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Short Term Load Forecasting Using Wavelet Transform With Artificial Neural Network: A Review

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Abstract:

With the deregulation of electrical energy industries, a prior estimated value of electrical power load with play a very significant role.An accurate forecasting for electric power load is essential for theoperation and planning of a utility company.

Any information related to pattern to be followed by connected Electrical Load will helps anyelectric utility organization to make important decisions regarding purchasingand generating electric power, unit commitment decisions, load switching, reduce spinning reserve capacity and infrastructure development. Hence load forecasting is viewed as field of research to develop a model so that efficient and reliable operation of power system could be carried out.

In present work, a literature review is done on Short Term Load Forecasting using Artificial Neural Network with wavelet transform.ANN is proposed platform to be used for solving present problem because of its capability to relationship between a nonlinear data. This review proposes an hourly load forecasting using different structure of ANN's.

1. Introduction:

For every electric company its very challenging to supply electricity to consumer in the most economic and secure manner due several operational difficulties. Among all challenges scheduling electric supply with load flow analysis comes at top. As electric load is a continuously varying and there is no direct way to actually guess the most accurate value at any coming time. There are many different factors which contribute to the value of electric load some may be random and other geographical. But all of them at last leads to variation of connected consumer load. Hence a method has to be developed to solve this problem. Many statistical methods have been proposed with time which give average results. Inthose methods, human instincts also play a big part. Every electric utility analysis network behavior using load forecasting results to determine whether or not if the system might be in a vulnerable situation. If yes, then utility should prepare a plan to deal with such situation which may include use of load shedding or purchasing extra required from market etc.

But estimation of future load with the help of past observation has remained to be difficult task for researchers. Since the recent development in the field of artificial neural network and data mining there is a sharp improvement in load forecasting results. Since beginning of artificial intelligence tool it been possible to solve various time series problems with great accuracy.

2. Related Work:

In past many authors have proposed different model for affective load forecasting. Some of the them are summaries as below:

Jinghua Li, Shanyang Wei, Wei Dai [1] in 2021 discussed that mid-term load forecasting (MTLF) is of great significance for power system planning, operation, and power trading. However, the mid-term electrical load is affected by the coupling of multiple factors and demonstrates complex characteristics, which leads to low prediction accuracy in MTLF. Furthermore, MTLF is faced with the "curse of dimensionality" problem due to a large number of variables. This article proposes an MTLF method based on manifold learning, which can extract the underlying factors of load variations to help improve the accuracy of MTLF and significantly reduce the calculation. Unlike linear dimensionality reduction methods, manifold learning has better nonlinear feature extraction ability and is more suitable for load data with nonlinear characteristics.

Shripad Desai Tanmay Dalal Sahil Kadam Sudhanshu Mishra [2] in 2021 discussed that Short-term predictive analysis on electrical load is of utmost importance to the utility company. Load forecasting plays a key role in effective energy planning as well as managing finances. Although machine learning models are already tested for predictive analysis, this paper has employed a newly developed forecasting model known as 'Prophet' developed by the IT major Facebook Inc. Owing to lack of research using this model, this paper predicts electrical load consumption based on several factors viz. Time, Temperature, Humidity, and Weather forecast. This model gives an approximate assumption and thus used for predictive modeling.

Aasim S, N.Singh,Abheejeet Mohapatra[3] in 2021 discussed that electrical load forecasting is an integral tool used by the grid operator to operate the smart power network. This paper proposes a hybrid model that combines the Wavelet Transform (WT) and Support Vector Machine (SVM) features in estimating a regression model for electrical load forecasting utilizing the historical time-series information of electrical load. The error contribution in forecasting due to the individual sub-series is estimated using Mean Absolute Error (MAE) in forecasting for each sub-series. The proposed Repeated WT-based SVM model (RWT-SVM) selects the sub-series with the highest MAE for further decomposition through WT. This results in a better forecasting model for the sub-series with the highest MAE, thereby improving the overall forecasting ability of the RWT-SVM model.

