Hybrid WT-PSO based Neural Networks for Single Step-Ahead Wind Power Prediction for Ontario Electricity Market

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Abstract: Wind Power forecasting is an important subject of concern for reliable operations of grid and it has been studied from different points of views of both accuracy and reliability. So with an aim of improvement in prediction accuracy this paper presents a hybrid wind power prediction machine for Ontario Electricity Market (OEM) on single step ahead basis in which Wavelet Transform (WT) is used for pre-processing of input wind power data, then the pre-processed data is trained by neural networks. In this initially, the parameters of neural networks (biases & weights) are initialized as random &then at second stage are optimized by Particle Swarm Optimization (PSO) base training algorithm. The varying time series input training data patterns are used in order to remove the overtraining & over-fitting problem so that the maximum accuracy is achieved. The results of proposed method are compared with Naive Predictor, Feed Forward Neural Networks (FFNN) & Particle Swarm Optimization based Neural Network (PSONN) and is presented in the form of comparative tables on Mean absolute error (MAE) & mean absolute percentage error (MAPE) scale with emphasis on weekly as well as monthly predictions. The data used by proposed model for estimation is collected from Ontario Electricity Market for the year 2009-12 and tested for such a long period of one year on single step ahead basis. It is found that the accuracy of proposed model is far better than the other models.

Keywords: Particle Swarm Optimization, wavelet transform, neural networks, time series, wind power

1. Introduction

The renewable energy sources are growing field of interest for mitigation of electricity demand/supply in restructured electricity market scenario. The energy generated by wind has remarkable growth among all renewable energy sources and become an alternative of fossil fuels [1]. Throughout whole world the name plate installed capacity of wind power at end of 2013 was 318,137 MW with a growing rate of 12.5 % and at end of 2017 it is predicted to be 61 GW with an annual growth rate of 7% [2]. The major utilization of these wind capacity installations is in large grid connected electric power systems [3].

Across the world lot of academicians, researchers & power system engineers have directed towards the estimation of wind power & speed with higher accuracy by keeping in mind all the uncertainties associated with wind. The highly accurate estimated wind power is useful for scheduling, state estimation, unit commitment and for calculation of price for generation. The wind power & speed is estimated by using two approaches called physical & statistical models. The statistical or time series approach uses historical on-line measurements as explanatory variables and usually employ recursive techniques like recursive least squares or artificial neural networks whereas physical or numerical weather prediction (NWP) approach keeps in mind the physical considerations of site and wind turbine [4]-[6].

The prediction is categorized in to single step ahead and multiple step ahead prediction. As compare to single step ahead forecasting multiple steps ahead forecasting is more difficult because it deals with some additional complications such as multiplication of error at every step and higher uncertainty. Guo et al. [7] proposed modified empirical mode decomposition

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(EMD) based on feed-forward neural network (FFNN) for multi-step ahead wind speed forecasting and in which EMD decomposed the input raw data. Liu et al. [8] proposed a short term wind speed and power prediction based on wavelet decomposition and classical time series analysis up to ten steps. Vaccaro et al. [9] compared a physical (white-box) model with a family of local learning techniques (black-box) for short and medium term forecasting. Moreover, a model integrating machine learning techniques with physical knowledge modeling (grey-box) has also been proposed. Chen et al. [10] proposed a model that uses wavelet decomposition based Gaussian process learning algorithm (WGP) for short-term wind speed forecasting up to four steps.

The standard back propagation neural network (BPNN) has been widely used for prediction because of its good non-linear quality, high fitting accuracy, flexibility and effective learning capabilities, fully distributed storage & hierarchical quality of model structure. The parameters of neural networks are determined by gradient search algorithm which encounters problem of local minima and sensitivity to initial values persists. So to resolve above said problems, global search techniques such as genetic algorithm (GA) have also been employed for learning of neural networks [11-20]. In comparison to traditional GA, a modified GA has been employed for prediction of load [11]. The particle swarm optimization (PSO) and Enhanced PSO (EPSO) has also been used for input parameterization of FFNN, RBF & SVM.

