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Wind Speed Forecasting Based on Neural Network and Least Mean Square Method

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Abstract — Prediction of future events and conditions are forecasts, and the act of making such predictions is called forecasting. Forecasting is an integral part of the decision making activities of power sector. The proposed neural network model is multilayer perceptron type with one hidden layer and one output layer Based on the mathematical explanations and the Adaptive filter theory we have proposed least mean square (LMS) algorithm for short term wind speed forecasting. We can make changes in the algorithm by changing the values of parameters disjointedly or combine. After obtaining the required simulation results the values are finalized. The value of step size chosen to be best suited for the original data to be generated. After training Neural Network algorithm we got the minimum error for daily data MAPE 9.59% and monthly data 32.26%.After training Least Mean Square algorithm we got the minimum error for daily data MAPE 16.68% and monthly data MAPE 54.86%. The results suggest that NN model with developed structure can perform good prediction with least error.

Keywords- Forecasting, Neural Network, Least mean square methods, Short term wind forecasting.

I. INTRODUCTION

Wind speed forecasting is an important area and in planning and control system it plays on important role. Intermediate term forecasts of a few months to a year ahead. Short term forecasts of few hours to few weeks ahead. Very short term forecasts of few minutes to an hour ahead. Modern forecast methods or models has its identifiable limitations since its depiction with mathematic illustration. The variation of wind speed is affected by circumstances of the weather and social accomplishments, where it is difficult to represent in unambiguous interpretations. Short term wind speed forecasting is an essential source of economic and safe process in power systems. Commitment to forecasts has grown as a result of several factors. The first has been the increasing complexity of organization and organization environments; it has become more and more difficult for decision makers to weigh all factors satisfactorily. Secondly, with the increasing sizes of organizations, the magnitude and importance of decisions have increased.

To design an accurate and rapid wind speed forecasting techniques at the turbine level by the combination of least square and neural network model. Comparing the results with the basic method of wind forecasting. Collecting the wind data from selected study site 50m wind mast at BEC, Bagalkot and then developing of wind forecasting model using least square and Neural Network. Forecasting using both least square and Neural Network models. Finally comparing both least square and Neural Network methods to find optimum value.

1.1 Neural Network Method:

Considerations of humans central nervous systems encouraged by the concept of artificial neural networks. In an artificial neural network, simple artificial nodes are known as "neurons", "processing elements" or "units", are associated together to form a network which impersonators a biological Neural Network. The neuron is statistics handling component where it is important to the process of neural network. Figure 1 describes the configuration of Neuron.

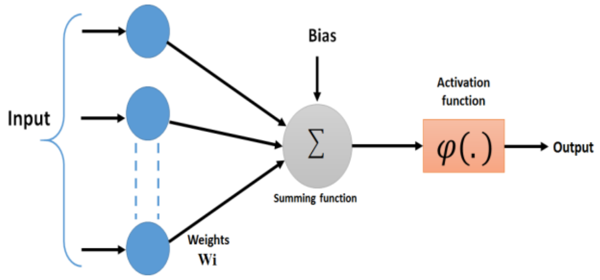

Figure 1: Configuration of a Neuron

The neural model has tree components; the synapses, adder and activation function. Summing the given inputs the adder function is used where it symbolized by the symbol of sigma. To obtain the optimum value of output in output layer the activation or threshold function is used.

Back propagation networks are essentially multilayer perceptron's (usually with one input, hidden, output layer). In order to serve useful function of hidden layer, a multilayer networks should have non-linear activation functions for multiple layers: a multilayer network uses only linear activation functions where it is equivalent to the single layer linear network. The back propagation algorithm is used to calculate a gradient.

1.2 Least Mean Square Method:

In 1954 the Gabor was introduced the nonlinear adaptive filter using volterra series. In 1959 windrow and hoff are introduced the Least mean square (LMS) algorithm. The LMS algorithm comprises an iterative method where it makes an uninterrupted modifications to weight vector which pointers to the lowest mean square error.

The figure 2 shows the linear adaptive filter LMS model for a data stream/input signal at an instant n, which will denote as u[n] and calculates a forecast i.e., the output of the filter as y[n] = wT[n]-u[n]. The output y[n] is compared to the input signal or the sample of the data stream the filter attempts to adapt to, denoted as d[n]. The forecast error e[n] is then calculated as: e[n] = y[n]-d[n] and served into the adaptation algorithm, so the filter weights can be restructured. The vector w[n] i.e., the weights are reformed at each time step n in order to reduce the mean square error.