Mortada Mohammed Abdulwahab,Hanaa Hamadalneel Magzob [4] in 2021 discussed that generation, Transmission and Distribution sections of the electric power grid system are a function of electric load forecasting. This is because, many benefits can be obtained by using load forecasting, such as reduction in the generating cost and increasing the reliability of the power system due to improving energy management. In this study, the independent variables that were applied to the developed short-term load forecasting Simulink model were time, temperature, and similar previous electric day load demand, and they were collected from the specific area load control center in Sudan. Fuzzy rules were prepared using Mamdani implication. The obtained fuzzy logic results were compared with the actual load demand, and it was found that there was an error that ranged between 12% and0.09%.

Shilpa. G. N,G. S. Sheshadri [5] in 2020 presented electrical load forecasting analysis and forecasted results based on identification of stochastic time series models for short term. Three predictive models namely, the autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA) and autoregressive integrated moving average model with exogenous variables (ARIMAX) are proposed. The mean absolute percentage errors (MAPE) of these models are computed and compared. Forecasting results show that ARIMA and ARIMAX Models performance is better ensured, thereby improving the forecasting accuracy significantly compared to ARMA Model. Further, it is shown that ARIMAX Model slightly outperforms ARIMA Model.

Xiangyu Kong Chuang LiChengshan WangYusen ZhangJian Zhang [6] in 2020 discussed that accurate short-term load forecasting (STLF) is an important basis for daily dispatching of the power grid, but the non-stationary characteristics of the load series add to the challenge of this task. Many researchers have been working to improve the accuracy and speed of forecasting models, but stability is equally important. This paper develops a forecasting method based on error correction using dynamic mode decomposition (DMD) for STLF, including data selection, error forecasting, and error correction. In the data selection stage, three types of data are selected as input data of the model, including previous day data, same day data in previous week and similar day data obtained by grey relational analysis (GRA).

Fei Peng Dan Li**,** Tianyu An, HanjunWang, Changyi Tian, ZhikuiChen [7] in 2020 discussed that nowadays, data in power system have become big data and have attracted much attention due to the huge treasure buried in them. There is a great demand for forecasting electrical load and avoiding unexpected losses in power system. How to deal with the tremendous amount of data and capture the hidden information has become an important question. Deep learning can effectively extract the intrinsic features from data, achieving state-of-the-art performance in electrical load forecasting. However, it is often stuck in local minimum because of random initialization of parameters and structure selection in the stochastic gradient descent (SGD) so that its robust performance which is attached importance to in electrical practice is not guaranteed.

Chengdong Li, Minjia Tang, Guiqing Zhang,Ruiqi Wang,Chongyi Tian [8] in 2020 discussed that accurate forecasting and scientific analysis of building electrical load can improve the level of building energy management to meet the requirements of energy saving. To further strengthen the forecasting accuracy, this study presents a hybrid model for building electrical load forecasting. In this method, in order to better reflect the actual characteristic of the electrical load, the wavelet transform method is firstly utilized to filter the original building electrical load data. Then, the daily periodic pattern is extracted from such filtered electrical load data, and the residual data are obtained through removing the daily periodic pattern. Further, the residual data-driven forecasting model is constructed by the functionally weighted single-input-rule-modules connected fuzzy inference system (FWSIRM-FIS).

Rui Wang Jiyang, Wang Yunzhen Xu [9] in 2019 discussed that accurate electrical load forecasting always plays a vital role in power system administration and energy dispatch, which are the foundation of the smooth operation of the national economy and people’s daily life. Thinking from this vision, many scholars have made great efforts to seek suitable optimization algorithms to improve the performance of existing forecasting algorithm. However, most of the studies ignore the inherent disadvantages of single optimization algorithm, which leads to sub-optimal forecasting performance.

