Wind Energy Conversion System Model Identification and Validation

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Abstract. Wind energy conversion system (WECS) is complex because of wind speed varies in time and space. Model identification is required to represent its dynamics for real-time implementation. In this paper a doubly-fed induction generator (DFIG) WECS is used. Different model structures are generated and simulated using MATLAB/SIMULINK. The models are generated using both nonlinear and linear system identification tool boxes. Linear system identification toolbox generates both model structure and model parameters; whereas the nonlinear system identification tool generates only the system model structures. From linear models, the BJ33221 model has better performance with best fit of 74.78%, final prediction error (FPE) value of 0.0445 and mean square error (MSE) is 0.04265. ARX211 model structure provides best fit of 74.39%, FPE of 0.0453, and MSE is 0.04465. This study shows as model order increases, the best fit value too, but the system become more complex. The nonlinear models have better performance than the linear models. The nlarx121 model structure provides the best fit of 96.43% and MSE of 0.0322, with other technique for its model parameters estimation. The output residuals are within the confident range (0.2 to −0.2), indicating the model structure was validated.

Keywords: WECS · Model identification · BJ33221 · nlarx121

1 Introduction

Wind energy conversion system (WECS) is a stochastic system, since wind speed varies in time and space. Therefore identification of the model is required to represent its dynamics which is used for real-time implementation. In a doubly-fed induction generator (DFIG) WECS, power and speed are the outputs for system, require regulation by controlling the torque and pitch angle. The WECS mathematical model representation requires multi structural input-output model identification. It is known as the Nonlinear Auto Regressive Moving Average with exogenous inputs model (NARMAX) [1, 2]. NARMAX was represented by Auto Regressive Moving Average with exogenous inputs model (ARMAX) model by interpolating between a set of

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ARMAX models [3]. An alternative representation for fitting NARMAX models was given based on the radial basis function [4]. The NARMAX model was also expressed as ARMAX model of single-input single-output linear systems [5]. This because of simplicity of ARMAX than NARMAX and even in MATLAB its function is not available. In this paper the other models such as Output Error (OE), Box Jenkins (BJ) and Nonlinear Auto Regressive with exogenous inputs (NLARX) were also generated and discussed. Single input single output system is considered and different model structures are generated and simulated using MATLAB/SIMULINK. The models fit criterions and simplicities are compared. The best model was selected. Actually, the models are generated using both nonlinear and linear system identification tool boxes. Linear system identification toolbox generates both model structure and model parameters; whereas the nonlinear system identification tool generates only the system model structures. For this purpose best fit percentage, FPE and MSE values were used as criterions. In [6, 7] MSE was well defined and used for measure of error introduced in neural network during its training and analysis for model selection.

2 Model Estimation

The most costly procedure in system identification is obtaining experimental data. The quality of final model depends on quality of data; hence great care must be taken to generate data. Model estimation of the wind energy conversion system experimental input-output data on Matlab/simulink system identification tool box is used. The general procedure was pre-processing the data, model structure selection, parameter estimation and model validation. Data preprocessing and examination is done by adjusting the experimental data to be loaded into Matlab in order to get good data which is suitable for system identification. Model structure is selected based on prior knowledge and taking into consideration model complexity. Validation is done to validate the estimated model output compare to the real output from the experiments. The model validation can be accepted if it satisfies the percentage of best fit and other criterions.

The accuracies of model of WECS is highly affects overall performances of the system. For instance, it has been shown that a very common 5% modeling error in the optimal tip speed ratio-λ alone can cause an energy loss of around 1%–3% [8–10] during the wind turbine operates below rated speed. This is a significant loss. Consider a 324 MW installed capacity wind farm (Ethiopia wind farm case), which is operating with a reasonable 32% capacity factor can produce about 908.237 GWh of energy per year. If the cost of energy is $0.09 per kWh, 1% loss of energy on this wind farm is equivalent to a loss of $817413 per year. To overcome this inaccuracy, system model validation is one of the first important steps.

