www.ijraset.com
IC Value: 13.98

Volume 4 Issue III, March 2016
ISSN: 2321-9653

International Journal for Research in Applied Science & Engineering Technology (IJRASET)

Forecasting Of Short Term Wind Power Using ARIMA Method

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Abstract- Wind power, i.e., electrical energy produced making use of the wind resource, is being nowadays constantly connected to the electrical system. This has a non-negligible impact, raising issues like network stability and security of the supply. An accurate forecast of the available wind energy for the forthcoming hours is crucial, so that proper planning and scheduling of the conventional generation units can be performed. Also, with the liberalization of the electrical markets worldwide, the wind power forecasting reveals itself critical to assure that the bids are placed with a minimum possible risk. The main application for wind power forecasting is to reduce the need for balancing energy and reserve power, which are needed to integrate wind power within the balancing of supply and demand in the electricity supply system. At times of maintenance it is required to know how much power would have been generated and should be supplied by other source. This work addresses the issue of forecasting wind power with statistical model, the Autoregressive Integrated Moving Average (ARIMA). The basic theory and the respective application of these models to perform wind power prediction are presented in this paper. Furthermore, their forecasting abilities are shown with the help of graphs.

Keywords- Autoregressive Moving Average, Energy, Forecasting, Model, Short Term, Wind Power.

I. INTRODUCTION

A wind power forecast corresponds to an estimate of the expected production of one or more wind turbines, referred to as a wind farm in the near future. By production is often meant available power for wind farm considered with units kW or MW depending on the wind farm nominal capacity. Forecasts can also be expressed in terms of energy, by integrating power production over each time interval. Un-forecasted wind fluctuations increase requirements for spinning reserves and raise electricity system production costs. Un-forecasted large ramp events can affect electricity system reliability. State of art forecasts have high economic value compared to their cost. Wind power forecasts are essential for effective grid management with high wind penetrations (>5%). Forecasting plays an important role in managing the variable output from wind farms on the grid making it appear more like conventional energy sources. Reduces cost of integrating wind on the grid and so reduces energy costs, both financial and environmental, for everyone. The advanced wind power forecasting methods are generally divided into two main groups; first is physical approach, consists of several sub-models which together deliver the translation from the NWP forecast at a certain grid point and model level to power forecast at the considered site and at turbine hub height. Every sub-model contains the mathematical description of the physical processes relevant to the translation, and the second is statistical approach which consists of emulating the relation between meteorological predictions, historical measurements and generation output.

II. THE FORECAST TIME HORIZONS AND METHODOLOGY

The very-short–term forecasting approach consists of statistical models that are based on the time series approach and includes such models as the Kalman Filters, ARMA, ARX, and Box-Jenkins forecasting methods. These types of models only take as inputs past values from the forecasted variable (e.g., wind speed, wind generation). At the same time, they can also use other explanatory variables (e.g., wind direction, temperature), which can improve the forecast error. Since these methods are based solely on past production data, they only outperform the persistence model (reference model) for forecast horizons between 3–6 hours. The medium term forecasting is up to a time horizon of 72 hours. It is generally used for aggregate production planning, man power planning and inventory. Several statistical models for day-ahead forecasts are clubbed together to decrease the forecast error. The methods used for forecasting are; Neural Networks, Support Vector Machines, Regression Trees with Bagging, Random Forests, Adaptive Neural Fuzzy System, Nearest Neighbour Search. In statistics and econometrics, and in particular in time series analysis an autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model. These models are fitted to time series data either to better understand the data or to predict future points in the series (forecasting). They are applied in some cases where data show evidence of non-stationary, where an initial differencing step

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ISSN: 2321-9653

(corresponding to the "integrated" part of the model) can be applied to remove the non-stationary. The model is generally referred to as an ARIMA (*p*,*d*,*q*) model where parameters *p*, *d*, and *q* are non-negative integers that refer to the order of the autoregressive, integrated, and moving average parts of the model respectively. ARIMA models form an important part of the Box-Jenkins approach to time-series modelling.

