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State of Arton Short Term Load Forecasting Using Artificial Neural Network

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Abstract:*Due to centralized power system and continuous varying nature of load it is very difficult to balance demand and generation at all time. It is due to the fact that generation can't be controlled with the same pace as load due to restriction in instantaneous change in input to power plant. Many different techniques have been proposed in the past for the purpose of short term load forecasting.In this paper a literature survey of load forecasting techniques is presented so as to compare different work that has happened previously.*

Keywords: ***S****hort-term load forecasting; multi-layer perceptron; artificial neural network, wavelet transform.*

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I. Introduction

Load forecasting is a term used for power needed to meet the demand and supply equilibrium. Short term load forecast ranges fromfew days to few weeks. Load connected/power demand to any system is dependent on many factors which can be weather and regional[1].Artificial Neural network is used in short term load forecasting due to its capacity to find relation between non-linear values thus making it very efficient modelin such type of cases[2]. Since result of artificial neural network is dependent on the way data is presented to it hence wavelet transform when performed on short term load forecasting parameters will help neural network to train better.

II. Literature Review

AbdollahkavousiFard have developed hybrid combination of evolutionary algorithms and ANN to forecast loadand found the most optimum results using modified Honey Bee Optimization[14].KishanBhushanSahay prepared a model to STLF for Toronto Canada and on evaluating results LM and BR showed almost same results hence should be used in forecasting load for short term[15].Sharad Kumar at al. in present study found that ANN is better performing model than regression hence it should be preferred for forecasting short term load[16].Victor Mayrink have generated a hybrid model combining exponential smoothing and gradient boostingusing a base learning model [17].Ni Ding have developed machine learning model for distribution system and found that it is far more accurate than time series forecasting. [18].Penghua Li et al. have developed a hybrid quantized Elman Neural Network for the purpose of STLF as for every 1 percent increase in forecasting error will lead to 10 million dollars increase in operating cost, which is sufficient enough motivation for forecasting[19].Hao Quanused Programmable System Optimization, along with Neural Network to fulfil the objective and are compared with models named ARIMA and ES models[20].Hao Quan have utilized lower upper bound estimation method and PSO for optimizing weightsafter studying concluded that this model has significant forecasting[21].Ajay Gupta developed a forecasting model using GA-ANN algorithm authors found GA has good capability in function optimization and thus GA has efficient optimized neural network [22].

Hence from above mentioned previous work it is clear that ANN is far superior to other statical methods. Also, it has been clear that load forecasting is a sensitive issue which require special attention and is dependence on input parameters and the way this input parameters are presented also affects output. Hence in this section it has been concluded that ANN and WT are a great combination to forecast load.

III. Problem Identification

In order to make sure smooth and safe functioning of electrical power system a lead time knowledge of its behavior based on various conditioning is very helpful. There are several techniques proposed by many different authors in over last decade. This method uses the difference between the true and the predicted values as a parameter to be minimized and there by tuning model parameters.Main advantages of using thesecurve fitting/traditional methods is that they cheap, easy to design and they provide timely predictions.

The disadvantage of above reviewed methods other than soft computing is that the prediction error increases as the prediction time scale increases as the tuning of weights stops after the end of historical data hence system becomes more vulnerable which leads to increment in errors.

The below table shows the comparison between Short Term Load Forecasting (STLF), Medium Term Load Forecasting (MTLF) and Long Term Load Forecasting (LTLF) based on Time duration & application.

Table 1 Comparison of various load forecasting range

Based on	STLF	MTLF	LTLF
• Time duration	1 Hour to 1 week ahead	Between one week to one year ahead	More than one year ahead
• Application	In controlling power plants for the minimization of cost of generation of electricity.	Making decision of purchasing / selling of additional power from or to the other power companies.	Planning future generation plants

The below table shows the comparison between Statistical methods, Knowledge based expert system, Hybrid methods and Artificial Neural Network used for Short Term Load Forecasting purpose.

Table 2 Comparison of various techniques used for load forecasting

No.	Statistical [13]	Knowledge based expert system	Hybrid Methods	ANN
1	Cheap	Less costly	Costly	Cheap
2	Easy to design	No design required	Complex	Easy to design & adapt
3	Provide timely prediction	Time consuming	Time consuming	Less time consuming
4	Less error chances	More error chances	Less error chances	Less error chances
5	Doesn't solve complex problem	Doesn't solve complex problem	Solves complex problems	Solves complex problems
6	Depends on data	Doesn't depend on data	Depends on data	Depends on data

The data at first is collected and input parameters are chosen wisely and calculation are done using various discussed methods like curve fitting, expert opinion, exponential smoothing etc. The results obtained are then evaluated. In case results are not appropriate change in parameters are done results are obtained again. On evaluation it has been found that such models are very time consuming and have poor efficiency.

Table 3 Different ANN methods comparison

ANN Methods	No. of Epoches (Iteration)	Time (in sec)	Complexity	Accuracy
ANN – LM	Normal (15-30)	2 – 20	Very easy	Accurate
ANN – BR	Average (around 100)	2 – 15	Normal	Less accurate
ANN - SCG	High (800-1000)	30 – 45	Highly complex	Accurate

The different methods like ANN-BR (Bayesian Regularization), ANN-SCG (Scaled Conjugate Gradient) and ANN-LM (Levenberg Marquardt) is illustrated according to their number of epchos (iteration), Time duration (in sec), complexity and accuracy.