Therefore, based on above literature survey, it can be observed that the accuracy of neural network model is improved by evolutionary based learning algorithm with pre-processing technique. So, in this proposed approach neural networks parameters are optimized by PSO using 'trainp so' function in MATLAB and pre-processing is done by WT. Two case studies have been presented for comparative accuracy analysis on Mean Absolute Error (MAE) & Mean Absolute Percentage Error (MAPE) scale: Case I model is tested for one year from Jan. 2012 to Dec. 2012 with one month moving window and in Case II prediction results considers three weeks considered seasonal, low & peak power demand curves of Ontario. All the models used for comparison are tested for two years and three years training data with one month moving window estimation and performance of proposed (WT+PSO+NN) model (MAPE 6.37 %) is far better than other models in both contexts (monthly & seasonal weeks) along with two years training data sets.

2. Proposed Model

In order to handle the non linear past wind power data patterns (time series) Wavelet Transform (WT) is used. The wavelets has an ability to produce a good local representation of the signal in both time and frequency domains.By using WT based multi-scale analysis and decomposition the original signal is break into low frequency (approximation) sub series and high frequency (detailed part) sub series. These constitutive series perform better than the original wind power series and hence better prediction accuracy can be achieved. The data sub series along with Auto Correlation Function (ACF) based time lag wind power series fed to FFNN. The weights & biases are optimized by PSO based learning algorithm. For the testing of proposed model different training data sets are used and tested for one year with one month moving window estimation.

A. Wavelet Transform

The WT is used to pre-process the input wind data because the collected data from the site is time varying random nature signal i.e. highly uncertain, non stationary& associated with non linearity. But WT is signal processing mathematical tool capable of handling time varying random signal of wind power whereas the Fourier Transform (FT) handling capability is limited up to stationary time signal. The FT associates the problem of predefined fixed window length in which the frequency & time is settled. WT resolves the problem of predefined window length with variable window for time series signal. WT permits the wind time series to be decomposed into set of some consecutive data pattern that performs better than the raw

input wind data pattern. It is of two types depending on the category of signal, (i) continuous wavelet transform (CWT) (ii) discrete wavelet transform (DWT).
The continuous wavelet transform (CWT) for an input wind power signal *f(t)* is defined at real axis from (-infinity to infinity) and it is given below:

$$W(a,b) = a^{-\frac{1}{2}} \int_{-\infty}^{\infty} f(t).\ \Psi^{*}\left(\frac{t-b}{a}\right) dt \tag{1}$$

In the above equation mother wavelet *W(a, b)* is scaled by *a* and time shifting is done by *b* known as translation variables and * denotes complex conjugate. The continuous wavelet means the continuous scaling and time shifting of mother wavelet corresponding to either high scaling (low pass filter) gives approximate information about wind pattern or low scaling (high pass filter) gives the details of wind patterns [8, 10], whereas the mother wavelet scaling factor *a* and translation variable *b* is discrete in DWT, with *a=2i*, *b=k2i*. The DWT decomposition and reconstruction equation of wind signal is given by:

$$W(a,b) = \frac{1}{\sqrt{2^{i}}} \int_{-\infty}^{\infty} f(t).\ \Psi^{*}\left(\frac{t-2^{i}k}{2^{i}}\right) dt \tag{2}$$

DWT involves both high pass and low pass filter corresponding to decomposition and reconstruction of original wind power data pattern. The approximate $(A_1, A_2, \ldots. A_N)$ and detailed coefficient$(D_1, D_2, \ldots. D_N)$ of wind data signal *f(t).*

B. Feed Forward Neural Networks

The Feed Forward Neural networks are the non-linear parallel structure networks that are inspired by human brain system. The source nodes in the input layer of the network supply respective elements of the activation pattern or input vector, which constitute the input signals applied to the neurons in the hidden layer. The output signals of the hidden layer are used as inputs to the output layer. The output signals of the neurons in the output layer of the network can constitute the overall response of the network to the activation patterns applied by the input layer neurons.