When two out of the three terms are zeros, the model may be referred based on the non-zero parameter, dropping "AR", "I" or "MA" from the acronym describing the model. For example, ARIMA(0,1,0) is I(1), and ARIMA(0,0,1) is MA(1). ARIMA ion 1,1,1) model with box Jenkins approach is used for determining the forecasting model.
P= 1 (only historic wind speed is considered as determining factor)
d= 1(for smoothing difference is taken for one time)
q= 1(moving average term)

III. RESULTS AND DISCUSSIONS

SUMMARY STATISTICS

Variable	Observations	Observation with missing data	Observation without missing data	Minimum	Maximum	Mean
Wspd (m/s)	98	0	98	0.353	3.054	1.598

Results of ARIMA modelling of the Wspd (m/s) series after optimization-

Goodness of fit statistics

Observations	97.000
DF	93.000
SSE	5.435
MSE	0.056
RMSE	0.237
WN Variance	0.056
MAPE(Diff)	108.253
MAPE	13.316
-2Log (Like)	-3.805
FPE	0.057
AIC	4.195
AICC	4.630
SBC	14.494
Iterations	108.000

Model parameters

Parameter	Value	Hessian standard error	Lower Bound (95%)	Upper Bound (95%)
Constant	1.829			
Observation	-0.005	0.003	-0.011	0.002

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ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

Parameter	Value	Hessian standard error	Lower Bound (95%)	Upper Bound (95%)	Asympt. standard error	Lower bound (95%)
AR(1)	0.290	0.149	-0.001	0.582	0.160	-0.023
MA(1)	0.385	0.138	0.114	0.656	0.154	0.082

Predictions and Residuals

Observations	Wspd (m/s)	ARIMA(Wspd) (m/s)	Residuals	Standardized residuals
1	1.582	1.582	0.000	0.000
2	1.560	1.574	-0.014	-0.059
3	1.456	1.544	-0.088	-0.373
4	1.335	1.389	-0.054	-0.227
5	1.212	1.276	-0.064	-0.271
6	2.229	1.149	1.080	4.563
7	2.191	2.936	-0.745	-3.149
8	2.035	1.890	0.146	0.615
9	1.393	2.043	-0.650	-2.745
10	0.585	0.953	-0.368	-1.556
11	0.849	0.205	0.644	2.721
12	1.563	1.171	0.393	1.659
13	2.168	1.918	0.250	1.056
14	2.598	2.437	0.161	0.680
15	2.911	2.781	0.130	0.549
16	3.054	3.049	0.005	0.023
17	2.958	3.095	-0.137	-0.578
18	2.865	2.874	-0.009	-0.038
19	2.619	2.831	-0.212	-0.897
20	2.488	2.462	0.026	0.108
21	2.498	2.456	0.042	0.178
22	2.704	2.514	0.189	0.800
23	2.908	2.833	0.075	0.319
24	2.868	2.993	-0.125	-0.527
25	2.739	2.805	-0.067	-0.281
26	2.607	2.672	-0.066	-0.278
27	2.360	2.540	-0.180	-0.760
28	2.055	2.216	-0.161	-0.680
29	1.685	1.901	-0.216	-0.912
30	1.253	1.491	-0.239	-1.009
31	0.780	1.032	-0.252	-1.065
32	0.353	0.542	-0.189	-0.799
33	0.493	0.153	0.340	1.437
34	1.002	0.662	0.341	1.439
35	1.400	1.278	0.122	0.514

