Modeling and Control of a Low Power Wind Turbine

Dana-Alexandra Ciupăgeanu,
Student Member, IEEE,
Gheorghe Lăzăroiu*, Member, IEEE*
Power Engineering Faculty
University Politehnica of Bucharest
Bucharest, Romania
dana_ciupageanu@yahoo.com,
glazaroiu@yahoo.com

Viorel Berbece
Mechanical Engineering and
Mechatronics Faculty
University Politehnica of Bucharest
Bucharest, Romania
vberbece@caz.mecen.pub.ro

Mihai Tîrșu, Victor Galbură
The Institute of Power Engineering
Academy of Sciences of Moldova
Kishinev, Republic of Moldova
mtirsu@ie.asm.md

***Abstract*— The unpredictability characterizing renewable energy sources severely impacts power systems as their share continuously enlarges. Choosing the right technology to exploit the available potential of the intended resource and implementing appropriate plant control represents a solution that improves system's operating conditions. This paper presents simulations results for a Permanent Magnet Synchronous Generator (PMSG) driven by a Wind Turbine (WT) considering a control strategy employing a Neural Network Predictive Controller (NNPC), as one of the most viable among suitable options for rising wind energy share while mitigating its highly stochastic characteristics. The model system was represented in Matlab programming environment, using Simulink/Simscape/Power Systems blocks. The behavior of the system is analyzed both in steady and dynamic conditions, in the hypothesis that the controller provides the torque reference for the generator.**

Keywords*— *low-power wind turbine; Matlab/Simulink; neural network predictive control; permanent magnet synchronous generator; wind energy

I. INTRODUCTION

Given the increasingly restrictive conditions regarding environmental conservation and fossil fuels depletion, concurrent with the evolutionary trends of electricity demand and actually changing status of the consumers, power systems are continuously facing change [1-3]. Only last decade, renewable energy generating capacities installed worldwide doubled, reaching 2 TW at the end of 2016; Wind Energy Conversion Systems (WECS) account near 24% of it. A great decreasing trend with respect to wind power costs encouraged by government policies and market dynamics led to halving its price [4-5].

Under the circumstances of progressively competitive renewable energy technologies and still very active research interest in the area, their variable nature involves many issues related to power network integration, especially concerning maintaining an adequate reliability level of the supply. Even with the constant growth of WECS rated power, considering the large dispersion of exploitable potential and the strong variability of the resource, small scale systems could represent the solution that answers not only this problem, but also facilitates integration into the power system. Furthermore, in low-power applications the power output fluctuations do not determine frequency variation [2-5].

A promising technology in order to achieve variable speed wind turbine operation without using a gearbox outstands the Permanent Magnet Synchronous Generator (PMSG), especially considering the lately remarkable advances in permanent magnet materials that increased their affordability [2], [6].

A small scale WECS model consisting of a WT directly driving a PMSG which further supplies a three-phase load is described in this paper. Its purpose is to establish an appropriate structure of a Neural Network Predictive Controller (NNPC), including choosing suitable input in order to achieve minimum deviation of the output. According to steady and dynamic simulations results, the behavior of the controller shows improved performance.

II. PMSG DRIVEN BY A WIND TURBINE

A. Advantages

Although most of the WECS are based on Doubly Fed Induction Generators (DFIG), the use of PMSG became very popular lately. That is due to numerous advantages, such as higher energy densities, which allows smaller dimensions of turbine's rotor for the same output as DFIG, self excitation system and the possibility of direct coupling to the wind turbine, avoiding therefore the use of gearboxes representing an element of mechanical vulnerability in the configuration, increasing its reliability, meaning lower maintenance and operation costs [7-8].

Moreover, PMSG allows a full control towards maximum wind power extraction within a large operating range and it is characterized by very good efficiency, precision and enhanced fault ride through capability. For these reasons, several manufacturers produce and develop such equipments, market demand highlighting new opportunities especially in low-power applications [9-11].

