ROBUST APPROXIMATION MODELS FOR PREDICTIVE CONTROL OF A VARIABLE PITCH WIND POWER DRIVETRAIN

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Abstract

This paper proposes a data-driven system identification strategy resulting in robust approximation models with minimal prediction-error for a wind turbine drivetrain. Based on this approximation model, a predictive controller is designed and tested on a variable wind profile. Non-linear models of a 10 kW and a 1.5 MW variable-pitch wind turbine are developed, based on a Nonlinear Auto Regressive with eXogenous (N-ARX) and a discrete-time state space model for approximating the wind turbine's dynamical behaviour. The model is based on the advanced NREL wind turbine simulator FAST. In this study, the approximation model has the wind speed, pitch angle and rotor speed as input variables, and the electrical power output as output. Simulation results reflect the interactions that occur between all three input variables affecting the wind turbine's operational performance. Moreover, using our approach, the predictive controller is designed to deal with non-linear system characteristics and wind variability. Results show the robustness of the controller based on the approximation model towards high wind speeds and high turbulent wind conditions.

1 Introduction

Wind turbines with a Permanent Magnet Synchronous Generator (PMSG) are designed to operate over a wide range of wind speeds. They are continuously increasing in size, recently exceeding the 10 MW mark. However, as the share of renewable sources in the grid increases, the need arises for these sources to take part in grid balancing and stabilisation, e.g., by providing ancillary services. Especially large wind farms have the potential to offer a positive contribution. However, accurate modelling techniques and control systems are required to provide these services in practise [1]. To get a better understanding of the wind farm supervisory control characteristics and local control systems of individual wind turbines, a large investigation of wind turbine modelling and identification techniques is needed. Physical modelling, besides its complexity, is not ideal to cope with uncertainty or prediction errors of dynamic modes of the system. However, data-driven system identification and black-box modelling may aid to provide a more accurate approximation of the wind turbine's dynamics against stochastic behaviour of the wind, which also incorporates the non-linearities of the system [2,3].

Model Predictive Control (MPC) is an advanced control algorithm which uses a linearised model of the system to make predictions about the future of the process. MPC is able to optimize future trajectories and selects the best control actions that force the system's outputs to track the desired reference [4]. A robust MPC can also handle the constraints and physical limitations. The only disadvantage of MPC is the possible heavy computational load, which requires powerful and fast processors with a large memory to execute the iterative optimization algorithm. However, it is undeniable that the advanced high-performance micro-processors are developing rapidly [5].

This paper proposes a simplified, high-order model of wind turbine dynamics which are identified based on data-driven approximation techniques, including prediction error minimization on both Subspace State Space System Identification (NS4ID) and nonlinear Auto Regressive with eXogenous (ARX). The approximated model apprehends the fundamental dynamics of the turbine in all operating regions. The simulations have been done on two wind turbines; one small wind turbine with a rated power of 10 kW and a large wind turbine with a rated power of 1.5 MW. The proposed techniques are applied on two very different power ratings to show the flexibility and reliability of the method.

The uniformly sampled data is obtained from simulations which have been carried out using the FAST wind turbine simulation software. The MPC is designed based on a state space model, which is obtained from the proposed system identification technique. The MPC aims to track the wind turbine's electrical power set-point for high wind speeds. To improve the robust performance, soft constraints are assumed which can be violated to let the optimisation algorithm select the optimal pitch control action that might cause significant load reduction on the blades.

This paper is organized into four sections. In section 2, the basics of wind turbine modelling and identification techniques are presented. Furthermore, the formulation of the MPC objectives and the constraints are discussed. Section 3 presents achieved simulation results and section 4 concludes and discusses further research.

