

On-line Wind Speed Estimation in IM Wind Generation Systems by Using Adaptive Direct and Inverse Modelling of the Wind Turbine

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Abstract—This paper presents a neural network (NN) based wind estimator and related Maximum Power Point Tracking (MPPT) technique for high performance wind generator with induction machine. The target is to develop an MPPT system, embedding an adaptive virtual anemometer which is able to correctly estimate the wind speed even in presence of variations of the wind turbine characteristic, caused by aging or even damages. This paper proposes the use of the adaptive properties of feed-forward neural networks to address the on-line estimation of the wind speed even in case of slowly time-varying wind-turbine parameters. The method is inspired to the inverse adaptive control but it is used for parameter estimation and not for control purposes. Once the wind speed is estimated, the machine reference speed is then computed by the optimal tip speed ratio. For the experimental application, a suitably developed test set-up has been used, with a back-to-back configuration with two voltage source converters, one on the machine side and the other on the grid side.

Index Terms—Micro-eolic generation, Neural Networks, Wind Turbine Modelling, IM control.

I. INTRODUCTION

At present, wind generators systems with induction machine and back-to-back inverter topology, where both inverters are vector controlled, are a widely accepted strategy for obtaining high performing energy conversion, especially if accompanied with MPPT (maximum power point tracking techniques) [1]–[4]. As is known, two control strategies are typically used for MPPT, one based on the torque control [5], the other on speed control [6]–[10]. The former uses the computation of the optimal electromagnetic torque as its reference, and is simple to implement; however it requires that the rotational speed of the machine be monitored to avoid stresses or to prevent speed from being above rated values. The latter approach, based on speed control, addresses the issue of sudden wind gusts thanks to the counteraction of the speed control loop. Moreover. Unlike the first approach, the torque control is an inner loop and possible mismatches in torque estimation should be inherently taken into account. Among the different approaches, like those based on “perturb-and-observe” (P&O) methods [8]–[10], others require an analytical description of

the wind turbine to compute the speed reference for optimal power extraction [11]–[14]. These last techniques however require the estimation of the wind speed. One possible solution is the use of neural networks (NN): either Radial Basis Function NN [15] or Neural Gas NN have been proposed so far [6]–[8], [16], [17]. However these approaches use the NN to learn off-line the wind turbine relationship and thus are based on a static intelligent mapping; as a consequence, they are not suitable for tracking the wind speed in case of modification of some characteristics of the wind turbine for whatever reason, like ageing. On the contrary, a very challenging issue to be faced up to in wind generation is to embed in the MPPT a capability of on-line estimation of the wind turbine characteristic, able to consider any modification of the turbine mechanical configuration due to damages or ageing. Such a feature would permit the controller to make the MPPT work properly, even in presence of consistent, unpredictable modifications of the wind turbine characteristics.

On the basis of the above, this paper addresses the issue of on-line wind speed estimation based on an adaptive neural model of the wind turbine characteristic. In particular, it presents a scheme where a direct and an adaptive inverse modelling of the wind turbine are employed. Two neural networks, both with a multilayer perceptron structure (MLP) trained on-line by a back-propagation (BPN) algorithm have been adopted. The first NN simulates the wind turbine direct model, the other its inverse model. An on-line training of the direct model is performed on the basis of the IM torque error which is then back-propagated to perform the on-line training of the inverse model. The proposed on-line NN wind speed estimator has been tested in both numerical simulation and experimentally on a suitably developed test set-up. It has been integrated in the whole wind generator control system [6], [16], [17].

