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Short Term Wind Speed Forecasting using PSO Optimized Regression Model

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Abstract: The main research results of wind speed prediction research. It only focuses on point prediction. Wind power depends on atmospheric variables that are always changing. Wind speed prediction is an important aspect of future safe operation and reliability of the power grid. Outline the new developments in wind forecasting and the practical significance of current developments. In this paper, Optimal Particle Swarm Optimization (PSO) based regression model is used to predict 1 hour wind speed For this study, wind time series data was obtained from the National Renewable Energy Laboratory (NREL) website. In this work, the hourly average 60-minute wind speed data set for 2016 and 2017 has been used for analysis. In this actual and predicted wind speed, the comparison of the entire data with a sub-series approximation and delayed samples is evaluated. After the predictive analysis (average absolute percentage error), the MAPE error is calculated. In this MAPE there are fewer compared to the rest of the methods, and the model is suitable for all seasons of the year with low complexity. This method is more accurate than the remaining methods.

Index Terms: Forecasting, Partical swarm optimization (PSO) , Regression, wind speed series data.

I. INTRODUCTION

The importance of renewable energy is now growing. Renewable energy is sufficient and reliable, and may be a very cheap technology and infrastructure improvement [1]. When the sun heats the surface of the earth, the movement of the air creates wind. As long as the sun is shining, the wind will be infinite. The use of wind power to generate electricity is best considered to be eco-friendly, socially beneficial and economically competitive. The behavior of the wind is essentially chaotic [2]. Wind power is a fast growing renewable source of energy. Wind power plays an important role. Wind power depends to a large extent on atmospheric

Changes, which themselves depend on the time of the season. Wind energy is one of the Important non-conventional source of energy, pollution-free and affordable energy, it directly avoids dependence on Fuel and transportation. It can lead to clean electricity. Then select the appropriate name on the style menu. Overview of the current and new

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developments in Wind Speed Forecast give the overall focus on actual implementation. Wind power forecasting is used to plan the future, helping to manage the power system is the most economical way and helps manage network congestion in the power system. Wind forecasting is very important for the importance and reliability of future power grids and for safe operation. Short-wind wind forecast is important to improve the efficiency of the wind energy system [3] and integrating wind energy into existing power systems. In [1], artificial neural network (ANN) and adaptive wavelet neural network (AWNN) were compared for wind speed prediction studies and the empirical wind decomposition (EEMD) technique and the support vector mechanism (SVM) are used to decompose the original wind signal into sub-signals of different frequencies. And as the input to the neural network configuration. Weight adjustment is done in the neural network structure using back-propagation algorithm (BPA).In [1], artificial neural networks and AWNN wind speed prediction methods were compared. In AWNN, wind speed sequence I is decomposed into 8 levels. 30 sample wind speed data is used for this analysis. And comparing all these results with both methods, AWNN gives a perfect prediction. In [2], they discussed different methods of wind energy prediction, namely persistence methods, physical methods, and heuristic methods. The hybrid approach provides a detailed literature review on forecasting wind speed. In [3], wind speed predictions between three artificial neural networks are compared. In [4], a wind power forecasting strategy consisting of a forecasting engine and feature selection is proposed. The predicted engine includes new enhanced PSO components and hybrid neural networks. Feature selection components apply irrelevance. The proposed wind power forecasting strategy is applied to actual data from wind power producers. A comprehensive study on particle swarm optimization algorithms is proposed in [5]. Detailed information on computational intelligence is available in [6]. A hybrid method for predicting wind speed is proposed in [7]. There, the method uses independent modeling algorithms such as Exponential Smoothing (ESM) , RBF Neural Networks and Seasonal Adjustment Algorithm (SAA),. In [8], a multi-layer perceptron (MLP) is used for short-term forecasting of wind speed and training processes using the Back Propagation Algorithm (BPA). In [9], wavelet genetic algorithm-MLP and wavelet particle swarm optimization (PSO)-MLP are compared, and it is proved that wavelet decomposition improves the performance of multi-layer perceptron (MLP). [10], A uses a statistical method based on principal component analysis (PCA) wind speed prediction algorithm. The method trains previous wind speed data to forecast speed signals. In [11], Ivankhnenko and Lapa released the first