The input to the system is wind speed (random) with mean value of 12 m/s and variance equal to one is used to drive turbine and then generator at different speed. The input and output signals are shown in Fig. 1 below. Number of data generated for training and validation is 2000 with sampling time 0.1 s. In order to estimate and validate the model, the data is divided into two parts. The first part, which is (1–1000) data sets are used to determine the model of the systems. The second (1001–2000) data sets are used to validate the model. All procedures to estimate the model is done by using System Identification Toolbox in Matlab/Simulink.

The objective of this paper is to find the model for wind energy conversion system which can be used for controller design. Both linear and nonlinear identification process were applied, but in the nonlinear identification only the model structure are determine since the model parameters are not identified by the matlab tools for non-linear case. The discrete time ARX and ARMAX model structures were selected because both the structure and parameters of the model are available. The input data shown in Fig. 1 was applied into the WECS simulink model shown in Fig. 2 so that the output on Fig. 1 was measured at the out port of the model. Figure 2 is the inter connection of aerodynamic, wind turbine, and electric generator subsystem in the WECS. All these subsystems have their components as shown in Figs. 3, 4, 5 and 6. For system identification purpose, the wind speed was used as input to simulator and the generator speed is considered as output of generator. Figure 3 is the model for the simulation of turbine blade pitch angle simulation diagram. In this diagram the relation of wind speed, generator speed, attack angle and blade radius to the pitch angle is represented. The disturbance due wind speed variation can be regulated by this block. The mathematical equations for aerodynamic to mechanical energy conversion by DFIG type wind turbine are described in Figs. 3, 4 and 5 using matlab/simulink subsystem simulation representation. For instance from Fig. 4 the wind turbine rotor instantaneous torque and power can be relate by

$$T_t = 0.5\rho A u^3 C_p(\lambda, \beta)/\omega_t \tag{1}$$

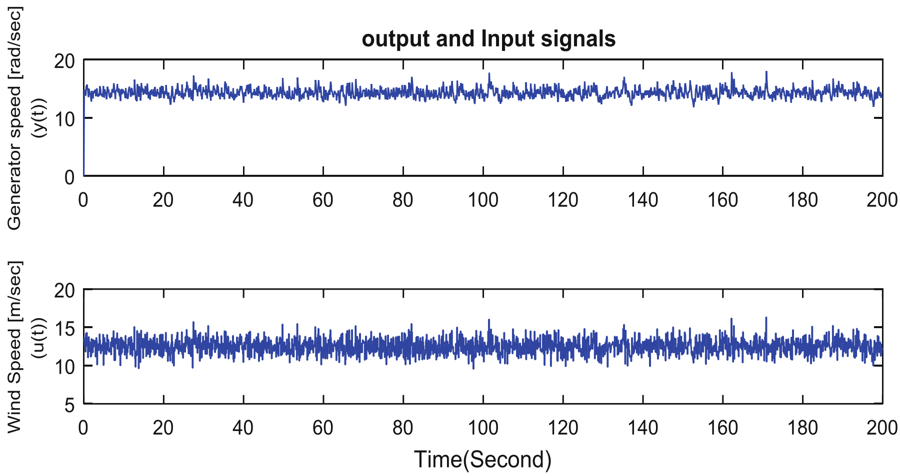

Fig. 1. WECS model identification and validation data

where, ρ is air density, A is area swept by turbine blade and u is the instantaneous wind speed and $C_p(\lambda, \beta)$ is wind power to mechanical power conversion efficiency as a function of the turbine's tip-speed ratio-λ and rotor blade Pitch angle-β and ω_t is wind turbine rotor rotational.

Figure 4 is the representation Simulation Model of aerodynamics energy conversion to mechanical energy through wind turbine. This model includes wind speed, area swept by wind turbine blade and power conversion efficiency. The mechanical power generated by turbine is divided by turbine and gives turbine torque. Figure 5 is simulation model of wind turbine blade tip speed ratio, which depends on wind speed, blade rotational speed, and percents of blade radius starting from hub to blade tip. The model for aerodynamics power to mechanical power conversion efficiency is required. The efficiency is highly depends on the blade pitch angle and tip speed ratio.