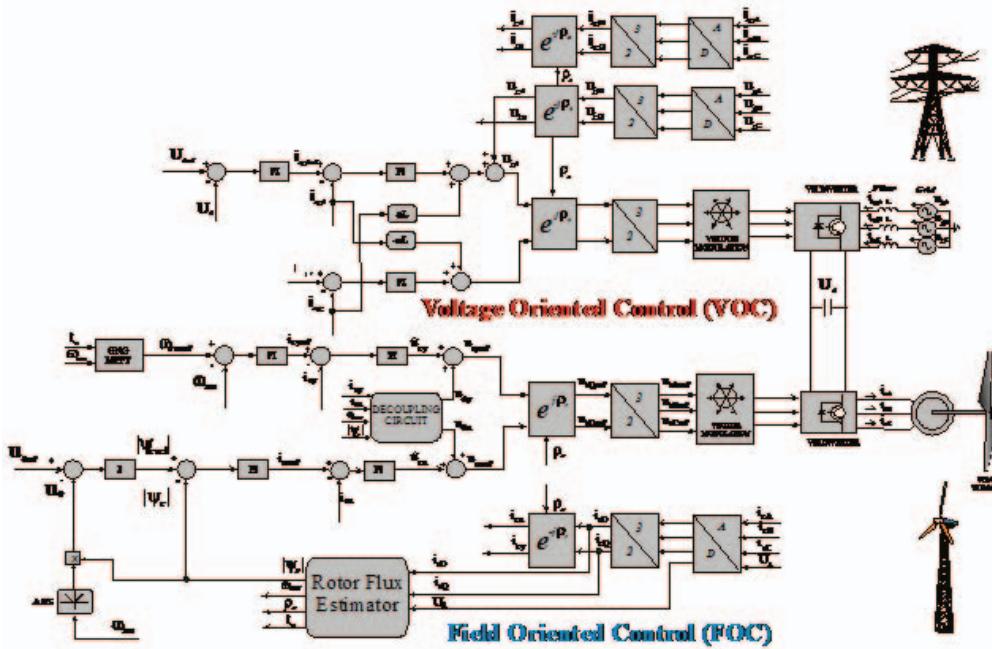


Fig. 1. Block diagram of the wind generator control scheme

II. CONTROL TECHNIQUES

A. Machine side Converter with Field Oriented Control (FOC)

As a matter of fact, since the wind turbine provides a torque which quickly changes with the wind speed, a high performance control technique of the induction machine has been chosen, in particular the so called Field Oriented Control (FOC). In the adopted FOC scheme (Fig. 1) current control is performed in the rotor flux oriented reference frame. The DC link control is provided by the grid side inverter. On the direct axis, a flux control loop commands the current loop and a voltage control loop commands the flux loop to permit the drive to work automatically in the field weakening region by maintaining constant the product between the rotor flux amplitude and the absolute value of the rotor speed. On the quadrature axis, a speed loop controls the current loop. The reference speed of the machine corresponding to the maximum power generable from the system at a given wind speed is retrieved by the GNG based MPPT technique [6], which has in inputs the estimated torque and the measured speed of the machine and gives in output the machine reference speed.

The classic flux model based on the rotor equations of the induction machine in the rotor flux oriented reference frame has been used. A flux model based on the rotor equations has been used to avoid high sensitivity to the stator resistance variation at low speed and the rotor flux oriented reference frame has been chosen to avoid the open loop flux integration problems [18]. All controllers used in the control loops are PI (Proportional Integral) type. An asynchronous space vectorial modulation (SVM) with $f_{PWM} = 5\text{ kHz}$ has been used to command the inverter.

B. Grid side Converter with Voltage Oriented Control (VOC)

Grid side converter control has been performed on the basis of a high performance technique: Voltage Oriented Control (VOC) [18]. VOC is based on the idea of decoupling instantaneously the direct and quadrature components of the injected current, working in the grid voltage vector reference frame. Fig. 1 shows that the direct (quadrature) component of the injected currents depends on the direct (quadrature) component of the inverter voltages. PI controllers can then be used to control the inverter current components in the grid voltage oriented reference frame. However, as it is in the electrical drive counterpart, there are some coupling terms on both axis equations, which should be compensated with feed-forward control terms.

Since the target here is to control directly the DC link voltage, the control scheme has been slightly modified adding another control loop, the DC link voltage one whose output is the direct reference current. The quadrature current reference is always set to zero, so that the reactive power flow with the grid can be kept to zero. Also in this case, an asynchronous space vector modulation (SVM) technique with PWM frequency of 5 kHz has been adopted.

