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Control and disturbances compensation for doubly-fed induction generators using the Derivative-Free Nonlinear Kalman Filter

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***Abstract*—The paper studies differential flatness properties and an input-output linearization procedure for doubly-fed induction generators (DFIGs). By defining flat outputs which are associated with the rotor's turn angle and the magnetic flux of the stator, an equivalent DFIG description in the Brunovksy (canonical) form is obtained. For the linearized canonical model of the generator a feedback controller is designed. Moreover, a comparison of the differential flatness theory-based control method against Lie algebra-based control is provided. At a second stage, a novel Kalman Filtering method (Derivative-free nonlinear Kalman Filtering) is introduced. The proposed Kalman Filter is redesigned as disturbance observer for estimating additive input disturbances to the DFIG model. These estimated disturbance terms are finally used by a feedback controller that enables the generator's state variables to track desirable setpoints. The efficiency of the proposed state estimation-based control scheme is tested through simulation experiments.**

***Index Terms*—doubly-fed induction generator, differential flatness theory, input-output linearization, nonlinear control, derivative-free nonlinear Kalman Filtering, disturbance estimator.**

I. Introduction

Doubly-fed induction generators (DFIG) have been widely used in variable-speed fixed frequency hydro-power generation systems, wind-power generation systems and turbine engine power generation systems [1-3]. Doubly-fed induction generators have proven to be more efficient than squirrel-cage induction generator systems (SCIG) and the synchronous generator systems in terms of cost and losses of the associated power electronics converters. DFIG systems can operate either in grid-connected mode or in stand-alone mode [4-9]. Results on the reliable connection of DFIGs to the electricity grid have been presented in [10-12]. Moreover, several field-oriented control schemes have been proposed for both operation modes. Additionally, to control electric power generators and the power electronics that enable their connection to the grid, feedback linearization approaches have been developed [13-14]. In parallel, several results have been published on sensorless control of DFIG [15-19]. Taking into account that the installation and maintenance of sensors for measuring several parameters of the generator's state vector can be technically difficult or costly, the need for developing sensorless control schemes for DFIG becomes apparent. In this paper, a novel sensorless control scheme is developed using flatness-based control theory and a state estimation method that is based on Kalman Filtering.

Using the electric equations of the stator and rotor a dynamic model for the doubly fed induction generator is derived. The doubly-fed induction generator is analogous to the induction motor. In an induction motor the stator voltage plays the role of an input variable, while the rotor voltage is a constant. In case of the doubly-fed induction machine it is quite similar but the other way round, with a dual analogy to hold between the stator and rotor parameters of the generator and the motor. This means that the rotor voltage now acts as an input, while the stator voltage is a constant parameter. The stator's and rotor's voltages, currents and magnetic flux are represented as vectors in a rotating orthogonal axis frame. The complete sixth order model of the DFIG captures efficiently transients at both the stator and the rotor side.

In this paper, differential flatness theory has been proposed for the control of the Doubly-fed induction generator. Differential flatness theory is currently a main direction in nonlinear dynamical systems and enables linearization and control for a wide class of systems, in a more efficient manner than Lie-algebra methods [20-23]. To find out if a dynamical system is differentially flat, the following should be examined: (i) the existence of the so-called flat output, i.e. a new variable which is expressed as a function of the system's state variables. The flat output and its derivatives should not be coupled in the form of an ordinary differential equation, (ii) the components of the system (i.e. state variables and control input) should be expressed as functions of the flat output and its derivatives [24-29]. In certain cases, differential flatness theory enables transformation to a linearized form (canonical Brunovsky form) for which the design of the controller becomes easier. In other cases by showing that a system is a differentially flat one can easily design a reference trajectory as a function of the so-called flat output and can find a control law that assures tracking of this desirable trajectory [25-26].

This paper is concerned with proving differential flatness of the model of the doubly-fed induction generator and its resulting description in the Brunovksy (canonical) form [20-21]. By

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defining flat outputs which are associated with the rotor's angle and with the magnetic flux of the stator, an equivalent DFIG description in the Brunovksy (linear canonical) form is obtained. It is shown that for the linearized DFIG's model it is possible to design a feedback controller. At a second stage, a novel Kalman Filtering method, the Derivative-free nonlinear Kalman Filter, is proposed for estimating the state vector elements of the linearized system which are not directly measurable. With the redesign of the proposed Kalman Filter as a disturbance observer, it becomes possible to estimate also disturbance terms affecting the DFIG model and to use these terms in the feedback controller. By avoiding linearization approximations, the proposed filtering method, improves the accuracy of estimation, and results in smooth control signal variations and in minimization of the tracking error of the associated control loop [30-32].

The structure of the paper is as follows: In Section II, the model of the DFIG is analyzed and the associated state-space equations are formulated. In Section III, input-output linearization for the DFIG model is performed using Lie algebra theory. In Section IV, differential flatness for nonlinear dynamical systems is analyzed. Conditions, which are based on differential flatness theory, are provided for transforming MIMO dynamical systems into the linear canonical form. In Section V, input-output linearization of the DFIG is performed using differential flatness theory. In Section VI, the design of a Kalman Filter-based disturbance observer for the DFIG model is explained. In Section VII, simulation tests are carried out to evaluate the performance of the DFIG control scheme that is based on differential flatness theory. Finally in Section VIII concluding remarks are given.

II. Model of the doubly-fed induction generator

A. The complete sixth-order model of the induction generator

The doubly-fed induction generator (DFIG) is not only the most widely used technology in wind turbines due to its good performance, but it is also used in many other fields such as hydro-power generation, pumped storage plants and flywheel energy storage systems. The DFIG model is derived from the voltage equations of the stator and rotor. It is assumed that the stator and rotor windings are symmetrical and symmetrically fed. Usually, the saturation of the inductances, iron losses, skin effect, and bearing friction is neglected. Moreover, the winding resistance is considered to be constant.

This type of wound-rotor machine is connected to the grid by both the rotor and stator side. The DFIG stator can be directly connected to the electric power grid while the rotor is interfaced through back-to-back converters (see Fig. 1). By decoupling the power system's electrical frequency and the rotor mechanical frequency the converter allows a variable speed operation of the wind turbine.

The doubly-fed induction generator is analogous to the induction motor. In an induction motor the stator voltage plays the role of an input variable, while the rotor voltage is a constant (it is usually zero). In case of the doubly-fed

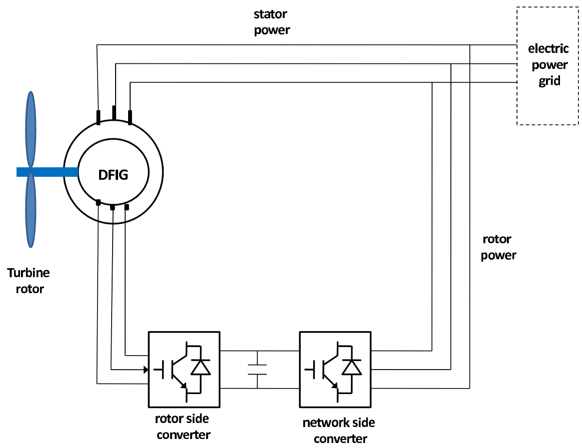

Fig. 1. Configuration of a doubly-fed induction generator unit in the power grid

induction machine it is very similar but the other way round, with a dual analogy to hold between the stator and rotor parameters of the generator and the motor. This means that the rotor voltage now acts as an input, while the stator voltage depends on the voltage at the bus to which the DFIG is connected, and in the dq reference frame is a constant parameter [33-35].

In a compact form, the doubly-fed induction generator can be described by the following set of equations in the $d-q$ reference frame that rotates at an arbitrary speed denoted as ω_{dq} [4]

$$\frac{d\psi_{s_q}}{dt} = -\frac{1}{\tau_s}\psi_{s_q} - \omega_{dq}\psi_{s_d} + \frac{M}{\tau_s}i_{r_q} + v_{s_q} \tag{1}$$

$$\frac{d\psi_{s_d}}{dt} = \omega_{dq}\psi_{s_q} - \frac{1}{\tau_s}\psi_{s_d} + \frac{M}{\tau_s}i_{r_d} + v_{s_d} \tag{2}$$

$$\begin{aligned}\frac{di_{r_q}}{dt} &= \frac{\beta}{\tau_s}\psi_{s_q} + \beta\omega_r\psi_{s_d} - \\ &-\gamma_2 i_{r_q} - (\omega_{dq}-\omega_r)i_{r_d} - \beta v_{s_q} + \frac{1}{\sigma L_r}v_{r_q}\end{aligned} \tag{3}$$

$$\begin{aligned}\frac{di_{r_d}}{dt} &= -\beta\omega_r\psi_{s_q} + \frac{\beta}{\tau_s}\psi_{s_d} + (\omega_{dq}-\omega_r)i_{r_q} - \\ &-\gamma_2 i_{r_d} - \beta v_{s_d} + \frac{1}{\sigma L_r}v_{r_d}\end{aligned} \tag{4}$$

where ψ_{s_q}, ψ_{s_d}, i_{r_q}, i_{r_d} are the stator flux and the rotor currents, v_{s_q}, v_{s_d}, v_{r_q}, v_{r_d} are the stator and rotor voltages, L_s and L_r are the stator and rotor inductances, ω_r is the rotor's angular velocity, M is the magnetizing inductance. Moreover, denoting as R_s and R_r the stator and rotor resistances the following parameters are defined

$$\begin{matrix} \sigma = 1 - \frac{M^2}{L_r L_s} & \beta = \frac{1-\sigma}{M\sigma} & \tau_s = \frac{L_s}{R_s} \\ \tau_r = \frac{L_r}{R_r} & \gamma_2 = (\frac{1-\sigma}{\sigma\tau_s} + \frac{1}{\sigma\tau_r}) & \end{matrix} \tag{5}$$

The angle of the vectors that describe the magnetic flux ψ_{s_α} and ψ_{s_b} is first defined for the stator, i.e.

$$\rho = tan^{-1}(\frac{\psi_{s_b}}{\psi_{s_a}}) \tag{6}$$

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The angle between the inertial reference frame and the rotating reference frame is taken to be equal to ρ.

Moreover, it holds that $cos(\rho) = \frac{\psi_{s_a}}{||\psi||}$, $sin(\rho) = \frac{\psi_{s_b}}{||\psi||}$, and $||\psi|| = \sqrt{\psi_{s_\alpha}^2 + \psi_{s_b}^2}$. Therefore, in the rotating $d-q$ frame of the generator, and under the condition of field orientation, there will be only one non-zero component of the magnetic flux ψ_{s_d}, while the component of the flux along the q axis equals 0.

