Short-Term Load Prediction with a Special Emphasis on Weather Compensation using a Novel Committee of Wavelet Recurrent Neural Networks and Regression Methods

Sanjay M. Kelo and Sanjay V. Dudul

Abstract - **In this paper, a novel committee of wavelet and recurrent neural networks to predict the next hour, 24 hour and one-week-ahead load is addressed. Using wavelet multi-resolution analysis, the load series are decomposed to different sub-series, which show the different frequency characteristics of the load. Different recurrent neural networks are optimally designed and developed to predict each sub-series according to its characteristics, finally the best recurrent neural network on each sub-series is chosen based on the performance measures such as mean square error, correlation coefficient and mean absolute percentage error on prediction dataset. Feasibility of Daubechies wavelet at different scales with suitable number of decomposition levels is investigated to choose the best mother wavelet for different seasonal load series. The estimated models are evaluated over different weather parameters in order to judge the impact on accurate load prediction. The reliability and consistency in prediction by the adopted technique is proved even in the presence of controlled Gaussian noise to the predicted temperature series. The traditional regression models are developed for the same data as a benchmark. The results are compared with traditional statistical techniques and offered a high prediction precision.**

***Index Terms*-- Daubechies, Recurrent neural networks, Short-term load prediction, Statistical methods, Weather information.**

I. INTRODUCTION

THE function of short-term load prediction (STLP) is to predict the load value of future days on the basis of characteristics of load profile of a typical region, country etc. The accurate prediction of short-term electric load is very important to the power system security and economy. Especially in power market, improving the accuracy of STLP is one of the most important means to improve the management of the power system.

There are many factors that have significant impact on electric load prediction. Complex nonlinear relationship exists between the future load and the available correlative factors, such as historic load and weather information. To construct a proper model, the characteristics of the load dynamics must be fully considered and analyzed.

A variety of models have been researched and proposed for STLP such as time series, ARMA, linear regression and general exponential smoothing [1]-[6]. In the time series model such as the ARMA, ARIMA and exponential smoothing, electrical load is modeled as a function of its past observed values. Such methods cannot properly represent the complex nonlinear relationship between the load and a series of stochastic factors such as daily, weekly and monthly time periodicity and social events which can cause high unpredictable variations in power demand.

In recent years, the ANN has been widely applied on STLP. The NNs have the outstanding ability to model the nonlinear system. In order to improve the prediction accuracy and stability, the ANNs are often combined with other techniques such as wavelet transform to set a hybrid model according to the characteristics of the practical system [7] - [11]. By analyzing the electric load we find that the load curve shows certain periodicities of year, month and day and the periodicities nested in each other. Therefore, the load series can be considered as a linear combination of sub-series characterized by different frequencies. Each sub-series corresponds to a range of frequencies and show much more regularities so they are predicted more precisely than the original load series.

There is a strong correlation between the behavior of electric power consumption and weather variables such as temperature, humidity, cloud cover and wind speed. Because of their uncertainty, these variables have stochastic effects on the load shape. As a result, weather data are introduced to the neural network on the input side and combined with historical load data to predict one-hour, 24-hour and one-week-ahead loads.

In this paper, 13 various RNN predictors for a suggested RNN committee for one hour, one day and one-week-ahead-load predictions are meticulously designed on each frequency band. The best predictor is chosen on each band on the grounds of validation performance with respect to the performance measures on training, cross validation and testing dataset. The best predictors explored on different frequency bands for one-day-ahead load prediction analysis are applied to predict one-hour and one-week-ahead load on the same data sets in order to examined the efficacy of the proposed models

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in different seasons. The results are encouraging for one-hour and one-week prediction horizon. Feasibility of Daubechies (Db) wavelet of orders (2-5) is considered in order to investigate the proper mother wavelet for different seasonal load series. Based on features of typical seasonal load series, two and three levels of decomposition have been considered and results have shown the superiority of order four and levels of decomposition two. The estimated models are evaluated on various weather information such as temperature and humidity in order to judge the impact on STLP. The robustness of the adopted models is proved even in the presence of uniform Gaussian noise.