Table 1. Wind turbine plant rating and specifications

Specifications	Values
Wind turbine and rotor	
Number of blades	3
Cut in speed	3.5 m/s
Cut out speed	25 m/s
Rated speed	9.5 m/s
Air density ρ	1.25 kg/m
Optimum tip speed ratio λ	8
Power coefficient Cp	0.49
Rated rotor speed ω	22 rpm
Maximum rotor speed	23 rpm
Blade diameter	77 m
Drive train	
Gear ratio	1:94
Turbine inertia	90×10^6 kgm^2
Low speed shaft torsion stiffness	160×10^6 Nm/rad
Low speed shaft torsion stiffness	10×10^6 Nm/rad
DFIG	
Rated power	1.5 MW
Maximum generator speed	1500 rpm
Terminal Voltage	690 ± 5% v
Generator inertia	60 kgm^2
Generator torque	13.4 k Nm

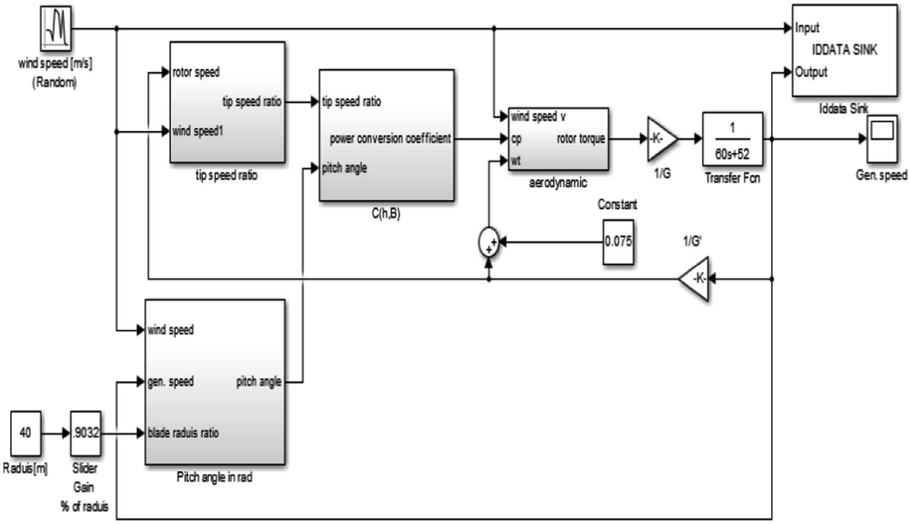

Fig. 2. Wind Turbine Generator Simulation Model

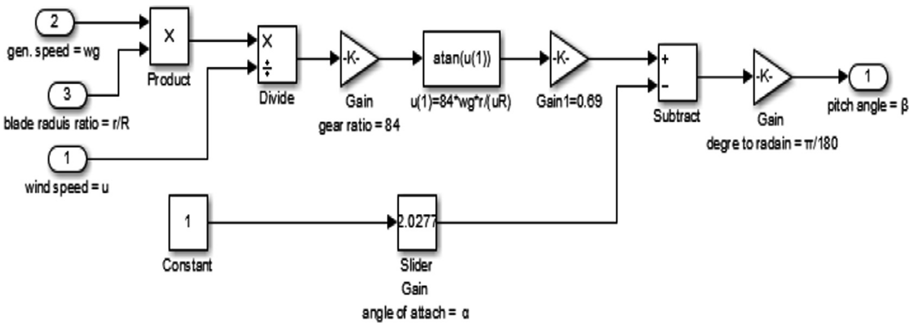

Fig. 3. Wind Turbine blade pitch angle Simulation model subsystem

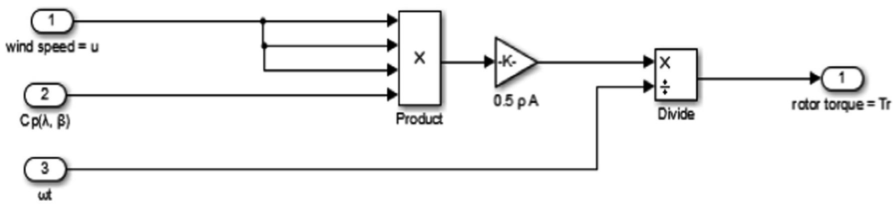

Fig. 4. Aerodynamics to wind turbine torque conversion Simulation Model subsystem