C. Particle Swarm Optimization Algorithm

Particle swarm optimization (PSO) is a heuristic self adaptive evolutionary algorithm based on searching of knowledge (food) by particles (birds) in a group or swarm. Each individual is learning from each other, optimization is done through individual best and global best by whole group. It is one of the earliest search evolutionary algorithms based on the biological and sociological behavior of animals that are searching their food in a group as demonstrated by Kennedy and Eberhart in 1995. The initialization of population is random &quite similar to Genetic Algorithms but because of absence of evolutionary operators like Crossover & mutation, its implementation is easy. The location of each particle is change according to their experience; adjacent particle location and velocity x_i represent the location of particle in D dimensional space with *n* number of particles [21-25].

$$x_i = (x_{i1}, x_{i2}, -------x_{iD})\ i = 1,2, ---n \tag{3}$$

The velocity of particle is:

$$v_i = (v_{i1}, v_{i2}, -------v_{iD}) \tag{4}$$

$x$is used as objective function used to calculate adaptive value. The best position for the particle $i$is:

$$v_i = (v_{i1}, v_{i2}, -------v_{iD}) \tag{5}$$

The best position for group

$$P_g = (P_{g1}, P_{g2}, - - - - - - - P_{gD}) \quad (6)$$

The velocity updating operation is:

$$v_{id} = (\omega\, v_{iD} + C_1 R_1\ (P_{iD} - X_{iD}) + C_2 R_2\ (P_{gD} - X_{gD}) \quad (7)$$

The position updating operation is:

$$X_{iD} = X_{iD} + v_{iD} \quad (8)$$

where, $i = 1,2, - - - n$, $d = 1,2, - - - D$; ω is no-negative constant is called inertia factor and it may reduced with linearly; learning factor C_1 and C_2 is no-negative constant; $R_1$and R_2 is [0,1] randomly;

$v_{iD} \in = [-v_{max}, v_{max}] v_{max}$is constant.

D. Proposed Hybrid Approach

In recent years, the various evolutionary algorithms have been implemented for various power systems problems. Most of the researchers mainly focus on the improvement of the algorithm in areas such as parameter selection, optimization and pre-processing of input data. In this paper, a novel hybrid approach is proposed in which the prediction of wind power for Ontario Electricity Market (OEM)is done by combining three strategies; first, the raw input wind power data is decomposed into approximated (A3) and detailed (D1, D2, D3) wind power signals by three level wavelet decomposition using Daubechies (Db) wavelet. The three layer neural network structure is used in which the number of input neurons for proposed model is ten (six wind time series time lags neurons by ACF and four WT decomposed time series signals neurons). Twelve hidden neurons selected as random by hit and trial method and one output neuron.

In second, the PSO is used to optimize the training time parameters associated with neural networks and in final; the six times series lags along with approximated and detailed signal decomposed by WT is trained.

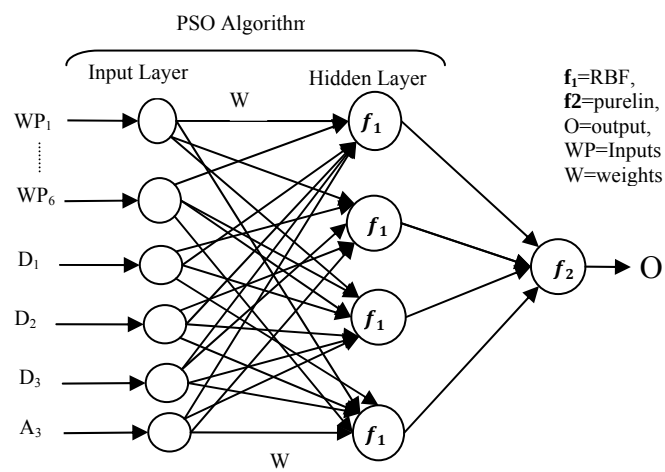


Figure 1. Structure of Proposed Model Used

Step 1 : From the raw data of wind power a wind power time series as an input signal (WP) is created.
Step 2 : Supply the created input signal to WT for performing multilevel decomposition on wind power signal by utilizing Daubechies (Db) wavelet.
Step 3 : Now extract the three level approximation A3 and 1, 2, 3 level detailed coefficients D1, D2 & D3 of input wind power signal for removing noised signal.
Step 4 : Reconstruct the signal from 3 level decomposition to D1, D2, D3 & A3 is obtained.
Step 5 : The statistical tool ACF and PACF is used to create time lag input signal.
Step 6 : The approximated and detailed signal of two and three years different data sets has been used as a training data for neural networks along with six time lag series obtained by ACF for next one month prediction up to next 12 months with moving window of one month.
Step 7 : Initially, the parameters of neural networks are initialized as random &then updated by PSO learning algorithm.
Step 8 : Finally, the output obtained by proposed model is compared with actual wind power.