III. WIND TURBINE MODEL

The mechanical power generated by a wind turbine can be written as [19]:

$$P = C_p(\lambda, \beta) \frac{\rho A}{2} v^3 \quad (1)$$

where P is measured in W , C_p is the power coefficient of the turbine, ρ is the air density in kg/m^3 , A is the turbine swept area in m^2 , v is the wind speed in m/s , λ is the tip

TABLE I
WIND TURBINE PARAMETERS

turbine radius (<i>m</i>)	2.5
optimal tip speed ratio λ_{opt}	7
maximum perf. coeff. $C_{p,max}$	0.45
gear ratio <i>n</i>	4.86
generator rated power (<i>kW</i>)	5.5
generator rated speed (<i>rpm</i>)	1500

speed ratio, defined as the ratio of the rotor blade tip to the free speed of the wind:

$$\lambda = \frac{\omega_T R}{v}$$

where ω_T is the turbine angular speed and *R* is the turbine radius, β is the blade pitch angle in deg [5]:

$$C_p(\lambda, \beta) = c_1 \left(\frac{c_2}{\lambda_i} - c_3 \beta - c_4 \right) e^{-\frac{c_5}{\lambda_i}} + c_6 \lambda \quad (2)$$

with:

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1}$$

and: $c_1 = 0.5176$, $c_2 = 116$, $c_3 = 0.4$, $c_4 = 5$, $c_5 = 21$, $c_6 = 0.0068$.

The torque produced by the turbine can be computed as:

$$T_T = \frac{P}{\omega_T} = C_T(\lambda, \beta) \frac{\rho \pi R^3}{v^2} \quad (3)$$

where the torque coefficient of the turbine is defined as

$$C_T(\lambda, \beta) = \frac{C_p(\lambda, \beta)}{\lambda}$$

It should be born in mind that both the turbine speed and the torque should be converted into the machine speed range, taking into account the gear ratio *n*, as:

$$\omega'_T = \omega_T n = \omega_{rm}$$

and

$$T'_T = \frac{T_T}{n}$$

The adopted turbine model parameters are shown in Tab. I, taken from [20].

Eqn.s (1) and (3) fully describe the turbine: the torque as function of the machine speed and the wind speed can be obtained together with the related MPP (Maximum Power Point).

In Fig. 2 the torque-versus-speed characteristics of the emulated wind turbine is plotted for different wind speeds, along with and the locus of the MPPs for each rotating speed of the turbine. It is apparent that the curve is nonlinear and its inversion is a hard task, justifying the use of two NNs to learn both the direct and the inverse relationships.

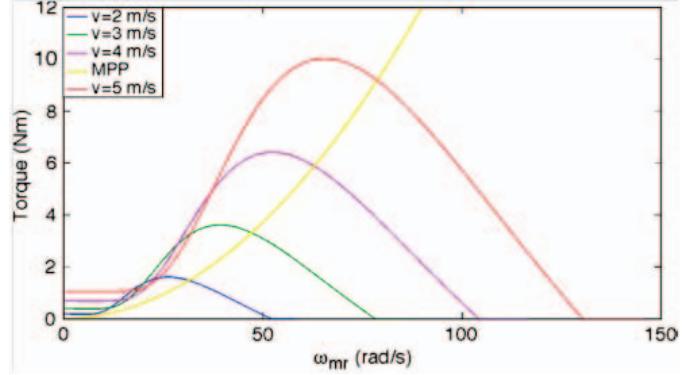


Fig. 2. Wind turbine torque versus speed characteristics for different wind speeds

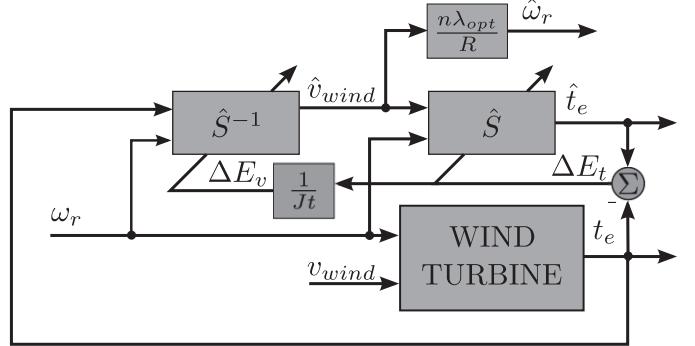


Fig. 3. Block diagram of the wind speed estimator

IV. THE NN BASED WIND SPEED ON-LINE ESTIMATOR

The proposed NN system is an adaptive wind speed estimator. As recalled above, wind speed estimation is crucial for retrieving the optimal value of IM reference speed, guaranteeing the extraction of the maximum power from the wind turbine.

