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Prediction of Consumption of Electrical Energy by Using Neural Network Forecasters

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Abstract: *Artificial Neural Network (ANN) is an important tool in solving many problems in Science, engineering, medicine and business organizations.In this present paper we have studied to forecast the daily consumption of Electrical Energy by using Artificial Neural Network Forecaster (ANNF).We have considered two ANNF such as Multi layer feed forward ANN and functional link ANN. Initially these forecasters are trained by back propagation algorithms where adaptive strategy is employed to adjust their weight during on-line forecasting. The proposed Electrical energy forecasting system has been divided into two stages.The results are tested on the real data from two sources such as hydroelectric and thermal stations.*

Key words: *Neural Network, fuzzy logic, functional link, Neurofuzzy, forecasters*

I. INTRODUCTION:

In the present days Electricity plays an important role in the day to day life. All types of activities are governed by machine which is useless without electricity. As it badly necessary in every field, so it should be managed efficiently. Generally we get electricity from thermal, Hydro electrical stations. Different organizations such as Government and private sectors are taking care of the production and distribution electricity. Due to the advancement of new technology more equipment are coming up for the service of mankind. It is an essential task to forecast the future requirements of the electricity for our survivals. Electricity is generated from different stations and it is sending out for the distribution through cables. The head of the organization who is in the charge of distribution should plan for the requirement. The forecast error for the consumption of electricity must be minimal otherwise it will have a great loss to the organization. Daily consumption of electricity depends on many factors. Electricity is used in lightening, heating and running machines in different purpose. The parameters involved in generation and distribution of electricity is complex and nonlinear. We use ANN for modeling this complex structure, Khotanzad [7] have studied the prediction of natural gas consumption by using ANN forecasts. Bates [1], Bunn [2], Clemen [3], Donaldson [4], Mostashimi [9] have studied different problems using ANN forecasts. All the problems are based on minimizing the variance of the forecast errors. In the present paper we have made an attempt to study the present day to day consumption of electricity and to project future consumption keeping the parameters involved in the process. In this system electricity demand is predicted as nonlinear function of the recent demand values and resources like coal deposits, rainfall and weather data. Makridake's [8] used traditional forecaster to carryout their problem. In our work we have used ANN forecaster a feed forward multiplayer perception and functional link.

ANN Forecaster: The proposed forecasting systems works in two stages. In the first stage both the two ANN forecasters such as Adaptive feed forward forecasters (AFFF) and Adaptive functional link forecaster (AFLF) run parallel and produce output forecaster independently for consumption of electricity. In the second stage both the output are considered as input and gives a combination module forecast.

1. Adaptive Feed forward Forecaster (AFFF):AFFF is a three layer (input, hidden, output) feed forward perceptron with a sigmoid node which is trained by backprogration learning Rule [10]. The following notations and parameters are used as input vector for AFFF in order to solve our problem.

i) $E(K-1), E(K-2)$denotes the electricity consumed for the two previous days and k is the parameter for the kth day.
ii) Average daily temperature in past two days $T(K-1), T(K-2)$.
iii) Average weather condition for the past day $W(K-1)$.
iv) Average consumption of coal in past day $C(K-1)$
v) Average rainfall in the past day $R(K-1)$.

All inputs are considered within [0, 1] for obtaining maximum and minimum values for each input E, T, W, C, R. The output of AFFF consists of a single node where output is the forecast send out for the next day denoted by$E(K)$. Initially AFFF is trained by the historical data using back propagation (Bp) learning rule. After the initial training the weights are updated by each day when the actual data for that day is available.

