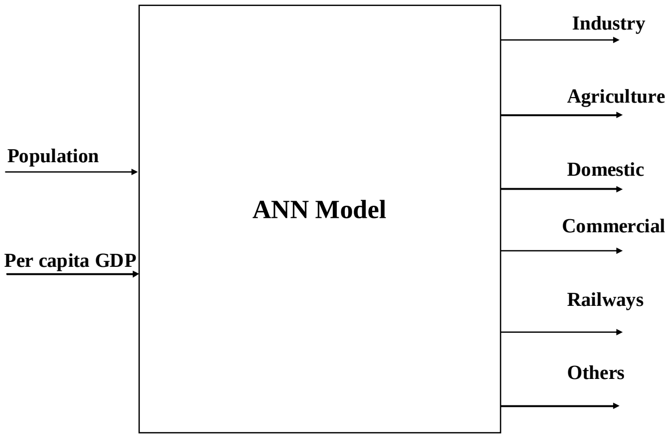

Fig. 1Block Diagram of PM

The input data of the per capita GDP and population, and the target data of six sector-wise energy demands form the database for developing the ANN model, which therefore contains two inputs and six outputs as shown in Fig. 1. The collected input-target data 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.

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

Where $data_n$ represents the normalized data

$data_{\min}$ 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. Traditionally back-propagation algorithm that requires complex training process involving longer training time and landing at sub-optimal traps, which influence the accuracy of the forecasting model. The training process can be modelled as an optimization problem with an objective of minimizing the following MSE function.

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

The FOA can be employed for training the ANN model. It involves representation of problem variables and the formation of a brightness function. Each firefly(F) in the FOA is defined to indicate the biases, and the connection weights between input, hidden and output layers as

$$F = [W_{ih},\ b_h,\ W_{ho},\ b_o] \tag{3}$$

The FOA explores the solution space for optimal solution by maximizing a brightness function (B), which is tailored as

$$Maximize \quad B = \frac{1}{1 + MSE} \tag{4}$$

Fireflies usually move towards the brighter fireflies. In FOA, i-th firefly move towards j-th firefly, if j-th firefly's brightness (B) is larger than that of i-th firefly's, by the following expression:

$$F_i(t) = F_i(t-1) + A_{i,j}\left(F_j(t-1) - F_i(t-1)\right) + \alpha\left(rand - 0.5\right) \tag{5}$$

Where $A_{i,j}$ denotes the attractiveness between i-th and j-th fireflies and is computed by

$$A_{i,j} = \left(A_{\max,i,j} - A_{\min,i,j}\right)\exp\left(-\theta_i\ E_{i,j}^{\ 2}\right) + A_{\min,i,j} \tag{6}$$

Where $E_{i,j}$ is the Euclidean distance between i-th and j-th fireflies.

α and θ_i are constants

An initial population of fireflies is obtained by generating random values to every individual in the population. The brightness (B) is evaluated for each firefly. The brightness of all fireflies are compared and the fireflies with lower brightness are allowed to move towards the brighter fireflies by Eq. (5). This process represents an iteration. The iterative procedure is repeated until the number of iterations reaches the maximum number of iterations. The ANN with the connection weights obtained from best firefly in the population is ready for forecasting the future energy demand.

III. SIMULATION RESULTS

The PM involving ANN needs appropriate training and testing data set. In this regard, India's per capita GDP and the population, and the corresponding sector wise energy demands over the years 1980-2012 were collected [11-13]. 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. In the PM, the hidden neurons were chosen by a trial and error process of changing the number of neurons from 3 to 10 and the corresponding MSE for testing data were computed. In the PM, six hidden neuron led to smallest MSE and was chosen for the ANN model. While forecasting, the PM requires the per capita GDP and population, which are not available. These two inputs were obtained by RM for the years 2013-2025 and treated as input for PM. 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 sector wise energy demands, offered by PM, are in general lower than that of the RM. This is pictorially portrayed in Fig. 2. The PM indicates that the policy makers can allocate little lower funds for construction of new power plants and transmission systems with a view of meeting the future energy demand.

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Table 1 Results of PM

Year	Input data obtained by RM		Forecasted Energy by PM					
	Per Capita GDP	Population (Millions)	Industry	Agriculture	Domestic	Commercial	Railways	Others
2013	5125	1209	316	152	206	84	17	47
2014	5690	1226	342	164	226	92	19	52
2015	6295	1248	369	175	248	97	19	55
2016	6938	1267	396	196	274	111	18	61
2017	7615	1287	426	208	293	122	22	64
2018	8321	1309	454	227	327	130	24	68
2019	9049	1330	484	254	357	141	25	75
2020	9792	1351	514	278	393	153	23	82
2021	10542	1372	543	305	425	169	27	86
2022	11287	1390	570	336	466	182	29	92
2023	12018	1406	597	371	512	198	29	98
2024	12721	1418	626	407	554	213	32	101
2025	13381	1431	648	448	605	231	34	108

Table 2 Results of RM

Year	Input data obtained by RM		Forecasted Energy by RM					
	Per Capita GDP	Population (Millions)	Industry	Agriculture	Domestic	Commercial	Railways	Others
2013	5125	1209	317	147	202	84	15	46
2014	5690	1226	347	165	224	97	16	51
2015	6295	1248	382	176	245	106	17	55
2016	6938	1267	418	195	279	119	20	61
2017	7615	1287	451	215	305	125	22	67
2018	8321	1309	489	233	342	142	24	73
2019	9049	1330	527	262	381	152	26	80
2020	9792	1351	556	289	426	165	27	87
2021	10542	1372	595	319	462	176	28	93
2022	11287	1390	623	348	503	192	30	100
2023	12018	1406	652	376	542	205	31	105
2024	12721	1418	674	417	596	219	33	110
2025	13381	1431	686	453	636	230	34	113

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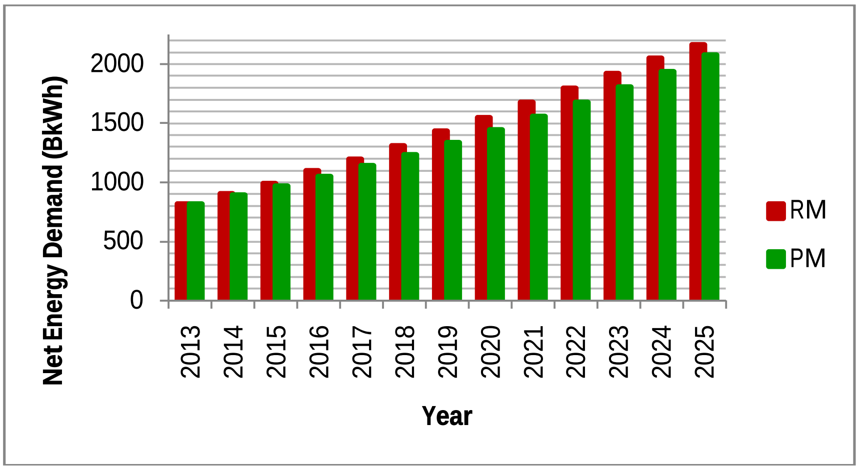

Fig. 2 Comparison of net energy demand

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 population and the per capita GDP as inputs of the ANN model. The FOA that mimics the flashing behavior of fireflies was employed for training the ANN model with a view of overcoming the drawbacks of the classical back-propagation training algorithm. The ANN models thus trained through FOA forecasts the sector-wise electrical energy demand. 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 portrays the superiority of the developed model.

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