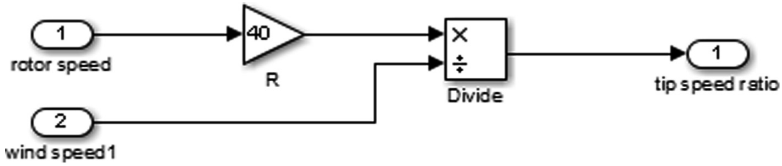

Fig. 5. Wind Turbine Blade Tip Speed Ratio Simulation Model subsystem

3 Result and Discussion

Substituting the specification in Table 1 in to system simulation diagram shown in Fig. 2 and applying the input data given in Fig. 1 with system identification tool, the results for different models of WECS were presented in Tables 2 and 3. For selected models validation curve were generated.

In system identification process model representation with adequate accuracy is required in order to analyse the system and/or design a suitable controller that will drive the output in a desired manner. For WECS based on best fit performance and other criteria like model simplicity, the appropriate system model can be selected from the lists in the Table 2. As instance BJ33221 is the best model to represent the system. From the results shown in Table 2, the BJ33221 model has better performance with 74.78% model best fit, 0.0445 final prediction error and 0.04265 mean square error. In this table, as it is shown next to BJ33221, the performance of armax2321 is better. Figures 6 and 7 illustrate the model validation using validation data for different model structures as indicated on the figures. The model structure of BJ33221 is given by Eq. (2).

$$y(t) = [B(z)/F(z)]u(t) + [C(t)/D(t)]e(t) \tag{2}$$

For *s*ample time is 0.1 s. Where y(t) is generator speed, u(t) is wind speed, e(t) is disturbances like wind turbulence. All these variables are functions of discrete time. B(z), F(z), C(z) and D(z) as given in Table 2 for sample time is 0.1 s. When the performance of BJ is compared with that of ARX211 (best fit = 74.39%, FPE = 0.0453, and MSE = 0.04465), approximately the same, but the BJ model structure is more complex. Therefore, it is good to use the simple model structure.

The selected model is ARX211. It can be represented by Eq. (3) which is derived from Eq. (1) for F(z) and D(z) are set to A(z) and C(z) is set to one.

$$y(t) = [B(z)/A(z)]u(t) + e(t)/A(z) \tag{3}$$

For $\mathrm{A(z)} = 1 - 0.4597\,\mathrm{z}^{-1} + 0.01125\,\mathrm{z}^{-2}$ and $\mathrm{B(z)} = 0.6333\,\mathrm{z}^{-1} - 0.004303\,\mathrm{z}^{-2}$.

The nonlinear model structures shown in the Table 3 have better fit criteria than the linear model structures given in Table 2. These nonlinear model structures are generated by using the nonlinear system identification toolbox and system which was shown by Fig. 2 with input data in Fig. 1. The tool box gives only model structure, and

Table 2. Different linear model structure and model representation with best fit criteria