A. Wind Speed Estimation

The idea is to use the direct NN model of the wind turbine to compute the torque and compare it with the actual torque of the turbine (estimated on-line on the basis of the flux model). The torque error is then used to compute a wind speed error by using the estimate of the Jacobian of the system and then use this error to tune the inverse system to output the wind estimation. The block diagram is described in Fig. 3, the algorithm is described in Appendix ??

In this approach, both the direct system and the inverse system are implemented by using a feed-forward neural network, i.e. a multi-layer perceptron trained with the algorithm of back-propagation with pattern learning. The scheme is very similar to the schemes introduced in [21], [22]. The NN for the direct system and the NN for the inverse systems have been initially trained off-line to ensure generalized learning [21]. Alternatively, the specialized learning has been applied where the torque error is back-propagated from S to S^{-1} to allow the inverse system to adapt its weights to compute the wind speed.

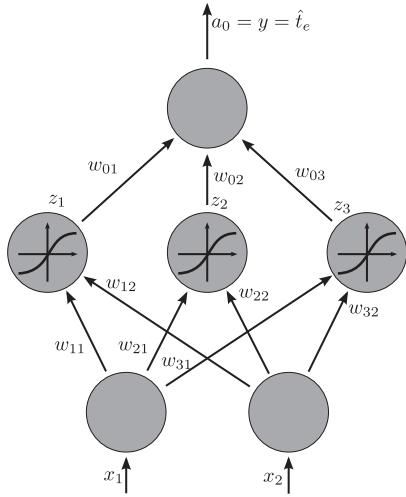


Fig. 4. Scheme of the direct Neural Network

TABLE II
WIND TURBINE PARAMETERS

radius (m)	2.5
λ_{opt}	7
$C_{p,max}$	0.45
n	4.86
rated power (kW)	5.5
rated speed (rpm)	1500

Unlike approaches presented in [6]–[8], [16], [17], the NN of the direct systems captures any variation of the wind turbine from original values and then adapts its weights to track the resulting torque variations. This error is also back-propagated to the inverse system to allow it to modify its weights and track the wind speed. In the end the output v estimated by the inverse system converges to the actual value of the wind.

It should be noted that the proposed system estimates the wind speed on the basis of a previous adaptation of the system model. It therefore inherently takes into consideration any variation of the wind turbine characteristics (direct system S).

B. NN based MPPT

The adopted MPPT technique uses the speed control of the machine instead of its torque control, with all the consequent advantages explained above. To compute the optimal machine reference speed, it is necessary to know in advance the instantaneous values of the wind speed v_{wind} , which has been estimated on the basis of the NN algorithm described in Sec. IV-A. The knowledge of this variable is particularly important for the wind generator also for other reasons, such as the information about the correct operation inside the minimum-maximum wind speed range which determines whether the generator should be disconnected from the grid in case of need. Once the wind speed \hat{v}_{wind} is estimated, the generator reference speed $\omega_{r,ref}$ can be computed:

$$\omega_{r,ref} = \frac{n\lambda_{opt}}{R} \hat{v}_{wind}$$

TABLE III
RATED DATA OF THE MOTOR

Rated power	2.2 kW	Rated speed	1425 rpm
Rated voltage	380 V	Rated torque	14.9 Nm
Rated frequency	50 Hz	Pole pairs	2
$\cos \phi$	0.75	Inertia moment	0.0067 kg·m ²

where λ_{opt} is the optimal value of the tip speed ratio, which is a known parameter and dependent on the characteristics of the turbine. For stability reasons, the optimal generator reference speed is provided to the machine control system by a first order filter with time constant τ .