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functional network with multiple layers in 1965, becoming the group method for data processing. In [12], ANN (artificial neural network), ARIMA (autoregressive integrated moving average model), and SVM (support vector machine) were compared in short-term wind speed prediction. Their results show that the performance of hybrid ARIMA-SVM and ARIMA-ANN is better than that of a single SVM and ARIMA model. A method based on BT (Bayesian) and SBM (Structural Fracture Model) is proposed in [13] for Very short-temporarily wind speed estimates. The Bayesian method is used in [14] to estimate the wind speed for the next hour. During these two years, wind speed data was modeled as an autoregressive process and the results obtained were compared to the persistence method. In [15], New wind speed estimates based on support vector machines (SVM) and Wavelet are proposed. In this method, the original wind speed sequence is first decomposed to coarse components, and then the each wavelet component is separately forecasted using the corresponding SVM model. Finally, the results of wind speed are obtained by wavelet reconstruction. A new technique based on the linear time series model is proposed in [16] for forecasting of wind direction and speed direction. The forecast interval is two years of data. The key issues of wind power forecasting, the challenges of wind power generation and wind power prediction. techniques are outlined in [17].

In order to estimate the real wind speed from the same variable preceding data, [18] a method is recommended for two layers of artificial nerve networks. In [19], a method for predicting short-term wind speed using wavelet, PSO and ANFIS is proposed (adaptive neural fuzzy inference system. The method based on AWNN (adaptive wavelet neural network) proposed in [20] is used to decompose the real wind speed. The sequence and prediction of the wind speed feed forward neural network (FFNN) for the next 30 hours is used for nonlinear mapping between wind speed and wind output, which helps to convert wind speed into wind forecast.

II. PARTICLE SWARM OPTIMIZATION TECHNIQUE

Very popular non-traditional tools local) best location (best). Particles with the greatest adaptability are called optimizations and are often referred to as particle swarm optimization in short PSOs. Proposed by Kennedy and Eberhart, 1995. It is a population-based evolutionary computing technique. By simulating bird flocking, fish education is developed. The algorithm begins with a population (group) of random solutions (particles). The particles have memory, and every particle has its previous (g_{best}) group track. PSO algorithm has powerful capacity and simple ability to solve non-linear and Linear problems used to reduce computational complexity and improve convergence speed [4] PSO uses it to solve optimization problems. In PSO, search space for each specific solution is a "bird". We call it "particle." Each particle has a fitness value. It is evaluated by a fitness feature that is optimized by and there is a movement that indicates particle flight.

III. WIND SPEED FORECASTING

The forecast of wind power production is traditionally predicted in the form of a dotted prediction. ie For each assigned time, one value, expected or exceeded. These unique values have something to do with what is expected of us and the future generations. Today, the body of the prediction of the wind is predictably predictive, the goal is to receive more interactions in the model, or to measure the local model to change the physical model. For example, these efforts can reduce the size of a bulletin(forecasted) error [2]. However, the better understanding & modeling of metabolism and energy processes are the natural and incoherent imbalances in each prediction. This knowledge store is not fully understood in processes that affect future events. Therefore, it is important to provide a method to evaluate the accuracy of these estimates by pointing out more points about wind power generation in days or days[4].By present practice, uncertainty is expressed in the form of predictable predictions or common predictions. Some decisions related to wind direction and business related sales have been proven to be more optimistic when determining concrete forecasts. Examples of business applications, studies show that realistic forecasts of aviation fields, advanced marketing methods. Other studies of this type involve optimal dynamic quantification of reserves requirements, including optimal operation of a combined wind system, or multi-zone multi-level regulation. Such studies include better integrated ventilation schemes, or better backup interventions at multiple multi-level monitoring sites.Wind speed prediction researchs helps to plan the future, help manage the power system in a robust and economical way, help plan wind farm maintenance in the next few days, plan power exchange/flow and fuel planning consumption with neighboring systems.

