Design of a Nonlinear Model-based Predictive Controller for a Wind Turbine Based on PMSG Using an Augmented Extended Kalman Filter

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Abstract**—In this paper, a novel nonlinear model-based predictive controller without speed/position sensors is designed for control of a wind turbine permanent magnet synchronous generator (PMSG) and grid. Here, both grid and generator sides are controlled via a predictive mechanism including an optimization subject to nonlinear constraints of current and voltage amplitudes as well as the harmonic distortion magnitude of currents. To have a sensorless design, a Kalman filter is also designed. First, an extended Kalman filter (EKF) is used to estimate the speed and then an augmented extended Kalman filter (AEKF) is designed to estimate the flux without the need to add complex equations. The simulation results show an acceptable performance of the proposed method despite the changes in the reference speed and disturbance.**

Index Terms**--Augmented extended Kalman filter, nonlinear predictive control, permanent magnet synchronous generator, wind turbine.**

I. INTRODUCTION

Today, with the growth in the population and improved standard of living and human welfare, the need for energy resources has significantly increased. However, due to the environmental problems and the exhaustible nature of fossil fuels, it is clear that clean and renewable energies should be taken into account as alternative sources. Advances in power electronics and their application in the wind energy field have made it possible to use variable speed turbines. Wind turbine equipped with a permanent magnet synchronous generator is one of the most popular types. Advantages of wind turbines based on PMSGs are high power factor, power generation at any wind speed, reduced maintenance cost due to the removal of the gearbox as a major fault source in wind turbines, proper performance under short-circuited output and variable wind speed conditions and low volume. Various methods have been proposed for control of these types of turbines [1]. Nonetheless, one of the most important issues in controlling PMSG is the requirement for the accurate information of rotor speed and position, commonly measured by an encoder and a tachometer. The sensors required for this measurements reduce reliability and safety and increase the overall cost, dimensions and noise pollution of the system. For this reason, recent studies on sensorless control methods have attracted the attention of researchers and several methods for speed and position estimation have been studied in articles [2].

In [3], the particle swarm optimization (PSO) algorithm is used to optimize the parameters of a proportional-integral (PI) controller to reach the maximum power point (MPP) in the variable speed wind turbine based on PMSG. Feedback linearization-based control is designed to track the MPP in a wind turbine based on PMSG [4]. In this method, the feedback controller coefficients are obtained using PSO. The proper performance of the proposed method is shown in variable wind speeds. In [5], an internal model feedback is used to control a wind turbine based on PMSG. In this method, the state feedback coefficients are optimally determined from linear quadratic regulator path to minimize the DC current tracking error. The back-propagation block method has been used to control the PMSG sensor in the wind turbine [6]. The radial basis function (RBF) neural networks are also used for speed estimation. In [7], the recursive least square estimation algorithm is designed for sensorless control of a wind turbine based on PMSG. The simulation results show the high accuracy of this algorithm in speed estimation. To achieve the MPP in the wind turbine with PMSG, generalized nonlinear Luenberger observer and PI controller has been used [8]. In this method, the speed of the generator is estimated using system current and voltage and employing the nonlinear dynamic model of the generator and nonlinear observer gain. The model-based predictive control (MPC) is presented for controlling the currents and speed of a wind turbine based on PMSG is presented in [9].

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Predictive control along with extended Kalman filter has been utilized in [10] for speed control and estimation of a wind turbine with a back-to-back inverter type PMSG. Dead-beat predictive controller and conventional predictive controller are used for torque control on the generator and power control on the grid sides respectively. The controller is implemented using FPGA on an experimental system and it has proved satisfactory performance. The MPC with a dead-beat structure is presented in [11] for a wind turbine with PMSG. Authors in [12] use robust predictive control for sensorless surface control of a PMSG. In this method, speed and position estimation of the rotor is carried out using an EKF while to encounter the model parameters changes and/or unmodeled dynamics a disturbance observer is employed.