V. TEST SET-UP

A test set-up has been adopted for the experimental application of the proposed NN-based wind speed estimator and related MPPT. The test set-up is composed of the following items:

- a three-phase induction motor with rated values shown in Table III;
- an electronic power converter (three-phase diode rectifier and VSI composed of 3 IGBT modules without any control system) of rated power 7.5 kVA;
- an electronic card with voltage sensors (model LEM LV 25-P) and current sensors (model LEM LA 55-P) for monitoring the instantaneous values of the stator phase voltages and currents;
- a voltage sensor (Model LEM CV3-1000) for monitoring the instantaneous value of the DC link voltage;
- An incremental encoder (model RS 256-499, 2500 pulses per round);
- A brushless Interior Mounted Permanent Magnets (IMPM) machine drive for creating an active load.
- A dSPACE card (model DS1103) with a floating-point DSP;

The test set-up is organized so that the IM drive can be supplied either by a three phase diode rectifier (only motoring operation) or by a VSI controlled by a VOC technique (both motoring and generating conditions are allowed). The VSI is driven by an asynchronous SV-PWM (Space-Vector Pulsewidth Modulation) with switching frequency of 5 kHz.

The wind turbine has been actively emulated by giving proper torque references to a Permanent Magnet Synchronous Motor (PMSM) drive, model Emerson Unimotor FM, mechanically coupled to the induction motor under test, behaving as an active load. The electromagnetic torque is measured on the shaft by a torquemeter model Himmelstein 59003V(4-2)-N-F-N-L-K. A photograph of the employed test set-up is shown in Fig. 5.

VI. EXPERIMENTAL RESULTS

The proposed on-line NN based wind speed estimator has been integrated in the GNG based MPPT [16] as well as in the entire wind generator control scheme of Fig. 1. Particularly, once the wind speed is estimated, the optimal IM rotating



Fig. 5. Photo of the experimental set-up.

speed corresponding to the MPP can be straightforwardly computed on the basis of the optimal value of the tip speed ratio n (a known quantity of the wind turbine). The proposed technique has been tested initially in numerical simulation and then experimentally in suitably developed test set-up. In such a test set-up, the wind turbine has been experimentally emulated by a torque-controlled PMSM drive, whose speed-torque characteristic instantaneously reproduces that one of a real wind turbine. The model of the emulated turbine is described in [6] and has not been rewritten here for lack of space. In any case its characteristics are shown in Table II.

As written above, the NNs need to be trained preliminary off-line (generalized learning). Fig. 6a shows the surfaces of the torque vs wind speed and rotational speed. In blue the actual turbine direct model, in red the surface estimated by the direct NN. The learning has been made by using a feed-forward multi-layer perceptron with 3 neurons in the hidden layer and by using the Levenberg-Marquardt method. Fig. 6b shows the surfaces of the wind-speed vs torque and rotational speed. In blue the actual turbine inverse model, in red the surface estimated by the inverse function implemented by the NN.

The wind estimation method has been then assessed in the experimental test where the wind turbine, in the beginning rotating in steady state with the free speed of 3 m/s, has been submitted to different wind step variations as shown in Fig. 7. Such a figure clearly shows the capability of the proposed NN estimator to correctly estimate on-line the wind speed, by adapting the weights of the direct and inverse neural models. The estimation error assumes very low values in transient (around 10% of the estimated wind speed) and almost null in steady-state. Fig. 8 shows the corresponding values of the IM reference and measured rotational speed. In such a test, the MPPT is working. Therefore, at each step wind speed variation, a corresponding modification of the IM rotation speed occur, coherently with the correct tracking of the MPP.

In particular, the higher is the wind speed, the higher is the IM rotational speed, as expected (see Fig. 2). It must be stressed that these variations are most challenging and unrealistic, since actual wind speed variations are less steep and allow the tracking system to follow them easier. The 2 NN in this case adapt their weights at each sample time by using the classical backpropagation law, that is by means of a gradient descent method in the weight space. During this operation is it important that the variations of the weights in the direct NN and in the inverse NN be different, at least one magnitude order. In the experiment at hand the learning rate of the inverse NN has been given the value 0.001 and the learning rate of the direct NN the value 0.01. The system estimates the actual wind speed accurately and quickly, and the ripples that were noticed in a previous work using another NN [6] are almost absent, showing the accuracy of the method and the good learning of the inverse model. Fig. 9 shows the corresponding torque variations of the turbine for the same experiment, where it is apparent the convergence of the direct system to the turbine emulator. Even in this case, the tracking of the wind turbine torque is very good, with limited values of the estimation error in both transient and steady-state condition.