E. Accuracy Criteria

The performance of the trained network is then evaluated by comparison of the network output with its actual value via statistical evaluation indices. The mean absolute percentage error (MAPE) and the mean absolute error (MAE) are used to evaluate the performance of forecasting in electricity prices. The MAPE can be defined as:

$$MAPE = \frac{1}{n}\sum_{n=0}^{n}\left|\frac{Y_t - F_t}{Y_t}\right| * 100 \tag{9}$$

The MAE is given by:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|Y_t - F_t| \tag{10}$$

where, Y_t and F_t are the actual and forecasted wind power of tth hour respectively, and n is the number of forecasted hours.

3. Wind Data Inputs Parameters Pre-processing

In this paper, in order to investigate the performance consistency of different forecasting models, wind generation data from Ontario Electricity market [26] has been considered as the test case system. Ontario currently has the installed capacity to generate more than 35,000 MW of electric power. Ontario has a diverse power sector in which the Nuclear and large hydro-electric facilities typically run 24 hours a day and provide what is referred to as “base load generation”. Fossil-fuel generators generally run during the day and ramp-up production during peak periods of demand. Hydroelectric facilities that have the capability to store water for generating electricity can often provide power during higher demand periods. Other forms of power production in Ontario include small amounts of wood-waste and wind facilities.

The installed capacity of wind generation in Canada had an average annual growth rate of 51% between 2000 and 2006 [27].Ontario is on the forefront of wind generation in Canada with almost 1,500 MW of installed capacity on the transmission grid. Currently, there are eight large-scale wind farms in operation in Ontario. The weekly and monthly average curves of wind generation and electricity demand have been shown in Figure. 2. It can be observed that although demand in Ontario is cyclical; the range of its magnitude has remained constant over the period under consideration. On the other hand, proportion of wind power generation in the overall generation has been rising consistently.

In 2012 the decentralized forecasting will eventually be replaced by centralized wind power forecasting. It is very effective and reliable mechanism for the wind power generating market participants to take part in day a head electricity markets. All the Wind operators provide their

forecasts to the ISO at 11 a.m. covering every hour of the remainder of that day and the next day. Forecasts are included in pre-dispatch every hour; results used to aid decisions on day-ahead unit commitment, spare generation on-line, and intertie transaction scheduling. The OEM is run on 5 minutes dispatch schedule where all the generators submit their bids and offers to supply energy and adjust their output on the basis of ISO instructions. During these five minutes wind power generating participants must also respond on their bids or dispatch signal for the next 24 hours or 7 days per week [28, 29].

The real data of hourly wind power is collected from Ontario Electricity market for the year 2009-12 from January 2009 to December 2012. We have considered one year test period for single step ahead forecasting of hourly wind power. In order to avoid the overtraining during the learning process and to get more accuracy a very large amount of data is not used. Wind power generation is dependent on weather conditions, temperature and even the season. The Figure 3 shows the time series data of wind power for the year 2012. It can be observed that there is a significant variation in wind power generation.

Training Set: To build the forecasting model for single step a head wind power forecasting, the training data from January 01, 2009 to December 31, 2011 has been considered. Two training data sets of two year, and three year period have been considered.

Test Set: The prediction has been done for the period of one year from January 1, 2012 to December 31, 2012 (366 days x 24 hours) on one month moving window with different training data set.

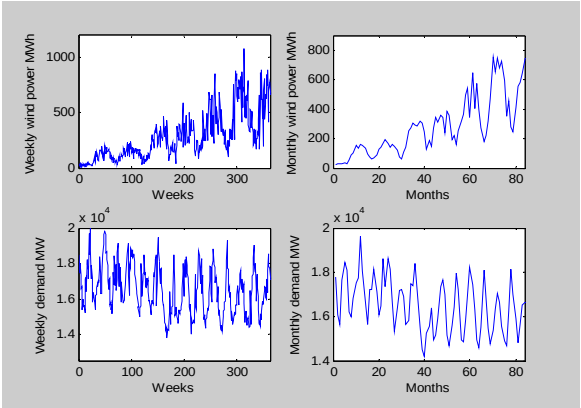


Figure 2. Weekly average and monthly average curves of wind power and Ontario demand (March, 2006 to February, 2013)

The selection of input variables is one of the most necessary step for a successful forecasting engine & it determines the input architecture of model. Although for neural networks based models there is no systematic approach to find out the number of relevant inputs.