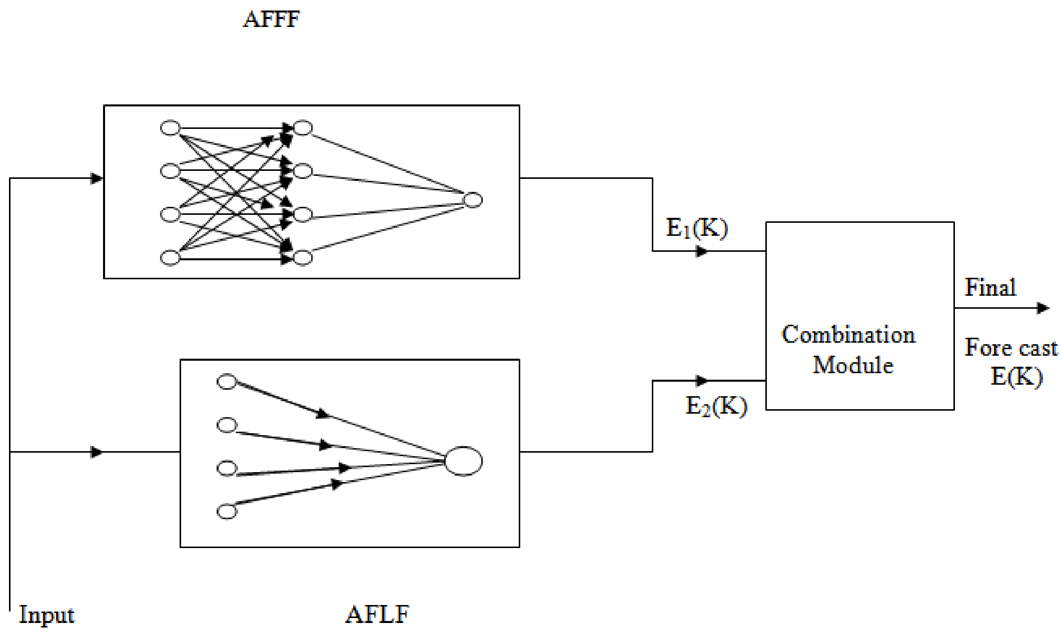
2. Adaptive Functional link Forecast (AFLF):

It is a two layer feed forward ANN with no hidden layer and sigmoid output node trained with BP rule. The basic idea behind a functional link ANN is the use of non linear transformation of some components of the input vector before it is fed to the input layer of the network. The inputs for the AFLF are the same inputs of AFFF and the following additional functional links of this variable for the cosine function.
(i)Function of previous days send out electricity $E^2(K-1); \cos[\pi E(K-1)]$
(ii)Function of the previous days temperature: $T^2(K-1); \cos[\pi T(K-1)]$
(iii)Function of the coal consumption of the past day $C^2(K-1); \cos[\pi C(K-1)]$
(iv)Function of the rainfall in the past day $R^2(K-1); \cos[\pi C(K-1)]$

The output send out by AFLF in the next day is denoted by $E_2(K)$ and the weights updated by the BP learning rule similar to that employed in AFFF.

Forecast Combination: The proposed forecast combination of AFFF and AFLF is made in the following methods and its module is depicted in the fig(1).

1) Average of forecasts
2) Recursive least squares
3) Adaptive feed forward ANN
4) Adaptive functional link ANN
5) Karmarkar's Linear programming algorithm



Fig(1): Forecast System Module

(1)Average of Forecast: The final output send out for the next day for the consumption of electricity is taken by the average of two forecasts AFFF & AFLF denoted by$E_A(K)$.

$$E_A(K) = \frac{E_1(K)+E_2(K)}{2} \quad [1]$$

(2)Recursive least Squares: This method employed for combining these forecasts as used by Haykin[5] to predict the next day consumption by $E_{RLS}(K) = \alpha_1 E_1(K) + \alpha_2 E_2(K$ [2]

Where $\alpha_1 > 0$ are the parameters computed during training rule such a way that it minimizes the sum of square of differences between past actual send out and the corresponding forecasts M where $M = \sum_{i=1}^{k-1} \beta^{(k-1)-i} \{E_1(i) - E_{RLS}(i)\}^2$ [3]

for $0 < \beta < 1$ called forgetting factor.

(3) Adaptive feed forward ANN: In this method $E_1(K)$ and $E_2(K)$ are combined by nonlinear function 'f' using adaptive feed forward perceptron of ANN where architecture and operation similar to that of AFFF. The input vectors to AFF consists of $E_1(K)$,$E_2(K)$,T(K),C(K),R(K) and the final consumption is given by

$E_{AFF}(K) = f(E_1(K),E_2(K),T(K),C(K),R(K))$

4) Adaptive functional link ANN: The combined forecast by this method is denoted by, $E_{AFL}(K)$ which is a nonlinear functional 'g' given by $E_{AFL}(K)=(E_1(k),h(E_1(k)),E_2(k),h(E_2(k),C(k),h(c(k)),R(k),h(R(k)),T(k),h(T(k)))$

Where $h(E_1(k)) = \cos[\pi.E_1(k)]$

$$h(E_1(k)) = \cos[\pi.E_1(k)]$$
$$h(E_2(k)) = \cos[\pi.E_2(k)]$$
$$h(T(k)) = \cos[\pi.T(k)]$$
$$h(R(k)) = \cos[\pi.R(k)]$$
$$h(C(k)) = \cos[\pi.C(k)]$$

The architecture and operation is similar to those of AFLF.