A finite-time and sensorless predictive controller is used for wind turbine based on PMSG in [13]. The study exploits a reference model adaptive observer to estimate the speed and position of the rotor. Performance of three control methods, including integral sliding mode control, finite-time MPC, and conventional PI controller are compared. According to simulation results, integral sliding mode controller provides a better tracking performance. However, implementation of the model-based predictive controller is much simpler. [15] reviews the estimation methods for wind turbines based on PMSG. In this paper, estimation methods such as single-order and quadratic polynomials, neural networks such as multilayer perceptron networks, RBF, adaptive neuro-fuzzy inference systems, nonlinear observers like EKF, recursive least square algorithm, maximum probability estimation, unknown input observer, PSO filter, and to name but a few, are analyzed and a summary of their characteristics are described. In [16], another classification for speed estimation methods for PMSGs is introduced. Based on [16], open-loop methods include algebraic and inductance- and flux-based methods, while closed-loop methods include disturbance observer-based control (DOBC), sliding mode, adaptive reference model, EKF, and state observers. In [17, 18], unscented Kalman filter is used for speed estimation of a PMSG in a wind turbine. Instead of linearization around the previous estimated point, the filter benefits an unscented transformation and the statistical characteristics of the estimated point. Refs. [19-22] employ a constrained nonlinear predictive control for control of biped robots and doubly-fed induction generators (DFIGs).

Considering the abovementioned challenges of a sensorless design for PMSG-based wind turbine, a nonlinear MPC method is proposed in this paper to control both the PMSG and grid sides. The novelty of this study is that the cost function of the proposed controller is selected with multiple objectives: tracking the current and speed reference paths, optimizing the input voltages, and taking into account the physical constraints of maximum allowable current ripple, as well as maximum allowable voltage and current. In other words, this design includes a constrained nonlinear optimization technique which has not been addressed for this type of generators before. To boost this design, an EKF is used to estimate the speed and position of the rotor. Due to the changes in the flux caused by temperature variations and its direct impact on the prediction equations of the controller, flux estimation is performed online. The other feature of the proposed design which makes it superior to the available studies is that in the suggested method, the speed, position, and flux are estimated simultaneously by adding only the flux estimation equation to Kalman filter equations and there is no need to add a new observer or parameter identification methods. This simultaneous state estimation and parameter identification using the Kalman filters have not been previously used for these systems as well.

Different sections of the paper are organized as follows. Section 2 describes the dynamic model of the wind turbine based on PMSG. Then, the nonlinear MPC, the cost function and the design constraints are given in Section 3. The design procedure of the augmented EKF for flux estimation is explained in Section 4. Simulation results of the proposed method are given and analyzed in Section 5. Finally, Section 6 provides the conclusions of the paper.

II. Dynamic of a Wind Turbine based on PMSG

A PMSG based wind turbine includes a synchronous generator (SG), where several permanent magnet (PM) components instead of an exciting winding are used on the rotor for supplying the rotor field. To establish a variable speed operation, a back-to-back inverter is embedded to connect the machine stator to the electrical grid. These inverters include s generator-side inverter and a grid-side inverter. The machine-side inverters control the generator so that the maximum possible energy is extracted from wind, while the grid-side inverter is responsible for controlling the DC-link voltage and reactive power exchanged with the grid. The advantage of using an inverter is to completely separate the turbine and gird and facilitate controlling the grid and the generator individually. Fig. 1 shows a schematic of the mentioned turbine.

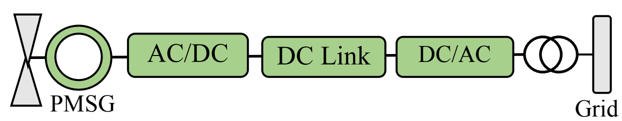


Figure 1. Schematic of a wind turbine based on PMSG

A. Permanent Magnet Synchronous Generator Model

Equations for PMSG expressed in d-q axes are given as follows [11]:

$$\frac{di_{sd}}{dt} = \frac{1}{L_{sd}}\left(V_{sd} - R_s i_{sd} + p\omega L_{sq} i_{sq}\right) \tag{1}$$

$$\frac{di_{sq}}{dt} = \frac{1}{L_{sq}}\left(V_{sq} - R_s i_{sq} - p\omega L_{sd} i_{sd} + p\omega\varphi_r\right) \tag{2}$$

$$\frac{d\omega}{dt} = \frac{1}{J}\left(p\varphi_r i_{sq} - f\omega - T_L\right) \tag{3}$$

$$\frac{d\theta}{dt} = \omega \tag{4}$$

where i_{sd} and i_{sq} are currents, V_{sd} and V_{sq} are voltages, and L_{sd} and L_{sq} are stator inductances of d-q axes. R_s denotes the stator resistance, ω and θ are the angular speed and position of the rotor, φ_r is the flux of the permanent magnet, J is the inertia coefficient, f shows the friction coefficient, p is the number of pole pairs, and T_L represents the load torque. Eqs. (1) to (4) can be written in the state space form:

$$\begin{cases} \dot{x} = f(x, V_s) \\ y = Cx \end{cases} \tag{5}$$

where $x = \left[i_{sd}, i_{sq}, \omega, \theta \right]^{\mathrm{T}}$ is the vector of state variables, C is the output matrix, $V_s = \left[V_{sd}, V_{sq} \right]^{\mathrm{T}}$ is the input matrix, and f is a nonlinear function as follows.