2 Methodology

2.1 System description

In this paper, a wind turbine system with a Permanent Magnet Synchronous Generator (PMSG) [6] and full-sale converter is considered. Fig. 1 gives an overview of the turbine configuration. The turbine's mechanical output power can be expressed by:

$$P_w = \frac{\rho \pi R^2}{2} C_p(\lambda, \beta) V^3$$

(1)

Where ρ is the air density, R is the length of the blades (m), V is wind speed (m/s) and C_p is the power coefficient. The power coefficient is determined by the tip speed ratio and the blade's pitch angle. The tip speed ratio is the dimensionless ratio between the blade's tip speed and the wind speed:

$$\lambda = \frac{\omega_r R}{V_w} \quad (2)$$

Figures 2 and 3 illustrate that a maximum value for the power coefficient is reached at a pitch angle of 2° for the 1.5 MW turbine and 7° for the 10 kW turbine. By controlling the turbine's rotor speed and pitch angle, the power coefficient can be regulated. Here, the generator speed is controlled by regulating the generator current through a cascaded control system. The slow outer controller provides a reference torque signal, which is proportional to the generator current, while the fast inner controller regulates the current itself by acting on the low-level converter control.

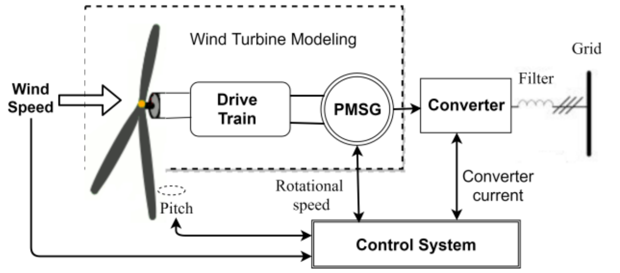

Fig. 1 General structure of a wind turbine with PMSG

In this study, system identification is performed, based on the closed-loop behaviour of the wind turbine. The pitch angle (control variable) and rotor speed (which is a consequence of regulating generator torque, drivetrain dynamics and rotational inertia) and wind speed (input parameter) are considered as the main inputs [7]. The electrical power injected into the grid is assumed to be the output. In the data-driven model approximation, it is necessary to apply perturbation signals and excite all of the system modes. Hence, the turbine is simulated at several wind speed levels. The turbulence level is gradually increased up to 18%, which can be considered as a highly turbulent condition. Saturation and rate limiters are applied on the pitch control signal to model the practical limitations of the pitching system.

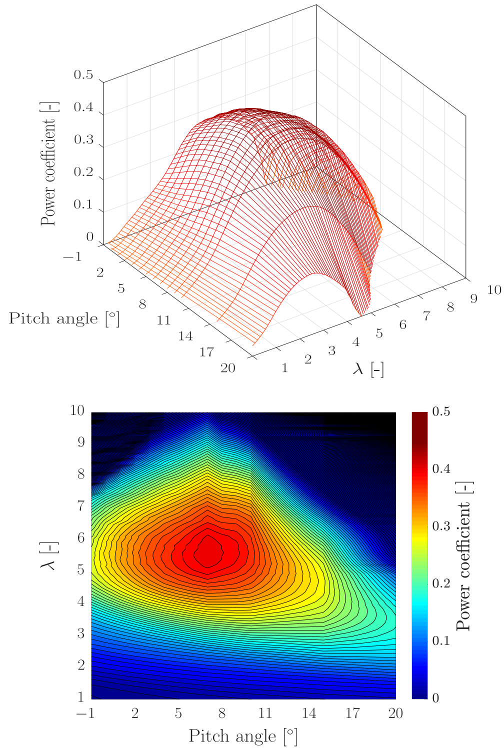

Fig. 2 Power coefficient of 10 kW wind turbine as a function of pitch and tip speed ratio (contour and 3D plot)