Regarding the power electronic interface between the WECS and the electrical grid, the fully scaled ac/dc/ac converter configuration ensures both optimal operating point, in order to extract maximum power from the air stream, and quality of electricity output. Moreover, this highly reliable

This work was supported in part by a grant of the Romanian Ministry of Research and Innovation, CCCDI – UEFISCDI, project number PN-III-P1-1.2-PCCDI-2017-0404/31PCCD/2018, within PNCDI and 37BMPNIII-P3-199/2016-I05.16.01, within PNCDI III.

978-1-5386-1495-2/18/$31.00 ©2018 IEEE

architecture enables total decoupling from the grid, protecting the generator in fault conditions [2], [7], [12].

Though, it has to be mentioned that increased installation costs and higher converter losses represent still a drawback of this technology [7], [9]. Finding a balance between investments and performances is, as always, a challenge that can be met by implementing adequate control in order to satisfy often emergent objectives.

B. Mathematical model

The mathematical model of the PMSG is given as it follows [2], [6], [9]:

$$v_{ds} = R_s i_{ds} + L_d \frac{d}{dt} i_{ds} - \omega_s L_q i_{qs} \tag{1}$$

$$v_{qs} = R_s i_{qs} + L_q \frac{d}{dt} i_{qs} + \omega_s L_d i_{ds} + \omega_s \lambda_m \tag{2}$$

where v_{ds}, v_{qs} are direct and quadrature axes stator voltages; R_s is stator's resistance; L_d, L_q are direct and quadrature axes stator inductances; λ_m is rotor's flux; ω_s is the steady state electrical speed.

The electromagnetic torque is given as:

$$T_e = \frac{3}{2} p \left[\lambda_m i_{qs} + \left(L_d - L_q \right) i_{ds} i_{qs} \right] \tag{3}$$

where p represents the number of pair of poles of the machine.

The dynamic equation of the rotor:

$$J \frac{d\omega_m}{dt} = T_e - T_m - F\omega_m \tag{4}$$

where J is the moment of inertia; F is the viscous friction coefficient; T_m is the mechanical momentum developed by the driving turbine.

The mechanical power of the prime mover coupled to the PMSG, here represented by the wind turbine, results according to (5) [12-13]:

$$P_m = \frac{1}{2} \cdot c_P \cdot \rho \cdot A \cdot w^3 \tag{5}$$

where c_P is turbine's power coefficient, ρ is the density of air flow, A is the surface swept by the rotor and w is the wind speed.

The power coefficient depends on the pitch angle of rotor's blades and the tip speed ratio as in (6) [14-15]:

$$c_P(\lambda, \beta) = k_1 \cdot \left(k_2 \cdot \frac{1}{\lambda_i} - k_3 \cdot \beta - k_4 \right) \cdot e^{-\frac{k_5}{\lambda_i}} + k_6 \cdot \lambda \tag{6}$$

where $k_i, i = \overline{1,6}$ are real coefficients, λ is the tip speed ratio, β is the blade's pitch angle. The value of λ_i can be determined according to (7):

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08 \cdot \beta} - \frac{0.035}{\beta^3 + 1} \tag{7}$$

The mechanical torque at turbine's shaft can be calculated based on (8):

$$T_m = \frac{P_m}{\omega_m} = \frac{P_m}{\frac{\omega_e}{p}} \tag{8}$$

III. PLANT CONTROL

The extensive development of WECS highlights the necessity of establishing adequate plant control to enhance power system reliability and improve operating conditions [8], [13].

Regarding control strategies of the main subsystems of a wind energy based power plant, among the most widely used are: the Field Oriented Control (FOC) and Direct Torque Control (DTC) for the machine side converter; the Voltage Oriented Control (VOC) and Direct Power Control (DPC) for the grid side converter; as for the pitch angle control, this becomes important at higher values of the wind speed, at lower values being fixed [2], [9], [17].

Modern power plants based on WECS need to overcome the uncertainty related not only to the renewable source itself but also to other interfering factors, such as load dynamics or power grid state. Conventional controllers encounter several problems in performing these functions, precisely because of the power output unpredictability, beside the nonlinearity and complexity of the system [13], [15-16].