Volume 4 Issue III, March 2016
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36	1.461	1.558	-0.097	-0.410
37	1.487	1.439	0.048	0.202
38	1.467	1.509	-0.042	-0.178
39	1.446	1.442	0.004	0.019
40	1.541	1.438	0.103	0.436
41	1.603	1.606	-0.003	-0.011
42	1.119	1.617	-0.498	-2.102
43	1.019	0.784	0.235	0.992
44	1.101	1.077	0.024	0.102
45	0.972	1.130	-0.159	-0.671
46	0.871	0.870	0.001	0.006
47	0.930	0.839	0.091	0.384
48	1.048	0.979	0.069	0.290
49	1.106	1.105	0.001	0.004
50	1.065	1.120	-0.054	-0.230
51	0.806	1.029	-0.224	-0.946
52	0.481	0.641	-0.159	-0.673
53	0.353	0.322	0.030	0.128
54	0.568	0.324	0.244	1.030
55	0.850	0.721	0.129	0.547
56	1.070	0.979	0.091	0.385
57	0.927	1.165	-0.238	-1.005
58	0.555	0.791	-0.236	-0.998
59	0.642	0.353	0.289	1.222
60	0.985	0.775	0.210	0.886
61	1.325	1.162	0.163	0.690
62	1.758	1.483	0.275	1.162
63	2.250	1.986	0.264	1.114
64	2.380	2.491	-0.111	-0.470
65	2.096	2.371	-0.275	-1.163
66	1.584	1.904	-0.321	-1.355
67	1.482	1.308	0.174	0.733
68	1.362	1.516	-0.154	-0.649
69	1.276	1.265	0.011	0.047
70	1.327	1.252	0.075	0.317
71	1.461	1.368	0.093	0.393
72	1.641	1.532	0.109	0.460
73	1.821	1.732	0.090	0.380
74	2.014	1.905	0.109	0.461
75	2.131	2.109	0.022	0.094
76	2.195	2.171	0.024	0.103
77	2.103	2.219	-0.117	-0.493

78	1.851	2.028	-0.177	-0.746
79	1.636	1.707	-0.071	-0.301
80	1.536	1.542	-0.006	-0.027
81	1.342	1.501	-0.159	-0.672
82	1.177	1.221	-0.044	-0.188
83	1.588	1.109	0.479	2.024
84	2.210	1.888	0.322	1.361
85	2.583	2.512	0.072	0.303
86	2.479	2.716	-0.237	-1.002
87	2.206	2.354	-0.148	-0.625
88	1.934	2.067	-0.132	-0.559
89	1.774	1.801	-0.027	-0.114
90	1.640	1.714	-0.074	-0.312
91	1.665	1.570	0.096	0.404
92	1.589	1.706	-0.117	-0.496
93	1.378	1.518	-0.140	-0.593
94	1.176	1.259	-0.083	-0.351
95	1.068	1.082	-0.014	-0.061
96	1.001	1.028	-0.027	-0.115
97	0.921	0.967	-0.047	-0.197
98	0.844	0.876	-0.032	-0.137