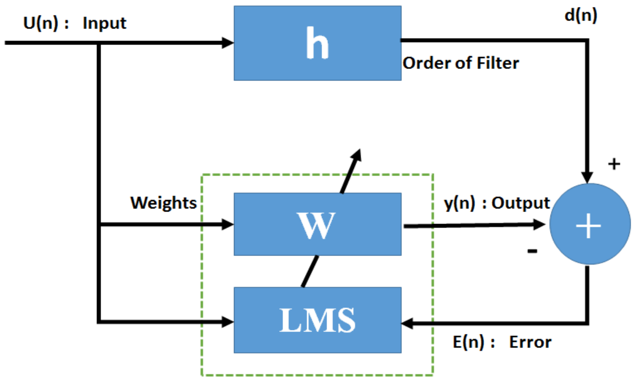

Figure 2: Block diagram of an adaptive filter LMS

II. PROPOSED METHODLOGY

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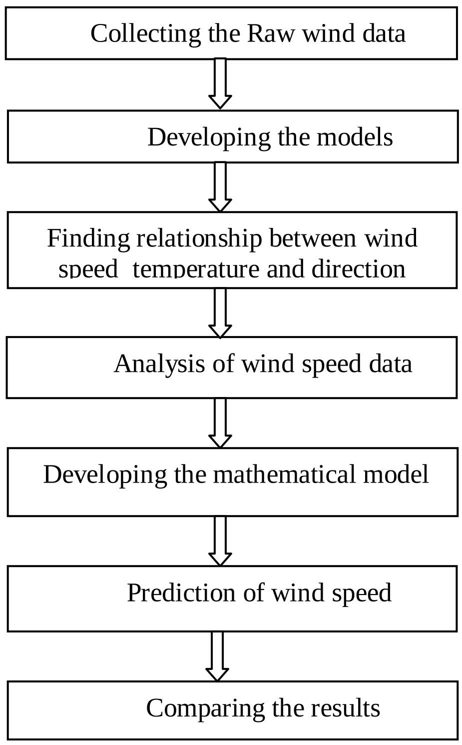

Step 1: Collecting the raw wind data from selected study site 50m wind mast at BEC, Bagalkot.

Step 2: Processing raw data to make it suitable for developing model.
Step 3: Developing the models using historical wind data &Neural Network.
Step 4: Finding relationship between wind speed temperature and direction.
Step 5: Analysis of wind speed data using auto correlation, partial correlation, spectrum & statistics.
Step 6: Developing mathematical model for wind speed temperature and direction.
Step 7: Prediction wind speed using mathematical model & relationship using.
1) Least square method
2) Neural network method
Step 8: Comparing both Neural Network and Least Mean Square results

III. EXPERIMENTAL RESULTS

The results are based on the following formulas:
Error is the difference between actual value and forecasted value.

$$\%\textbf{Error} = Actual - Forecasted$$

Absolute Error (AE) is defined as

$$AE = Abs(Error)$$

Absolute Percentage Error (APE) is defined as

$$APE = \frac{AE}{Actual} \times 100$$

Maximum Absolute Percentage Error (MAPE) is defined as

$$MAPE = AVERAGE(APE)$$

The table 1 shows the daily data for Jan 2010, which we have converted from 10min interval data to hourly data and gives the comparison between actual and forecasted data by using neural network Bayesian regulation algorithm.

Bayesian Regulation				
Actual Speed	**Forecasted Speed**	**Error**	**AE**	**APE**
7.32	6.51	0.81	0.81	11.05
7.18	6.41	0.77	0.77	10.77
6.10	5.83	0.27	0.27	4.43
5.60	5.97	-0.37	0.37	6.68
6.07	6.54	-0.47	0.47	7.72
6.10	6.39	-0.29	0.29	4.75
6.48	6.55	-0.07	0.07	1.06
5.73	6.51	-0.78	0.78	13.54
5.15	5.97	-0.82	0.82	15.95
5.60	5.95	-0.35	0.35	6.33
6.00	5.42	0.58	0.58	9.66
5.95	5.55	0.40	0.40	6.79
5.80	5.30	0.50	0.50	8.66
5.58	5.52	0.06	0.06	1.06
4.00	5.30	-1.30	1.30	32.48
4.80	4.94	-0.14	0.14	2.84
4.97	4.85	0.12	0.12	2.44
4.27	4.62	-0.35	0.35	8.28
6.12	5.75	0.37	0.37	6.03
7.00	6.64	0.36	0.36	5.18
7.17	6.70	0.47	0.47	6.50
6.90	6.82	0.08	0.08	1.17
7.02	6.79	0.23	0.23	3.26
6.80	6.80	0.00	0.00	0.05