No.	Model structure	Best fit (%)	FPE	MSE	Linear model representation
1	ARX211	74.39	0.0453	0.04465	$A(z) = 1 - 0.4597\,z^{-1} + 0.01125\,z^{-2}$ $B(z) = 0.6333\,z^{-1} - 0.004303z^{-2}$
2	ARX231	74.44	0.0451	0.04422	$A(z) = 1 - 0.5285\,z^{-1} + 0.03795\,z^{-2}$ $B(z) = 0.6369\,z^{-1} - 0.0452\,z^{-2} - 0.01058\,z^{-3}$
3	ARX321	74.46	0.0451	0.04424	$A(z) = 1 - 0.5272\,z^{-1} + 0.04451\,z^{-2} + 0.004223\,z^{-3}$ $B(z) = 0.638\,z^{-1} - 0.04329\,z^{-2}$
4	ARX331	74.40	0.0451	0.04409	$A(z) = 1 - 0.5271\,z^{-1} + 0.00683\,z^{-2} + 0.01614\,z^{-3}$ $B(z) = 0.6385\,z^{-1} - 0.04337\,z^{-2} - 0.02961\,z^{-3}$
5	ARMAX2221	74.44	0.0447	0.04351	$A(z) = 1 - 0.3926\,z^{-1} - 0.008379\,z^{-2}$ $B(z) = 0.64\,z^{-1} + 0.04316\,z^{-2}$ $C(z) = 1 + 0.1342\,z^{-1} + 0.1393\,z^{-2}$
6	ARMAX2321	74.73	0.0449	0.04346	$A(z) = 1 + 0.2827\,z^{-1} - 0.3044\,z^{-2}$ $B(z) = 0.6372\,z^{-1} + 0.4713\,z^{-2} + 0.007185\,z^{-3}$ $C(z) = 1 + 0.8055\,z^{-1} + 0.1576\,z^{-2}$
7	ARMAX3321	74.45	0.0451	0.04342	$A(z) = 1 + 0.09438\,z^{-1} - 0.2034\,z^{-2} - 0.005598\,z^{-3}$ $B(z) = 0.6383\,z^{-1} + 0.3528\,z^{-2} + 0.01862\,z^{-3}$ $C(z) = 1 + 0.6171\,z^{-1} + 0.1817\,z^{-2}$
8	ARMAX3331	74.45	0.0451	0.04327	$A(z) = 1 + 0.4487\,z^{-1} - 0.3563\,z^{-2} - 0.005191\,z^{-3}$ $B(z) = 0.6383\,z^{-1} + 0.58\,z^{-2} + 0.02187\,z^{-3}$ $C(z) = 1 + 0.9782\,z^{-1} + 0.2333\,z^{-2} + 0.08585\,z^{-3}$
9	ARMAX3441	74.71	0.0445	0.04233	$A(z) = 1 - 0.628\,z^{-1} - 0.7424\,z^{-2} + 0.3976\,z^{-3}$ $B(z) = 0.6508\,z^{-1} - 0.09641\,z^{-2} - 0.5359\,z^{-3} + 0.01264\,z^{-4}$ $C(z) = 1 - 0.1184\,z^{-1} - 0.7337\,z^{-2} - 0.08582\,z^{-3} - 0.05154\,z^{-4}$
10	ARMAX4441	74.71	0.0447	0.04234	$A(z) = 1 - 0.6248\,z^{-1} - 0.7481\,z^{-2} + 0.4007\,z^{-3} - 0.0005654\,z^{-4}$ $B(z) = 0.6508\,z^{-1} - 0.09429\,z^{-2} - 0.5387\,z^{-3} + 0.01343\,z^{-4}$ $C(z) = 1 - 0.1151\,z^{-1} - 0.738\,z^{-2} - 0.0833\,z^{-3} - 0.05301\,z^{-4}$
11	BJ22221	74.47	0.0449	0.04334	$B(z) = 0.6401\,z^{-1} - 0.03059\,z^{-2}$ $C(z) = 1 + 0.5496\,z^{-1} + 0.1425\,z^{-2}$ $D(z) = 1 + 0.02626\,z^{-1} - 0.2208\,z^{-2}$ $F(z) = 1 - 0.5082\,z^{-1} + 0.04257\,z^{-2}$
12	BJ33221	74.78	0.0445	0.04265	$B(z) = 0.6511\,z^{-1} + 0.6379\,z^{-2} + 0.0003357\,z^{-3}$ $C(z) = 1 - 0.7787\,z^{-1} - 0.04604\,z^{-2} - 0.1752\,z^{-3}$ $D(z) = 1 - 1.3\,z^{-1} + 0.3001\,z^{-2}$ $F(z) = 1 + 0.5014\,z^{-1} - 0.459\,z^{-2}$
13	OE221	74.47	0.0625	0.06128	$B(z) = 0.6308\,z^{-1} + 0.05367\,z^{-2}$ $F(z) = 1 - 0.3841\,z^{-1} - 0.01572\,z^{-2}$

not able to generates model parameters. It requires other techniques for parameters estimation as it is indicated by [11–13].

Any appropriate nonlinear model structure listed in Table 3 can be selected for WECS representation. The result in Table 3 shows that specific model structure has different performance criteria for different nonlinearity types such as tree partition, wavenet and sigmoidnet. The nlarx121 provides the best fit (96.43%) and small MSE (0.0322). This is when the nonlinearity type is tree partition and was represented by Eq. (4).

$$y(t) = f(y(t-1), u(t-1), u(t-2)) + e(t) \tag{4}$$

Where *f(.)* is some polynomial or rational nonlinear function with known model structure.