The dynamic model of the doubly-fed induction generator can be also written in state space equations form by defining the following state variables: $x_1 = \theta$, $x_2 = \omega_r$, $x_3 = \psi_{s_d}$, $x_4 = \psi_{s_q}$, $x_5 = i_{r_d}$ and $x_6 = i_{r_q}$. It holds that

$$\dot{x}_1 = x_2 \tag{7}$$

$$\dot{x}_2 = -\frac{K_m}{J}x_2 - \frac{T_m}{J} + \frac{\eta}{J}(i_{r_q}x_3 - i_{r_d}x_4) \tag{8}$$

$$\dot{x}_3 = -\frac{1}{\tau_s}x_3 + \omega_{dq}x_4 + \frac{M}{\tau_s}x_5 + v_{s_d} \tag{9}$$

$$\dot{x}_4 = -\omega_{dq}x_3 - \frac{1}{\tau_s}x_4 + \frac{M}{\tau_s}x_6 + v_{s_q} \tag{10}$$

$$\begin{array}{c}\dot{x}_5 = -\beta x_2 x_4 + \frac{\beta}{\tau_s}x_3 + \\ +(\omega_{dq} - x_2)x_6 - \gamma_2 x_5 + \frac{1}{\sigma L_r}v_{r_d} - \beta v_{s_d}\end{array} \tag{11}$$

$$\begin{array}{c}\dot{x}_6 = \frac{\beta}{\tau_s}x_4 + \beta x_2 x_3 - \\ -(\omega_{dq} - x_2)x_5 - \gamma_2 x_6 + \frac{1}{\sigma L_r}v_{r_q} - \beta v_{s_q}\end{array} \tag{12}$$

In the above set of equations J is the moment of inertia of the rotor, T_m is the externally applied mechanical torque that makes the turbine rotate, K_m is the friction coefficient, η is a variable that is associated to the number of poles and to the mutual inductance M. Variable η in turn determines the electrical torque T_e which is associated to rotor currents and stator magnetic flux. Eq. (7) to Eq. (12) can be written also in the form

$$\dot{x} = f(x) + g_a(x)v_{r_d} + g_b(x)v_{r_q} \tag{13}$$

where $x = [x_1, x_2, x_3, x_4, x_5, x_6]^T$ and

$$f(x) = \begin{pmatrix} x_2 \\ -\frac{K_m}{J}x_2 - \frac{T_m}{J} + \frac{\eta}{J}(i_{r_q}x_3 - i_{r_d}x_4) \\ -\frac{1}{\tau_s}x_3 + \omega_{dq}x_4 + \frac{M}{\tau_s}x_5 + v_{s_d} \\ -\omega_{dq}x_3 - \frac{1}{\tau_s}x_4 + \frac{M}{\tau_s}x_6 + v_{s_q} \\ -\beta x_2 x_4 + \frac{\beta}{\tau_s}x_3 + (\omega_{dq} - x_2)x_6 - \gamma_2 x_5 - \beta v_{s_d} \\ \frac{\beta}{\tau_s}x_4 + \beta x_2 x_3 - (\omega_{dq} - x_2)x_5 - \gamma_2 x_6 - \beta v_{s_q} \end{pmatrix}$$

$$g_a(x) = \begin{pmatrix} 0 & 0 & 0 & 0 & \frac{1}{\sigma L_r} & 0 \end{pmatrix}^T$$

$$g_b(x) = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & \frac{1}{\sigma L_r} \end{pmatrix}^T \tag{14}$$

The active and reactive power delivered by the DFIG stator are associated to the real and imaginary part of the power at the stator's terminals, i.e.

$$P_s = Re\{U_s I_s^*\} = v_{s_d}i_{s_d} + v_{s_q}i_{s_q} \tag{15}$$

$$Q_s = Im\{U_s I_s^*\} = v_{s_d}i_{s_q} - v_{s_q}i_{s_d} \tag{16}$$

III. Input-output linearization of the DFIG using Lie algebra theory

A. Input-output linearization of the DFIG model

The following variables are defined

$$\begin{array}{c} h_1(x) = x_1 = \theta \\ h_2(x) = x_3^2 + x_4^2 = \psi_{s_d}^2 + \psi_{s_q}^2 \end{array} \tag{17}$$

Next, based on h_1, h_2 the following transformed state variables are defined

$$z_1 = h_1(x) = \theta \tag{18}$$

$$\begin{array}{c} z_2 = L_f h_1(x) \Rightarrow \\ z_2 = f_1 \Rightarrow z_2 = x_2 \Rightarrow z_2 = \omega \end{array} \tag{19}$$

Similarly, one has

$$\begin{array}{c} z_3 = L_f^2 h_1(x) = L_f z_2 \Rightarrow \\ z_3 = f_2 \Rightarrow z_3 = -\frac{K_m}{J}x_2 - \frac{T_m}{J} + \frac{\eta}{J}(i_{r_q}x_3 - i_{r_q}x_4) \Rightarrow \\ z_3 = -\frac{K_m}{J}x_2 - \frac{T_m}{J} + \frac{\eta}{J}(x_6 x_3 - x_5 x_4) \end{array} \tag{20}$$

For the transformed state variable z_4 one has

$$z_4 = h_2(x) = \psi_{s_d}^2 + \psi_{s_q}^2 = x_3^2 + x_4^2 \tag{21}$$

and

$$\begin{array}{c} z_5 = L_f h_2(x) \Rightarrow\ z_5 = 2x_3 f_3 + 2x_4 f_4 \Rightarrow \\ z_5 = 2x_3[-\frac{1}{\tau_s}x_3 + \omega_{dq}x_4 + \frac{M}{\tau_s}x_5 + v_{s_d}] + \\ +2x_4[-\omega_{dq}x_3 - \frac{1}{\tau_s}x_4 + \frac{M}{\tau_s}x_6 + v_{s_q}] \end{array} \tag{22}$$

After the change of the state variables it holds (the complete proof is given in Appendix 1)

$$\begin{array}{c} \dot{z}_1 = z_2 \\ \dot{z}_2 = z_3 \\ \dot{z}_3 = L_f^3 h_1(x) + (L_{g_a}L_f^2 h_1(x))u_1 + (L_{g_b}L_f^2 h_1(x))u_2 \\ \dot{z}_4 = z_5 \\ \dot{z}_5 = L_f^2 h_2(x) + (L_{g_a}L_f h_2)(x)u_1 + (L_{g_b}L_f h_2(x))u_2 \end{array} \tag{23}$$

The inputs of the above linearized and decoupled DFIG model are $u_1 = u_{r_d}$ and $u_2 = u_{r_q}$. The system of Eq. (23) can be written in the input-output linearized form

$$\begin{pmatrix} z_1^{(3)} \\ \ddot{z}_4 \end{pmatrix} = f_a + \tilde{M}u \tag{24}$$

where

$$\begin{array}{c} f_a(x) = \begin{pmatrix} L_f^3 h_1(x) \\ L_f^2 h_2(x) \end{pmatrix} \\ \tilde{M} = \begin{pmatrix} L_{g_a}L_f^2 h_1(x) & L_{g_b}L_f^2 h_1(x) \\ L_{g_a}L_f h_2(x) & L_{g_b}L_f h_2(x) \end{pmatrix} \end{array} \tag{25}$$

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or equivalently one has the system's description in the MIMO canonical form

$$\begin{pmatrix} \dot{z}_1 \\ \dot{z}_2 \\ \dot{z}_3 \\ \dot{z}_4 \\ \dot{z}_5 \end{pmatrix} = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \\ z_5 \end{pmatrix} + \begin{pmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} \tag{26}$$

where

$$\begin{array}{c} v_1 = L_f^3 h_1(x) + (L_{g_a}(L_f^2 h_1(x))u_1 + (L_{g_b} L_f^2 h_1(x))u_2 \\ v_2 = L_f^2 h_2(x) + (L_{g_a} L_f h_2(x))u_1 + (L_{g_b} L_f h_2(x))u_2 \end{array} \tag{27}$$

Returning to the compact form of Eq. (25) one has

$$\begin{pmatrix} z_1^{(3)} \\ \ddot{z}_4 \end{pmatrix} = \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} \tag{28}$$

and the control signal that assures convergence of the z_1 and z_4 to the reference setpoints z_1^d and z_4^d is given by

$$\begin{array}{c} v_1 = z_1^{d(3)} - k_1^{(1)}(\ddot{z}_1 - \ddot{z}_1^d) - k_2^{(1)}(\dot{z}_1 - \dot{z}_1^d) - k_3^{(1)}(z_1 - z_1^d) \\ v_2 = \ddot{z}_4^d - k_1^{(2)}(\dot{z}_4 - \dot{z}_4^d) - k_2^{(2)}(z_4 - z_4^d) \end{array} \tag{29}$$

B. State estimation-based control

For the implementation of the aforementioned control law, there is need to obtain measurements of all elements of the DFIG's state vector. The rotor's turn angle can be measured directly with the use of an encoder [36-37]. Knowing the rotor's angle, and with the use of the decoupled induction machine's model of Eq. (26) it is possible to estimate the rotor's angular speed. Similarly, after obtaining measurements of the magnetic flux at the stator and with the use of the decoupled induction machine's model of Eq. (26) it is possible to estimate the derivatives of the magnetic flux. Due to the fact that the magnetic flux of the stator ψ_s cannot be measured directly, equations that provide indirect measurements of the flux (computed through measurements of the stator and rotor currents) will be used, that is

$$\begin{array}{c} \psi_{s_d} = L_s i_{s_d} + M i_{r_d} \\ \psi_{s_q} = L_s i_{s_q} + M i_{r_q} \end{array} \tag{30}$$

It is noted that the currents are measured in the ab reference frame and their computation in the dq reference frame requires the application of the associated reference frame transformation.

Using the model of Eq. (26) the state estimator for the DFIG is given by

$$\dot{\hat{z}} = A\hat{z} + Bv + K(z^{meas} - C\hat{z}) \tag{31}$$

where the estimator's gain $K \in R^{5\times 2}$

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} \quad B = \begin{pmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{pmatrix} \tag{32}$$

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

IV. Differential flatness for nonlinear dynamical systems

A. Definition of differentially flat systems

Differential flatness is a structural property of a class of nonlinear systems, denoting that all system variables (such as state vector elements and control inputs) can be written in terms of a set of specific variables (the so-called flat outputs) and their derivatives. The following nonlinear system is considered:

$$\dot{x}(t) = f(x(t), u(t)) \tag{33}$$

The time is $t \in R$, the state vector is $x(t) \in R^n$ with initial conditions $x(0) = x_0$, and the input is $u(t) \in R^m$. Next, the properties of differentially flat systems are given [20-29]:

The finite dimensional system of Eq. (33) can be written in the general form of an ordinary differential equation (ODE), i.e. $S_i(w, \dot{w}, \ddot{w}, \cdots, w^{(i)}), \quad i = 1, 2, \cdots, q$. The term w is a generic notation for the system variables (these variables are for instance the elements of the system's state vector $x(t)$ and the elements of the control input $u(t)$) while $w^{(i)}$, $i = 1, 2, \cdots, q$ are the associated derivatives. Such a system is differentially flat if there are m functions $y = (y_1, \cdots, y_m)$ of the system variables and of their time-derivatives, i.e. $y_i = \phi(w, \dot{w}, \ddot{w}, \cdots, w^{(\alpha_i)}), \ i = 1, \cdots, m$ satisfying the following two conditions [23-27]:

1. There does not exist any differential relation of the form $R(y, \dot{y}, \cdots, y^{(\beta)}) = 0$ which implies that the derivatives of the flat output are not coupled in the sense of an ODE, or equivalently it can be said that the flat output is differentially independent.

