

Wind Farm Power Prediction Based on Wind Speed and Power Curve Models

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Abstract Accurate prediction of wind farm power is essential for increasing wind penetration in the electricity grid. It also aids the power system operators in planning unit commitment, economic scheduling, and dispatch. In this paper, combined wind farm power prediction models have been built based on wind speed prediction models and power curve models. The wind speed prediction models have been built using nonlinear autoregressive models with and without external variables. The wind turbine power curve has been modeled using parametric and nonparametric models. Parametric models are built using four- and five-parameter logistic expression, whose parameters are solved using particle swarm optimization (PSO) and differential evolution (DE). Nonparametric models were built based on data mining algorithms. Multistep prediction model for wind power forecasting has been developed for very short-term forecasting of wind power. Real-time data obtained from Sotavento Galicia Plc. has been used for testing the proposed model.

Keywords Data mining • Differential evolution • Particle swarm optimization
Time-series model • Wind speed forecasting

1 Introduction

Wind power has definitely gone a long way in solving the problems of energy and environmental crisis. Though wind energy promises to be a clean and sustainable source of energy, its integration into the existing electrical supply system is a great

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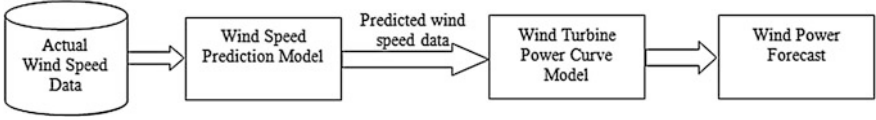


Fig. 1 Combined prediction model for wind power

challenge. Wind power prediction has been a hot area of research, and several techniques have been evolved for both onshore and offshore power prediction [1–5].

This paper presents a novel combined model for very short-term wind power forecast. It consists of the combination of a wind speed prediction model and wind turbine power curve model (Fig. 1). Many of the research works carried out earlier have built the univariate model of wind speed time-series data. In this paper, nonlinear autoregressive models (NAR1) for time-series wind speed data with and without external variables have been built. These models have been solved using data mining algorithms. Multistep prediction models for predicting wind speeds at 10 min interval up to 1 h have been built. These values are given as inputs to the wind turbine power curve models which have been built using parametric and nonparametric techniques. The parametric models of wind turbine power curve are built using the four- and five-parameter logistic expression whose variables are solved using nontraditional optimization techniques such as PSO and DE.

These techniques have the advantage of enhanced accuracy and are very easy to implement even for huge datasets. The nonparametric models are built using data mining algorithms. The combined models are used to predict the wind farm power over 10 min interval, for the next six time steps.

2 Wind Speed Prediction Model

Building an accurate model for wind speed forecasting is the first important requisite for realizing the combined prediction model shown in Fig. 1. Four different models have been built for very short-term wind speed forecasting. WS11, WS10, and WS09 refer to the 10 min averaged wind speed data of December in the years 2011, 2010, and 2009, respectively, and WD represents wind direction. The first one is a nonlinear autoregressive model (NAR1), and the remaining models are built based on exogenous variables, namely the wind direction and wind speed of the previous two years. These nonlinear models are solved using data mining algorithms, namely SMOreg, Lazy k-star, bagging, M5R, and M5P.

The defining equation for the NARX model is

$$y(t) = f(y(t-1), y(t-2), \dots, y(t-n_y), u(t-1), u(t-2), \dots, u(t-n_u)) \quad (1)$$

where the next value of the dependent output signal, the wind speed at a particular time $y(t)$ is regressed on previous values of the output signal and previous values of

an exogenous input signal u , n_y is the AR order, and n_u is the input order [6]. The function f can be approximated using any nonlinear algorithms such as neural networks and data mining algorithms.

2.1 NAR and NARX Models for Wind Speed

The NAR models do not have any exogenous input signal. The expression for the NAR model developed for wind speed (NAR1) using the sequential feature selection algorithm is given in Eq. 2.

$$y(t) = f(y(t-1), y(t-2), y(t-3), y(t-5)) \quad (2)$$

The wind direction and wind speeds of the corresponding time in the previous two years are the exogenous variables that have been taken into consideration.