Figs. 11 and 12 show, respectively, the grid side i_{sd} , i_{sq} reference and measured currents, and the active P and reactive Q power flowing into the power grid. They show that both the i_{sq} current and reactive power Q are controlled to zero, showing that no reactive power exchange with the power grid exists. On the contrary, increases (decreases) in both the i_{sd} current and the active power P occur in accordance with the increases (decreases) in the estimated wind speed.

VII. CONCLUSIONS

The estimation of the wind speed is most important for MPPT and many methods have been adopted so far to retrieve it from measured torque and rotational speed of the wind turbine. One difficulty lies in the high nonlinearity of the relationship between torque vs rotational speed and wind speed. The use of the analytical model might be employed, but then, in case of variations of its parameters, due for example to ageing, its parameters should be adjusted so as to give an accurate estimation of the wind. This paper proposes the use of the adaptive properties of feedforward neural networks to address the on-line estimation of the wind speed even in case of slowly time-varying wind-turbine parameters. The method is inspired to the inverse adaptive control but it is used for parameter estimation and not for control purposes. The results have been obtained experimentally on a suitably developed experimental test set-up show the goodness of the approach.

APPENDIX BPN ALGORITHM DESCRIPTION

The output $a_0 = \hat{t}_e$ of the direct NN can be expressed as:

$$a_0 = \sum_j w_{0j} z_j$$

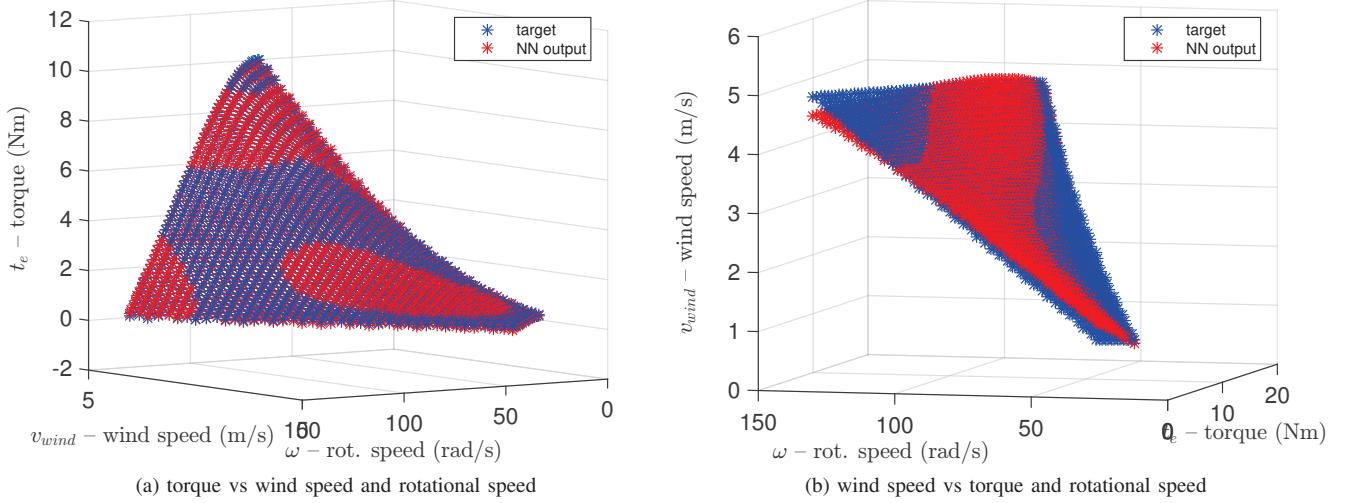


Fig. 6. Trained NN surfaces

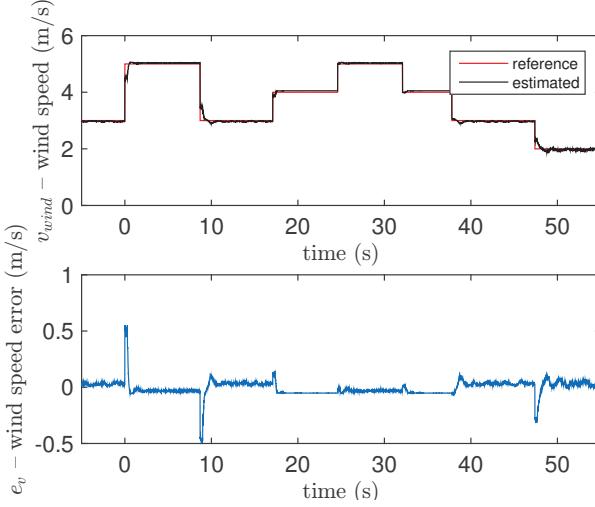


Fig. 7. Wind speed variations given to the system and its estimated values with corresponding speed estimation error

being w_{0j} the outputs neurons weights and z_j the outputs of the hidden layer neurons, given by:

$$z_j = g(a_i)$$

where $g(\cdot)$ is the activation function and a_i is the input of the generic hidden layer neuron, linked to the NN inputs in the following way:

$$a_i = \sum_j w_{ij} x_j$$

being x_j the inputs of the direct NN. The NN estimation error ΔE_t is defined by:

$$\Delta E_t = \frac{1}{2} (t_e - \hat{t}_e)^2 \quad (4)$$

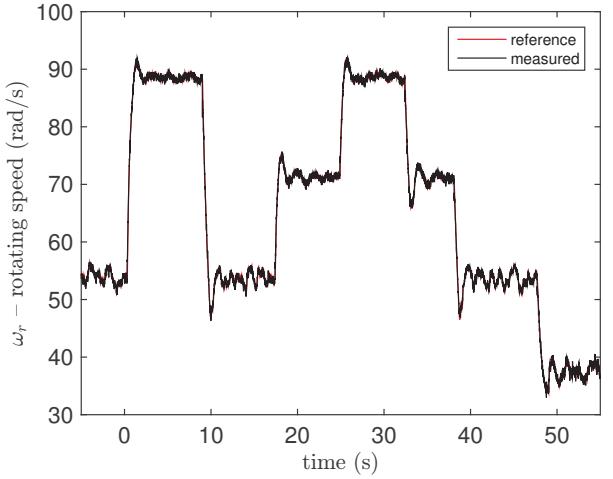


Fig. 8. Reference and measured IM rotational speed

Derivating (4) respect to the outputs neurons weights w_{0j} :

$$\frac{\partial \Delta E_t}{\partial w_{0j}} = \frac{\partial \Delta E_t}{\partial a_0} \frac{\partial a_0}{\partial w_{0j}} = \delta_0 z_j$$

where:

$$\delta_0 = \frac{\partial \Delta E_t}{\partial a_0} = \frac{\partial \Delta E_t}{\partial y} \frac{\partial y}{\partial a_0} = -(t_e - \hat{t}_e) \quad (5)$$

In a similar fashion, deriving the error ΔE_t respect to the hidden layer input weights:

$$\frac{\partial \Delta E_t}{\partial w_{ij}} = \frac{\partial \Delta E_t}{\partial a_j} \frac{\partial a_j}{\partial w_{ij}} = \delta_j x_i$$

where:

$$\delta_j = \frac{\partial \Delta E_t}{\partial a_j} = \frac{\partial \Delta E_t}{\partial a_0} \frac{\partial a_0}{\partial a_j} = \delta_0 w_{0j} g'(a_j) \quad (6)$$

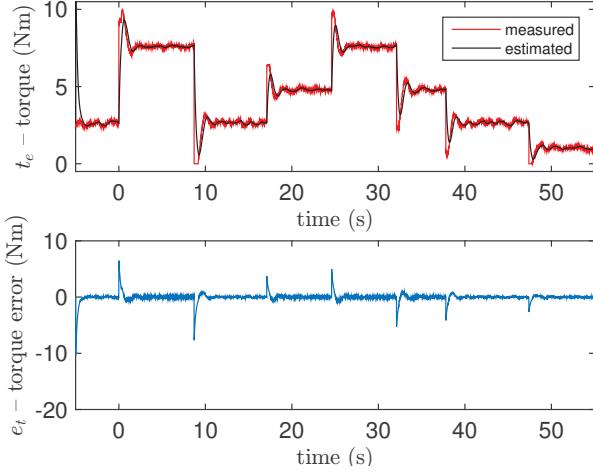


Fig. 9. Torque variations of the system and its estimated values with corresponding torque estimation error