To obtain better results and ensure that the adopted models results in convergence, this work investigate factors that influence the overall performance of the RNNs such as the determination of the right network topology, good selection of data patterns and the selection of appropriate and efficient training algorithm and a number of possible combinations of inputs load and various weather variables exist. Next, a comparison between proposed technique and conventional statistical techniques such as linear, nonlinear, nonparametric and partial least square regression as considered in this paper is carried out on the basis of their validation performance with respect to the performance measures such as mean square error (MSE), correlation coefficient (r) hourly mean absolute percentage error (HMAPE), daily MAPE (DMAPE) and weekly MAPE (WMAPE) for different seasonal load series of the year 2009.

II. Wavelet Multi-Resolution Analysis

The main idea of the wavelet multi-resolution analysis (MRA) is that any function $f(t)$ can be approximated step by step, and the approximation of each step is just to smooth $f(t)$ by a low-pass function $\Phi(t)$ which will also expand or contract according to step. Therefore, $f(t)$ was approximated in different precision in different steps. In this paper, the Mallat algorithm [12] is adopted to decompose the load signal.

Fig.1 shows one week load curve in rainy season. It is seen that, reconstructed sub-series show much more regularities. The approximation A2 varies with the period of a day and the value is relatively large, which is the basic load of the system. D2 has appears to be small value and strong regularities. D1 is the random component in the the load, whose value is fairly trivial in the entire load. In this paper, for the sub-series A2, D2 and D1, different RNNs are optimally designed and developed to predict them. After getting the prediction result of each sub-series by different optimally designed RNNs, the best RNN is chosen on the basis of their validation performance such as MSE, r and MAPE on the prediction test data set. Finally, prediction of best RNN of each sub-series is added in order to achieve final prediction in all seasons.

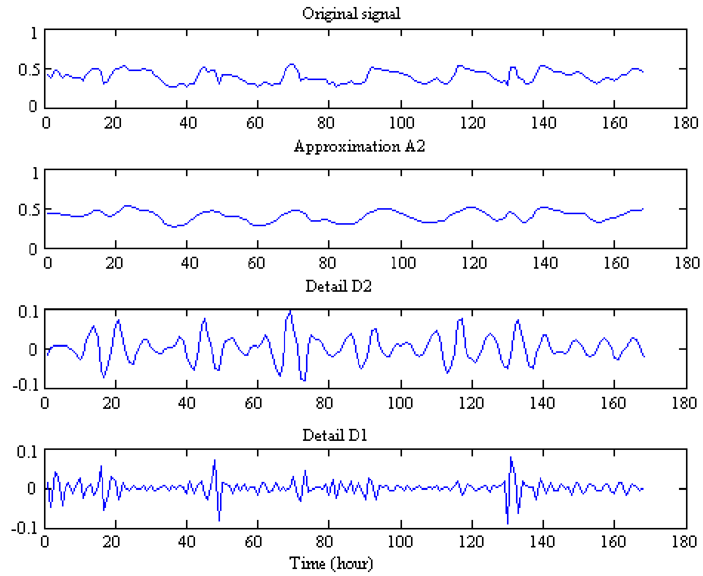

Fig. 1. Wavelet-transformed load time series of one week load data (July 1 to July 7, 2009)

III. Proposed Methodology

A typical load profile of one week contains basic component, peak and valley components, average component, periodic component and random component [13]. Conventional techniques like time series methods, regression based methods are able to extract only some of these components from the historic data. But, ANNs by its non-linear nature can extract all the components from the training data. However, RNN when modeled on original load data could not extract all of them in a well defined manner. A certain regularity of the data is an important precondition for the successful application of neural networks (NNs) [14].

Hence, a novel method is proposed for the prediction of the next hour, next day and next week load. Fig 2 shows block diagram of proposed technique for one-hour, one-day & one-week-ahead load prediction. For this work, the feasibility of Daubechies of orders 2 to 5 has been investigated on different seasonal load series and results have shown the superiority of Db4. Moreover, based on features of typical load curves the different seasonal load series are decomposed at resolution levels of two and three for 1-hr, one-day and 1-week-ahead load predictions. The empirical results show that two levels of resolution are adequate for all seasons over different prediction time horizon. Here, the idea is to model different frequency components via individual fitting of each level of resolution (frequency bands). That is, each component (A2, D2 & D1) is modeled separately and the final prediction is obtained by adding those three predictions. Notice that, the approximation A2 and all two levels of details (D2 & D1) are taken into account to “reconstruct” the load series. Each of its sub-models is introduced in sequel.