2. All system variables (i.e. the elements of the system's state vector w and the control input) can be expressed using only the flat output y and its time derivatives $w_i = \psi_i(y, \dot{y}, \cdots, y^{(\gamma_i)}), \ i = 1, \cdots, s$. An equivalent definition of differentially flat systems is as follows:

Definition: The system $\dot{x} = f(x, u)$, $x \in R^n$, $u \in R^m$ is differentially flat if there exist relations

$$\begin{array}{l} h: \ R^n \times (R^m)^{r+1} \rightarrow R^m, \\ \phi: \ (R^m)^r \rightarrow R^n \text{ and} \\ \psi: \ (R^m)^{r+1} \rightarrow R^m \end{array} \tag{34}$$

such that

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$$\begin{array}{l} y = h(x, u, \dot{u}, \cdots, u^{(r)}), \\ x = \phi(y, \dot{y}, \cdots, y^{(r-1)}), \text{ and} \\ u = \psi(y, \dot{y}, \cdots, y^{(r-1)}, y^{(r)}). \end{array} \tag{35}$$

This means that all system dynamics can be expressed as a function of the flat output and its derivatives, therefore the state vector and the control input can be written as

$$\begin{array}{l} x(t) = \phi(y(t), \dot{y}(t), \cdots, y^{(r)}(t)), \text{and} \\ u(t) = \psi(y(t), \dot{y}(t), \cdots, y^{(r+1)}(t)) \end{array} \tag{36}$$

It is noted that for linear systems the property of differential flatness is equivalent to that of controllability.

B. Conditions for applying differential flatness theory

The generic class of nonlinear systems $\dot{x} = f(x, u)$ is considered. Such a system can be transformed to the form of an affine in the input system by adding an integrator to each input [28]

$$\dot{x} = f(x) + \sum_{i=1}^{m} g_i(x) u_i \tag{37}$$

If the system of Eq. (37) can be linearized by a diffeomorphism $z = \phi(x)$ and a static state feedback $u = \alpha(x) + \beta(x)v$ into the following form

$$\begin{array}{c} \dot{z}_{i,j} = z_{i+1,j} \text{ for } 1 \leq j \leq m \text{ and } 1 \leq i \leq v_j - 1 \\ \dot{z}_{v_{i,j}} = v_j \end{array} \tag{38}$$

with $\sum_{j=1}^{m} v_j = n$, then $y_j = z_{1,j}$ for $1 \leq j \leq m$ are the 0-flat outputs which can be written as functions of only the elements of the state vector x. To define conditions for transforming the system of Eq. (37) into the canonical form described in Eq. (38) the following theorem holds [28]

Theorem: For the nonlinear systems described by Eq. (37) the following variables are defined: (i) $G_0 = \text{span}[g_1, \cdots, g_m]$, (ii) $G_1 = \text{span}[g_1, \cdots, g_m, ad_f g_1, \cdots, ad_f g_m]$, $\cdots$ (k) $G_k = \text{span}\{ad_f^j g_i \text{ for } 0 \leq j \leq k, \ 1 \leq i \leq m\}$. Then, the linearization problem for the system of Eq. (37) can be solved if and only if: (1). The dimension of $G_i, \ i = 1, \cdots, k$ is constant for $x \in X \subseteq R^n$ and for $1 \leq i \leq n-1$, (2). The dimension of G_{n-1} is of order n, (3). The distribution G_k is involutive for each $1 \leq k \leq n-2$.

C. Transformation of MIMO nonlinear systems into the Brunovsky form

It is assumed now that after defining the flat outputs of the initial MIMO nonlinear system, and after expressing the system state variables and control inputs as functions of the flat output and of the associated derivatives, the system can be transformed in the Brunovsky canonical form:

$$\begin{array}{ll} \dot{x}_1 = x_2 & \\ \cdots & \\ \dot{x}_{r_1 - 1} = x_{r_1} & \\ \dot{x}_{r_1} = f_1(x) + \sum_{j=1}^{p} g_{1_j}(x) u_j + d_1 & y_1 = x_1 \\ \dot{x}_{r_1 + 1} = x_{r_1 + 2} & \cdots \\ \cdots & y_p = x_{n - r_p + 1} \\ \dot{x}_{p-1} = x_p & \\ \dot{x}_p = f_p(x) + \sum_{j=1}^{p} g_{p_j}(x) u_j + d_p & \end{array} \tag{39}$$

where $x = [x_1, \cdots, x_n]^T$ is the state vector of the transformed system (according to the differential flatness formulation), $u = [u_1, \cdots, u_p]^T$ is the set of control inputs, $y = [y_1, \cdots, y_p]^T$ is the output vector, f_i are the drift functions and $g_{i,j}, \ i, j = 1, 2, \cdots, p$ are smooth functions corresponding to the control input gains, while d_j is a variable associated to external disturbances. In holds that $r_1 + r_2 + \cdots + r_p = n$. Having written the initial nonlinear system into the canonical (Brunovsky) form it holds

$$y_i^{(r_i)} = f_i(x) + \sum_{j=1}^{p} g_{ij}(x) u_j + d_j \tag{40}$$

Next the following vectors and matrices can be defined $f(x) = [f_1(x), \cdots, f_n(x)]^T$, $g(x) = [g_1(x), \cdots, g_n(x)]^T$ with $g_i(x) = [g_{1i}(x), \cdots, g_{pi}(x)]^T$, and also $A = diag[A_1, \cdots, A_p]$, $B = diag[B_1, \cdots, B_p]$, $C = diag[C_1, \cdots, C_p]$, $d = [d_1, \cdots, d_p]^T$, where matrix A has the MIMO canonical form, i.e. with block-diagonal elements

$$A_i = \begin{pmatrix} 0 & 1 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & 1 \\ 0 & 0 & \cdots & 0 \end{pmatrix}_{r_i \times r_i} \tag{41}$$

$$\begin{array}{c} B_i^T = \begin{pmatrix} 0 & 0 & \cdots 0 & 1 \end{pmatrix}_{1 \times r_i} \\ C_i = \begin{pmatrix} 1 & 0 & \cdots 0 & 0 \end{pmatrix}_{1 \times r_i} \end{array}$$

Thus, Eq. (40) can be written in state-space form

$$\begin{array}{c} \dot{x} = Ax + Bv + B\tilde{d} \\ y = Cx \end{array} \tag{42}$$

where the control input is written as $v = f(x) + g(x)u$.

V. INPUT-OUTPUT LINEARIZATION OF THE DFIG USING DIFFERENTIAL FLATNESS THEORY

A. Differential flatness properties of the DFIG

The flat outputs of the system are defined as

$$\begin{array}{c} y_1 = \theta \text{ or } y = x_1 \\ y_2 = \psi_{s_d}^2 + \psi_{s_q}^2 \text{ or } y_2 = x_3^2 + x_4^2 \end{array} \tag{43}$$

It holds that

$$\begin{array}{c} \dot{y}_1 = \omega \text{ or } \dot{y}_1 = x_2 \Rightarrow \\ \ddot{y}_1 = \dot{\omega} = -\frac{K_m}{J} x_2 - \frac{T_m}{J} + \frac{\eta}{J}(x_6 x_3 - x_5 x_4) \Rightarrow \\ \ddot{y}_1 = \dot{\omega} = -\frac{K_m}{J} \dot{y}_1 - \frac{T_m}{J} + \frac{\eta}{J}(x_6 x_3 - x_5 x_4) \end{array} \tag{44}$$

Deriving the last row of Eq. (44) with respect to time one obtains

$$\begin{array}{l} y_1^{(3)}=-\frac{K_m}{J}\ddot{y}_1+\frac{\eta}{J}(\dot{x}_6x_3+x_6\dot{x}_3-\dot{x}_5x_4-x_5\dot{x}_4)\Rightarrow \\ y_1^{(3)}=-\frac{K_m}{J}\ddot{y}_1+\frac{\eta}{J}x_3\{[\frac{\beta}{\tau_s}x_4+\beta x_2x_3+(\omega_{dq}-x_2)x_5- \\ -\gamma_2x_6-\beta v_{s_q}]+\frac{1}{\sigma L_r}u_1\}+\frac{\eta}{J}x_6[-\frac{1}{\tau_s}x_3+\omega_{dq}x_4+\frac{M}{\tau_s}x_5+v_{s_d}] \\ -\frac{\eta}{J}x_4\{[-\beta x_2x_4+\frac{\beta}{\tau_s}x_3+(\omega_{dq}-x_2)x_6-\gamma_2x_5- \\ -\beta v_{s_d}]+\frac{1}{\sigma L_r}u_2\}-\frac{\eta}{J}x_5[-\omega_{dq}x_3-\frac{1}{\tau_s}x_4+\frac{M}{\tau_s}x_6+v_{s_q}] \end{array} \tag{45}$$

Moreover, about the second flat output it holds

$$\begin{array}{c} \dot{y}_2=2x_3\dot{x}_3+2x_4\dot{x}_4\Rightarrow \\ \dot{y}_2=2x_3[-\frac{1}{\tau_s}x_3+\omega_{dq}x_4+\frac{M}{\tau_s}x_5+v_{s_d}]+ \\ +2x_4[-\omega_{dq}x_3-\frac{1}{\tau_s}x_4+\frac{M}{\tau_s}x_6+v_{s_q}]\Rightarrow \end{array} \tag{46}$$