MAPE=7.36

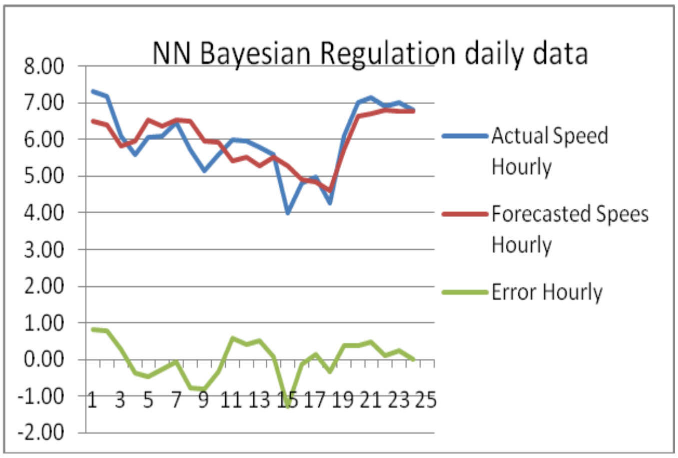

Figure 3. Comparison of Actual and Forecasted wind speed for NN for Bayesian regulation Jan 2010 day data

The table 2 shows the daily data for Jan 2010, which we have converted from 10min interval data to hourly data and gives the comparison between actual and forecasted data by using Least Mean Square algorithm.

Least Mean Square				
Actual Speed	**Forecasted speed**	**Error**	**AE**	**APE**
7.3200	6.8393	0.4807	0.4807	6.5674
7.2200	6.9000	0.3200	0.3200	4.4315
6.0000	7.0707	-1.0707	1.0707	17.8446
5.6000	7.1189	-1.5189	1.5189	27.1238
6.0800	7.1292	-1.0492	1.0492	17.2572
6.3600	5.9111	0.4489	0.4489	7.0583
6.5400	4.3893	2.1507	2.1507	32.8848
5.3400	5.0509	0.2891	0.2891	5.4134
4.9000	4.8019	0.0981	0.0981	2.0012
5.8800	3.8526	2.0274	2.0274	34.4799
5.8400	5.7167	0.1233	0.1233	2.1107
6.0600	5.7716	0.2884	0.2884	4.7595
5.7800	5.8712	-0.0912	0.0912	1.5780
4.9000	5.9126	-1.0126	1.0126	20.6648
4.3400	5.4640	-1.1240	1.1240	25.8980
5.0000	5.2824	-0.2824	0.2824	5.6488
4.6800	5.9064	-1.2264	1.2264	26.2041
4.6400	6.5071	-1.8671	1.8671	40.2399
6.9200	6.0409	0.8791	0.8791	12.7030
7.0600	6.0946	0.9654	0.9654	13.6737
7.2600	5.6241	1.6359	1.6359	22.5334
6.8000	6.1796	0.6204	0.6204	9.1241
6.9000	7.2153	-0.3153	0.3153	4.5699

MAPE=14.99

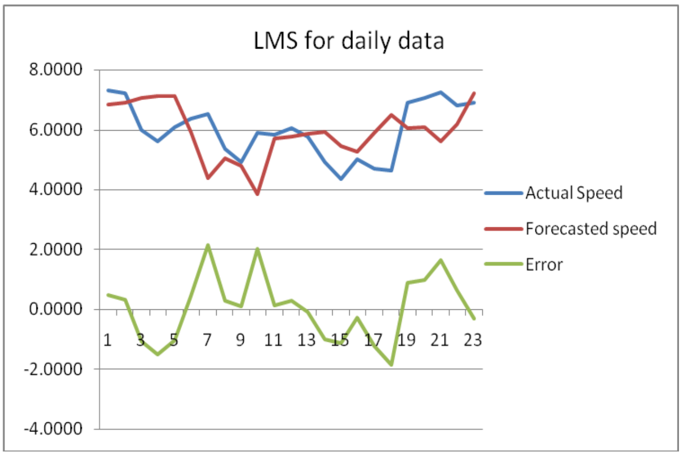

Figure 4. Comparison of Actual and forecasted wind speed for least mean square for Jan 2010 daily data.

The table 3 shows the Monthly data for June 2010 to July 2010, which gives the comparison between actual and forecasted data by using neural network Bayesian regulation algorithm.