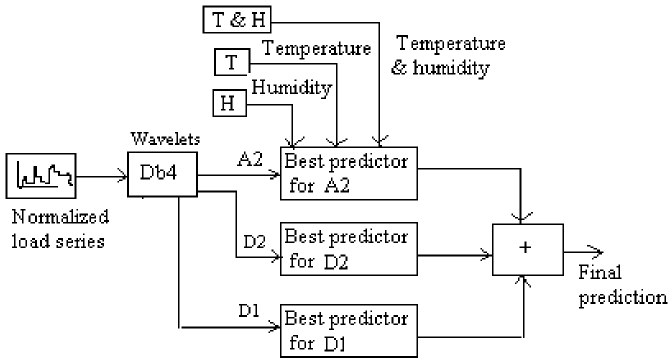

Fig. 2: Proposed technique for one-hour, one-day & one-week-ahead load prediction

A. Best predictor for A2

Different recurrent neural networks (RNNs) are optimally designed and developed for the approximation A2 which is a smoothed version of the load series. The best RNN for A2 in the different seasonal load series is chosen on the basis of their validation performance with respect to the performance measures like MSE, r and MAPE. The various input variables for this best RNN are depicted and shown in Table I. This submodel consists of ten hidden PEs and one PE in the output layer.

B. Best predictor for D2 and D1

Table I presents the set of inputs / output and best RNN for these submodels. It is noticed that these submodels are different from the previous submodel. The main differences are 1) five and six load input variables (instead of two) have been selected. 2) Weather information like temperature and humidity have not been considered, this is due to the fact that when weather information is considered as input variable with the set of input of detail components, computer simulation results show the considerable degradation in the prediction accuracy. This shows that the weather factors have little impact on detail components. The submodels D2 and D1 consist of ten and five PEs in hidden layer, respectively and one PE at output layer.

The level of detail D1 is more related to the noisy part which is a random component of the load series. Predictions for this level of resolution are evaluated by using the proposed best of RNN model and weighted multiple linear regression models and results have shown the superiority of the first one.

TABLE I

INPUT VARIABLES OF PROPOSED ARCHITECTURES FOR DIFFERENT SEASONS

Input			Variable name	Lagged (h)	output
S	R	W			
2	5	2	Approximation (A2)	1,2,24,168,336	A2 (h)
1	1	1	Predicted temperature	0	
1	1	1	Predicted humidity	0	
6	6	3	Detail (D2)	1,2,24,168,336,504	D2 (h)
3	3	5	Detail (D1)	1,2,24,168,336	D1 (h)

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IV. COMPUTER SIMULATION OF DIFFERENT PREDICTORS FOR RNN COMMITTEE

An exhaustive and careful experimental study has been carried out on a Laptop PC (Intel® Core2,Duo CPU T5670 @ 1.80 GHz, 2 GB RAM). The simulation models and design of experiments are implemented in 'MATLAB 7.0' and 'Neurosolutions 5.06'. All possible variations of various RNNs such as number of hidden layers, number of PEs in each hidden layer, different transfer function of PEs in the output layer and different supervised learning rules are investigated in computer simulation. The step size and momentum are gradually varied from 0.1 to 1.0 for a static backpropagation, quick propagation and modified delta-bar-delta learning rules. Again additive, multiplicative and smoothing factor in hidden layer and in output layer are varied from 0.01 to 1.0 for a delta-bar-delta algorithm. After meticulous examination of the performance measures like MSE, r and MAPE of the various RNNs on the low and high frequency bands of different seasonal test data set of year 2009, the optimal parameters are decided for the best RNNs. In computer simulation, laguarre and gamma coefficient of focused time lagged recurrent neural network (FTLRNN), partially RNN (PRNN) and fully RNN (FRNN) model is gradually varied from 0.0 to 1.5 in the interval of 0.1 with respect to the default value of tap [16]. Various transfer functions of context unit in case of Elman and Jordan RNN are optimally designed in computer simulation.