Consequently, it holds

$$\begin{array}{c} \ddot{y}_2=2\dot{x}_3[-\frac{1}{\tau_s}x_3+\omega_{dq}x_4+\frac{M}{\tau_s}x_5+v_{s_d}]+ \\ +2x_3[-\frac{1}{\tau_s}\dot{x}_3+\omega_{dq}\dot{x}_4+\frac{M}{\tau_s}\dot{x}_5]+ \\ 2\dot{x}_4[-\omega_{dq}x_3-\frac{1}{\tau_s}x_4+\frac{M}{\tau_s}x_6+v_{s_q}]+ \\ +2x_4[-\omega_{dq}\dot{x}_3-\frac{1}{\tau_s}\dot{x}_4+\frac{M}{\tau_s}\dot{x}_6] \end{array} \tag{47}$$

or equivalently

$$\begin{array}{c} \ddot{y}_2=2[-\frac{1}{\tau_s}x_3+\omega_{dq}x_4+\frac{M}{\tau_s}x_5+v_{s_d}]^2+ \\ -\frac{2}{\tau_s}x_3[-\frac{1}{\tau_s}x_3+\omega_{dq}x_4+\frac{M}{\tau_s}x_5+v_{s_d}] \\ -2\omega_{dq}x_3[-\omega_{dq}x_3-\frac{1}{\tau_s}x_4+\frac{M}{\tau_s}x_6+v_{s_q}] \\ +\frac{2M}{\tau_s}x_3\{[-\beta x_2x_4+\frac{\beta}{\tau_s}x_3+(\omega_{dq}-x_2)x_6- \\ -\gamma_2x_5-\beta v_{s_d}]+\frac{1}{\sigma L_r}u_1\} \\ +2[-\omega_{dq}x_3-\frac{1}{\tau_s}x_4+\frac{M}{\tau_s}x_6+v_{s_q}]^2 \\ -2\omega_{dq}x_4[-\frac{1}{\tau_s}x_3+\omega_{dq}x_4+\frac{M}{\tau_s}x_5+v_{s_d}] \\ -\frac{2}{\tau_s}x_4[-\omega_{dq}x_3-\frac{1}{\tau_s}x_4+\frac{M}{\tau_s}x_6+v_{s_q}] \\ 2x_4\frac{M}{\tau_s}\{[\frac{\beta}{\tau_s}x_4+\beta x_2x_3+(\omega_{dq}-x_2)x_5- \\ -\gamma_2x_6-\beta v_{s_q}]+\frac{1}{\sigma L_r}u_2\} \end{array} \tag{48}$$

It holds that $x_1=y_1$, $x_2=\dot{y}_1$. From the second row of Eq. (43) and considering that the field orientation condition requires $x_4=\psi_{s_q}=0$ one obtains that $x_3=\sqrt{y_2}$. Moreover, from Eq. (44) it holds

$$\begin{array}{c} \ddot{y}_1=-\frac{K_m}{J}\dot{y}_1-\frac{T_m}{J}+\frac{\eta}{J}\sqrt{y_2}x_6\Rightarrow \\ x_6=\frac{\ddot{y}_1+\frac{K_m}{J}\dot{y}_1+\frac{T_m}{J}}{\frac{\eta}{J}\sqrt{y_2}},\ y_2\neq 0 \end{array} \tag{49}$$

From Eq. (46) one obtains

$$\begin{array}{c} \dot{y}_2=-\frac{2}{\tau_s}x_3^2+\frac{2M}{\tau_s}x_3x_5+2v_{s_d}x_3\Rightarrow \\ \dot{y}_2+(\frac{2}{\tau_s}x_3-2v_{s_d})x_3=\frac{2M}{\tau_s}x_3x_5\Rightarrow \\ x_5=\frac{\dot{y}_2+(\frac{2}{\tau_s}\sqrt{y_2}-2v_{s_d})\sqrt{y_2}}{\frac{2M}{\tau_s}\sqrt{y_2}}\ \ y_2\neq 0 \end{array} \tag{50}$$

Therefore, x_5 is also a function of the flat output and of its derivatives. Additionally, by solving the system of Eq. (45) and Eq. (48) with respect to the control inputs u_1 and u_2 one obtains that the control inputs are functions of the flat output and its derivatives. Therefore, the model of the DFIG is a differentially flat one.

Next, to design the flatness-based controller for the DFIG the following transformation of the state variables is introduced: $z_1=y_1$, $z_2=\dot{y}_1$, $z_3=\ddot{y}_1$, $z_4=y_2$, $z_5=\dot{y}_2$ for which holds

$$\begin{array}{c} \dot{z}_1=z_2 \\ \dot{z}_2=z_3 \\ \dot{z}_3=L_f^3h_1(x)+(L_{g_a}L_f^2h_1(x))u_1+(L_{g_b}L_f^2h_1(x))u_2 \\ \dot{z}_4=z_5 \\ \dot{z}_5=L_f^2h_2(x)+(L_{g_a}L_fh_2(x))u_1+(L_{g_b}L_fh_2(x))u_2 \end{array} \tag{51}$$

Therefore, one obtains the decoupled and linearized representation of the system

$$\begin{array}{c} \begin{pmatrix} z_1^{(3)} \\ \ddot{z}_4 \end{pmatrix}=\begin{pmatrix} L_f^3h_1(x) \\ L_f^2h_2(x) \end{pmatrix}+ \\ +\begin{pmatrix} L_{g_a}L_f^2h_1(x) & L_{g_b}L_f^2h_1(x) \\ L_{g_a}L_fh_2(x) & L_{g_b}L_fh_2(x) \end{pmatrix}\begin{pmatrix} u_1 \\ u_2 \end{pmatrix} \end{array} \tag{52}$$

or equivalently

$$\begin{pmatrix} z_1^{(3)} \\ \ddot{z}_4 \end{pmatrix}=f_a+\tilde{M}u \tag{53}$$

where

$$f_a=\begin{pmatrix} L_f^3h_1(x) \\ L_f^2h_2(x) \end{pmatrix}\quad \tilde{M}=\begin{pmatrix} L_{g_a}L_f^2h_1(x) & L_{g_b}L_f^2h_1(x) \\ L_{g_a}L_fh_2(x) & L_{g_b}L_fh_2(x) \end{pmatrix} \tag{54}$$

By defining the control inputs $v_1=L_f^3h_1(x)+(L_{g_a}L_f^2h_1(x))u_1+(L_{g_b}L_f^2h_1(x))u_2$ and $v_2=L_f^2h_2(x)+(L_{g_a}L_fh_2(x))u_1+(L_{g_b}L_fh_2(x))u_2$ one can also have the description in the MIMO canonical form

$$\begin{pmatrix} \dot{z}_1 \\ \dot{z}_2 \\ \dot{z}_3 \\ \dot{z}_4 \\ \dot{z}_5 \end{pmatrix}=\begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}\begin{pmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \\ z_5 \end{pmatrix}+\begin{pmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{pmatrix}\begin{pmatrix} v_1 \\ v_2 \end{pmatrix} \tag{55}$$

The control input for the linearized and decoupled model of the DFIG is chosen as follows

$$\begin{array}{c} v_1=z_1^{d(3)}-k_1^{(1)}(\ddot{z}_1-\ddot{z}_1^d)-k_2^{(1)}(\dot{z}_1-\dot{z}_1^d)-k_3^{(1)}(z_1-z_1^d) \\ v_2=\ddot{z}_4^d-k_1^{(2)}(\dot{z}_4-\dot{z}_4^d)-k_2^{(2)}(z_4-z_4^d) \end{array} \tag{56}$$

and finally the control input that is applied to the system is

$$u=\tilde{M}^{-1}(-f_a+v) \tag{57}$$

The proposed control scheme can work with the use of measurements from a small number of sensors. That is, there is need to obtain measurements of only $y_1=\theta$ which is the turn angle of the generator's rotor, and of the magnetic flux $y_2=\psi_s^2=\psi_{s_d}^2+\psi_{s_q}^2$, or due to the orientation of the magnetic field $y_2=\psi_s^2=\psi_{s_d}^2$. The stator flux ($\psi_s$) cannot be measured directly from a sensor (e.g. the use of Hall sensor in an electric machine with a rotating part would not be efficient), however Eq. (30) that relates stator flux and stator and rotor currents can be used to calculate ψ_s. Thus one has:

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$$\begin{matrix} \psi_{s_d} = L_s i_{s_d} + M i_{r_d} \\ \psi_{s_q} = 0 \end{matrix} \tag{58}$$

which means that by measuring stator and rotor currents one can obtain an indirect measurement of the stator's magnetic flux ψ_{s_d}. Next, one can compute the dynamics of the magnetic flux, jointly with the dynamics of the rotor's motion through the use of the Derivative-free Nonlinear Kalman Filter. This estimation method is based on the application of the Kalman Filter recursion to the linearized equivalent of the generator's model which is given by Eq. (55). Actually, Eq. (55) can be written in the state-space form

$$\begin{matrix} \dot{z} = Az + Bv \\ z^{meas} = Cz \end{matrix} \tag{59}$$

where

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} \quad B = \begin{pmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{pmatrix} \tag{60}$$

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

The estimator's dynamics is:

$$\dot{\hat{z}} = A{\cdot}\hat{z} + B{\cdot}v + K(z^{meas} - C\hat{z}) \tag{61}$$

where $K{\in}R^{5\times 2}$ is the state estimator's gain. Defining as $\tilde{A}_d$, $\tilde{B}_d$, and $\tilde{C}_d$, the discrete-time equivalents of matrices A, B and C respectively, the associated Kalman Filter-based estimator is given by [38-42]

measurement update:

$$\begin{matrix} K(k) = P^-(k)C_d^T[C_d{\cdot}P^-(k)C_d^T + R]^{-1} \\ \hat{z}(k) = \hat{z}^-(k) + K(k)[z^{meas}(k) - C_d\hat{z}^-(k)] \\ P(k) = P^-(k) - K(k)C_dP^-(k) \end{matrix} \tag{62}$$

time update:

$$\begin{matrix} P^-(k+1) = A_d(k)P(k)A_d^T(k) + Q(k) \\ \hat{z}^-(k+1) = A_d(k)\hat{z}(k) + B_d(k)v(k) \end{matrix} \tag{63}$$

Remark 1: The first linearization approach followed in Section III was based on differential geometry and the computation of Lie Derivatives. The second linearization approach followed in Section V was based on differential flatness theory. For multi-input systems which admit static feedback linearization the differential flatness theory-based approach is equivalent to linearization based on Lie algebra. As it can be confirmed from Eq. (26) and Eq. (55) the two linearization methods provided the same linearized model of the DFIG. The differential flatness theory can be also extended to MIMO systems that admit only dynamic feedback linearization. In the latter case an extended state vector of the controlled system is defined containing as additional state variables the derivatives of the control input. In dynamic feedback linearization the control input that is finally applied to the system contains integral terms of the error's state vector. In terms of computation the differential flatness theory-based linearization is simpler because it does not require the calculation of Lie derivatives. Moreover, by expressing all state variables as functions of the flat output and its derivatives, the differential flatness theory-based linearization enables to perform state estimation and to reconstruct the state variables of the initial nonlinear system. This is not possible for the Lie algebra-based approach, where to perform filtering it is necessary to compute and invert the Jacobian matrix of the transformed state vector [43].