2.1.1 Model Incorporating Wind Direction

Sensing of wind direction is essential to capture maximum power from the wind. It is usually measured in cardinal directions or in azimuth degrees and is measured using a wind vane. The nonlinear autoregressive model including wind direction (NARX1), using the sequential feature selection algorithm, is given in Eq. 3.

$$y(t) = f(y(t-1), y(t-2), y(t-3), y(t-5), u_1(t-1), u_1(t-3)) \quad (3)$$

where u_1 is the wind direction of the corresponding period.

2.1.2 Model Incorporating Annual Trends

A linear time-series-based model for forecasting wind speed and direction was proposed by relating the predicted interval to its corresponding one- and two-year old data [7]. The one-year model performed better than the two-year model for smaller prediction horizons, while the two-year models performed better for larger prediction horizons. The nonlinear autoregressive model with wind direction and wind speed of the corresponding period in the previous year (u_2) as exogenous variables (NARX2), after application of feature selection algorithm, is defined in Eq. 4.

$$y(t) = f(y(t-1), y(t-2), y(t-3), y(t-5), u_1(t-1), u_1(t-3), u_2(t-4)) \quad (4)$$

The nonlinear autoregressive model with wind direction and wind speed of the corresponding period one year before and two years before (u_3) as exogenous variables (NARX3), after application of feature selection algorithm, is defined in Eq. 5

$$y(t) = f(y(t-1), y(t-2), y(t-3), y(t-5), u_1(t-1), u_1(t-3), u_2(t-4), u_3(t-1), u_3(t-7)) \quad (5)$$

Multistep prediction up to six consecutive time steps has also been developed.

3 Wind Turbine Power Curve Model

The theoretical power captured by the rotor of a wind turbine (P) is given by

$$P = 0.5\rho\pi R^2 C_p y^3 \quad (6)$$

where ρ is the air density, R is the radius of the rotor, C_p is the power coefficient, and y is the wind speed [8]. In this paper, parametric and nonparametric models are built for the wind turbine power curve. Parametric models are built using four- and five-parameter logistic expression [9]. The parameters of these expressions are solved using PSO and DE. Nonparametric models were built using data mining algorithms.

3.1 Parametric Models

The shape of the power curve resembles the four-parameter logistic function which is defined as

$$P = a(1 + me^{-y/\tau}/1 + ne^{-y/\tau}) \quad (7)$$

where a , m , n , and τ are the vector parameters. The five-parameter logistic expression has been used for modeling the wind turbine power curve in [9]. It is defined by

$$P = d + (a - d) / \left(1 + \left(\frac{y}{c} \right)^b \right)^g \quad (8)$$

where a , b , c , d , and g are the vector parameters that are solved using PSO and DE.

3.2 Nonparametric Models

A nonparametric model for the power curve is built on the assumption that

$$P = f(y) \quad (9)$$

Nonparametric models are built using four different data mining algorithms, namely MLP, bagging, M5R, and M5P. The combined power prediction models are the major contribution of this paper. The output of the best wind speed model is given as input to the best wind turbine power curve model. Multistep prediction models for the next six consecutive time steps have been built.

4 Modeling Techniques

The nonparametric models were developed using various data mining algorithms such as SMOreg, Lazy k-star, bagging, M5R, M5P, and MLP. The optimization techniques such as PSO and DE have been employed in this paper to find the parameters of the four- and five-parameter logistic function. The optimization problem is defined as follows:

$$\text{Objective function: } \min \sum_{i=1}^N [P_e(y_i) - P_a(i)]^2 \quad (10)$$

where $P_e(y_i)$ is the power estimated by the logistic expressions, $P_a(i)$ is the actual power, and N is the total number of data. The constraints of the four- and five-parameter logistic expression are given in Eqs. 11 and 12, respectively.

$$\{a_{\min} \leq a \leq a_{\max}, m_{\min} \leq m \leq m_{\max}, n_{\min} \leq n \leq n_{\max}, \tau_{\min} \leq \tau \leq \tau_{\max}\} \quad (11)$$

$$\{a_{\min} \leq a \leq a_{\max}, b_{\min} \leq b \leq b_{\max}, c_{\min} \leq c \leq c_{\max}, d_{\min} \leq d \leq d_{\max}, g_{\min} \leq g \leq g_{\max}\} \quad (12)$$

5 Results and Analysis

The data used for this research, the results obtained, and the analysis of results have been presented in this section.