V. SIMULATION RESULTS AND OBSERVATIONS

A. Effect of weather compensation

The proposed architectures of best predictors are trained for different seasonal load data sets with and without considering the weather variables such as temperature and humidity as one of the input variables. The results of the predicted load for Tuesday, September 1, 2009 without considering weather information, Considering lone temperature, lone humidity and with temperature as well as humidity are shown in Fig 3, Fig 4, Fig 5 and Fig 6, respectively. The daily mean absolute percentage error (DMAPE) and maximum absolute percentage error (maximum APE) of the days in a typical week of a winter season (16 to22 October 2009) are shown in Table II.

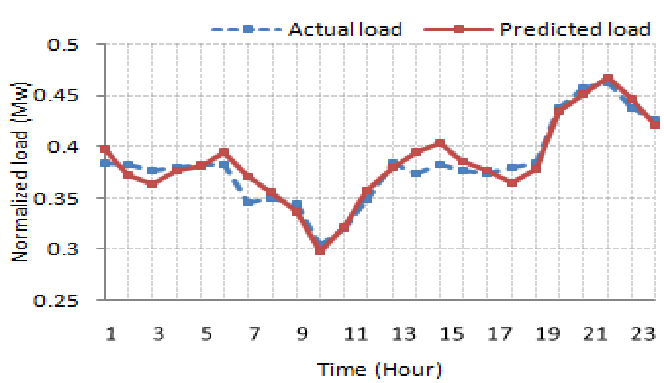

Fig.3: Comparison of the actual and the predicted load for Tuesday without considering weather variables.

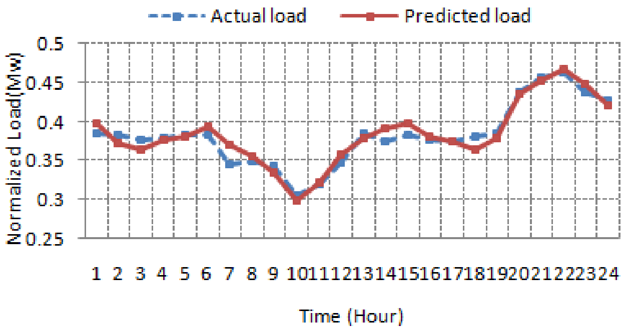

Fig.4: Comparison of the actual and the predicted load for Tuesday with temperature.

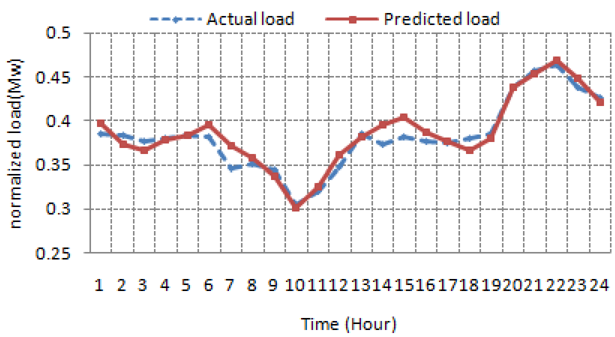

Fig.5 Comparison of the actual and the predicted load for Tuesday with humidity.

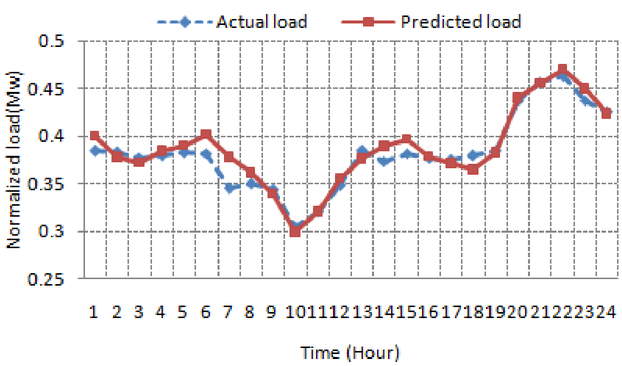

Fig. 6: Comparison of the actual and predicted load for Tuesday together with temperature and humidity.