Remark 2: Regarding comparison to existing results, it is noted that in other control approaches for DFIGs, e.g. control of the rotor's speed and of the stator's magnetic flux in cascading loops analyzed in Ref. [33], one has to use measurements of the rotor currents. Alternatively, one can estimate these currents with filtering methods that make use of the initial nonlinear model of the system, such as the Extended or the Unscented Kalman Filter. Being based on an exact linearization method, the control and state estimation approach for the DFIG that is presented in Section V has the advantage of using a reduced number of sensors while at the same time remaining robust to modeling uncertainties and external perturbations and avoiding numerical approximation errors.

Remark 3: It has been explained that the concept of sensorless control is to reduce the number of sensors needed for the implementation of feedback control. As explained in Section III and in Section V the DFIG MIMO nonlinear model is transformed into two decoupled systems in the canonical linear form. The first system has as output the turn angle of the rotor which can be measured with the use of an encoder. The second system has as output the magnetic flux of the stator, where due to the field orientation condition only the d-axis flux component is nonzero. Using measurements of the stator's and rotor's currents one can obtain a measurement of the stator's magnetic flux too. By considering as measurable outputs the rotor's turn angle and the stator's magnetic flux the observability of the linearized DFIG model is assured. Thus it is possible to perform state estimation for the nonmeasurable state variables and to develop sensorless control, using the observers of Eq. (31) and (61).

VI. Kalman Filter-based disturbance observer for the DFIG model

A. Application of a disturbance observer to the DFIG model

Next, it will be considered that additive input disturbances (e.g. due to load variations) affect the DFIG model. The simultaneous estimation of the non-measurable elements of the DFIG state vector as well as the estimation of additive disturbance terms affecting the generator is possible with the use of a disturbance estimator [44-47].

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It is assumed that the third and fifth row of the state-space equations of the Doubly-Fed Induction Generator of Eq. (51) include a disturbance term

$$\begin{array}{l} \dot{z}_3 = L_f^3 h_1(x) + L_{g_a}(L_f^2 h_1(x))u_1 + L_{g_b}(L_f^2 h_2(x))u_2 + \tilde{d}_1 \\ \dot{z}_5 = L_f^2 h_2(x) + L_{g_a}(L_f h_2(x))u_1 + L_{g_b}(L_f h_2(x))u_2 + \tilde{d}_2 \end{array} \quad (64)$$

Without loss of generality, the dynamics of the disturbance terms is described by their second order derivatives and the associated initial conditions, i.e. $\ddot{\tilde{d}}_1 = \tilde{f}_a(x)$ and $\ddot{\tilde{d}}_2 = \tilde{f}_b(x)$. Next, an extended state-space model of the system is defined that comprises as additional state variables the disturbance terms $z_6 = \tilde{d}_1$, $z_7 = \dot{\tilde{d}}_1$, while $z_8 = \tilde{d}_2$, and $z_9 = \dot{\tilde{d}}_2$. Thus, the extended state-space model is written as $\dot{z}_1 = z_2$, $\dot{z}_2 = z_3$, $\dot{z}_3 = v_1 + z_6$, $\dot{z}_4 = z_5$, and $\dot{z}_5 = v_2 + z_8$, $\dot{z}_6 = z_7$, $\dot{z}_7 = \tilde{f}_a$, $\dot{z}_8 = z_9$ and $\dot{z}_9 = \tilde{f}_b$, or in matrix form one has

$$\begin{array}{c} \dot{\tilde{z}} = \tilde{A}\tilde{z} + \tilde{B}\tilde{v} \\ \tilde{z}^{meas} = \tilde{C}\tilde{z} \end{array} \quad (65)$$

$$\begin{pmatrix} \dot{z}_1 \\ \dot{z}_2 \\ \dot{z}_3 \\ \dot{z}_4 \\ \dot{z}_5 \\ \dot{z}_6 \\ \dot{z}_7 \\ \dot{z}_8 \\ \dot{z}_9 \end{pmatrix} = \begin{pmatrix} 0&1&0&0&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0 \\ 0&0&0&0&0&1&0&0&0 \\ 0&0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&0&0&1&0 \\ 0&0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&1 \\ 0&0&0&0&0&0&0&0&0 \end{pmatrix} \begin{pmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \\ z_5 \\ z_6 \\ z_7 \\ z_8 \\ z_9 \end{pmatrix} + \begin{pmatrix} 0&0&0&0 \\ 0&0&0&0 \\ 1&0&0&0 \\ 0&0&0&0 \\ 0&1&0&0 \\ 0&0&0&0 \\ 0&0&1&0 \\ 0&0&0&0 \\ 0&0&0&1 \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \\ \tilde{f}_a \\ \tilde{f}_b \end{pmatrix}$$

$$\begin{pmatrix} z_1^{meas} \\ z_4^{meas} \end{pmatrix} = \begin{pmatrix} 1&0&0&0&0&0&0&0&0 \\ 0&0&0&1&0&0&0&0&0 \end{pmatrix} \begin{pmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \\ z_5 \\ z_6 \\ z_7 \\ z_8 \\ z_9 \end{pmatrix} \quad (66)$$

The associated state estimator is

$$\dot{\hat{z}} = \tilde{A}_o\hat{z} + \tilde{B}_o\tilde{v}_1 + K_o(\tilde{z}^{meas} - \tilde{C}\hat{z}) \quad (67)$$

where

$$\tilde{A}_o = \begin{pmatrix} 0&1&0&0&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0 \\ 0&0&0&0&0&1&0&0&0 \\ 0&0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&0&0&1&0 \\ 0&0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&1 \\ 0&0&0&0&0&0&0&0&0 \end{pmatrix} \quad \tilde{B}_o = \begin{pmatrix} 0&0&0&0 \\ 0&0&0&0 \\ 1&0&0&0 \\ 0&0&0&0 \\ 0&1&0&0 \\ 0&0&0&0 \\ 0&0&0&0 \\ 0&0&0&0 \end{pmatrix} \quad (68)$$

$$\tilde{C}_o = \begin{pmatrix} 1&0&0&0&0&0&0&0&0 \\ 0&0&0&1&0&0&0&0&0 \end{pmatrix}$$

while the estimator's gain $K_o \in R^{9\times 2}$ is obtained from the standard Kalman Filter recursion [38-42].

Defining as $\tilde{A}_d$, $\tilde{B}_d$, and $\tilde{C}_d$, the discrete-time equivalents of matrices $\tilde{A}_o$, $\tilde{B}_o$ and $\tilde{C}_o$ respectively, a Derivative-free nonlinear Kalman Filter can be designed for the aforementioned representation of the system dynamics [23],[31]. The associated Kalman Filter-based disturbance estimator is given by

measurement update:

$$\begin{array}{l} K(k) = P^-(k)\tilde{C}_d^T[\tilde{C}_d{\cdot}P^-(k)\tilde{C}_d^T + R]^{-1} \\ \hat{\tilde{z}}(k) = \hat{z}^-(k) + K(k)[\tilde{C}_d\tilde{z}(k) - \tilde{C}_d\hat{\tilde{z}}^-(k)] \\ P(k) = P^-(k) - K(k)\tilde{C}_dP^-(k) \end{array} \quad (69)$$

time update:

$$\begin{array}{l} P^-(k+1) = \tilde{A}_d(k)P(k)\tilde{A}_d^T(k) + Q(k) \\ \hat{\tilde{z}}^-(k+1) = \tilde{A}_d(k)\hat{\tilde{z}}(k) + \tilde{B}_d(k)\tilde{v}(k) \end{array} \quad (70)$$

Remark 4: The advantages of the proposed nonlinear feedback control method for DFIGs (that is based on differential flatness theory and on the Derivative-free nonlinear Kalman Filter) against PID type control (included in vector control loops) are obvious. In most cases the application of PID control to electric machines is based on heuristic parameters tuning, has no stability proof, and has limited robustness to the change of operating points or to the effects of external perturbations. Moreover, in the case of multi-variable systems such as DFIGs the application of PID control is known to have questionable performance. The first vector control approaches for asynchronous machines (e.g. Blascke, 1971 [35]) made use of multiple PID loops which were implemented in a cascaded manner (for controlling separately the magnetic flux and the rotation angle of the machine). Such methods were based on the assumption that the flux and the rotation speed become finally decoupled at steady state. However, there is no proof about that (it cannot be always assured that transients will be eliminated and the machine will reach a steady-date) and therefore the performance of the control loop is not always guaranteed (see attached paper). Consequently, although PID control is met in some cases in asynchronous machines, it is not the recommended solution.

Remark 5: Field-oriented (vector) control has been for many years a common approach for the control of DFIGs. However, comparing to the flatness-based control approach developed in this paper, vector control exhibits several weaknesses which make its performance be questionable [50-51]. As it is shown in detail in Appendix 2, the implementation of vector control requires measurement or estimation of the stator's magnetic flux. Therefore, one comes against the observer or Kalman Filter design problem that was solved in a conclusive manner in Section 6 of this manuscript. Moreover, vector control for DFIGs requires the tuning of the several PID and PI controllers and this limits its reliability only round local operating points. Consequently, the stability and robustness properties of the field-oriented control for DFIGs are doubtful.

Remark 6: It is confirmed that the linearized equivalent model of the DFIG, after application of the pole placement technique has poles, exclusively in the left complex semi-plane. Besides the inclusion of the additional control input that compensates for the estimated additive disturbance terms improves the robustness features of this control loop. It is also noted that the linearized equivalent model of the DFIG exhibits multiple poles at the origin. This particular form implies an infinite gain margin and a sufficiently large phase margin. Finally, it is noted that the stability and robustness features of the control scheme which comprises also estimation and compensation of the disturbances are similar to those of LQG control. According to the above, the paper justifies sufficiently the stability and disturbance rejection capability of the proposed feedback control scheme. On the other hand, the presented simulation experiments demonstrated the efficiency of the control method in tracking rapidly changing reference setpoints while also succeeding good transients. The disturbances appearing in the simulation experiments could be met in adverse operating conditions of the power generator. Even for the latter case the good performance of the control loop is confirmed.

VII. Simulation tests

The structure of the proposed control scheme is depicted in Fig. 2. The control scheme comprises (i) the flatness-based control part which computes the control signal for the system's equivalent model that is transformed to the linear canonical form, (ii) a Kalman Filter-based disturbances estimator which provides estimates for the elements of the state vector of the DFIG, such as rotor's speed , magnetic flux at the stator as well as disturbances affecting the generator's model.