$$f = \begin{bmatrix} \frac{1}{L_{sd}}\left(V_{sd} - R_s i_{sd} + p\omega L_{sq} i_{sq}\right) \\ \frac{1}{L_{sq}}\left(V_{sq} - R_s i_{sq} - p\omega L_{sd} i_{sd} + p\omega\varphi_r\right) \\ \frac{1}{J}\left(p\varphi_r i_{sq} - f\omega - T_L\right) \\ \omega \end{bmatrix} \tag{6}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

B. Grid-side Model

The mathematical model of the grid side on d-q axes is expressed as follows [11]:

$$\frac{di_{gd}}{dt} = \frac{1}{L_g}\left(V_{gd} - R_g i_{gd} + \omega_g L_g i_{gq} - V_{convd}\right) \tag{7}$$

$$\frac{di_{gq}}{dt} = \frac{1}{L_g}\left(V_{gq} - R_g i_{gq} - \omega_g L_g i_{gd} - V_{convq}\right) \tag{8}$$

$$P_g = V_{gd} i_{gd} + V_{gq} i_{gq} \tag{9}$$

$$Q_g = V_{gq} i_{gd} - V_{gd} i_{gq} \tag{10}$$

where i_{gd} and i_{gq} are currents, V_{gd} and V_{gq} are grid voltages, V_{convd} and V_{convq} are output voltages of the inverter on d-q axes, ω_g shows the angular frequency of the grid voltage, R_g and L_g are resistance and inductance of the filter used on the grid side, and P_g and Q_g are active and reactive power of the grid. The DC-link voltage V_{dc} is calculated as:

$$CV_{dc}\frac{dV_{dc}}{dt} = P_s - P_g \tag{11}$$

where P_s is the output power of the generator inverter and C is the capacity. Eqs. (7) to (11) can be written in the state space form:

$$\dot{x}_g = f_g\left(x_g, V_g, P_s\right) \tag{12}$$

where $x_g = \left[i_{gd}, i_{gq}, V_{dc} \right]^{\mathrm{T}}$ is the vector of state variables, $V_g = \left[V_{gd}, V_{gq} \right]^{\mathrm{T}}$ represents the input vector, and f_g is a nonlinear function as follows.

$$f_g = \begin{bmatrix} \frac{1}{L_g}\left(V_{gd} - R_g i_{gd} + \omega_g L_g i_{gq} - V_{convd}\right) \\ \frac{1}{L_g}\left(V_{gq} - R_g i_{gq} - \omega_g L_g i_{gd} - V_{convq}\right) \\ \frac{P_s - V_{gd} i_{gd} - V_{gq} i_{gq}}{CV_{dc}} \end{bmatrix} \tag{13}$$

III. Nonlinear Model-based Predictive Control

In recent decades, predictive control methods have been significantly and widely addressed in the research and control of industrial systems. An important feature of predictive control is the consideration of saturation and the ability of actuators to produce control inputs. Regarding the prediction of future output, this method is much suitable for systems with varying reference inputs as well as for systems subject to disturbance. This method has the capability of dealing with the linear and nonlinear physical and practical constraints of the system for obtaining the control signal and provide a desired output. The following three items are the fundamentals of the predictive control: 1) Explicit use of system model for predicting the system's future outputs during the prediction horizon, 2) Calculation of the sum of the future control signal by minimizing the cost function based on the difference between the system's future outputs and the determined suitable values, 3) Applying the first optimized, calculated control signal to the system and repeating the whole prediction and optimization cycle.