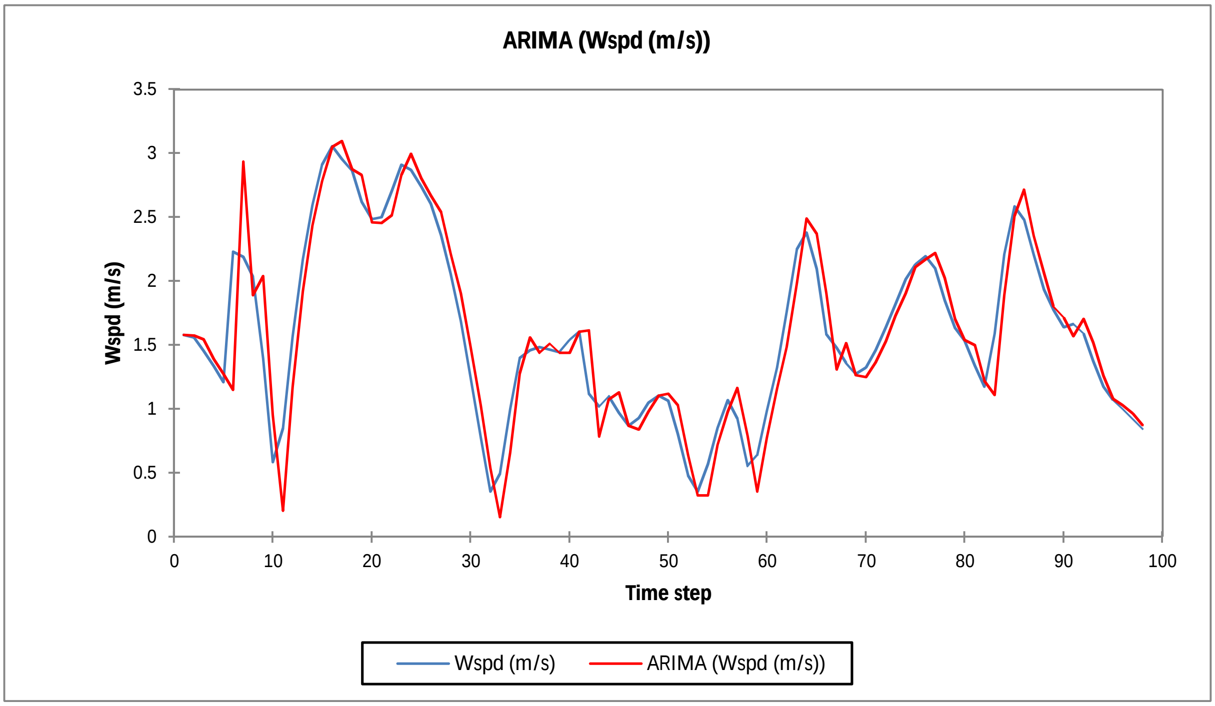

FIG 1 - FORECASTED AND ACTUAL DATA COMPARISON

Volume 4 Issue III, March 2016
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

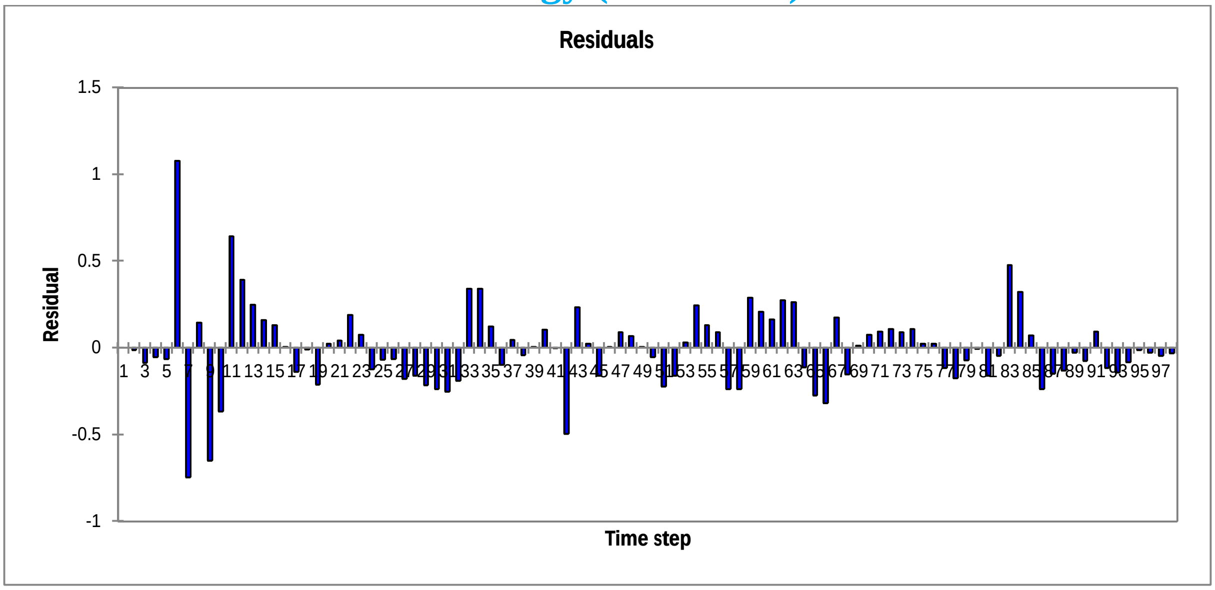

FIG 2 - RESIDUALS AT LAG1 (ACF FOR SMOOTHING)

IV. CONCLUSION

A mathematical model for Wind forecasting is created and tested. The presented results show that the model is fitting all the data's efficiently. XLSTAT application was used for obtaining parameters. Parameters can also be calculated with the Yule Walker equation using correlation lags. Difference was taken for smoothing the curve with lag1. ARIMA model can be made for smooth or stationary data only. ACF and PACF plots can be made to check the authenticity of the model. ARIMA, ARMA, and AR are effective tools for non-seasonal short term wind power forecasting.

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