IV. Proposed Methodology

Neurons are simple processing units, which has the ability to store experimental data and which work as parallel distributed processor. A network of connected artificial neurons can be designed, and a learning algorithm can be applied to train it. Signals are passed between neurons over connection links and each connection link has an associated weight, which in a neural network, multiplies the signal transmitted. The weights represent information being used by the network to solve a problem. Then the weighted sum is operated upon by an activation function (usually nonlinear), and output data are conveyed to other neurons. The weights are continuously altered while training to improve accuracy and generalize abilities.

By means of wavelet transform a time series can be decomposed into a time dependent sum of frequency components. As a result,we are able to capture seasonality's with time-varying period and intensity, which nourishes the belief that incorporating the wavelet transform in existing forecasting methods can improve their quality. The article aims to verify this by comparing the power of classical and wavelet-based techniques on the basis of four-time series, each of them having individual characteristics. Depending on the data's characteristics and on the forecasting horizon we either favor a denoising step plus an ANN forecast or a multiscale wavelet decomposition plus an ANN forecast for each of the frequency components.

The Levenberg –Marquardt algorithm is a fine mixture of the steepest descent method and the Gauss–Newton algorithm. The following relation helps on understanding LM algorithm computation,

$$W_{k+1} = W_k - \left[J_K{}^T J_k + \mu I\right]^{-1} J_K{}^T e_k \quad (1)$$

Where,W_k represents current weight, $W_{(k+1)}$ represents next weight, I represent the identity matrix and e_k represents last error, μ represents combination coefficient.

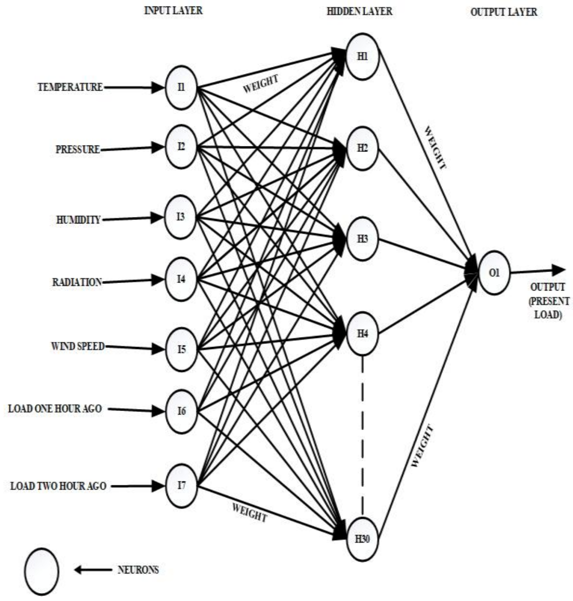

Figure 1 *Proposed ANN diagram*

Fourier analysis consists of breaking up a signal into sine waves of various frequencies. Similarly, wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet. Just looking at wavelets and sine waves, we can see intuitively that signals with sharp changes might be better analyzed with an irregular wavelet than with a smooth sinusoid, just as some foods are better handled with a fork than a spoon.

Discrete Wavelet Transform (DWT) The disadvantage of the continuous wavelet transform lies in its computational complexity and redundancy. In order to solve these problems, the discrete wavelet transform is introduced. Unlike CWT, the DWT decomposes the signal into mutually orthogonal set of wavelets. The discrete wavelet is defined as:

$$\psi_{j,k}(t) = \frac{1}{\sqrt{s_0^j}}\psi\left(\frac{t - k\,\tau_0^j s_0^j}{s_0^j}\right) \qquad (2)$$

where j and k are integers, $s_0 > 1$ is a fixed dilation step and the translation factor τ_0 depends on the dilation step. The scaling function and the wavelet function of DWT are defined as:

$$\phi(2^j t) = \sum_{i=1}^{k} h_{j+1}(k)\phi(2^{j+1}t - k) \quad (3)$$

$$\psi(2^j t) = \sum_{i=1}^{k} g_{j+1}(k)\phi(2^{j+1}t - k) \quad (4)$$

And then, a signal f(t) can be written as:

$$f(t) = \sum_{i=1}^{k} \lambda_{j-1}(k)\phi(2^{j-1}t - k) + \sum_{i=1}^{k} v_{j-1}(k)\phi(2^{j-1}t - k) \qquad (5)$$

The below table shows thecomparison of different wavelets (Harr, db10, Symlet, Maxicanhat and Morlet)

Table 4Comparison of various wavelets

S. No	Haar	db10	Symlet	Maxican hat	Morlet
1	Symmetry	Asymmetry	Near Symmetry	Symmetry	Symmetry
2	Biorthogonal	orthogonal	Both	None	None
3	Discontinuous	continuous	-	Indefinitely derivable	Continuous

The discrete wavelet transform can be done by using the filter bank scheme developed.In the decomposition phase, the low-pass filter removes the higher frequency components of the signal and high pass filter picks up the remaining parts. Then, the filtered signals are down sampled by two and the results are called approximation coefficients and detail coefficients. The reconstruction is just a reversed process of the decomposition and for perfect reconstruction filter banks, we have x = x'.

V. Conclusion

Short-termload forecasting techniques reported by different researchers, it can beconcluded that the artificial neural network-based forecasting algorithms are proved to be potential techniques for thischallenging job of nonlinear time series prediction. Further a wavelet transform based forecasting could result in much better results much close prediction of nonlinear time series.

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