A. Categorization of wind speed forecasts based on Time-Scales

Methods distributed based on time or methods can be used for prediction of wind speed. Over time, the wind speed forecast methods below is shown.

1 Ultra short term forecast from the first afew minutes to 1 hour.

2 Short term forecasts range from hours to hours.

3 The medium term forecast has never been a few hours to a week earlier.

4 Long-term predictions range from 1 week to 1 year or longer.

IV. REGRESSION

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It is used for predicting, causal relationships between time series modeling and finding variables. Regression analysis is an useful tool for testing, modeling and analyzing function approximations.

A. *Linear Regression*

The "Regression analysis" is a method of statistical analysis used to test two or more of the volatile relationships.. That is, the relationship between (target) and independent variables (predictors). Linear regression is a commonly used predictive analysis. With these two variables, the linear equation is paired with the expected data. A dynamic description is an explanation, and the other variables are considered dependent. Several linear regression functions are a statistical tool for analyzing many free variables related to variable variables. For the effect of two or more single variables to influence a given variable, several direct linear regimes are used. It is here that the relationship between two or more of the interest variables and response variables is comparing to the actual divergence. The independent variable X value of every value is relative to the constant variable Y value.. The model loocks at the most suitable predictors of the NWP and selects the best predictor to fit the regression equation that minimizes the prediction error using wind power measurements.

B. Multiple regression

Multiple regression resolves co-identified coefficients a0, a1, and a2 minimizing the sum o deviations of the model data (Least or minimum square fit).Multiple linear regression is such a technique and the most commonly used short-term prediction method, which will predict wind speed. Which method gives less prediction error.

V. DATA ANALYSIS

wind speed data is used in this, which is collected from National Renewable Energy Laboratory (NREL). Two years of total data were collected from January 1, 2016 to December 31, 2017. 24 samples of wind power series (1 per hour) were collected every day. The same is January. There were 744 samples in the month, of which 720 were used for training and used to predict day 31.

VI. SIMULATION RESULTS

The proposed PSO model has been applied to all 24 months in 2016 and 2017 for a one-day forecast with an interval of 60 minutes. Model Prediction To evaluate the performance model, Below Equation is required to calculate the mean absolute percent error (MAPE) of the corresponding data.

$$\text{MAPE} = \sum \frac{|A-F|}{A} \times 100/N$$

Here A: Actual wind speed,
F: forecasted wind speed,
N:No. of wind samples

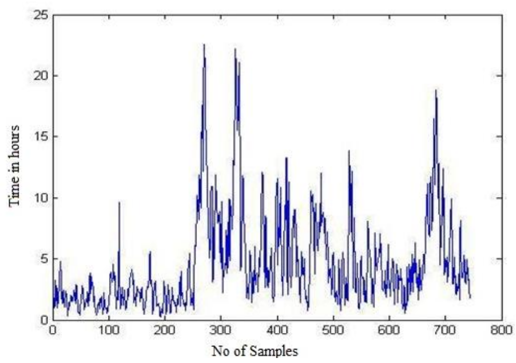

Fig: 1 variations of wind samples with respect to time (hours)

Figure 1 shows the forecast one day ahead, with a monthly interval of 60 minutes (1 hour) in January 2016 and 2017, and a wind speed of 50 ms in 2 cases.

Case-1 Prediction using one delayed sample

$$w(t+1) = w(t) + w_0$$

In this prediction model, w(t + 1) is the predicted value of time period t + 1.

In order to consider a period in advance, the prediction is obtained based on the available observations and the predicted value of w(t + 1).