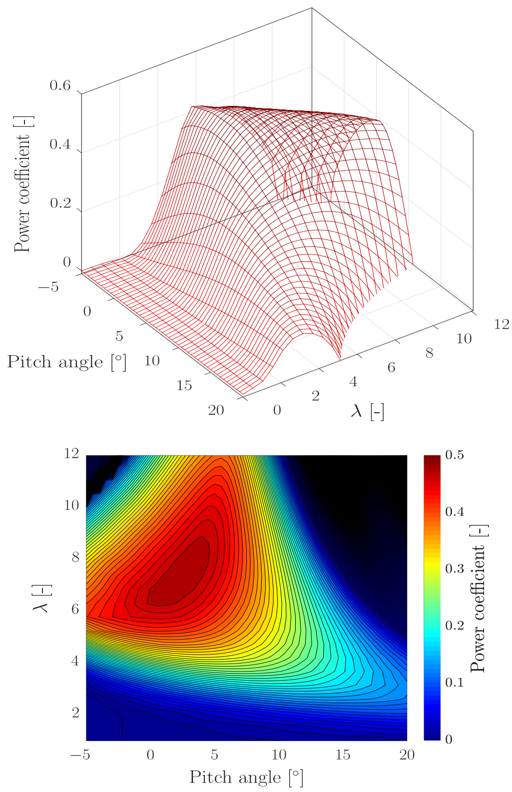

Fig. 3 Power coefficient of the 1.5 MW wind turbine as a function of pitch and tip speed ratio (contour and 3D plot)

2.1.1 State space model: In this section, a fourth-order linear state space model is derived based on the closed-loop behaviour of the wind turbine system. The model includes the turbine rotor and drivetrain. The main focus of this section is to discuss a novel and practical approach to approximate the dynamic control of a wind turbine generator from captured data, under non-stationary and highly turbulent wind conditions. It is worth noting that the wind turbine dynamics can be split into a static non-linearity and a linear time invariant (LTI) subsystem. The LTI part can be identified using a closed loop subspace identification.

Consider a combined deterministic-stochastic discrete-time state space model as:

$$\begin{aligned} x(kT+T) &= Ax(kT)+Bu(kT)+Ke(kT) \\ y(kT) &= Cx(kT)+Du(kT)+e(kT) \end{aligned} \tag{3}$$

With $T=0.01$ being the sampling interval at time instant *k*, $u(kT)=[\delta\beta,\delta\omega]$ is the vector of measured inputs, $y(kT)=[P_e]$ is the electrical power considered as the vector of measured output and $x(kT)$ is a four-dimensional unknown discrete state vector which does not necessarily have physical interpretation but with a conceptual relevance.

It is assumed that $e(kT)$ is an unmeasured Gaussian zero-mean white noise. System matrices *A, B, C, D* and *K* are unknown as well as the initial condition. In this section, the Subspace State Space System Identification (N4SID) method, based on QR decomposition, is used to estimate the system state variables [8]. Figures 4 and 5 show the results for the N4SID method compared to FAST simulations, the latter can be regarded as synthetic data originating from an actual wind turbine drivetrain. Adequate tracking performances of both the 10 kW (Fig. 4) and 1.5 MW (Fig. 5) wind turbine drivetrain can be observed when using the N4SID based model.

2.1.2 Nonlinear ARX model: A nonlinear data-based approximation approach is proposed, based on a low-order nonlinear ARX model, which involves the detection of the system structure by finding the regressors that have the highest contribution to the output. The NARX model has the following structure:

$$y(t)=f(y(t-1),\ldots,y(t-na),u(t-1),\ldots,u(t-nb)) \tag{4}$$

With inputs *u(t)=[u1,u2,u3]* (corresponding with the wind speed, pitch angle and rotor speed) and *y(t)* the sampled output with a maximum of two lags (are known as model regressors) and *f* is a nonlinear function which acts as the nonlinearity estimator block and maps the regressors to the model output [9].