Table 3. Nonlinear model structures and model representation with best fit criteria

No.	Nonlinear model structure	Best fit (%)	FPE	MSE	Nonlinear model structures regresses representation
1	NLARX121	96.43	NA	0.0322	**Nonlinearity: tree partition** $y(t) = f(y(t-1), u(t-1), u(t-2)) + e(t)$
2	NLARX221	89.50	0.01125	0.04564	**Nonlinearity: wavenet** $y(t) = f(y(t-1), y(t-2), u(t-1), u(t-2)) + e(t)$
3	NLARX221	93.48	NA	0.01535	**Nonlinearity: tree partition** $y(t) = f(y(t-1), y(t-2), u(t-1), u(t-2)) + e(t)$
4	NLARX221	89.64	0.00440	0.00573	**Nonlinearity: sigmoidnet** $y(t) = f(y(t-1), y(t-2), u(t-1), u(t-2)) + e(t)$
5	NLARX341	81.93	0.04211	0.08438	**Nonlinearity: wavenet** $y(t) = f(y(t-1), y(t-2), y(t-3), u(t-1), u(t-2), u(t-3), u(t-4)) + e(t)$
6	NLARX341	85.73	0.02100	0.2277	**Nonlinearity: wavenet** $y(t) = f(y(t-1), y(t-2), y(t-3), u(t-1), u(t-2), u(t-3), u(t-4)) + e(t)$
7	NLARX341	83.13	NA	0.05202	**Nonlinearity: wavenet** $y(t) = f(y(t-1), y(t-2), y(t-3), u(t-1), u(t-2), u(t-3), u(t-4)) + e(t)$
8	NLARX231	81.53	0.03340	0.07163	**Nonlinearity: wavenet** $y(t) = f(y(t-1), y(t-2), u(t-1), u(t-2), u(t-3)) + e(t)$
9	NLARX321	83.66	0.02680	0.06309	**Nonlinearity: wavenet** $y(t) = f(y(t-1), y(t-2), y(t-3), u(t-1), u(t-2)) + e(t)$
10	NLARX441	81.34	0.04080	0.09058	**Nonlinearity: wavenet** $y(t) = f(y(t-1), y(t-2), y(t-3), y(t-4), u(t-1), u(t-2), u(t-3), u(t-4)) + e(t)$

4 Model Validation Test

For linear system identification, as it was shown in the simulation Figs. 6 and 7 and results in Table 2, the curve fit is almost 74%. This indicates linear model for wind energy conversion less validate. But based on the result in Table 3 and in Fig. 9 the best fit is in the range of 81% to 96.43%, according to the selected corresponding nonlinear model structure. This shows the nonlinear model the best validate structure.

The other important result is the *whiteness* criterion was indicated in Fig. 9. A good model has the output autocorrelation function inside the confidence interval of the corresponding estimates, indicating that the outputs are uncorrelated. Typically Fig. 9 is the autocorrelation of the output, and cross correlation between output and input of the nlarx121 model of wind energy conversion system. On both correlations graphs, the output residuals are within the confident range (0.2 to −0.2). This indicates that residual of outputs are not correlated and independent from past inputs for the desired model structure which proves the model structure is validated (Fig. 8).