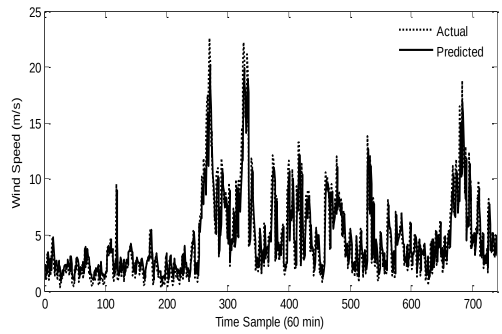

Fig 2: Actual and predicted wind speed comparisons of entire data with one sub series approximation

Figure 2 shows the wind sample for January 2016, 744 samples for 31 days, of which 720 samples were used for training and used to predict the 31st day scenario.

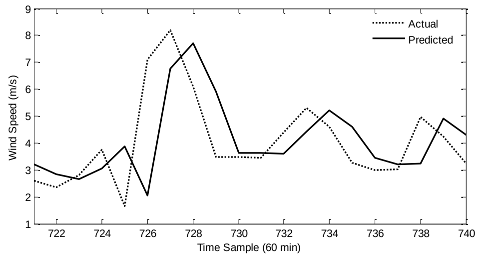

Fig:3 Actual and predicted wind speed comparisons entire data with one sub series approximation

Fig:3 shows comparison of actual and predicted wind speeds of entire data with one sub series approximation for

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the data of 20 wind samples. i.e., these 20 samples are used for testing.

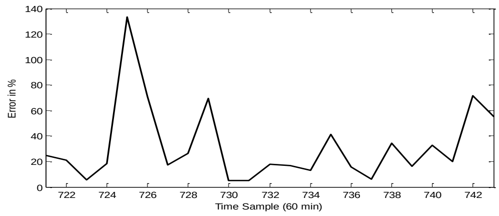

Figure 4: Percentage error between actual wind speed and predicted wind speed.

Fig 4 shows percentage error between actual wind speed and predicted wind speed of 20 samples of wind data.

Suppose we measure the number of several values of X1 The model of the data is in the form

$$y = a_1 x_1 + a_0$$

Equation: X1= [0.863 0.6102]

[0.6396 0.1798]

These values are written in the form of above equation ,we get

$$w(t+1) = 0.863w(t) + 0.6102$$

$$w(t+1) = 0.6396w(t) + 0.1798$$

The above equation is the identifier of the map,The current system is related to history System output. When using the identified model Used for forecasting

Objective function is Min(Y_{actual}-$Y_{predicted}$)

Here we have to find the values of a_0, a1 with the help of PSO and which must be the best values for minimization Of MAPE Overall error on 720 samples (objective function) -2659.3755; 151.4444.

Table: 1 comparison of linear regression and multiple regression of wind forecasting according to % of errors.

Actual	Predicted	% of Error	Predicted	%of Error
2.5821	3.2154	24.5267	2.0966	18.8019
2.3623	2.8548	20.8492	1.8313	22.4776
2.8154	2.6637	5.3865	1.6907	39.9472
3.7434	3.0576	18.3195	1.9805	47.0928
1.6544	3.8643	133.5794	2.5741	55.5899
7.0890	2.0484	71.1050	1.2380	82.5370
8.1797	6.7727	17.2015	4.7139	42.3704
6.0989	7.7208	26.5935	5.4115	11.2703
3.4850	5.9120	69.6406	4.0807	17.0920
3.4705	3.6397	4.8757	2.4088	30.5920
3.4490	3.6271	5.1640	2.3995	30.4282
4.3791	3.6084	17.5991	2.3858	45.5189
5.2938	4.4170	16.5637	2.9807	43.6950
4.6090	5.2121	13.0853	3.5657	22.6358
3.2744	4.6168	40.9969	3.1277	4.4797
2.9942	3.4566	15.4444	2.2741	24.0496
3.0341	3.2131	5.8982	2.0949	30.9551
4.9610	3.2477	34.5345	2.1204	57.2584
4.2290	4.9228	16.4057	3.3529	20.7175
3.2233	4.2865	32.9839	2.8847	10.5057
4.2623	3.4122	19.9443	2.2414	47.4128
2.5139	4.3154	71.6623	2.9060	15.5960
1.8026	2.7955	55.0834	1.7877	0.8271

Table:1 refers comparison between linear regression and multiple regression of wind forecasting according to % of errors. By comparing these two methods multi linear regression gives less prediction error.