A. Prediction Model

Based on the use of constrained optimization function fmincon in MATLAB, the following discrete predictive model is taken into account, where T_s is the sampling time.

$$x(k+1) = x(k) + f(x, V_s)T_s \tag{14}$$

$$x_g(k+1) = x_g(k) + f_g\left(x_g, V_g, P_s\right)T_s \tag{15}$$

B. Cost Function

The cost function for control of the generator and the grid side to track the reference signals and generate the minimum input is defined as (16) and (17) where ω^{ref}, i_{sd}^{ref}, V_{dc}^{ref}, and i_{gq}^{ref} are the paths for the reference speed, stator current of d-axis, DC-voltage and grid-side current of q-axis, respectively. N_p (prediction horizon) is the time interval at which the tracking error will be minimized and N_c (control horizon) is the time interval at which the control input will be minimized. $Q_1,\ldots,Q_6$ are the weighting coefficients of the cost function.

$$
\begin{aligned}
J^{\mathrm{PMSG}} = &\sum_{i=0}^{N_p} Q_1\left(\omega(k+i\Delta k)-\omega^{ref}(k+i\Delta k)\right)^2 \\
&+Q_2\left(i_{sd}(k+i\Delta k)-i_{sd}^{ref}(k+i\Delta k)\right)^2 \\
&+\sum_{i=0}^{N_c} V_s^{\mathrm{T}}(k+i\Delta k)Q_3 V_s(k+i\Delta k)
\end{aligned}
\tag{16}
$$

$$
\begin{aligned}
J^{\mathrm{Grid}} = &\sum_{i=0}^{N_p} Q_4\left(V_{dc}(k+i\Delta k)-V_{dc}^{ref}(k+i\Delta k)\right)^2 \\
&+Q_5\left(i_{gq}(k+i\Delta k)-i_{gq}^{ref}(k+i\Delta k)\right)^2 \\
&+\sum_{i=0}^{N_c} V_g^{\mathrm{T}}(k+i\Delta k)Q_6 V_g(k+i\Delta k)
\end{aligned}
\tag{17}
$$

C. Constraints

The following constraints are considered to limit the phase currents of the generator and the grid within the acceptable range and reduce instantaneous total harmonic distortion (THD) in optimizing the cost function of the generator and grid:

$$-10 \le i_{sabc} \le 10; \quad -10 \le i_{gabc} \le 10 \tag{18}$$

$$\mathrm{THD}i_s \le 5\%; \quad \mathrm{THD}i_g \le 5\% \tag{19}$$

$$THD(I)=\frac{\sqrt{I_3^2+I_5^2+\ldots+I_n^2}}{I_1} \tag{20}$$

where I_1 and I_n are fundamental and n[th] harmonics [23-24].

IV. AUGMENTED EXTENDED KALMAN FILTER

Kalman filter is a powerful and widely used tool for estimating the states of the systems described by the state-space model. Using a recursive algorithm and due to the availability of process and measurement noise distributions and application of matrix operators, the filter predicts new states of the system in continuous and discrete spaces. Kalman filter is known as the optimal estimator because leads to an unbiased estimation with the minimum variance of the states of a linear state-space model. To design an EKF, discrete nonlinear system equations are taken into account as follows:

$$
\begin{cases}
x(k+1)=f\left(x(k),u(k)\right)+w(k) \\
y(k)=Cx(k)+v(k)
\end{cases}
\tag{21}
$$

where x is the state vector, u is the input vector, y is the output vector, f is a nonlinear function, C is the output matrix, and w and v are the process and output noises. The following assumptions are taken into account for these noises:

$$
\begin{aligned}
&E\{w(k)\}=0;\ E\left\{w(k)w^{\mathrm{T}}(k+\tau)\right\}=Q\delta(\tau) \\
&E\{v(k)\}=0;\ E\left\{v(k)v^{\mathrm{T}}(k+\tau)\right\}=R\delta(\tau) \\
&E\left\{v(k)w^{\mathrm{T}}(k+\tau)\right\}=0
\end{aligned}
\tag{22}
$$

where Q and R are positive matrices with appropriate dimensions for the covariance of the noises and δ is the impulse function. EKF equations include time updating equations and then measurement updating as:

a) Time Updating

$$P(k+1|k)=F(k)P(k)F^{\mathrm{T}}(k)+Q \tag{23}$$

$$\hat{x}(k+1|k)=f\left(\hat{x}(k),u(k)\right) \tag{24}$$

where $\hat{x}$ is the vector of estimated states and P is the covariance matrix of the estimation error with the following initial conditions:

$$
\begin{aligned}
&\hat{x}(0)=E\{x(0)\} \\
&P(0)=E\left\{\left(x(0)-\hat{x}(0)\right)\left(x(0)-\hat{x}(0)\right)^{\mathrm{T}}\right\}
\end{aligned}
\tag{25}
$$