AfafTaïk, SoumayaCherkaoui [10] in 2020 discussed that in the smart grid, huge amounts of consumption data are used to train deep learning models for applications such as load monitoring and demand response. However, these applications raise concerns regarding security and have high accuracy requirements. In one hand, the data used is privacy-sensitive. For instance, the fine-grained data collected by a smart meter at a consumer's home may reveal information on the appliances and thus the consumer's behavior at home. On the other hand, the deep learning models require big data volumes with enough variety and to be trained adequately.

Naveen Kumar, Thokala, AakankshaBapna, M. Girish Chandra [11] in 2018 discussed that electrical load forecasting for buildings plays a key role in the smart-grid paradigm, since accurate forecasts help in efficient energy management. This paper presents a practical solution, which can be readily deployed, by considering various real-life issues. Load forecasting algorithms are developed using Non- linear Auto Regressive model with eXogenous input (NARX) neural network and Support Vector Regression (SVR) to forecast the power consumption for day ahead, week ahead and month ahead at 15-minute granularity.

3. A Brief Introduction to Artificial Neural Network (ANN):

Artificial Neural Networks (ANN) are computing systems or technique that are inspired by the learning architecture of human brain to discover the relations between the input and target variables of a system. Human brain consists of a large set of structural constituents, known as neurons, which form a well-connected network to respond to an input signal to perform all its computations / calculations in a certain complex task such as image and voice recognition task and they do this with incredible speed and accuracy. Neurons are simple processing units, which has the ability to store experimental data and which work as parallelly distributed processor. A network of connected artificial neurons can be designed, and a learning algorithm can be applied to train it. Signals (Input data) 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.

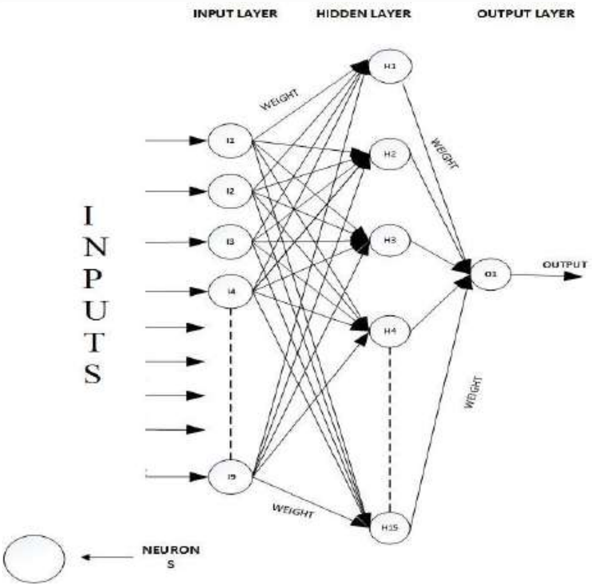

Fig 3.1 Proposed ANN diagram

4. Wavelet Transform for Time series problem:

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.

Now that we know some situations when wavelet analysis is useful, it is worthwhile asking the questions "What is wavelet analysis?" A wavelet is a waveform of effect, having a limited duration that has an average value of zero. Comparing wavelets with sine waves, which are the basis of Fourier analysis yields that Sinusoids do not have a limited duration, i.e.they extend from minus infinity to plus infinity, and while sinusoids are smooth and predictable, wavelets tend to be irregular and asymmetric as seen from the figure below:

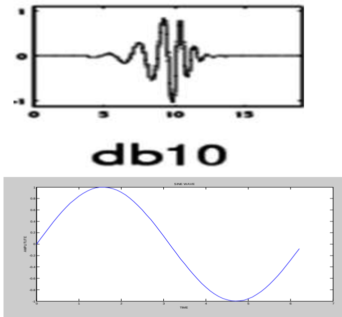

Fig 4.1: (a) db-10 Wavelet (b) Sinewave

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 pictures of 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. It also makes sense that local features can be described better with wavelets, which have local extent.

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:

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

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:

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

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

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

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

The discrete wavelet transform can be done by using the filter bank scheme developed. Figure 3.1 shows a two-channel filter bank scheme for DWT.