Case-2 Prediction using two delayed sample

$$w(t+1) = w(t) + w(t-1) + w_0$$

In this prediction model, the predicted value is w(t + 1) for time period t + 1. In order to consider a period in advance, the prediction is obtained based on the available observations and the predicted value w(t + 1)

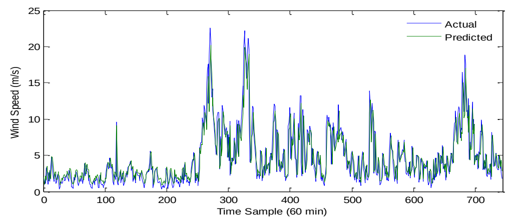

Fig5: Actual and predicted wind speed comparisons of entire data with one sub series approximation

Fig 5 shows no of wind samples in January 2016 i.e.,744 samples for 31days.out of these 720 samples used for training and used to predict the 31^{st} day scenario.

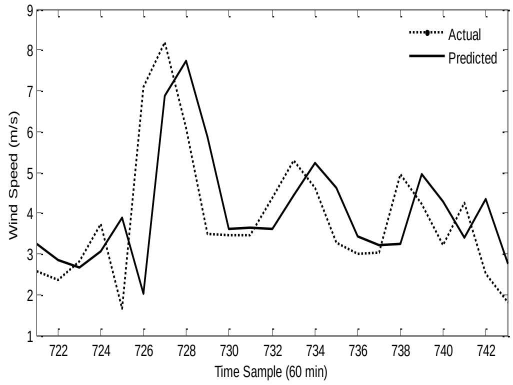

Fig6:Comparision between actual and predicted wind speeds

Figure 6: Comparison of actual and predicted wind speeds The entire data has a sub-series approximation. Hypothesis We measure the number of values for X1 and X2 The model of the data is in the form

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$$y = a_2 x_2 + a_1 x_1 + a_0$$

Equation:

[0.8852 −0.0187 0.6250]
[0.6841 -0.0477 0.2045]
[0.6841 −0.0477 0.2045]

These values are written in the form of above equation , we get,

$$w(t+1) = 0.8852w(t) - 0.0187w(t-1) + 0.6250$$

$$w(t+1) = 0.6841w(t) - 0.0477w(t-1) + 0.2045$$

The above equation is the identifier of the map,The current system is related to history System output. When using the identified model Used for forecasting

Objective function is Min (Y_{actual}-$Y_{predicted}$)

Here we have to detect the values of a_0, a1 and a2 with the help of PSO and which must be the best values for Minimization of MAPE.

a_0,a_1,a_2 values to be taken for the analysis which should be the best fitting values for minimization of error.

Overall error on 720 samples (objective function) – 2656.6087; 150.6886

Table: 2 comparison of linear regression and multiple regression of wind forecasting according to % of errors.

Table: 2 comparison between linear regression and multiple regression of wind forecasting according to % of errors. By comparing these two methods multilinear regression gives less prediction error.

Case 3: similarly prediction using twelve delayed sample is as follows

$$w(t+1) = w(t) + w(t-1) \ldots\ldots.. w(t-11) + w_0$$

In this forecasting model (t+1) is the predicted value for time period t+1.

To consider one period in advance, the forecast is obtained based on the available observations and the predicted value of w(t+1)

Equation:

$$w(t+1) = 0.8738w(t) - 0.1285w(t-1) + 0.0094w(t-2) + 0.1524w(t-3) + 0.0046w(t-4) - 0.337w(t-5) - 0.0264w(t-6) + 00967w(t-7) - 0.0908w(t-8) + 0.0259w(t-9) - 0.0127w(t-10) + 0.0406w(t-11) + 0.4175$$

The above equation is the identifier of the map,The current system is related to history System output. When using the identified model Used for forecasting

Objective function is Min (Y_{actual}-$Y_{predited}$)

Objective function to minimize the MAPE Overall error on 720 sample (objective function)-

2502. 8746 ; 139.2004

Table: 3 comparison of linear regression and multiple regression of wind forecasting according to % of errors.