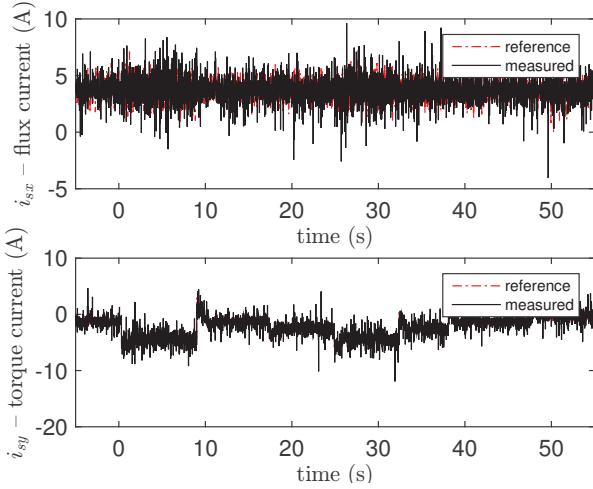


Fig. 10. Reference and measured values of stator current space vector

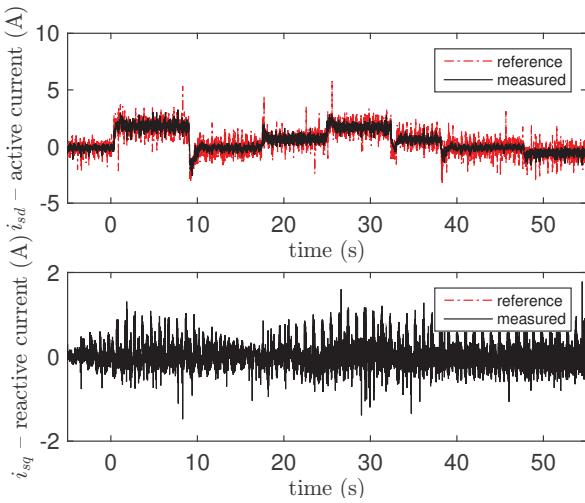


Fig. 11. Reference and measured values of grid current space vector

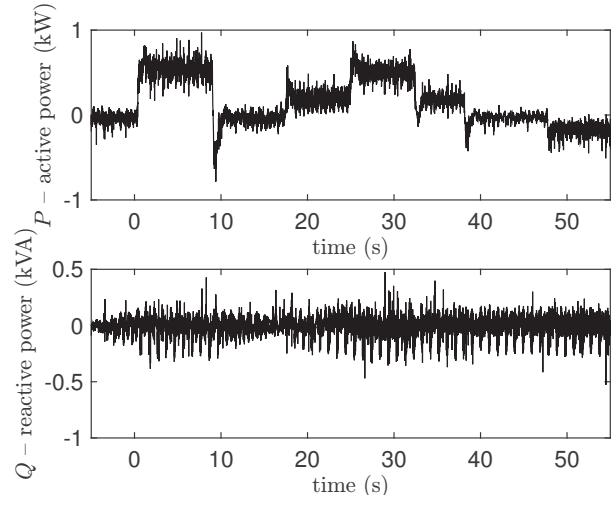


Fig. 12. Grid injected active and reactive power

Finally, the weights update rule can be applied:

$$w^{k+1} = w^k - \eta \frac{\partial \Delta E_t}{\partial w} \quad (7)$$

where η is a learning factor, to be properly chosen.

The same method can be applied for the inverse NN S^{-1} , with the estimated wind speed error ΔE_v that substitutes the estimated torque error ΔE_t :

$$\Delta E_t = \frac{\partial \Delta E_t}{\partial v} \Delta E_v = Jt \Delta E_v \quad (8)$$

where the Jacobian Jt can be computed as:

$$Jt = \frac{\partial \hat{t}}{\partial x} = \sum_i w_{0i} w_{1i} g'(a_i) \quad (9)$$

leading finally to:

$$\Delta E_v = \frac{1}{Jt} \Delta E_t$$

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