It has been observed from Table II that the DMAPE and maximum APE are less when temperature as an additional input weather variable is given to the network. From the results depicted in Table II, it is clearly seen that, lone temperature as one of the input weather variable play a significant role in improving the prediction accuracy in all seasons. It is also confirmed that, when temperature and humidity are considered simultaneously and also for lone humidity, average prediction accuracy over one week period is degraded reasonably. Hence, from the results, it is clearly seen that lone temperature as an input weather variable has significant effect on 24 hour-ahead load prediction as considered in this paper. Table III depicts the effect of various weather parameters on prediction accuracy over different time prediction horizon in different seasons.

TABLE II
EFFECT OF DIFFERENT WEATHER PARAMETERS ON PREDICTION ERROR

Date	Performance metrics	Effect of weather parameters on prediction error			
		Without weather parameters	With temperature	With humidity	With humidity & temperature
16/10/09	Maximum	9.71	9.39	10.93	11.48
	MAPE (%)	3.67	3.19	3.64	3.45
17/10/09	Maximum	7.10	5.96	7.40	7.88
	MAPE (%)	2.77	2.60	2.70	2.98
18/10/09	Maximum	7.61	7.24	7.41	10.02
	MAPE (%)	2.40	2.19	2.19	2.32
19/10/09	Maximum	6.77	5.51	7.23	6.01
	MAPE (%)	2.55	2.38	2.54	2.40
20/10/09	Maximum	15.68	13.39	15.37	16.19
	MAPE (%)	4.13	3.98	4.11	4.19
21/10/09	Maximum	12.26	11.71	13.11	15.52
	MAPE (%)	4.16	3.93	4.13	4.89
22/10/09	Maximum	16.01	15.75	17.46	18.37
	MAPE (%)	4.271	4.04	4.37	4.27

TABLE III
EFFECT OF WEATHER PARAMETERS ON PREDICTION ERRORS FOR DIFFERENT SEASONS

Effect of weather parameter	Prediction horizon					
	1-hour-ahead			1-week-ahead		
	s	r	w	s	r	w
Without weather parameters	4.52	4.45	4.32	4.01	3.69	4.58
With temperature	3.88	3.45	4.01	3.78	3.65	3.98
With humidity	4.34	3.87	4.25	3.98	3.87	4.58
Together with humidity & temperature	4.30	3.98	4.35	4.12	4.21	4.98

(S: Summer, R: Rainy, W: Winter)

B. *The effect of noise*

In this case, the effect of adding Gaussian noise of zero mean and varying variance from 1% to 10% to the predicted temperature series is observed, in order to notice the effect on performance in terms of r and MSE has been investigated. From Table IV, it is noticed that the performance does not degrade much. The r decreases from 0.99 to 0.95 with respect to the change in variance from 1% to 10% in case of addition of Gaussian noise. The prediction accuracy changes of 4.04%, however, MSE increases from 0.0008 to 0.002 with a minimum standard deviation of only 0.0003. This means that our adopted models are immune to the noise i.e. they are fairly robust.

TABLE IV
AVERAGE GLOBAL EVALUATION FOR 24 HOUR-AHEAD WITH SIMULATED TEMPERATURE PREDICTIONS

Mean (0) and vary variance	Correlation coefficient (r)	MSE
1%	0.97	0.0015
2%	0.97	0.0014
3%	0.98	0.0010
4%	0.97	0.0018
5%	0.97	0.0016
6%	0.99	0.0008
7%	0.98	0.0011
8%	0.98	0.0011
9%	0.95	0.0014
10%	0.98	0.0013

C. Effect on performance of prediction accuracy (MAPE) for different decomposition level (considering with temperature)

TABLE V
EFFECT OF RESOLUTION LEVEL IN DIFFERENT SEASONS

Wavelet	Summer		Rainy		Winter	
Db4	Level 2	Level 3	Level 2	Level 3	Level 2	Level 3
	4.06 %	4.17%	3.13%	3.27%	3.47%	3.78%

Table V shows the effect of resolution level on prediction accuracy in terms of its average MAPE (%) for one-day-ahead load prediction task. Empirical results clearly reveal that, a resolution level up to 2 is adequate for all seasons.