The nonlinear estimator block, which is based on a wavelet network as an estimation algorithm [10], includes linear and nonlinear terms in parallel and can be formulated as:

$$\begin{aligned} &F(x)=A+B \\ &A=\left\{L^T(x-r)+d\right\}\rightarrow linear \\ &B=\left\{\sum_{\Re=1}^{n} a_{\Re}\kappa(\beta_{\Re}(Q(x-r)-y_{\Re}))\right\}\rightarrow nonlinear \end{aligned} \tag{5}$$

x is a vector of regressors. *L* is the linear function. *d* is a scalar offset. *r* is the mean of the regressors and *Q* is a projection matrix. The discrete equation for two-order NARX model with 8 units is shown in equation (6).

$$\begin{aligned} y(t)=f(&y(t-1),y(t-1),u_1(t-1),\ldots \\ &u_1(t-2),u_2(t-1),u_2(t-2),u_3(t-1),u_3(t-2)) \end{aligned} \tag{6}$$

Results show that higher order models may produce an unstable output. The performance of the NARX model with the prediction error minimization is shown in Fig. 4 and 5.

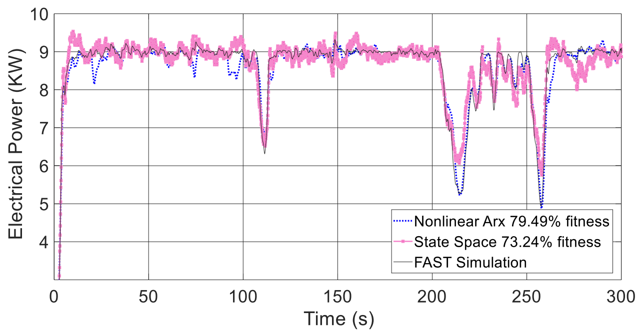

Fig. 4 FAST and Identified model output of 10 kW

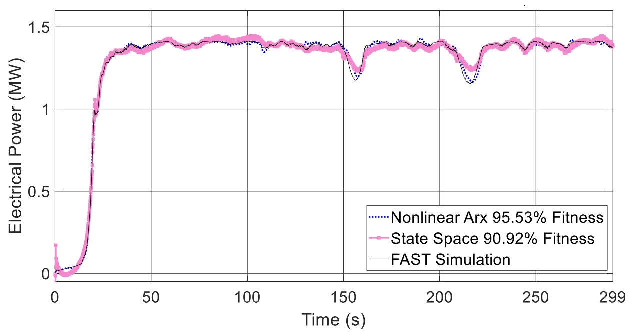

Fig. 5 FAST and Identified model output of 1.5 MW

2.1.3 Identification using prediction error minimization: The complexity of system identification of wind turbines with robust approximation techniques is still a challenge. To tackle this, two main steps are proposed in this study. First, applying subspace system identification and NARX on inputs/output sampled data for identification (simulation focus) and next, minimizing an identification error criterion or maximizing a certain likelihood function. This can also be interpreted as minimization of the least square criterion (prediction focus) over the estimated error [11]. The performance of the error prediction minimization on both models is summarized in Tables 1 and 2 in terms of the percentage of best fit, Final Prediction Error (FPE) and Mean Square Error (MSE).

Table 1 Performance of system identification methods
10 kW PMSG

	Simulation focus		Prediction focus	
	N4SID	NARX	N4SID	NARX
Best Fit	73.24%	79.49%	98.03%	96.76%
MSE	0.0872	0.001281	0.00047	0.00128
FPE	0.0061	0.001295	0.00048	0.00129

Table 2 Performance of system identification methods
1.5 MW PMSG

	Simulation focus		Prediction focus	
	N4SID	NARX	N4SID	NARX
Best Fit	90.92%	95.53%	97.89%	99.3%
MSE	864.3	5.183	46.63	5.179
FPE	127.8	5.53	47.39	5.53

2.2 Model predictive control

The purpose of this section is to design a model predictive controller for the 1.5 MW and 10 kW variable-pitch variable-speed wind turbines. The primary goal of this MPC is to regulate the wind turbine power production by control of the blade's pitch angle for wind speeds above the nominal value. In this work, the MPC uses the state-space model generated by the data-driven system identification.