Table: 3 comparison of linear regression and multiple regression of wind forecasting according to% of errors. By comparing these two methodsmultilinear regression gives less prediction error.

Actual	Predicted	% of Error	Predicted	% of Error
2.5821	3.2388	25.4340	2.1551	16.5356
2.3623	2.8546	20.8413	1.8280	22.6194
2.8154	2.6678	5.2418	1.6974	39.7108
3.7434	3.0730	17.908	2.0178	46.0962
1.6544	3.8860	134.889	2.6311	59.0344
7.0890	2.0195	71.5126	1.1577	83.6689
8.1797	6.8692	16.0208	4.9752	39.1766
6.0989	7.7331	26.7951	5.4621	10.4414
3.4850	5.8708	68.4587	3.9866	14.3927
3.4705	3.5959	3.6125	2.2977	33.7942
3.4490	3.6319	5.3035	2.4124	30.0541
4.3791	3.6132	17.4909	2.3984	45.2303
5.2938	4.4369	16.1872	3.0357	42.6551
4.6090	5.2292	13.4559	3.6171	21.5208
3.2744	4.6059	40.6637	3.1050	5.1734
2.9942	3.4373	14.7990	2.2247	25.7008
3.0341	3.2142	5.9370	2.0966	30.8974
4.9610	3.2548	34.3924	2.1373	56.9179
4.2290	4.9597	17.2793	3.4536	18.3355
3.2233	4.2757	32.6510	2.8609	11.2425
4.2623	.3992	20.2500	2.2078	48.2008
2.5139	4.3377	72.5491	2.9666	18.0074
1.8026	2.7706	53.7002	1.7209	4.5297

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Actual	Predicted	% ofError	Predicted	% of Error
2.581	3.4749	34.5772	2.4498	5.1248
2.363	3.0724	30.0589	1.7799	24.6541
2.814	2.4494	12.9996	1.7030	39.5118
3.744	3.3092	11.6003	1.9395	48.1888
1.654	3.9127	136.5012	2.5697	55.3278
7.080	1.6084	77.3110	1.2488	82.3844
8.177	6.9136	15.4789	4.9603	39.3588
6.099	7.3582	20.6486	4.9013	19.6368
3.480	5.0876	45.9869	3.4450	1.1482
3.475	3.7789	8.8877	2.4836	28.4358
3.440	4.3555	26.2831	2.5710	25.4555
4.371	3.9593	9.5858	2.8581	34.7329
5.298	3.8986	26.3560	3.1893	39.7543
4.600	5.3298	15.6386	3.4531	25.0802
3.274	4.3268	32.1407	2.9589	9.6345
2.992	3.3723	12.6282	2.6693	10.8500
3.031	3.2481	7.0531	2.5025	17.5197
4.960	3.5642	28.1555	2.2850	53.9402
4.220	4.9807	17.7739	3.4214	19.0978
3.223	4.0843	26.7111	2.6907	16.5223
4.263	3.2830	22.9758	2.1464	49.6421
2.519	4.5259	80.0353	3.2071	27.5732
1.806	2.7027	49.9362	1.8361	1.8588

VII. CONCLUSION

Accurate wind speed & power prediction can determine the operation and maintenance of the power system. Wind speed and power forecasting are important tools to improve the reliability and efficiency of power systems. In this paper, wind speed prediction has been completed one hour ahead of schedule. Wind speed prediction was performed using an optimized regression model based on techniques Particle Swarm Optimization (PSO) and multilinear regression In this work, the hourly average 60-minute wind speed data set for 2016 and 2017 has been used for analysis. There is a sub-series approximation of the actual and predicted wind speed comparisons.

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VIII. AUTHORS PROFILE

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