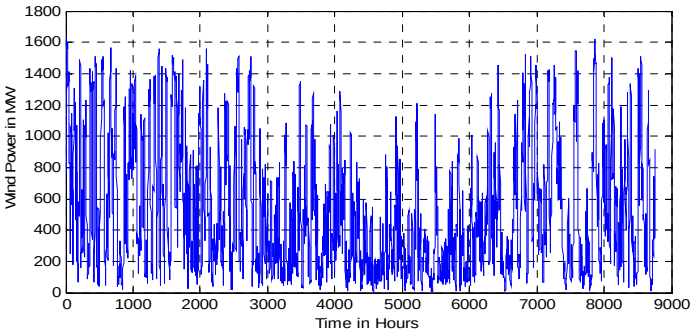


Figure 3. Wind data series of Ontario Electricity Market for year 2012

But a statistical approach such as auto-correlation function (ACF) of a sample wind series over 60 lag hours is shown in Figure. 4that is used for prediction. It shows that correlation between successive lags is very strong and it drops off very quickly over large time lags. The wind forecast problem aims to find an estimate $f_{(t+k)}$ of the wind vector $y_{(t+k)}$ based on the previous n measurements $y_{(t)}, y_{(t+1)}, \ldots, y_{(t-m+1)}$. In order to have accurate wind speed forecast, k is chosen to be small and this is called short-term wind speed forecast.

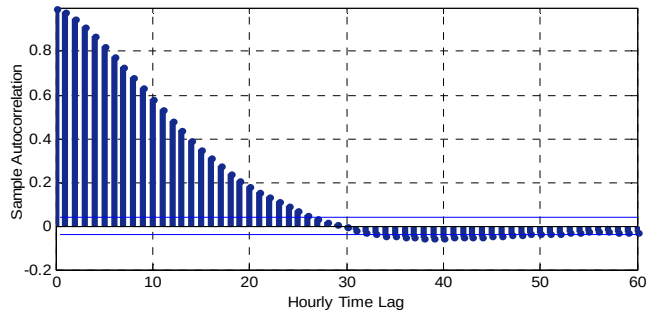


Figure 4. ACFP lot of Ontario Wind Power Generation

For training an ANN model by using time series, it is necessary to know the relation that exists between the series and their lags. These methods come from the development of linear models, but, since neural networks are non-linear approaches, so their calculation gives an indication rather than a standard tool for finding useful variables and lags.

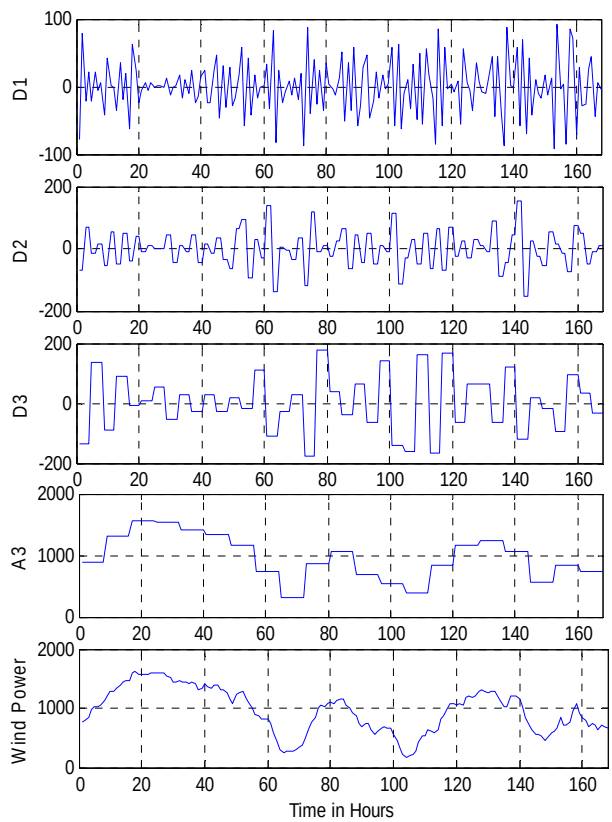


Figure 5. Hourly Curve of Wind Power, Detailed & Approximate Signals by Wavelet Transformation