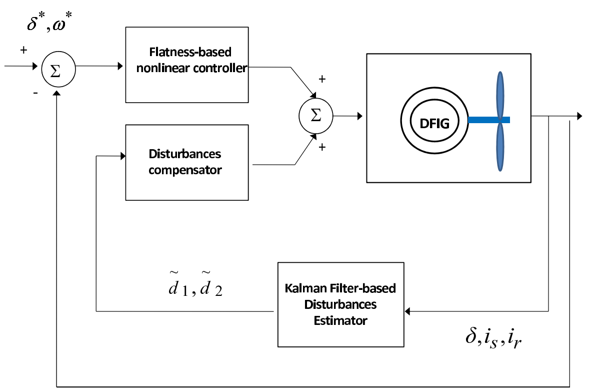
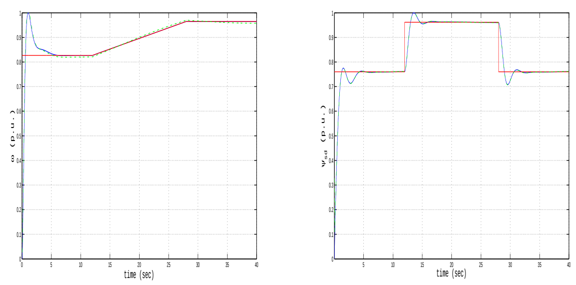


Fig. 2. Control loop of the DFIG comprising a flatness-based control element and an estimator for disturbances compensation

Indicative numerical values for the parameters of the considered doubly-fed induction generator model are given in Table I.

Table I: Ratings of the modeled DFIG	
Rated power	$15.5kW$
Number of Pole pairs	4
Stator Resistance	0.58Ω
Stator Inductance	$13{\cdot}mH$
Rotor Resistance	1.30Ω
Rotor Inductance	$3{\cdot}mH$
Mutual Inductance	$10{\cdot}mH$
Rotor's inertia	$20.0kg{\cdot}m^2$

Simulation tests were carried out for two different setpoints of the turn speed of the generator's rotor. The values of the generator's state vector elements are actually measured in SI units, however in the simulation results they are expressed in the per unit (p.u.) system. The results obtained for the first setpoint are depicted in Fig. 3 and Fig. 4. Similarly, the results obtained for the second setpoint are depicted in Fig. 5 and Fig. 6. It can be observed that the proposed control scheme assures that the rotor's turn speed follows a specific setpoint, while tracking of reference setpoints is succeeded for the components of the magnetic flux and for the rotor's currents. Several reference setpoints have been defined for the DFIG state variables, i.e. rotor's angular speed ω, rotor currents i_{r_d}, i_{r_q} and the magnetic flux ψ_{s_d} and as it can be observed from the associated diagrams, the proposed control scheme resulted in fast and accurate convergence to these setpoints. The disturbance observer that was based on the Derivative-free nonlinear Kalman Filter was capable of estimating the unknown and time-varying input disturbances affecting the DFIG model.



(a) **(b)**

Fig. 3. DFIG setpoint 1: (a) Control of state variable $x_2 = \omega$, (b) Control of state variable $x_3 = \psi_{s_d}$

The selection of the magnetic flux setpoints appearing in Fig. 3 and Fig. 5 did not aim to be restricted only to the case that the DFIG is connected to a grid, which is characterized by constant voltage amplitude and frequency. The purpose of the simulation experiments was to show the capability of the proposed nonlinear control scheme to succeed convergence to time-varying magnetic flux setpoints (e.g. piecewise constant ones). Of course, the analyzed control method for the DFIG enables also convergence of the stator's flux to constant

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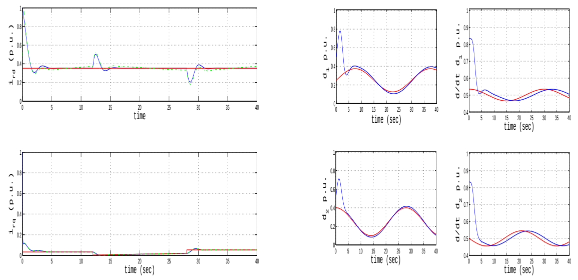
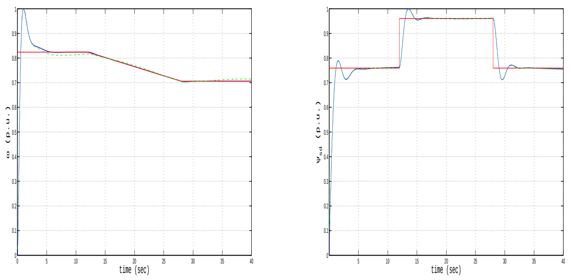


(a) **(b)**

Fig. 4. DFIG setpoint 1: (a) Control of state variable $x_5 = i_{r_d}$ and of state variable $x_6 = i_{r_q}$, (b) Estimation of disturbance inputs $d_i,\ i = 1, 2$ and of their derivatives

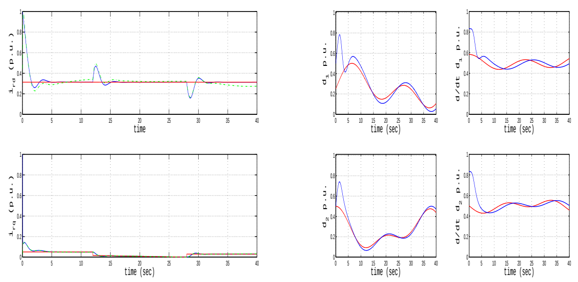


(a) **(b)**

Fig. 5. DFIG setpoint 2: (a) Control of state variable $x_2 = \omega$, (b) Control of state variable $x_3 = \psi_{s_d}$

setpoints, but this is a subcase of what has already been presented.

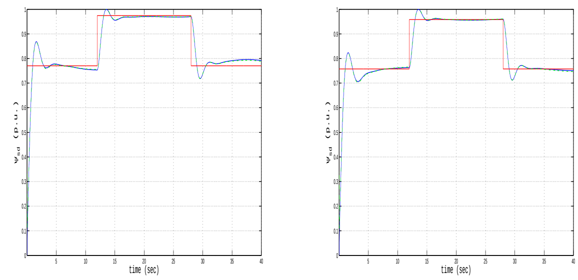
The improvement in the performance of the control loop that is due to the use of a disturbance observer based on the Derivative-free nonlinear Kalman Filter is explained as follows: (i) compensation of the disturbance terms which are generated by parametric uncertainty or unknown external inputs (ii) more accurate estimation of the disturbance terms because the filtering procedure is based on an exact



(a) **(b)**

Fig. 6. DFIG setpoint 2: (a) Control of state variable $x_5 = i_{r_d}$ and of state variable $x_6 = i_{r_q}$, (b) Estimation of disturbance inputs $d_i,\ i = 1, 2$ and of their derivatives

linearization of the system's dynamics and does not introduce numerical errors (as for example in the case of the Extended Kalman Filter). This is shown in Fig. 7.



(a) **(b)**

Fig. 7. Convergence of the stator's magnetic flux ψ_{s_d} to the reference setpoint (a) without using the disturbance observer (b) when using the disturbance observer

Remark 7: The implementation of the control scheme with the use of a digital processor does not exhibit any difficulty. The application of Kalman Filter-based control loops is a common practice in other complicated and demanding cases (e.g. in autonomous navigation of aircrafts, in robots, etc [23]). Therefore, the method can be also applied, through a programmable digital controller, in the case of asynchronous electric machines too. As explained, the use of the Derivative-free nonlinear Kalman Filter as a disturbance observer enables identification and compensation of external perturbations in real-time (such as disturbances due to grid faults). Therefore, the proposed control scheme exhibits improved robustness.

Remark 8: The generator's speed can be efficiently controlled and the associated rotation speed setpoints can be reached by applying the proposed control scheme. It is possible to operate the generator at variable speed, thus also changing the levels of the generated power. Moreover, as shown in Section V all currents and voltages defining the active and reactive power of the generator, according to Eq. (15) and Eq. (16), can be written explicitly or implicitly, as functions of the flat outputs of the DFIG model. This explains why these variables are finally associated with the turn speed of the rotor and consequently why the produced power of the generator is determined by the rotor's angular velocity.

Remark 9: The differential flatness properties of the DFIG dynamic model are initially proven, considering that the external mechanical torque is constant or piecewise constant. Equivalently, it can be considered that T_m stands for an unknown time-varying disturbance term to the DFIG model [48-49]. In such a case, variable T_m is omitted from the DFIG model, which at a second stage is transformed into the linear canonical and decoupled form using the diffeomorphism provided by differential flatness theory. For the linearized equivalent of the DFIG model a Kalman Filter-based disturbance observer is designed following the method of Section VI. The Kalman Filter-based disturbance

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estimator can identify in real-time the aggregate disturbance term which incorporates the time varying torque T_m. Therefore, the proposed nonlinear control scheme, that is based on disturbances estimation with the use of the Derivative-free nonlinear Kalman Filter, can work well even if the mechanical torque T_m causing the turbine's rotation is completely unknown and time-varying.

Remark 10: Variables $\tilde{d}_1$ and $\tilde{d}_2$ appearing in Eq. (64) are aggregate disturbance terms which include any type of perturbations that may be due to load variations and change of the stator currents, change of the mechanical torque, voltage fluctuation and faults in the grid (v_{s_d} and v_{s_q} non constant) or modeling uncertainty and changes in the numerical values of the parameters appearing in the DFIG model. Representing the aggregate disturbances effects as in Eq. (64) enables the design of a disturbances estimator and compensator based on the Derivative-free nonlinear Kalman Filter.

VIII. Conclusions

The paper has proposed a nonlinear control scheme for doubly-fed induction generators. Estimation of disturbance terms affecting the DFIG model has been performed with the use of a new nonlinear filtering approach, the so-called derivative-free nonlinear Kalman Filter. First, it was proven that the dynamic model of the doubly-fed induction generator is a differentially flat one, and this enabled its description in the Brunovksy (linear canonical) form. It has been shown that for the linearized DFIG model it is possible to design a state feedback controller. At a second stage, a novel Kalman Filtering method, the Derivative-free nonlinear Kalman Filter, has been proposed for estimating the non-measurable elements of the dynamic model of the DFIG. It has been shown that by avoiding linearization approximations, the proposed filtering method, improves the accuracy of estimation, and results in smooth control signal variations and in minimization of the tracking error of the DFIG control loop. Moreover, with the redesign of the proposed Kalman Filter as a disturbance observer, it became possible to obtain estimates of disturbance terms affecting the DFIG model. The DFIG's control input was generated by including in the state-feedback control law an input that is based on the estimate of the disturbance terms. Simulation tests have been provided to evaluate the performance of the nonlinear control scheme.