To improve plants and, forwards, networks performances, new control strategies should be designed and optimized considering all involved subsystems and the quality of the output. There is a considerable probability that classical PI controller shall encounter difficulties relatively to indefinite derivatives in conditions of highly variable wind speed [7], [10].

The Neural Network Predictive Controller (NNPC) represents a very suitable option in stochastic input conditions. Based on biological evolution considerations and taking into account human expertise, it brings the great benefits of robustness and easy understanding without jeopardizing control performances [16].

Previous approaches to implementing NNPC based strategies employed as input either turbine's mechanical power, generator's speed or blade pitch angle aiming to provide an estimate of variables of interest such as optimal pitch angle, power factor, wind speed, torque at the shaft or maximum power output. Depending on both the complexity of the system and the considered objective, training algorithms and network structure vary [18].

IV. CASE STUDY

A. System parameters

The plant architecture discussed previously was implemented in Matlab/Simulink software, using Simscape/Power Systems blocks. The overall concept on which NNPC relies is a closed loop control, feeding the measured output of the plant to the input of the controller, together with the set reference, as shown in Fig. 1.

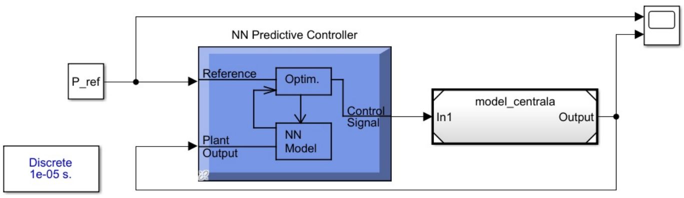

Fig. 1. General structure of the simulation model

The model considered for the simulation of the wind power plant implements a variable pitch wind turbine, directly driving a 500 kW PMSG which in turn feeds a three phase load. First, it was required to establish the input and output of the plant, in terms of the control strategy.

Table I presents the parameters of the three-phase PMSG used in the simulation [17], [19-20].

TABLE I. PMSG PARAMETERS

Characteristic quantity	Symbol	Measurement unit	Value
Stator phase resistance	RS	Ω	0.0225
d-axis inductance	Ld	H	0.0085
q-axis inductance	Lq	H	0.0085
Flux linkage established by magnets	ψ	V·s	0.600125
Inertia	J	kg·m2	0.03
Viscous damping	F	N·m·s	0.004
Pole pairs	p	-	10
Static friction	Tf	N·m	0

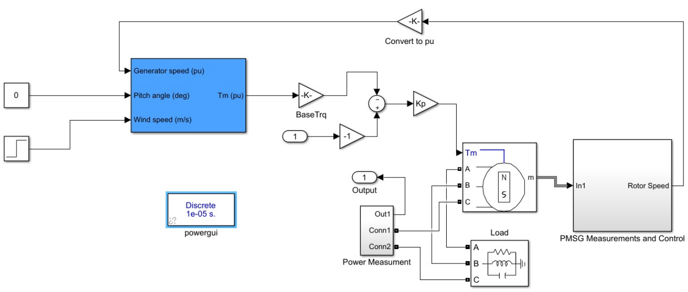

Fig. 2. Wind power plant model

The neural network, trained as it shall be described forward, elaborates the control signal, representing plant input. After analyzing several options for the input, including as alternatives the pitch angle and the torque reference, and considering the power supplied to the load as the output, the best results in terms of load following were obtained if the NNPC provides the torque reference, as presented in Fig. 2. This allows avoiding the use of integral component, simplifying and stabilizing torque control behavior in a wide range of conditions.

The values of the coefficients involved in calculating the variable power coefficient of the wind turbine, according to (6), are mentioned in Table II [14].

TABLE II. WIND TURBINE COEFFICIENTS

Coefficient	Value
k_1	0.5176
k_2	116
k_3	0.4
k_4	5
k_5	21
k_6	0.0068

The maximum power coefficient is obtained for a pitch angle of $\beta = 0°$, corresponding to a tip speed ratio of $\lambda = 8.1 : c_P^{max} = 0.48$. The characteristics $c_P = c_P(\lambda)$ for the wind turbine employed in the model are illustrated in Fig. 3.

