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Firefly Optimization Based ANN Model for Primary Fuels' Demand Forecasting

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ABSTRACT: This article suggests an artificial neural network (ANN) model that is trained by a firefly optimization(FO),for forecasting primary fuels' demand for future years. FO 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 primary fuels' demand. The forecasted results up to the year 2025 portray the superiority of the developed model.

KEYWORDS: primary fuels' demand; forecasting; artificial neural networks; firefly optimization

I. INTRODUCTION

Fuel energy consumption that represents social and economic growth of any nation, increases with the population growth and Gross Domestic Product (GDP). Fuel Energy, the most requirement of any country, is considered as a `strategic commodity', whose shortage can affect the functioning of the economy of the country. The coal, lignite, crude oil and natural gas are considered as primary fuels, while wind, solar, small hydro, biomass, cogeneration bagasse etc. are considered as renewable energies [1].

Table 1 India's primary fuel energy consumption

	2005-06	2012-13	Major Consumer
Raw coal	407.04 MTs	570.23 MTs	Electric Power Generation Steel Plants
Lignite	30.23MTs	46.41 MTs	Electric Power Generation
Crude oil	130.11 MMTs	219.21 MMTs	Transport Systems
Natural Gas	31.03 BCMs	38.4 BCMs	Electric Power Generation Fertilizer Industry Domestic Use

The consumption of primary fuel energies coal, lignite, crude oil and natural gas during the years 2005-06 and 2012-13 are furnished in Table 1. It can be seen that the demand of these fuels sharply increases and reaches the peaks in the forthcoming years. Among these fuels, coal is abundantly available in India, but the quality is inferior to those available in Australia or Canada. Besides coal washing facility is not sufficient to provide washed coal to steel industries. Because of these reasons, high quality coal is being imported from foreign countries, and such import is steadily increasing from year to year. Nearly 70% of crude oil requirements are met from imports from foreign countries and there is steady increase in the import level. However, India has the facilities to export processed petroleum products [2].

Fuel Energy forecasting is a prime problem of any country with a view of allocating funds for the import of fuels from foreign countries and mining from various regions of the country. Since 1950, various classical techniques such as exponential smoothing, decomposition methods, multiple regression, econometric models, Box-Jenkins method, and autoregressive integrated moving average method (ARIMA) have been applied to forecasting problems [3-7]. But recently, soft computing techniques such as artificial neural networks and fuzzy logic have been applied in forecasting

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problems. Besides hybrid forecasting methods, combining ANN, fuzzy logic and classical approaches, have been applied to forecasting problems.

Recently, Firefly Optimization (FO), a swarm intelligence based algorithm imitating the flashing behaviour of fireflies, was suggested for solving optimization problems by Xin She Yang[10]. This paper endeavours to develop a new hybrid model combining ANN and FO for forecasting primary fuel' requirements of India in future years. The model receives the per-capita GDP and population as inputs and forecasts the demand of coal, lignite, crude oil and natural gas.

II. PROPOSED MODEL

The objective of the article is to build a forecasting model with reduced number of collected data for predicting the primary fuel' 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 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 withprimary fuels' 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 primary fuel energy requirement. Among these parameters, the population growth and the per capita GDP representing the revenue and living standards of public can be associated with primary fuels' consumption [7], and therefore these two factors are chosen as inputs in the PM. The forecasted outputs are chosen as the demands for coal, lignite, crude oil and natural gas.

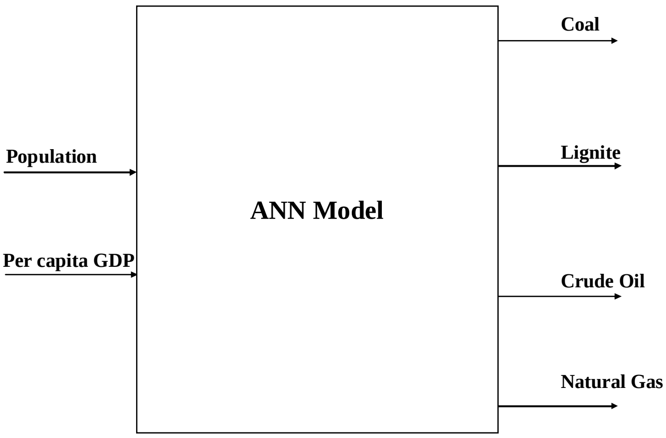

Fig. 1Block Diagram of PM

The input data of the per capita GDP and population, and the target data of four primary fuel demands form the database for developing the ANN model, which therefore contains two inputs and four 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.

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

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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.

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

The FO 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 FO 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 FO 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 FO, 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 primary fuels' 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 primary fuel's demands over the years 1980-2012 were collected [2,11,12]. 70% of collected data was considered as training data and the remaining 30% 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, five 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

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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 2 and 3 respectively. It can be observed from these tables that the primary fuels' demands, offered by PM, are in general lower than that of the RM. The PM indicates that the policy makers can allocate little lower funds for import of primary fuels' demand of future years.

Table 2 Results of PM

Year	Input data obtained by RM		Forecast by PM			
	Per Capita GDP	Population (Millions)	Coal	Lignite	Crude Oil	Natural Gas
2013	5125	1209	598	434	227	41
2014	5690	1226	611	46	242	42
2015	6295	1248	639	47	254	43
2016	6938	1267	666	49	267	46
2017	7615	1287	689	51	279	46
2018	8321	1309	704	52	292	47
2019	9049	1330	736	53	304	49
2020	9792	1351	753	55	317	51
2021	10542	1372	779	57	329	52
2022	11287	1390	806	59	342	54
2023	12018	1406	825	62	354	55
2024	12721	1418	844	63	365	56
2025	13381	1431	860	65	375	57

Table 3 Results of RM

Year	Input data obtained by RM		Forecast by RM			
	Per Capita GDP	Population (Millions)	Coal	Lignite	Crude Oil	Natural Gas
2013	5125	1209	605	49	234	44
2014	5690	1226	632	53	248	48
2015	6295	1248	659	58	263	51
2016	6938	1267	687	64	277	54
2017	7615	1287	716	68	292	58
2018	8321	1309	745	74	306	62
2019	9049	1330	774	79	320	65
2020	9792	1351	802	85	334	69
2021	10542	1372	828	91	348	72
2022	11287	1390	854	95	361	75
2023	12018	1406	878	99	372	78
2024	12721	1418	901	103	385	79
2025	13381	1431	919	104	394	80

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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 FO 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 FO 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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