Above the nominal wind speed, the output power of the turbine is classically kept constant and the rotational speed should be kept as close as possible to the nominal value to avoid excess rotor speed. In practice, this is done by a combination of the pitch control, which keeps the rotor speed constant, and by maintaining a nearly constant generator torque [12,13]. In the MPC design, wind speed is considered as the measured disturbance and the pitch angle is the main manipulated variable to keep the rotor speed close to the nominal value with minimum stress on the generator. When the turbine is used to provide flexibility services to the grid, the power should be regulated instead of keeping it constant. The MPC is also capable of providing this power control.

2.2.1 Performance and constraints specifications: The goal of the MPC is to track the electrical power to the desired level by determining the optimal pitch angle and minimizing the deviation of rotor speed from the nominal value. The MPC satisfies this goal by making predictions about the future behaviour of the system using the linearised state space model and using an optimizer which guarantees the optimal trajectory. This is done by minimizing the following cost function:

$$J = \sum_{i=1}^{P} \left\{ k^{y} \left[y_r(k+i) - y(k+i) \right] \right\} + \sum_{i=1}^{M} \left\{ \left[k^{\Delta\beta} \Delta\beta(k+i-1) \right]^2 + \left[k^{\Delta\omega} \Delta\omega(k+i-1) \right]^2 \right\} \quad (6)$$

With the constraints:

$$\beta_{\min} \le \beta \le \beta_{\max}$$
$$\omega_{\min} \le \omega \le \omega_{\max}$$
$$y_{\min} \le y \le y_{\max}$$

P and *M* are the prediction and control horizon, respectively. $\Delta\beta(k+i-1)$ is the predicted adjustment in blade pitch angle and $\Delta\omega(k+i-1)$ is the predicted rotational speed deviation during the sampling interval. $k^{y}, k^{\Delta\beta}$ and $k^{\Delta\omega}$ are the weighting factors. The weighting factor $k^{\Delta\omega}$ is used for penalising rotor speed deviation from its nominal value by choosing it sufficiently lager than the factor which is used for the pitch control as the main manipulated variable. The state space model described in section 2.1.1 with (*A*, *B*, *C* and *D*) matrices is providing the MPC's internal model. The column of *D* can be defined as the measured disturbance channel entering the plant and therefore can reflect the effect of high wind speeds, which is specified as measured noise. The optimization problem has been solved by using the standard quadratic programming method.

2.2.2 Controller Design and robustness: After defining the plant model, the cost function and the constraints, choosing proper values for the MPC parameters would be the next step. This does not only affect the control performance but also affects the complexity and computational load. The rate at which the controller executes the optimal control algorithm is defined by choosing the sample time in the range where the controller is able to react to the disturbances sufficiently fast but without introducing an excessive computational load to the controller. The best is to fit 10 to 20 samples within the rise time of the steady state response (sample time for the 1.5 MW turbine is set at 0.06s and 0.1s for the 10 KW). The prediction horizon is set at 10 time-steps. The control horizon is chosen at 20% of the prediction horizon.

Although the main objective of using MPC is to control the wind turbine's electrical power above the nominal wind speed, it also results in load mitigation by a significant reduction in blade pitch amplitude and its rate of change. Therefore, by choosing soft output constraints, the quadratic programming might not be feasible, but the performance of the MPC becomes more robust. On the other hand, increasing the value of weighting factors on the control actions forces the controller to make smaller and more cautious moves and to be less sensitive to prediction inaccuracy, such that the robustness of the control actions improves. This can however result in output set-point tracking that is more slow moving [12]. Therefore, as the result of the optimal action of the pitch controller, the mechanical load on the wind turbine blades can be mitigated. It is noteworthy to mention that the mechanical load on the blades is known as the significant part of wind turbine structural load caused by the effect of wind above its nominal value and usually experienced by the blade's roots. Thus, structural load mitigation comes subsequently as the secondary result of reference-tracking MPC.