Bayesian Regulation				
Actual Speed	**Forecasted speed**	**Error**	**AE**	**APE**
6.8611	6.4255	0.4356	0.4356	6.3484
5.6035	5.8195	-0.2160	0.2160	3.8552
6.3375	5.9438	0.3937	0.3937	6.2123
5.4597	5.7983	-0.3386	0.3386	6.2013
7.1201	5.8583	1.2618	1.2618	17.7217
6.0431	5.9054	0.1377	0.1377	2.2778
5.7271	5.6873	0.0398	0.0398	0.6943
3.9576	5.7864	-1.8288	1.8288	46.2095
4.7319	5.5429	-0.8109	0.8109	17.1373
4.9514	5.6029	-0.6515	0.6515	13.1573
4.8194	5.8725	-1.0531	1.0531	21.8505
5.7278	6.1369	-0.4091	0.4091	7.1420
6.2139	5.9152	0.2987	0.2987	4.8064
6.2139	5.9152	0.2987	0.2987	4.8064
6.0542	6.1736	-0.1194	0.1194	1.9727
5.0139	6.1990	-1.1851	1.1851	23.6361
5.1597	6.0849	-0.9252	0.9252	17.9310
6.2500	6.3465	-0.0965	0.0965	1.5437
5.7160	6.0472	-0.3312	0.3312	5.7945
6.0896	5.8678	0.2218	0.2218	3.6420
6.5479	5.6478	0.9002	0.9002	13.7473
6.8021	5.7792	1.0228	1.0228	15.0371
6.3868	5.6814	0.7055	0.7055	11.0454
5.9542	6.1738	-0.2196	0.2196	3.6887
7.8194	6.4049	1.4146	1.4146	18.0907
6.6493	6.4533	0.1960	0.1960	2.9476
7.0576	6.4905	0.5671	0.5671	8.0353
7.0417	6.5772	0.4645	0.4645	6.5965
5.3813	5.8740	-0.4927	0.4927	9.1562
5.3979	5.2478	0.1502	0.1502	2.7819

MAPE=10.13

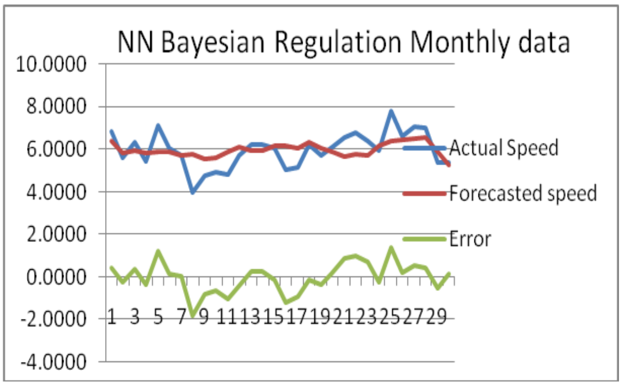

Figure 5. Comparison of Actual and Forecasted wind speed for NN Bayesian regulation for June 2010 to July 2010 monthly data.

The table 4 shows the Monthly data for June 2010 to July 2010, which we have converted from 10min interval data to daily data and gives the comparison between actual and forecasted data by using Least Mean Square algorithm.

Least Mean Square				
Actual Speed	**Forecasted Speed**	**Error**	**AE**	**APE**
7.7083	6.8126	0.8957	0.8957	11.6199
7.3174	6.0692	1.2481	1.2481	17.0570
7.7479	5.7237	2.0242	2.0242	26.1256
8.0472	4.9706	3.0766	3.0766	38.2323
6.5285	4.1480	2.3805	2.3805	36.4635
6.8194	4.2678	2.5517	2.5517	37.4179
7.0097	4.8486	2.1612	2.1612	30.8311
6.5653	4.8348	1.7305	1.7305	26.3585
6.7264	4.2553	2.4710	2.4710	36.7365
6.2528	3.6063	2.6465	2.6465	42.3251
5.9389	3.8354	2.1035	2.1035	35.4185
4.7521	5.0837	-0.3316	0.3316	6.9781
5.5083	7.8455	-2.3372	2.3372	42.4303
5.5083	4.5297	0.9787	0.9787	17.7669
4.7847	3.2352	1.5495	1.5495	32.3840
2.9903	2.9746	0.0157	0.0157	0.5248
3.2271	4.7533	-1.5262	1.5262	47.2937
4.5194	5.4982	-0.9788	0.9788	21.6568
7.8646	5.5184	2.3462	2.3462	29.8322
5.0785	4.7247	0.3538	0.3538	6.9659
3.8375	5.9393	-2.1018	2.1018	54.7697
3.6222	6.2513	-2.6291	2.6291	72.5813
4.2632	6.7313	-2.4681	2.4681	57.8937
4.8083	6.5290	-1.7206	1.7206	35.7844
4.8451	6.9809	-2.1357	2.1357	44.0802
4.2715	6.8051	-2.5336	2.5336	59.3136
4.1326	6.5144	-2.3817	2.3817	57.6325
4.9910	8.0284	-3.0374	3.0374	60.8581
5.7167	7.7521	-2.0355	2.0355	35.6060
6.1174	7.3239	-1.2066	1.2066	19.7236
6.8292	7.6919	-0.8628	0.8628	12.6337
				MAPE=34.04