5.1 Experimental Data

The real-time data used for development of wind speed and wind power prediction models was obtained from Sotavento Galicia Plc., an experimental wind farm supported by the “Xunta de Galicia”, the regional autonomous government [10]. The 10 min averaged data for the month of December 2011 has been used for the combined wind power prediction models (Fig. 2). The total number of data is 4446,

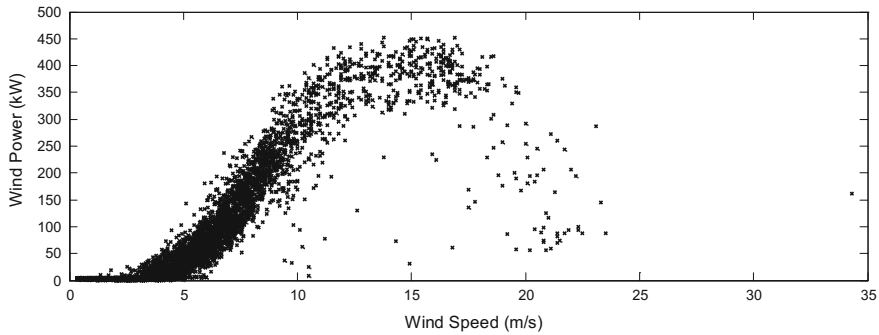


Fig. 2 Real-time data of December 2011

half of which was used for training and the other half was used for testing the data mining algorithms. The parametric algorithms which involved the application of optimization techniques were built using the entire set of data.

5.2 Results of Wind Speed and Power Prediction Models

As the combined model for wind power prediction is built using the best wind speed model and best wind power curve model, the performance of the various models built in this regard has been analyzed in the following section. The performance of these parametric and nonparametric models has been evaluated using the metrics mean absolute error (MAE) and root mean squared error (RMSE). If N is the total number of input data, S_e is the estimated variable, and S_a is the actual variable, MAE and RMSE are defined as follows:

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |S_e(i) - S_a(i)| \quad (13)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (S_e(i) - S_a(i))^2} \quad (14)$$

The variables can either be wind speed or power based on the model being tested.

5.2.1 Performance of Wind Speed Prediction Models

The performance of the time-series models for wind speed built using data mining algorithms was compared and the M5R algorithm performed best for the nonlinear

autoregressive model for wind speed. The M5P and bagging algorithms give the lowest MAE and RMSE, respectively, for all the other models that are built including the different external variables. The multistep prediction models were also built for wind speed using these algorithms.

5.2.2 Performance of Wind Power Prediction Models

In order to identify the best wind power prediction model, the parametric and nonparametric wind turbine power curve models are built. The data mining algorithms used for nonparametric models were developed and tested in WEKA. The optimization techniques, PSO and DE, used for solving the logistic expressions of the parametric models were built in MATLAB. The population size and maximum number of iterations of PSO and DE were selected as 50 and 100, respectively. The control parameters of PSO are $w = 0.5$, $C_1 = 2$, and $C_2 = 2$. The control parameters of DE are $F = 1$ and $C_R = 0.5$. The parameters of four-parameter logistic expression (a, m, n, τ) solved by PSO are (383.4822, -0.3050 , 271.1179, 1.5341) and by DE are (384.09, -3.4636 , 216.5773, 1.5634). The parameters of five-parameter logistic expression (a, b, c, d, g) solved by PSO are (395.9986, -6.31994 , 9.7276, -2.7150 , 0.5682) and by DE are (393.9342, -6.4761 , 9.7280, -3.0050 , 0.5521).

When the best wind speed prediction models are given as input to the wind power curve models, it was observed that the parametric power curve models totally outperform the nonparametric models. The wind turbine power curve built using five-parameter logistic expression whose parameters are optimized using PSO give best results for all the NARX models of wind speed. Parametric models solved using DE algorithm give the best performance for the NAR model of wind speed.

Multistep prediction models of wind power are built for the best combination of wind speed and power, and their performance is tabulated in Table 1.