3 Results

The simulation results of the wind turbine robust model predictive controller under turbulent high wind speed conditions, compared with the conventional PI control, are shown in Figures 6 and 7.

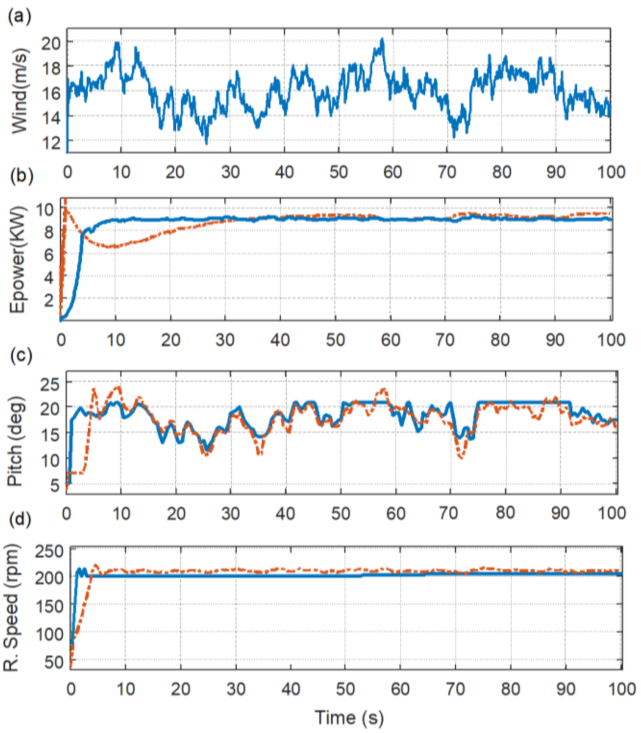

Fig. 6 Simulation results of the 10 kW wind turbine using robust MPC (in red (dotted)) and PI (blue (solid)) performance for certain wind speed. The electric power, pitch angle (β) and rotational speed (ω_r) are depicted.

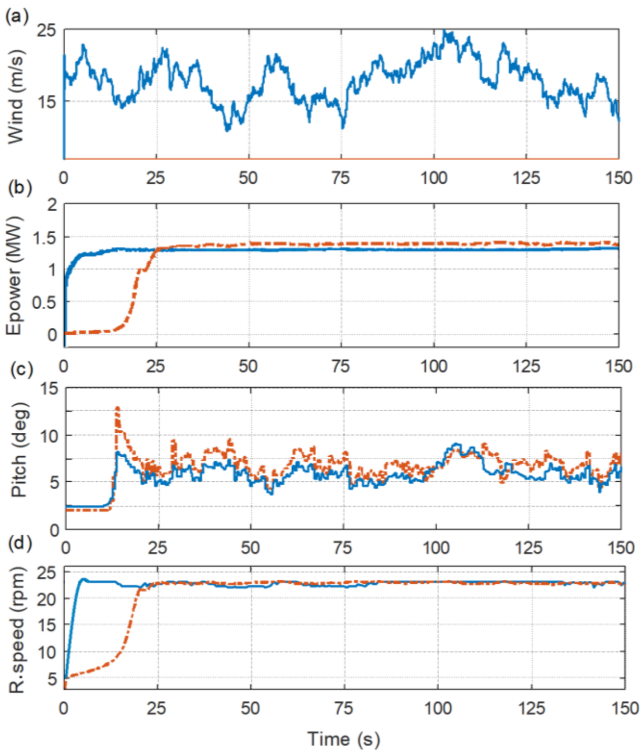

Fig. 7 Simulation results of the 1.5 MW wind turbine, robust MPC (in red (dotted)) and PI (blue (solid)) performance for certain wind speed. The electric power, pitch angle (β) and rotational speed (ω_r) are depicted.