Matrix F is a Jacobian linearization of nonlinear equations of the system (21) around the previous estimated point, and is calculated as follows:

$$F^{\mathrm{T}}(k)=\left.\frac{\partial f^{\mathrm{T}}}{\partial x}\right|_{x=\hat{x}(k|k-1)} \tag{26}$$

b) Measurement Updating

$$K(k)=\hat{x}(k+1|k)P(k+1|k)\times C^{\mathrm{T}}\left(CP(k+1|k)C^{\mathrm{T}}+R\right)^{-1} \tag{27}$$

$$P(k+1)=P(k+1|k)-K(k+1)CP(k+1|k) \tag{28}$$

$$\hat{x}(k+1)=\hat{x}(k+1|k)+K(k+1)\left(y(k+1)-C\hat{x}(k+1|k)\right) \tag{29}$$

where K is the gain of the EKF. In PMSG, the state equations of the system with an augmented flux state are considered as follows.

$$
\begin{cases}
\dot{x}_{aug}=f_{aug}\left(x_{aug},V_s\right) \\
y=C_{aug}
\end{cases}
\tag{30}
$$

where $x_{aug}=[x,\varphi_r]^{\mathrm{T}}$ is the augmented state vector, and according to $\dot{\varphi}_r=0$ the function f_{aug} will be as follows:

$$f_{aug}=\left[f^{\mathrm{T}},0\right]^{\mathrm{T}} \tag{31}$$

Therefore, after discretization and linearization of the Jacobian matrix, F is obtained as (32).

V. SIMULATION RESULTS

To simulate the proposed method, parameters of the generator and grid are listed in Tables I and II. The initial covariance matrix of the estimation error is assumed as $P(0) = 10^3 \mathrm{I}$. The design parameters are considered as follows: $Q_1 = Q_4 = 1$; $Q_2 = Q_5 = 0.1$; $Q_3 = Q_6 = 10^{-2}\mathrm{I}$.

$$F = \begin{bmatrix} \frac{1}{T_s} - \frac{R_s}{L_s} & p\omega & pi_{sq} & 0 & 0 \\ -p\omega & \frac{1}{T_s} - \frac{R_s}{L_s} & -pi_{sd} + p\frac{\varphi_r}{L_s} & 0 & p\frac{\omega}{L_s} \\ 0 & p\frac{\varphi_r}{J} & \frac{1}{T_s} - \frac{f}{J} & 0 & p\frac{i_{sq}}{J} \\ 0 & 0 & 1 & \frac{1}{T_s} & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{T_s} \end{bmatrix} T_s$$

$$C_{aug} = \begin{bmatrix} C & \begin{matrix} 0 \\ 0 \end{matrix} \end{bmatrix} \qquad (32)$$

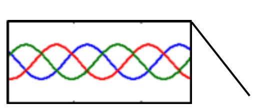
TABLE I. PMSG PARAMETERS [14]

Parameter	Value	Parameter	Value
R_s	$0.295\,\Omega$	J	$0.00679\,\mathrm{kg.m^2}$
$L_{sd} = L_{sq}$	3 mH	f	$0.0034\,\mathrm{kg.m^2.s^{-1}}$
φ_r	0.33 Wb	p	3

TABLE II. GRID PARAMETERS [1]

Parameter	Value	Parameter	Value
R_g	$3\,\Omega$	C	$1100\,\mu\mathrm{F}$
L_g	50 mH	ω_g	$2\pi \times 50$

To evaluate the performance of the method in the presence of disturbances, a disturbance of $T_L = 10Nm$ is applied at t = 0.1 s for a duration of 0.05 s to the generator [11]. Also a noise with the variance of 0.001 is considered in the system. Fig. 2 illustrates the phase currents of the stator. By applying the load torque disturbance, currents are increased and then returned to the normal condition. The current amplitudes are within the allowable range and the average THD is 4.96. Figs. 3 and 4 depict the tracking and estimation of the speed and its error for the generator. The tracking is performed in less than 0.01 s and the steady-state error is zero. After the occurrence of the disturbance, a small overshoot appears with a (4%) error. The tracking speed of the DC-link voltage is depicted in Fig. 5. Voltage tracking in the presence of disturbance is carried out with proper speed and acceptable overshoot. The flux estimation using Kalman filter is provided in Fig. 6. This parameter reaches its real value in less than 0.03 s.