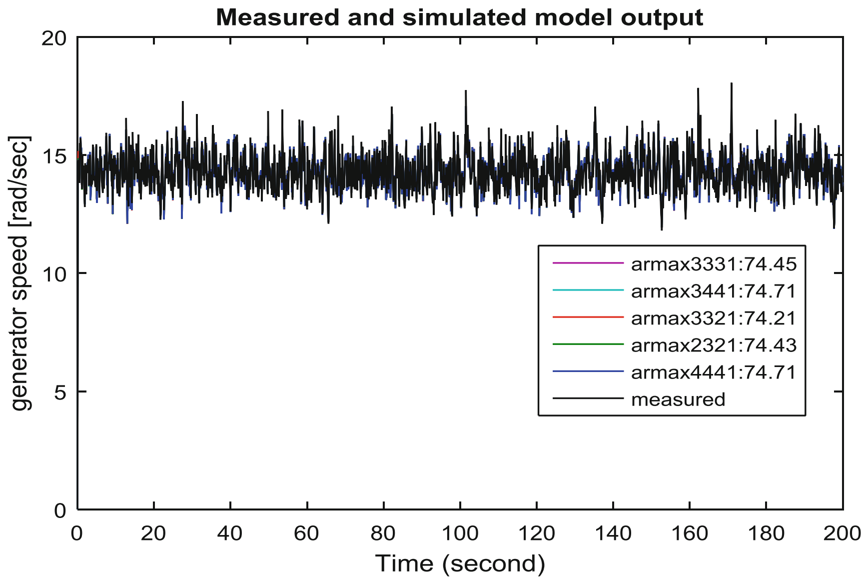

Fig. 6. Model validation curves (ARMAX….)

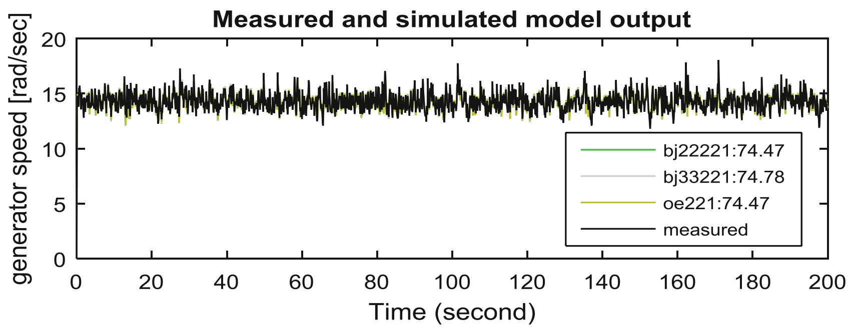

Fig. 7. Model validation curves for BJ22221, BJ33221 and OE221

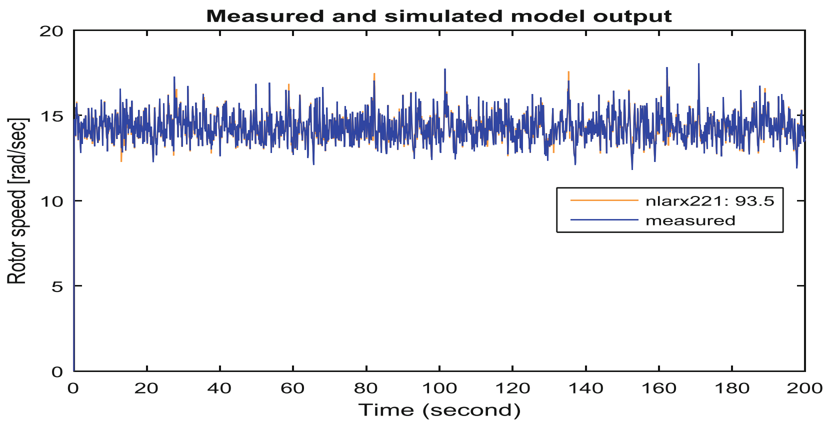

Fig. 8. Model validation curves for nlarx221 model structure

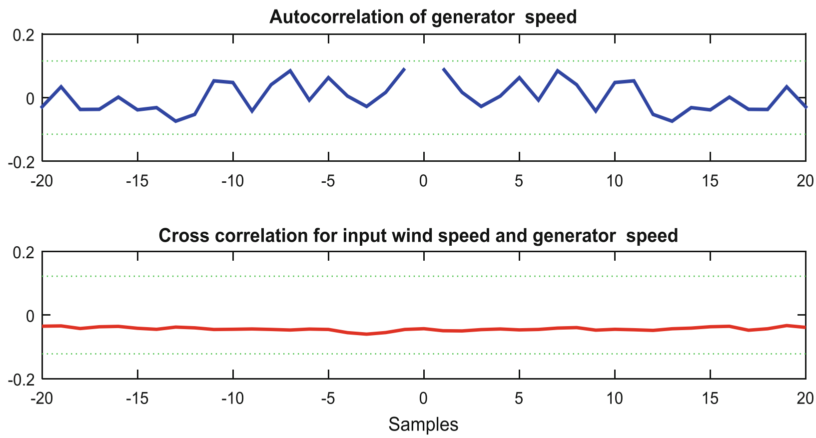

Fig. 9. Correlation curves of the output and input.