The wavelet performs an appropriate smoothness of the signal with respect to wave length which results in an appropriate behavior of input data pattern for a wind power prediction tool. The Figure 5 shows three level decomposed approximations (A3) and detailed (D1, D2, D3) curves that correspond to the wind power input series by Daubechies (Db) wavelet. The approximate signal represents the low frequency band trend of wind power signal, whereas detailed curves represents the corresponding high frequency band. The level, whose approximation series is having the characteristics of normal distribution curve and yet closest to the shape of the original series, represents the filtered version of the original signal in a better way than the others.

4. Results and Discussion

Case I: The proposed wind power prediction model is compared with three other models on single step ahead basis up to one year by using different input training data sets. The methodology described above has been applied to predict the wind power for Ontario Electricity market. The software used for training and testing of neural network is MatLab version R2010a. The MAPE & MAE results for one step ahead forecasting for year 2012 wind power forecast are shown in Table 1. It can be observed that accuracy is better in winters, (low demand period) as compared to summer (high demand period). This observation also confirms that overall wind is well matched with winter load than summer load [30]. In table 1, the performance of all the models along with proposed model is compared. The performance of neural networks varies with variation of input training data set, input neurons, parameters (weight & biases), hidden nodes and training algorithms used etc. These parameters results in over-fitting & overtraining of neural networks due to the poor accuracy of forecasting machine. The input neurons used for the FFNN & PSONN model is 6, learning rate 0.001, 12 hidden neurons with different training set (two & three year). For the training purpose, Levenberg-Marquardt (LM) training algorithms is used with tangential sigmoid and pure linear activation function. Initially weights and biases are initialized as random for both FFNN and PSONN.

Table 1.Test Results of both the models using Different input Data Set

DATA	3 year training data						2 year training data					
	FFNN		PSONN		WTPSONN		FFNN		PSONN		WTPSONN	
	MAPE	MAE	MAPE	MAE	MAPE	MAE	MAPE	MAE	MAPE	MAE	MAPE	MAE
JAN	9.49	48.76	9.29	48.86	4.43	21.3	9.62	49.31	9.62	49.36	4.31	20.85
FEB	10.56	45.69	10.57	45.64	5.4	20.76	10.62	46.32	10.62	46.34	4.96	19.04
MAR	10.87	49.81	11.07	50.15	5.14	21.23	11.01	50.28	11.04	50.38	4.83	20.8
APR	13.72	51.75	13.82	52.07	6.97	24.42	13.85	53.13	13.87	53.26	6.51	23.75
MAY	16.87	48.05	16.79	47.4	8.46	22.06	16.63	47.46	16.63	47.46	7.94	20.84
JUN	14.83	49.99	15.03	49.94	7.37	21.96	15.02	50.02	15.02	50.05	7.13	21.49
JUL	21.04	38.63	21.74	38.99	11.4	17.88	21.31	38.58	21.27	38.58	10.51	16.93
AUG	17.35	33.71	17.49	33.89	9.59	16.24	17.82	33.65	17.81	33.7	8.95	15.51
SEP	15.39	41.38	15.35	40.99	7.43	18.86	15.46	41.34	15.46	41.37	6.91	17.51
OCT	9.15	46.31	9.11	46.45	4.27	20.65	9.17	46.78	9.07	46.81	4.05	19.64
NOV	10.98	34.23	10.85	34.61	5.74	15.82	11.18	34.58	11.08	34.67	5.41	15.15
DEC	11.69	44.83	11.04	44.45	5.4	20.12	11.78	44.7	11.49	44.7	5.03	19.56
Average	13.49	44.42	13.51	44.45	6.8	20.1	13.62	44.67	13.59	44.72	6.37	19.25

But in second stage PSO based training algorithm is used for the later model and LM algorithm is used for former. The proposed model is well discussed in previous section 3. In table 1, the average MAPE achieved by proposed model is 6.37% (from Jan. 2012 to Dec. 2012) which is far better than the other models i.e. by using two years training data set FFNN (13.62%) and PSONN (13.59%). In spite of MAPE accuracy scale, the performance is also presented on monthly & average MAE scale for the same time period from Jan. 2012 to Dec. 2012. The accuracy achieved by proposed model is 19.25 MWh and is much better than FFNN (44.67 MWh) and PSONN (44.72 MWh).