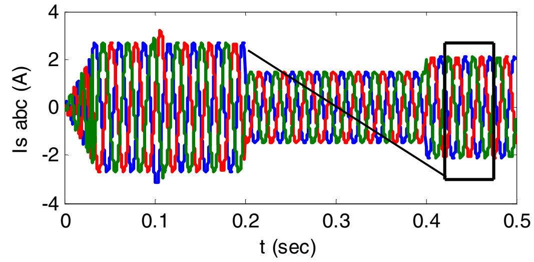


Figure 2. Stator current signals

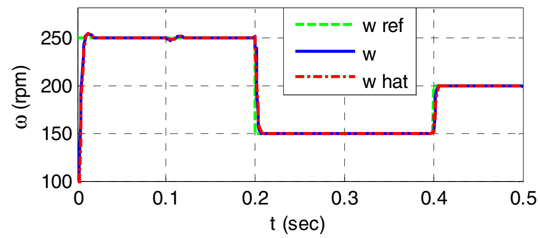


Figure 3. Speed signals

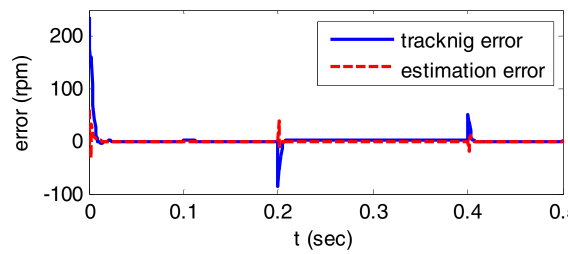


Figure 4. Speed tracking and estimation error signals

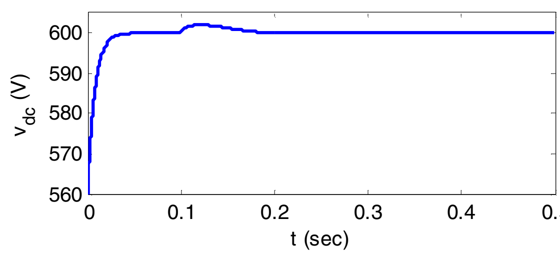


Figure 5. DC-link voltage

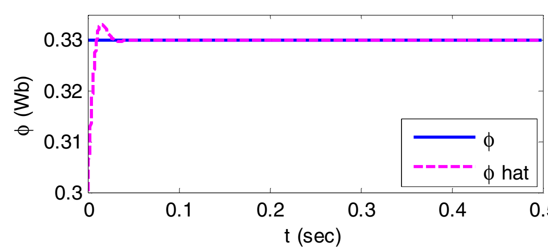


Figure 6. Flux

In order to compare our method to [11], the speed and DC-link voltage are plotted in Fig. 7 and Fig. 8. As it is shown, the speed of tracking in the proposed method is more than [11]. In the proposed method, ω tracks the reference signal in 0.03 second but in [11] is 0.25 second. V_{dc} tracks its reference in 0.07 and 1.7 second in the proposed method and [11].

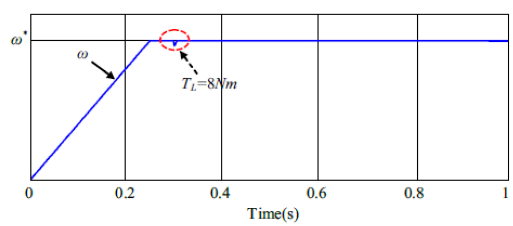


Figure 7. Speed signal in [11]

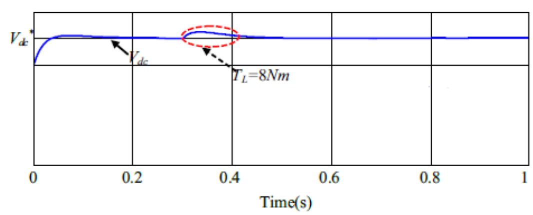


Figure 8. DC- link voltage in [11]

VI. Conclusions

The paper employs a novel framework of a nonlinear MPC based on an augmented EKF to control a wind turbine based on PMSG. The cost function of this controller is comprised of current tracking errors, DC voltage, and control speed and input terms for their optimization. One of the advantages of the proposed controller is that physical constraints such as allowable amplitude and acceptable current ripples, actuators saturation, applicable changes in the variables, etc are taken into account. Besides, using the augmentation technique instead of separate equations and/or different methods for identifying nonlinear systems, flux estimation is performed only via a small change in the EKF set of equations. Simulation results prove the accuracy and efficiency of the proposed method in tracking and estimation of the speed, DC voltage, current and flux in the presence of changes in the reference speed.

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