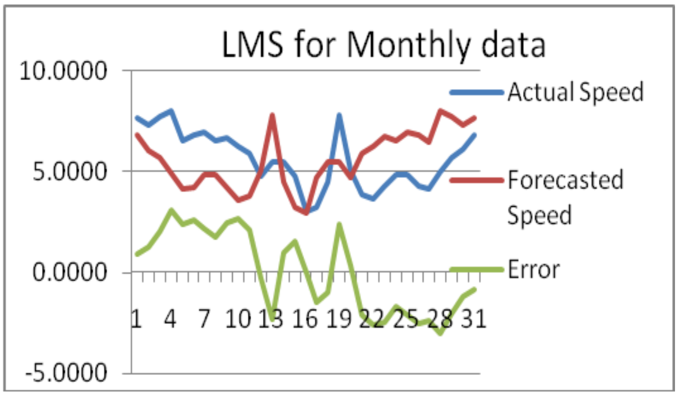

Figure 6. Comparison of Actual and forecasted wind speed for least mean square for June 2010 to July 2010 monthly data.

By experimenting both NN and LMS algorithm for wind forecasting we can conclude that NN is the best method for forecasting. The table 5 shows the comparison of both neural network and least mean square method and minimum absolute percentage error (MAPE).

Neural Network Daily Data		
NN Training Algorithm	**Jan 2010 Daily data**	**MAPE**
Levenberg-Marquardt	144	**7.65%**
Bayesian regulation	144	**7.36%**
Scaled conjugate gradient	144	**7.37%**
LMS Daily Data		
LMS Training Algorithm	**Jan 2010 daily data**	**MAPE**
Lms_Type2	144	**14.99%**

Neural Network Monthly Data		
NN Training Algorithm	**June-July 2010 Monthly data**	**MAPE**
Levenberg-Marquardt	4320	**10.15%**
Bayesian regulation	4320	**10.13%**
Scaled conjugate gradient	4320	**10.14%**
LMS Monthly Data		
LMS Training Algorithm	**June 2010 and July 2010 data**	**MAPE**
Lms_Type2	4320	**34.04%**

IV. CONCLUSION

Wind speed forecasting based on Neural Network and least mean square is implemented. Results are obtained by using MATLAB R2014a.Neural network and least mean square trained by varying error tolerance, number of epochs, learning parameter to get minimum Mean Absolute Percentage Error (MAPE). The forecasting reliability is evaluated by computing Mean Absolute Percentage Error between exact values and predicted values. The wind site selected for study is located at Basaveshwar Engineering College, Bagalkot, and Karnataka, India. After training Neural Network algorithm we got the minimum error for daily data MAPE 9.59% and monthly data 32.26% .After training Least Mean Square algorithm we got the minimum error for daily data MAPE 16.68% and monthly data MAPE 54.86%. Comparing both results, we can conclude that Neural Network is the best method for wind speed forecasting. Comparing both results, we can conclude that Neural Network is the best method for wind speed forecasting

Based on the mathematical explanations and the Adaptive filter theory we have proposed least mean square (LMS) algorithm for short term wind speed forecasting. With the discrepancy in step size in the noise are concentrated but stable state error increases. At the same time we can make changes in the algorithm by changing the values of parameters disjointedly or combine. After obtaining the required simulation results the values are finalized. The value of step size chosen to be best suited for the original data to be generated.

V. FUTURE SCOPE

Following are the possibilities of future scope of the model presented herewith

- Proposed Neural Network and Least mean square models is developed for short term forecasting of wind speeds. Further it can be extended for medium and long term forecasting of wind speeds.
- Neural network model can be used for On-Line training and Forecasting of wind speeds and it can be used for forecasting of Load Demand with minor modifications.
- In Least mean square module the proper functioning of the filter can make the changes in the filter itself, by selecting the type of filter and the order of the Filter.

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