5 Conclusion

This paper has focused on the model identification technique for wind energy to electrical energy conversion system to select best mathematical model that would be equivalently represents the behavior of a physical system specifically for DFIG type wind turbine and can be used for analysis and controller design. Among ARX, ARMAX, OE and BJ model structures, it seems reasonable to pick BJ model structure as a better choice; since it gives better model estimation and validation than the others. Its best fit is 74.78%. It also observed that except OE, all linear model structures have FPE and MSE less than 0.04600, passing model validation test under output (generator speed) residual analysis. On the other hand, BJ model structure increases model complexity due to increase in system order. This indicates there is a contradiction between system order and percentage of model best fit. Therefore to overcome the model complexity of BJ, ARX211 model structure can be used. Because it has almost the same best fit with simplest model. Comparing the best fit of linear model structures with that of the nonlinear model structures, it has lower value. For illustration nlarx121 has best fit of 96.43%. This is due to the nonlinear behaviour of the wind energy plant. The nonlinear system identification toolbox gives only model structure without model parameters. As illustrated, the output residuals are within the confident range (0.2 to −0.2). This indicates that residual of outputs are not correlated and independent from past inputs for the desired model structure which proves that the selected model structure is validated.

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References

1. Bidyadhar, S., Pedda, S.: Non-linear autoregressive moving average with exogenous input model-based adaptive control of a wind energy conversion system. J. Eng. **2016**, 218–226 (2016)
2. Billings, S.A., Chen, S., Korenberg, M.J.: Identification of MIMO non-linear systems using a forward-regression orthogonal estimator. Int. J. Control **49**, 2158–2159 (1989)
3. Johansen, T.A., Foss, B.: Constructing NARMAX models using ARMAX models. Int. J. Control **58**, 1126–1142 (2007)
4. Chen, S., Billings, S.A., Cowan, C.F.N., Grant, P.M.: Practical identification of NARMAX models using radial basis functions. Int. J. Control **52**, 1328–1330 (2007)
5. Leontaritis, I.J., Billings, S.A.: Input-output parametric models for non-linear systems part II: stochastic non-linear systems. Int. J. Control **41**, 343 (2007)
6. Perez-Llera, C., Fernadez-Baizan, M.C., Feito, J.L., Gonzalez del Valle, V.: Local short-term prediction of wind speed: a neural network analysis. In: International Congress on Environmental and Software, p. 126 (2002)
7. Cadenas, E., Rivera, W.: Wind speed forecasting in three different regions of Mexico, using a hybrid ARIMA-ANN model. J. Renew. Energy **35**, 2737 (2010)
8. Johnson, K.E., Pao, L.Y., Balas, M.J., Fingersh, L.J.: Control of variable speed wind turbine: standard and adaptive techniques for maximizing energy capture. IEEE Control Syst. Mag. **26**, 74–75 (2006)
9. Pao, L.: A tutorial on the dynamics and control of wind turbines and wind farms. In: Proceedings of the American Control Conference, St. Louis, MO, USA, pp. 18 & 32 (2009)
10. Keesman, K.J.: System Identification: An Introduction, pp. 156–158. Springer, London (2011). https://doi.org/10.1007/978-0-85729-522-4
11. Asma, A., Saida, B., Kamel, A.: System identification: parameter and time-delay estimation for wiener nonlinear systems with delayed input. Trans. Inst. Meas. Control **40**, 1035–1044 (2018)
12. Wang, C., Zhu, L.: Parameter identification of a class of nonlinear systems based on the multi-innovation identification theory. J. Franklin Inst. **352**, 4625–4635 (2015)
13. Chen, S., Billings, S.A., Luo, W.: Orthogonal least squares methods and their applications to nonlinear system identification. Int. J. Control **50**, 1873–1896 (1989)