VI. COMPARISON WITH VARIOUS REGRESSION MODELS

Traditional STLP models, such as regression or stochastic time series are widely used in electric generation units as they have proven their validity especially for weekday predictions. Any new method having a different approach than these conventional ones should give better results in order to be accepted. Therefore, the models proposed in this work should be compared with a classical model that does the same task. Stochastic time series method appears to be the most popular approach that has been used and is still being applied to STLP in the electric power industry.

TABLE VI
COMPARISON BETWEEN STATISTICAL TOOLS AND PROPOSED TECHNIQUE FOR DMAPE OF A TYPICAL WEEK IN THEDIFFERENT SEASONS OF THE YEAR 2009

Days in different seasons	LR	NLR	NPR	PLSR	PT
Summer (1-7 May 09)	8.2	8.3	8.0	7.9	3.5
Rainy (1-7 Sept 09)	6.4	6.6	6.9	6.6	2.5
Winter (16-22 October 09)	9.8	9.6	10.4	10.3	3.36

LR: linear regression, NLR: non LR, NPR: nonparametric regression, PLSR: partial least square regression, PT: proposed technique

Table VI enlists the MAPE (%) computed by various statistical models based on regression analysis are developed for the same data as a benchmark for STLP in order to compared with a novel wavelet-RNN-committee. For estimating the parameters, 'XLSTAT 2010' is used. Results are shown in Table VI, together with the errors obtained by the proposed technique of typical weekdays in the different seasons of the year 2009. It is obvious and easy to comment about Table VI. Regression based models give worst predictions for weekdays as compared to proposed model. These results show that, these traditional methods depend only on a time series and not making use of other parameters, such as temperature, humidity and day of the week etc. Hence, our proposed novel hybrid intelligent technique is without a doubt outperformed the traditional statistical technique as one considered in this work.

VII. CONCLUSIONS

The major contribution of this research is the increase in the one-hour, one-day and one-week-ahead prediction accuracy in all seasons by employing the proposed novel wavelet-RNN-committee. The exhaustive experimentation is made to explore the best RNN on different frequency component according to the characteristics of each component and finally, prediction is achieved by adding the predictions of best RNNs on different frequency components. The proposed technique offers reliable and encouraging results. The FTLRNN (Laguarre) performs consistently well in case of approximation components at resolution level 2 in summer and rainy seasons, but Jordan perform consistently reasonable in rainy season up to resolution level 2. PRNN (laguarre), PRNN (gamma) and FRNN (laguarre) are able to predict D2 in summer, rainy and winter seasons, respectively. However, PRNN (gamma), PRNN (TDNN) and FTLRNN (TDNN) show reasonable performance on D1for summer, rainy and winter season, respectively. Feasibility of Daubechies of orders 2-5 are tested at decomposition levels 2 and 3 in order to investigate proper mother wavelet and suitable level of decomposition in each season. The empirical results show that, Db4 is consistently performing reasonably in all seasons. Resolution up to Level 2 is adequate for all seasons. The adopted models in the proposed technique are evaluated with different weather information in order to judge the effect of a particular weather parameter on accurate load prediction. It has been observed from Table II that the DMAPE and maximum APE are less when lone predicted temperature was introduced as one of the input variable. Further, lone predicted humidity as well as predicted both temperature and humidity were also considered in order to gauze the effect on prediction performance. The computer experimental results reveal that lone temperature plays a significant role for STLP. The robustness of the proposed models against noise is evaluated by injecting Gaussian noise to the predicted temperature series by maintaining mean 0.0 and varying variance from 1% to 10%. Simulation results reveal that degradation in the performance is not much significant with respect to the change in variance. Hence, the proposed technique sounds robust and accurate. Different regression models are developed for the same data as a benchmark for STLP in order to compare with the proposed model of wavelet-RNN-committee. The empirical results obtained in this work show that the traditional statistical technique considered in this work gives worst prediction results. This means that the suggested classical method fails to capture the nonlinear dynamics of the load series for one-hr, 24- hour and one-week-ahead prediction. Hence, the novel combination of wavelet-RNN-committee has without a doubt outperformed the regression methods for 1-hour, 24- hour and 168-hours-ahead load prediction task such as the one considered in this work.

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