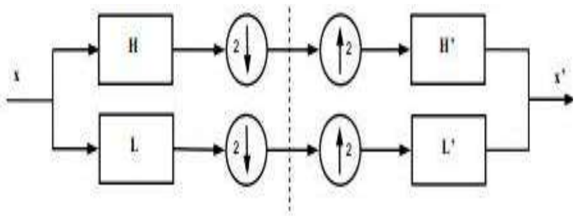

Figure 4.2: Filter Bank Scheme for DWT

In the figure, H,L,and H',L' are the high-pass and low-pass filters for wavelet decomposition and reconstruction respectively. 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'. A signal can be further decomposed by cascade algorithm as shown in Equation 4.1:

$$\begin{aligned} x(t) &= A1(t) + D1(t) \\ &= A2(t) + D2(t) + D1(t) \\ &= A3(t) + D3(t) + D2(t) + D1(t) \\ &= An(t) + Dn(t) + Dn_{-1}(t) + \ldots\ldots + D1(t) \qquad (4.1) \end{aligned}$$

where Dn(t) and An(t) are the detail and the approximation coefficients at level n respectively. Fig 4.3 illustrates the corresponding wavelet decomposition tree.

A significant potential problem with the DWT is that it is a shift variant transform. Shift-variance is a phenomenon of not necessarily matching the shift of the one-level DWT with the one-level DT of the same shift of a data sequence. Due to shift-variance, small shifts in the input waveform. Wavelet Transform cause large changes in the wavelet coefficients and this makes the DWT suitable for this study because we relate the information at a given time point at the different scales.

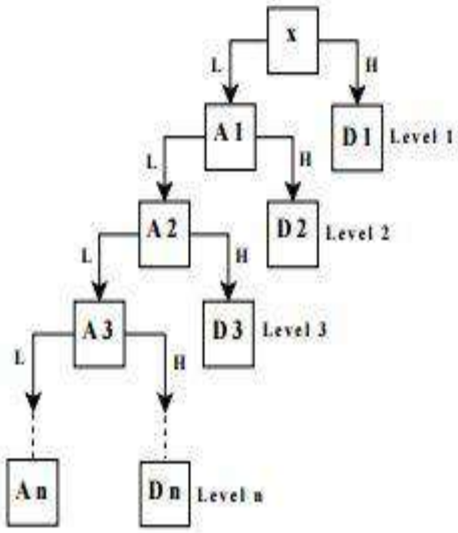

Fig 4.3: Wavelet Decomposition Tree

5. Load Forecasting:

Load forecasting is the closeness between the actual and predicted future load values. The electrical short term load forecasting has been emerged as one of the most essential field of research for efficient and reliable operation of power system in last few decades. Load forecasting helps in energy management, load flow analysis, planning and maintenance of power system and contingency analysis.

A Precise forecasting is expected from proposed model since under-forecasted value will lead in negative consequences on demand response and finally on power installation. This under forecasted value will also result in difficulty to manage the overload situations. In case of over-forecasted value, the negative effect can be seen in installation and hence the efficiency of the system.

Broadly, the load forecasting techniques can be divided into two categories such as parametric or non-parametric techniques. The linear regression, auto regressive moving average (ARMA), general exponential technique and stochastic time series techniques are some examples of parametric (statistical) technique. The main drawback of this technique is its capability in abrupt change of any types of environment or social changes. However, this shortcoming is overcome by applying non-parametric (artificial intelligence) based technique because of its potentiality to global search. Among these artificial intelligences-based methodology, artificial neural network has emerged as one of the most prominent technique that receive much more attention of researchers. The ability to solve the complex relationships, adaptive control, image denoising, decision making under uncertainty and prediction patterns make ANN a powerful performer than previously implemented techniques.

6. Conclusion:

In this paper, we have presented different load forecasting techniques. From the work reported by different researchers, it can beconcluded that the artificial intelligence-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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