In Table 1 test result of one year single step ahead prediction is presented on three years and two years training data set with varying level of accuracy. It is also observed that the training data of two years gives more accurate and reliable results as compared to other training data sets. But for naïve model there is no training data utilization take place. The performance of all models with proposed is given in table 2.

Table 2. MAPE Comparison Results of All Models

	Naïve	FFNN	PSONN	Proposed
	MAPE	MAPE	MAPE	MAPE
JAN	11.56	9.62	9.62	4.31
FEB	12.66	10.62	10.62	4.96
MAR	13.23	11.01	11.04	4.83
APR	15.22	13.85	13.87	6.51
MAY	18.5	16.63	16.63	7.94
JUN	17.56	15.02	15.02	7.13
JUL	24.5	21.31	21.27	10.51
AUG	19.15	17.82	17.81	8.95
SEP	17.08	15.46	15.46	6.91
OCT	10.04	9.17	9.17	4.05
NOV	11.55	11.18	11.18	5.41
DEC	13.03	11.78	11.79	5.03
Average	15.34	13.62	13.62	6.378

Case II: On the basis of Table 1&2, it is clear that the results produced by proposed model are far better than the persistence as well as the other models. Figure 6 to figure 8 show the results obtained by simulating the different forecasting models in graphical form for one week test period. As it can be observed that, all the models seem to be work is in a reasonable way by considering the stochastic nature of the wind power.

For the results analysis of wind power the three seasonal aspects has been considered. Because during these three spans of one week time duration the demand curve of Ontario is highly volatile and contains all seasonal aspects of time series. The winter's test period with high-demand curve start from December 13-19, 2012. The spring's test period with low demand start from April 26 to May 2, 2012, whereas the summer's test period with peak demand start from July 26 to August 2, 2012. The comparison of proposed model for same dates with other models on MAPE and MAE accuracy criteria has been presented in Table 3 & 4 respectively. These three weeks average MAPE has been presented in Table 3 and the MAPE result of proposed model (WT+PSONN) varies from 6.3% to 11.37% whereas results from other models-Naïve, FFNN, PSONN varies from 15.19-23.44%, 13.9-22.65%,& 13.61-18.22% respectively. In Table 4 the performance is also presented on MAE scale for the same three weeks time period and the MAE achieved by proposed (WT+PSONN) varies from 16.1 MW/h to 25.74 MW/h whereas the results of other models Naïve, FFNN, & PSONN is 36.38-64.95 MWh, 36.77-60.44 MWh, and 36.13-55.79 MWh respectively. Every time the results obtained by feed forward neural network is be slightly different from the previous one this is due to random initializations and updating of weights and biases by standard back propagation neural network. But in the proposed model the weights and biases are initialized as random but updated by PSO algorithm that reduces the uncertainty of result at every simulation as a result of this reliability is increase.

Table 3.Weekly MAPE Results

Test Period	week	Naive	FFNN	PSONN	Proposed
April 26 to May 2, 2012	week 1	21.09	18.64	18.22	8.8
July 26 to Aug. 1, 2012	week 2	23.44	22.65	22.14	11.37
Dec 13 to Dec 19, 2012	week 3	15.19	13.9	13.61	6.3
Average		**19.04**	**16.35**	**16.65**	**9.74**

Table 4.Weekly MAE Results

Test Period	week	Naive	FFNN	PSONN	Proposed
April 26 to May 2, 2012	week 1	64.95	60.44	55.69	25.74
July 26 to August 1, 2012	week 2	36.38	36.77	36.13	16.1
Dec 13 to Dec 19, 2012	week 3	44.29	39.14	38.53	17.4
Average		48.54	45.45	43.45	19.746