The robust MPC is applied on both the 10 kW and 1.5 MW wind turbines based on data-driven system identification using MATLAB SIMULINK. The results include the simulation of wind speed via the TurbSim simulator (see Figures 6(a) and 7(a)), the reference tracking of the PI and the robust-MPC is shown in Figures 6(b) and 7(b). Figures 6(c) and 7(c) illustrates the pitch angle response. The rotational speed of the generator around nominal speed is presented in Figures 6(d) and 7(d)). It can be observed that the performance of the robust MPC is slightly improved compared to the classical PI control.

4 Conclusion

In this paper, the focus lies on data-driven system identification techniques and the robust approximation of the simplified model of variable pitch wind turbine drivetrains consisting of a PMSG. This research also shows the potential of the proposed model in developing the model predictive controller with the goal of electrical power output tracking, which is imperatively needed when providing grid balancing services with wind farms. It has also been taken into account that a deviation from the predefined wind conditions can be in contrast with structural load mitigation using the pitch controller. Hence, the weighting factors are chosen in a way that the MPC is less sensitive to prediction errors and uncertainty. Therefore, the robustness of the optimal pitch controller above nominal wind speed is enhanced which gives rise to the load mitigation consequently.

The linearised state space model, which is the approximation of the nonlinear dynamics of the wind turbine, is directly used in the MPC formulation. However, using a nonlinear model might turn the MPC into a non-convex optimization problem which does not guarantee a global optimum. On the other hand, the linearized model does not allow a long prediction horizon due to changes in the operating points of the system as a function of wind speed. Therefore, gain-scheduled MPC or adaptive MPC are recommended as the more adequate control approaches for a wide range of wind turbine operating points which can also benefit from predictive capabilities.

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6 References

[1] Pao, Lucy Y., and Kathryn E. Johnson: 'A tutorial on the dynamics and control of wind turbines and wind farms', 2009, American Control Conference. IEEE, 2009, p. 2076-2089

[2] Shen Yin, Wang Guang, and Karimi Hamid Reza: 'Data-driven design of robust fault detection system for wind turbines', Mechatronics 24.4, 2014, 298-306

[3] van der Veen, Gijs J., et al.: 'Global data-driven modeling of wind turbines in the presence of turbulence', Control Engineering Practice 21.4, 2013, 441-454

[4] Mayne, David Q., et al.: 'Constrained model predictive control: Stability and optimality', Automatica 36.6, 2000, 789-814.

[5] Geer, David.: 'Chip makers turn to multicore processors', Computer 38.5, 2005, 11-13.

[6] Yin, Ming, et al.: 'Modeling of the wind turbine with a permanent magnet synchronous generator for integration', 2007 IEEE Power Engineering Society General Meeting. IEEE, 2007, p. 1-6

[7] Van der Veen, Gijsbrecht Jan: 'Identification of wind energy systems', PhD project, Delft Center for Systems and Control (DCSC), 2013

[8] Katayama, Tohru: 'Subspace methods for system identification', Springer Science & Business Media, 2006, p: 23-27

[9] Billings, Stephen: 'A Nonlinear system identification: NARMAX methods in the time, frequency, and spatio-temporal domains', John Wiley & Sons, 2013

[10] Zhang, Qinghua: 'Using wavelet network in nonparametric estimation', Diss. INRIA, 1994.

[11] In Jae, Myung: 'Tutorial on maximum likelihood estimation', Journal of Mathematical Psychology 47.1, 2003, 90-100

[12] Schlipf, David, Dominik Johannes Schlipf, and Martin Kühn: 'Nonlinear model predictive control of wind turbines using LIDAR', Wind energy 16.7, 2013, 1107-1129

[13] Wright, A. D., and L. J. Fingersh: 'Advanced control design for wind turbines', NREL, tp-500-42437, Technical Report, National Renewable Energy Laboratory, Golden, CO, USA, 2008.