5) Karmarkar's Linear Programming Algorithm: It is an alternative to simplex method given by Karmarkar[6] which is used for combining the two forecast output denoted by $E_{LP}(k)$ which is a linearcombination of $E_1(k)$ and $E_2(k)$ where

$E_{LP}(K) = \alpha_1 E_1(k) + \alpha_2 E_2(k)$

The parameters $\alpha_i$are computed to minimize $M = \sum_{i=1}^{K-1} |E(i) - E_{LP}(i)|$

the steps involved in the algorithm are

Let $A = \begin{pmatrix} E_1(1) & E_2(1) \\ \vdots & \vdots \\ E_1(K-1) & E_2(K-1) \end{pmatrix}, B = \begin{pmatrix} E(1) \\ \vdots \\ E(k-1) \end{pmatrix}$

$A^T = (\alpha_1, \alpha_2)$, ϵ =some small positive number

i) Initialize $U = (u_1, u_2, \text{------} u_{k-1})^T$, $u_i = .2$, I=1,2-------k-1

ii) Compute $V=(v_1, v_2, \text{-----} v_{k-1})^T = [1,1,\text{-----}1]^T - (u_1, u_2, \text{------} u_{k-1})^T$

iii) Input W the diagonal matrix of weights $w_{ii} = \left(\frac{u_i^2 v_i^2}{u_i^2 + v_i^2}\right)$, $i = 1,2, \ldots k-1$

iv) Compute $a^T = (A^T W A)^{-1} A^T W B$

v) Compute error $e = B - Aa^T$

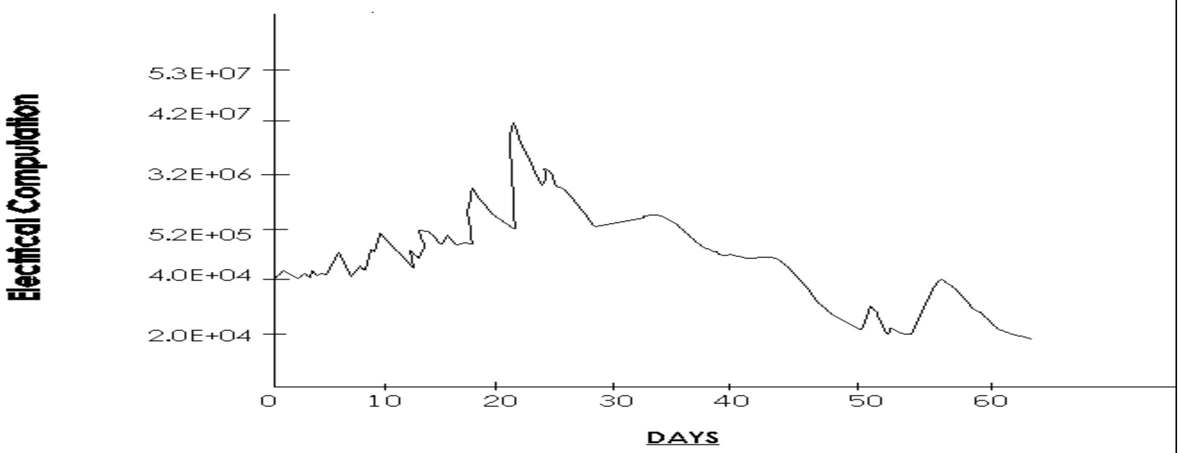
vi) Compute vector $r = (r_1, r_2, \ldots r_{k-1})$, $where r_i = \left(\frac{u_i^2 v_i^2}{u_i^2 + v_i^2}\right) e_i$

vii) If $\frac{1 - I_r^T}{\|e\|}$ where $\|e\|$ is the norm of vector e and 1=(1,1,...1),otherwise go to next step

viii) Compute vector δ

ix) Update U by U = U + βδ with $\beta = \frac{0.092}{\max\{\max\left({}^{\delta_i}/_{u_i}\right), \max\left({}^{\delta_i}/_{u_i}\right)\}}$

x) Return to step (ii)