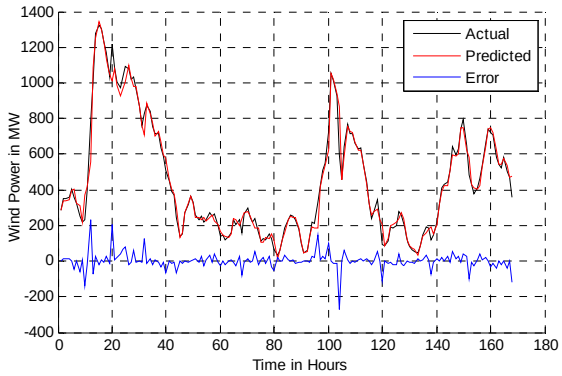


Figure 6.Weekly actual & Predicted Wind Power curve during Week 1 (April 26 to May 2, 2012)

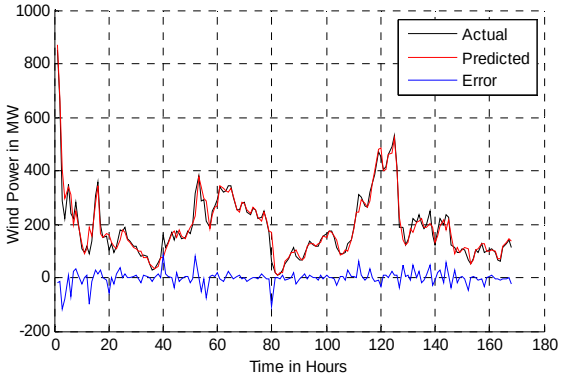
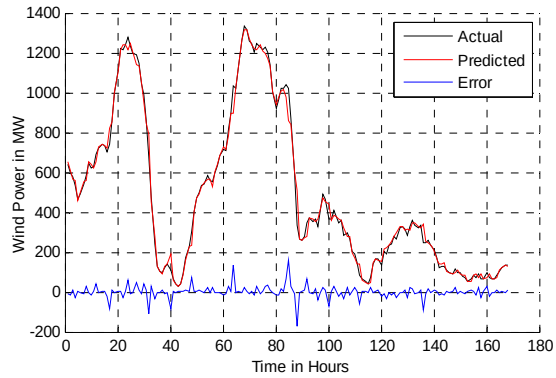


Figure 7. Weekly Actual & Predicted Wind Power curve during Week 2 (July 26 to August 1, 2012)



Figuree 8.Weekly Actual &Predicted Wind Power curve during Week 3 (December 13-19, 2012)

In the given figure 9 shows the MAPE performance curve of all models used for comparative analysis in this paper. The performance curve of FFNN is same as that of PSONN but the performance of proposed model is lies within MAPE range of 5 to 10 in graph for 12 months.

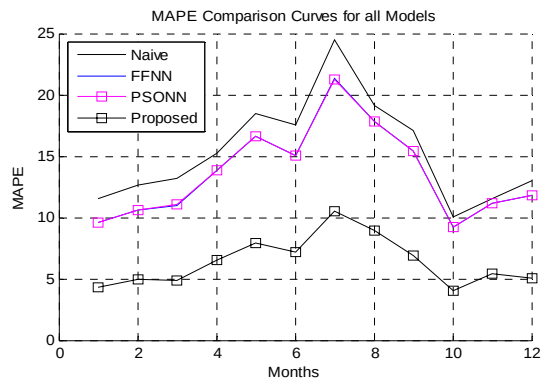


Figure 9. MAPE Comparison of all models with Proposed

5. Conclusion

This paper presents a comparison of Naïve; FFNN &PSONN model with proposed Wavelet Transform & PSO based hybrid neural networks model for single step a head wind power forecasting in time-series framework. An experimental analysis has been made regarding the proper selection of input training data, time lag, hidden neurons, learning rate and learning algorithms so that better accuracy can be achieved. The data of four years from year 2009-12 of Ontario Electricity Market has been used. The performance accuracy of all the models has been compared on MAE and MAPE performance metrics. The performance of proposed model (MAPE 6.37 %) is far better than other models in both contexts (monthly & seasonal weeks) along with two years training data sets. So, this model improves the reliability and accuracy of prediction machine.

6. References

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