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Appendix 1: Input-output linearization of the DFIG model with use of Lie algebra

The following variables have been defined

$$\begin{matrix} h_1(x)=x_1=\theta \\ h_2(x)=x_3^2+x_4^2=\psi_{s_d}^2+\psi_{s_q}^2 \end{matrix} \tag{71}$$

Next, based on h_1, h_2 the following transformed state variables are defined

$$z_1=h_1(x)=\theta \tag{72}$$

$$\begin{matrix} z_2=L_fh_1(x)\Rightarrow \\ z_2=f_1\Rightarrow z_2=x_2\Rightarrow z_2=\omega \end{matrix} \tag{73}$$

Similarly, one has

$$\begin{matrix} z_3=L_f^2h_1(x)=L_fz_2\Rightarrow \\ z_3=f_2\Rightarrow z_3=-\frac{K_m}{J}x_2-\frac{T_m}{J}+\frac{\eta}{J}(i_{r_q}x_3-i_{r_q}x_4)\Rightarrow \\ z_3=-\frac{K_m}{J}x_2-\frac{T_m}{J}+\frac{\eta}{J}(x_6x_3-x_5x_4) \end{matrix} \tag{74}$$

Moreover, one has

$$\dot{z}_3=L_f^3h_1(x)+(L_{g_a}L_f^2h_1(x))u_1+(L_{g_b}L_f^2h_2(x))u_2 \tag{75}$$

It holds that

$$L_f^3h_1(x)=L_fz_3 \tag{76}$$

$$\begin{matrix} L_f^3h_1(x)=-\frac{K_m}{J}[-\frac{K_m}{J}x_2-\frac{T_m}{J}+\frac{\eta}{J}(x_6x_3-x_5x_4)] \\ +\frac{\eta}{J}x_6[-\frac{1}{\tau_s}x_3+\omega_{dq}x_4+\frac{M}{\tau_s}x_5+v_{s_d}] \\ -\frac{\eta}{J}x_5[-\omega_{dq}x_3-\frac{1}{\tau_s}x_4+\frac{M}{\tau_s}x_6+v_{s_q}] \\ -\frac{\eta}{J}x_4[-\beta x_2x_4+\frac{\beta}{\tau_s}x_3+(\omega_{dq}-x_2)x_6-\gamma_2x_5-\beta v_{s_d}] \\ +\frac{\eta}{J}x_3[\frac{\beta}{\tau_s}x_4+\beta x_2x_3+(\omega_{dq}-x_2)x_5-\gamma_2x_6-\beta v_{s_q}] \end{matrix} \tag{77}$$

Equivalently one has

$$\begin{matrix} L_{g_a}(L_f^2h_1(x))=L_{g_a}z_3\Rightarrow \\ L_{g_a}(L_f^2h_1(x))=-\frac{\eta}{J}\frac{1}{\sigma L_r}x_4 \end{matrix} \tag{78}$$

and similarly

$$\begin{matrix} L_{g_b}(L_f^2h_1(x))=L_{g_b}z_3\Rightarrow \\ L_{g_b}(L_f^2h_1(x))=\frac{\eta}{J}\frac{1}{\sigma L_r}x_3 \end{matrix} \tag{79}$$

For the transformed state variable z_4 one has

$$z_4=h_2(x)=\psi_{s_d}^2+\psi_{s_q}^2=x_3^2+x_4^2 \tag{80}$$

and

$$\begin{matrix} z_5=L_fh_2(x)\Rightarrow\ z_5=2x_3f_3+2x_4f_4\Rightarrow \\ z_5=2x_3[-\frac{1}{\tau_s}x_3+\omega_{dq}x_4+\frac{M}{\tau_s}x_5+v_{s_d}]+ \\ +2x_4[-\omega_{dq}x_3-\frac{1}{\tau_s}x_4+\frac{M}{\tau_s}x_6+v_{s_q}] \end{matrix} \tag{81}$$

and equivalently one has

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$$\dot{z}_5 = L_f^2 h_2(x) + L_{g_a}(L_f h_2(x))u_1 + L_{g_b}(L_f h_2(x))u_2 \quad (82)$$

It holds that

$$\begin{array}{l} L_f^2 h_2(x) = \\ (-\frac{4}{\tau_s}x_3 - \frac{2M}{\tau_s}x_5 + 2v_{s_d})[-\frac{1}{\tau_s}x_3 + \omega_{dq}x_4 + \frac{M}{\tau_s}x_5 + v_{s_d}] + \\ (-\frac{4}{\tau_s}x_4 + \frac{2M}{\tau_s}x_6 + 2v_{s_q})[-\omega_{dq}x_3 - \frac{1}{\tau_s}x_4 + \frac{M}{\tau_s}x_6 + v_{s_q}] + \\ (\frac{2M}{\tau_s}x_3)[-\beta x_2 x_4 + \frac{\beta}{\tau_s}x_3 + (\omega_{dq} - x_2)x_6 - \gamma_2 x_5 - \beta v_{s_d}] + \\ (\frac{2M}{\tau_s}x_3)[\frac{\beta}{\tau_s}x_4 + \beta x_2 x_3 + (\omega_{dq} - x_2)x_5 - \gamma_2 x_6 - \beta v_{s_q}] \end{array} \quad (83)$$

Moreover, it holds that

$$L_{g_a}(L_f h_2(x)) = \frac{2M}{\tau_s}x_3 g_{a_5} \Rightarrow L_{g_a}(L_f h_2(x)) = \frac{2M}{\tau_s}\frac{1}{\sigma L_s}x_3 \quad (84)$$

and in a similar manner

$$L_{g_b}(L_f h_2(x)) = \frac{2M}{\tau_s}x_4 g_{a_6} \Rightarrow L_{g_a}(L_f h_2(x)) = \frac{2M}{\tau_s}\frac{1}{\sigma L_s}x_4 \quad (85)$$

Next, it is confirmed that after change of the state variables it holds

$$\begin{array}{c} \dot{z}_1 = z_2 \\ \dot{z}_2 = z_3 \\ \dot{z}_3 = L_f^3 h_1(x) + L_{g_a}(L_f^2)h_1(x)u_1 + L_{g_b}(L_f^2)h_1(x)u_2 \\ \dot{z}_4 = z_5 \\ \dot{z}_5 = L_f^2 h_2(x) + L_{g_a}(L_f)h_2(x)u_1 + L_{g_b}(L_f)h_2(x)u_2 \end{array} \quad (86)$$

It holds that $z_1 = \theta$, $\dot{z}_1 = \omega = z_2$, $\dot{z}_2 = \dot{\omega} = f_2(x) + g_{a_2}u_1 + g_{b_2}u_2 \Rightarrow \dot{z}_2 = f_2(x) + 0u_1 + 0u_2$ which finally gives $\dot{z}_2 = f_2(x)$. Moreover, it has been proven that $z_3 = f_2$ therefore it holds $\dot{z}_2 = z_3$. Moreover, it holds that

$$\dot{z}_3 = \frac{\partial z_3}{\partial x_1}\dot{x}_1 + \frac{\partial z_3}{\partial x_2}\dot{x}_2 + \frac{\partial z_3}{\partial x_3}\dot{x}_3 + \frac{\partial z_3}{\partial x_4}\dot{x}_4 + \frac{\partial z_3}{\partial x_5}\dot{x}_5 + \frac{\partial z_3}{\partial x_6}\dot{x}_6 \quad (87)$$

which in turn gives

$$\begin{array}{c} \dot{z}_3 = \frac{\partial z_3}{\partial x_1}f_1 + \frac{\partial z_3}{\partial x_2}f_2 + \frac{\partial z_3}{\partial x_3}f_3 + \frac{\partial z_3}{\partial x_4}f_4 + \\ + \frac{\partial z_3}{\partial x_5}(f_5 + \frac{1}{\sigma L_r}u_1) + \frac{\partial z_3}{\partial x_6}(f_6 + \frac{1}{\sigma L_r}u_2) \end{array} \quad (88)$$

that is also written as

$$\dot{z}_3 = L_f^3 h_1(x) + L_{g_a}(L_f^2 h_1(x))u_1 + L_{g_b}(L_f^2 h_2(x))u_2 \quad (89)$$

Similarly, one has

$$\begin{array}{c} z_4 = x_3^2 + x_4^2 \Rightarrow \\ \dot{z}_4 = 2x_3\dot{x}_3 + 2x_4\dot{x}_4 \Rightarrow \dot{z}_4 = 2x_3 f_3 + 2x_4 f_4 \\ \dot{z}_4 = 2x_3[-\frac{1}{\tau_s}x_3 + \omega_{dq}x_4 + \frac{M}{\tau_s}x_5 + v_{sd}] + \\ +2x_4[-\omega_{dq}x_3 - \frac{1}{\tau_s}x_4 + \frac{M}{\tau_s}x_6 + v_{s_q}] \Rightarrow \dot{z}_4 = z_5 \end{array} \quad (90)$$

Additionally, it holds

$$\dot{z}_5 = \frac{\partial z_5}{\partial x_1}\dot{x}_1 + \frac{\partial z_5}{\partial x_2}\dot{x}_2 + \frac{\partial z_5}{\partial x_3}\dot{x}_3 + \frac{\partial z_5}{\partial x_4}\dot{x}_4 + \frac{\partial z_5}{\partial x_5}\dot{x}_5 + \frac{\partial z_6}{\partial x_6}\dot{x}_6 \quad (91)$$

which in turn gives

$$\begin{array}{c} \dot{z}_5 = \frac{\partial z_5}{\partial x_1}f_1 + \frac{\partial z_5}{\partial x_2}f_2 + \frac{\partial z_5}{\partial x_3}f_3 + \frac{\partial z_5}{\partial x_4}f_4 + \\ + \frac{\partial z_5}{\partial x_5}(f_5 + \frac{1}{\sigma L_r}u_1) + \frac{\partial z_5}{\partial x_6}(f_6 + \frac{1}{\sigma L_r}u_2) \end{array} \quad (92)$$

which subsequently gives

$$\dot{z}_5 = L_f^2 h_2(x) + L_{g_a}(L_f h_2(x))u_1 + L_{g_b}(L_f h_2(x))u_2 \quad (93)$$

which is the anticipated relation about $\dot{z}_5$. Consequently, Eq. (23) is confirmed to hold. The system of Eq. (23) can be written in the input-output linearized form

$$\begin{pmatrix} z_1^{(3)} \\ \ddot{z}_4 \end{pmatrix} = f_a + \tilde{M}u \quad (94)$$

where

$$\begin{array}{c} f_a(x) = \begin{pmatrix} L_f^3 h_1(x) \\ L_f^2 h_2(x) \end{pmatrix} \\ \tilde{M} = \begin{pmatrix} L_{g_a}L_f^2 h_1(x) & L_{g_b}L_f^2 h_2(x) \\ L_{g_a}L_f h_1(x) & L_{g_b}L_f h_2(x) \end{pmatrix} \end{array} \quad (95)$$

or equivalently one has the system's description in the MIMO canonical form

$$\begin{pmatrix} \dot{z}_1 \\ \dot{z}_2 \\ \dot{z}_3 \\ \dot{z}_4 \\ \dot{z}_5 \end{pmatrix} = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \\ z_5 \end{pmatrix} + \begin{pmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} \quad (96)$$

where

$$\begin{array}{c} v_1 = L_f^3 h_1(x) + L_{g_a}(L_f^2 h_1(x))u_1 + L_{g_b}(L_f^2 h_2(x))u_2 \\ v_2 = L_f^2 h_2(x) + L_{g_a}(L_f h_1(x))u_1 + L_{g_b}(L_f h_2(x))u_2 \end{array} \quad (97)$$