Experimental Analysis: The performance of the proposed system and the eight discussed combination is tested using real data collected from six different local daily consumption (LCD) of electricity. The performance index mean absolute percentage error (MAPE) of forecast has been computed by

$$MAPE = 1/N \sum (\left|E(i) - \tilde{E}(i)\right| / E(i) \times 100$$

Where N is the total number of test samples

$E(i)$:Actual send out electricity of the i^{th} sample

$\tilde{E}(i)$:Corresponding send out forecast

The proposed system performance one- day- ahead forecasting is made in a recursive manner. For example to obtain a two- day- ahead forecast $\tilde{E}(i+1)$, the one-day- ahead forecast $\tilde{E}(i)$ is computed first and used in place of $E(i)$which is required input for generating $\tilde{E}(i+1)$. The detail observation is given in the following table.

MAPE's for one –day ahead forecasting using actual weather data. best results for each case shown in bold and underline

Method	**LCD1**	**LCD2**	**LCD3**	**LCD4**	**LCD5**	**LCD6**	**Average MAPE**	**Average Std. Dev.**
AFFF(E1)	**2.87**	**5.06**	**3.43**	**3.56**	**3.64**	**5.44**	**4.02**	**4.03**
AFLF(E2)	**2.82**	**5.16**	**3.45**	**3.75**	**3.52**	**5.06**	**4.00**	**4.06**
$\mathbf{E_A}$	**2.78**	**4.92**	**3.35**	**3.58**	**3.60**	**5.14**	**3.90**	**3.99**
$\mathbf{E_{RLS}}$	**2.80**	**4.95**	**3.36**	**3.55**	**3.56**	**5.07**	**3.88**	**4.00**
$\mathbf{E_{FL}}$	**2.70**	**4.87**	**3.31**	**3.58**	**3.53**	**5.06**	**3.84**	**4.00**
$\mathbf{E_{AFF}}$	**2.75**	<u>**4.66**</u>	**3.37**	**3.54**	**3.60**	**5.00**	**3.82**	**3.87**
$\mathbf{E_{AFL}}$	<u>**2.66**</u>	**4.71**	**3.31**	**3.54**	**3.59**	<u>**4.90**</u>	<u>**3.78**</u>	<u>**3.83**</u>
$\mathbf{E_{TS}}$	**2.75**	**4.86**	<u>**3.28**</u>	<u>**3.49**</u>	<u>**3.46**</u>	**5.01**	**3.81**	**3.88**
$\mathbf{E_{LP}}$	**2.69**	**4.90**	**3.33**	**3.57**	**3.57**	**5.06**	**3.85**	**3.90**
$\mathbf{E_{MNN}}$	**2.72**	**5.03**	**3.32**	**3.58**	**3.54**	**5.06**	**3.87**	**4.00**

II. CONCLUSIONS

Prediction of daily consumption of electric energy discussed in this paper is based on two stage forecasters .Thenon linear and complex relationship between temperature and past send out electricity with future requirement is modeled using two ANN forecasters with different topology. The first one has a multilayer feed forward architecture where as the second forecasters is a functional link ANN with some inputs being nonlinear functions of the considered parameters. An adoptive scheme is employed that adjust the weights of the ANN forecasters during on- line forecasting making them adoptive. Both the forecasters are initially trained with the error back propagation (BP) algorithm.

In the second stage, the two individual forecasters are mixed together to arrive at the final forecast. Eight different combination strategies are considered, they include both linear and non linear approaches based on averaging, recursive least squares, fuzzy logic, feed forward ANN, functional link ANN, a temperature space approach, linear programming and MNN. The system is tested on real data from six different industries. Two sets of experiments with actual and forecast weather data are carried out for the computation. The result for forecasting consumption of electricity is studied for taking the data collected two stations (hydro & Thermal) and found efficient one the graphical representation is given in the above graph.

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