5.3 Analysis of Results

The multistep prediction of the combined models of wind power has been analyzed in Table 2 using two criteria, mean and standard deviation (Std) of the errors. The mean value gives an idea about the error magnitude in every consecutive step and Std is a measure that is used to quantify the amount of variation or dispersion of a set of data values. The combination of nonlinear autoregressive wind speed model without any external variables (NAR1) built using M5R algorithm and wind turbine power curve model built using four-parameter logistic expression solved by DE algorithm registers lowest mean and standard deviation when the RMSE is considered. Though the mean of its MAE errors is higher than the other models, its standard deviation is the lowest.

Table 1 Multistep prediction of combined models of wind power

	WS model	NAR1 (M5R)	NAR1 (M5R)	NARX1 (M5P)	NARX1 (M5P)	NARX2 (M5P)	NARX2 (M5P)	NARX3 (M5P)	NARX3 (M5P)
		DE (4P)	DE (5P)	DE (4P)	PSO (5P)	DE (4P)	PSO (5P)	DE (4P)	PSO (5P)
First time step	MAE	20.7971	20.6379	20.5797	20.4825	20.5343	20.4323	20.5491	20.4407
	RMSE	32.3466	32.5559	32.6416	32.8376	32.4872	32.6725	32.4585	32.6198
Second time step	MAE	22.5446	22.4762	22.0703	22.0046	22.0344	21.9560	22.0813	21.9897
	RMSE	34.5132	34.8309	33.8235	33.9954	33.8607	34.0038	34.0114	34.1267
Third time step	MAE	24.0281	24.0235	23.9381	23.9253	23.9176	23.8909	23.9530	23.9258
	RMSE	36.3888	36.7815	36.6484	36.8099	36.7724	36.9071	36.8793	37.0102
Fourth time step	MAE	25.4151	25.4377	25.3981	25.4329	25.3087	25.3378	25.2108	25.2568
	RMSE	38.1803	38.5999	38.4410	38.6175	38.5202	38.6891	38.3307	38.5526
Fifth time step	MAE	26.6340	26.6208	26.7813	26.8438	26.5982	26.6718	26.4239	26.5089
	RMSE	39.5764	40.0281	40.1185	40.3744	40.0322	40.3333	39.5346	39.8296
Sixth time step	MAE	27.5459	27.5661	27.7663	27.8824	27.5451	27.6744	27.4879	27.6430
	RMSE	40.8588	41.3502	41.4779	41.7974	41.2307	41.5826	40.9997	41.4174

The values that are in bold represent best values
In MAE and RMSE the least values are the best values

Table 2 Analysis of multistep prediction of combined models of wind power

Combined models of wind power prediction	MAE		RMSE	
	Mean	Std	Mean	Std
NAR1 (M5R) + DE (4P)	24.49	2.547	36.98	3.198
NAR1 (M5R) + DE (5P)	24.46	2.608	37.36	3.298
NARX1 (M5P) + DE (4P)	24.42	2.765	37.19	3.488
NARX1 (M5P) + PSO (5P)	24.43	2.845	37.41	3.533
NARX2 (M5P) + DE (4P)	24.32	2.694	37.15	3.451
NARX2 (M5P) + PSO (5P)	24.33	2.782	37.36	3.518
NARX3 (M5P) + DE (4P)	24.28	2.631	37.04	3.279
NARX3 (M5P) + PSO (5P)	24.29	2.733	37.26	3.375

This model which has the lowest standard deviation augurs well for multistep prediction. Prediction of wind power based on this model would definitely give a very reliable result for very short-term horizon spanning from 10 min to 1 h.

6 Conclusion

Wind power prediction models can revolutionize electricity trading, aid the power system operators in planning and control. Combined power prediction models consisting of wind speed and wind turbine power curve models have been proposed in this paper. The combination of nonlinear auto regressive wind speed model built using M5R algorithm together with the wind turbine power curve model built using the four-parameter logistic expression, whose parameters were solved using DE, performed best. The multistep prediction of this combined model of wind power is very impressive as it records the lowest standard deviation for both the error measures, namely MAE and RMSE. These models can be effectively used to predict power for consecutive time steps, using wind speed as the only input. Development and implementation of this model will definitely go a long way in making wind-generated power more attractive, reliable, and competitive.

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