Appendix 2: Field oriented control of the doubly-fed induction generator

The classical method for induction machines control was introduced by Blascke (1971) and in the DFIG case is based on a transformation of the rotor's currents ($i_{r\alpha}$) and (i_{rb}) and of the magnetic fluxes of the stator (ψ_{s_α} and ψ_{s_b}) to the reference frame $d-q$ which rotates together with the rotor. Thus the controller's design uses the currents i_{rd} and i_{rq} and the fluxes ψ_{sd} and ψ_{sq} [35]. The angle of the vectors that describe the magnetic fluxes ψ_{s_α} and ψ_{sb} is first defined, i.e.

$$\rho = tan^{-1}(\frac{\psi_{s_b}}{\psi_{s_a}}) \quad (98)$$

The angle between the inertial reference frame of the stator and the rotating reference frame of the rotor is taken to be equal to ρ. The transition from $(i_{r\alpha}, i_{rb})$ to (i_{rd}, i_{rq}) is given by

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$$\begin{pmatrix} i_{rd} \\ i_{rq} \end{pmatrix} = \begin{pmatrix} cos(\rho) & sin(\rho) \\ -sin(\rho) & cos(\rho) \end{pmatrix} \begin{pmatrix} i_{r\alpha} \\ i_{rb} \end{pmatrix} \quad (99)$$

The transition from $(\psi_{s\alpha}, \psi_{rb})$ to (ψ_{sd}, ψ_{sq}) is given by

$$\begin{pmatrix} \psi_{sd} \\ \psi_{sq} \end{pmatrix} = \begin{pmatrix} cos(\rho) & sin(\rho) \\ -sin(\rho) & cos(\rho) \end{pmatrix} \begin{pmatrix} \psi_{s\alpha} \\ \psi_{sb} \end{pmatrix} \quad (100)$$

Moreover, it holds that $cos(\rho) = \frac{\psi_{s_a}}{||\psi||}$, $sin(\rho) = \frac{\psi_{s_b}}{||\psi||}$, and $||\psi|| = \sqrt{\psi_{s_\alpha}^2 + \psi_{s_b}^2}$. Using the above transformation ones obtains

$$\begin{matrix} i_{rd} = \frac{\psi_{s\alpha} i_{r\alpha} + \psi_{sb} i_{rb}}{||\psi||} & \psi_{sd} = ||\psi|| \\ i_{rq} = \frac{\psi_{s\alpha} i_{rb} - \psi_{sb} i_{r\alpha}}{||\psi||} & \psi_{sq} = 0 \end{matrix} \quad (101)$$

Therefore, in the rotating frame $d-q$ of the generator there will be only one non-zero component of the magnetic flux ψ_{s_d}, while the component of the flux along the d axis equals 0. The new inputs of the system are considered to be v_{rd}, v_{rq}, which are connected to v_{ra}, v_{rb} according to the relation

$$\begin{pmatrix} v_{r\alpha} \\ v_{rb} \end{pmatrix} = ||\psi|| \cdot \begin{pmatrix} \psi_{sa} & \psi_{sb} \\ \psi_{sb} & \psi_{sa} \end{pmatrix}^{-1} \begin{pmatrix} v_{rd} \\ v_{rq} \end{pmatrix} \quad (102)$$

In the new coordinates, the induction generator model has been described in Eq. (7) to Eq. (12). The state-space model of the induction generator has been defined in Eq. (13) and Eq. (14). Using the state variables notation the DFIG model was written in the form

$$\begin{aligned} &\dot{x}_1 = x_2 \\ &\dot{x}_2 = -\frac{K_m}{J}x_2 - \frac{T_m}{J} + \frac{\eta}{J}(x_6x_3 - x_5x_4) \\ &\dot{x}_3 = -\frac{1}{\tau_s}x_3 + \omega_{dq}x_4 + \frac{M}{\tau_s}x_5 + v_{s_d} \\ &\dot{x}_4 = -\omega_{dq}x_3 - \frac{1}{\tau_s}x_4 + \frac{M}{\tau_s}x_6 + v_{s_q} \\ &\dot{x}_5 = -\beta x_2x_4 + \frac{\beta}{\tau_s}x_3 + (\omega_{dq} - x_2)x_6 - \gamma_2x_5 + \frac{1}{\sigma L_r}v_{r_d} - \beta v_{s_d} \\ &\dot{x}_6 = -\frac{\beta}{\tau_s}x_4 + \beta x_2x_3 - (\omega_{dq} - x_2)x_5 - \gamma_2x_6 + \frac{1}{\sigma L_r}v_{r_q} - \beta v_{s_q} \end{aligned} \quad (103)$$

Next, the following nonlinear feedback control law is defined

$$\begin{pmatrix} v_{rd} \\ v_{rq} \end{pmatrix} = \sigma L_r \begin{pmatrix} \beta x_2x_4 - \frac{\beta}{\tau_s}x_3 - (\omega_{dq} - x_2)x_6 + \beta v_{s_d} + \beta v_1 \\ \frac{\beta}{\tau_s}x_4 - \beta x_2x_3 + (\omega_{dq} - x_2)x_5 + \beta v_{s_q} + \beta v_2 \end{pmatrix} \quad (104)$$

The terms in Eq. (104) have been selected so as to linearize the fifth and sixth row of the state space model of the induction generator in Eq. (103) and to produce first-order linear differential equations. The control signal in the inertial coordinates system $a-b$ will be

$$\begin{pmatrix} v_{r\alpha} \\ v_{rb} \end{pmatrix} = ||\psi||\sigma L_r \begin{pmatrix} \psi_{s\alpha} & \psi_{sb} \\ -\psi_{sb} & \psi_{s\alpha} \end{pmatrix}^{-1} \cdot \begin{pmatrix} \beta x_2x_4 - \frac{\beta}{\tau_s}x_3 - (\omega_{dq} - x_2)x_6 + \beta v_{s_d} + \beta v_1 \\ \frac{\beta}{\tau_s}x_4 - \beta x_2x_3 + (\omega_{dq} - x_2)x_5 + \beta v_{s_q} + \beta v_2 \end{pmatrix} \quad (105)$$

Substituting Eq. (104) into Eq. (103) one obtains:

$$\dot{x}_1 = x_2 \quad (106)$$

$$\dot{x}_2 = -\frac{K_m}{J}x_2 - \frac{T_m}{J} + \frac{\eta}{J}(x_6x_3 - x_5x_4) \quad (107)$$

$$\dot{x}_3 = -\frac{1}{\tau_s}x_3 + \omega_{dq}x_4 + \frac{M}{\tau_s}x_5 + v_{s_d} \quad (108)$$

$$\dot{x}_4 = -\omega_{dq}x_3 - \frac{1}{\tau_s}x_4 + \frac{M}{\tau_s}x_6 + v_{s_q} \quad (109)$$

$$\dot{x}_5 = -\gamma_2x_5 + \beta v_1 \quad (110)$$

$$\dot{x}_6 = -\gamma_2x_6 + \beta v_2 \quad (111)$$

The system of Eq. (106) to Eq. (111) comprises two linear subsystems, where the first one has as output the magnetic flux $x_3 = \psi_{sd}$ and the second has as output the rotation speed $x_2 = \omega$ [35].

Thus, from Eq. (108) and Eq. (110) one obtains

$$\dot{x}_3 = -\frac{1}{\tau_s}x_3 + \frac{M}{\tau_s}x_5 + v_{s_d} \quad (112)$$

$$\dot{x}_5 = -\gamma_2x_5 + \beta v_1 \quad (113)$$

while from Eq. (107) and Eq. (111) one obtains

$$\dot{x}_2 = -\frac{K_m}{J}x_2 - \frac{T_m}{J} + \frac{\eta}{J}x_3x_6 \quad (114)$$

$$\dot{x}_6 = -\gamma_2x_6 + \beta v_2 \quad (115)$$

For $x_3 = \psi_{s_d}$, it holds that if $\psi_{sd} \to \psi_{sd}^{\text{ref}}$, i.e. the transient phenomena for ψ_{sd} have been eliminated and therefore ψ_{sd} has converged to a steady state value, then the two subsystems described by Eq. (112)-(113) and Eq. (114)-(115) are decoupled.

The subsystem that is described by Eq. (112) and Eq. (113) is linear with control input v_1, and can be controlled using methods of linear control, such as optimal control, or PID control. For instance the following PI controller has been proposed for the control of the magnetic flux [35]

$$v_1(t) = -k_{d1}(\psi_{sd} - \psi_{sd}^{\text{ref}}) - k_{d2}\int_0^t (\psi_{sd}(\tau) - \psi_{sd}^{\text{ref}}(\tau)d\tau \quad (116)$$

Thus, if Eq. (116) is applied to the subsystem that is described by Eq. (112) and Eq. (113), one anticipates to succeed $\psi_{sd}(t) \to \psi_{sd}^{\text{ref}}(t)$.

Now, the subsystem that consists of Eq. (114) and Eq. (115) is examined. The term $T = \frac{\eta}{J}x_6x_3$ denotes the torque developed in the rotor. After succeeding $\psi_{sd} \to \psi_{sd}^{\text{ref}}$, one can also control the generator's speed ω, using linear feedback control algorithms. A first approach to the control of the speed ω is to use nested PI loops, i.e.

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$$\begin{array}{c} v_2 = -K_{q_1}(T - T_{\text{ref}}) - K_{q_2}\int_0^t (T(t) - T_{\text{ref}}(t))d\tau \\ T_{\text{ref}} = -K_{q_3}(\omega - \omega_{\text{ref}}) - K_{q_4}\int_0^t (\omega(t) - \omega_{\text{ref}}(t))d\tau \end{array} \quad (117)$$

From the above analysis it becomes clear that a remaining problem in the implementation of field-oriented control for DFIGs is how to measure efficiently $x_3 = \psi_{sd}(t)$. Therefore one comes against the need for applying a state observer or Kalman Filtering. Besides, the tuning of the multiple PID and PI controllers that constitute the field-oriented control scheme, as described in Eq. (116) and Eq. (117), remains valid only round local operating points and thus the stability and robustness of the field-oriented control for DFIGs cannot be assured.

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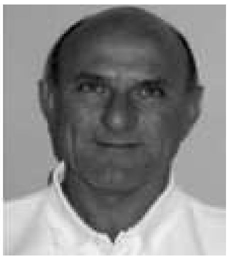

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