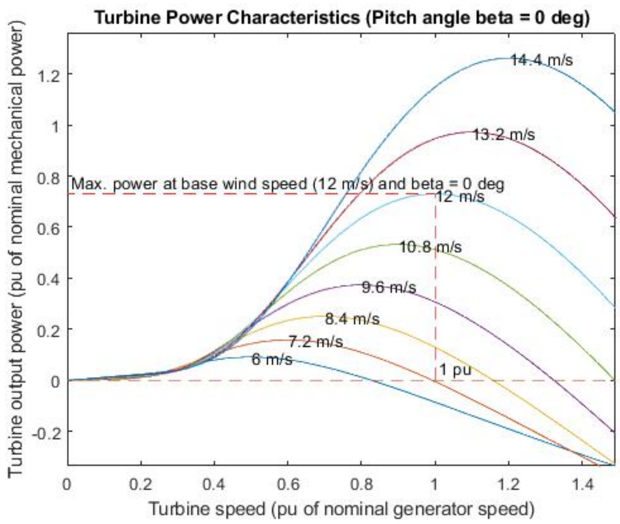

Fig. 3. Wind turbine charateristics

B. NNPC design

The general structure of the NNPC consists of a double hidden layer amidst the input and the output of the controller. Further, its design aimed finding the parameters that will ensure improved performance.

Following several preliminary tests, the cost and control horizons, cost weighting factor and search parameter resulted as in Fig. 4.

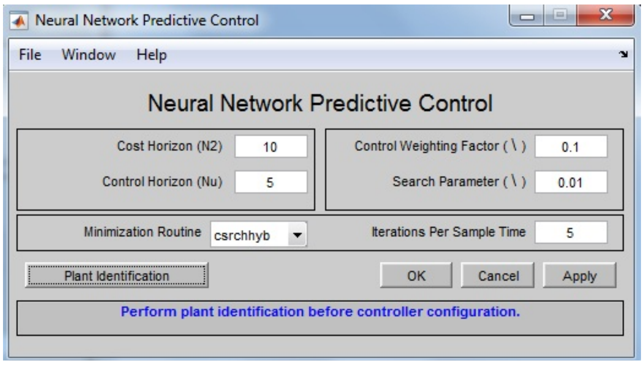

Fig. 4. NNPC block parameters

In order to generate the training samples, the reference provided to the plant was given as a random number, following a normal distribution having the mean equal to the rated capacity of the load and the distribution equal to the allowable percentage of variation. Plant input was considered to vary between zero and nominal value of the torque, determined according to (8):

$$T_m \approx 1.5 \cdot 10^3\, N \cdot m$$

The response of the plant to the variable reference is presented in Fig. 5, for a 1000 samples training set. During simulation time (t_s=10 s), wind speed was considered variable, with a maximum value of 15 m/s.

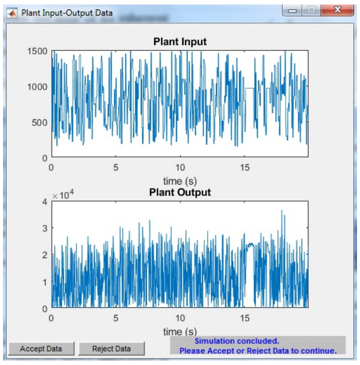

Fig. 5. Training set

Further, performing neural network training employing different algorithms and considering various numbers of neurons on the hidden layer, best performances led to a first hidden layer with a log-sigmoid activation function and 20 neurons, and a second one with a single neuron and linear transfer function.

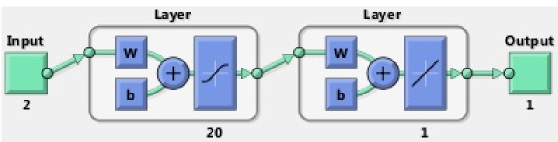

Fig. 6. Neural network architecture

The training algorithm which performed best and behaved the fastest convergence was Levenberg-Marquardt backpropagation.

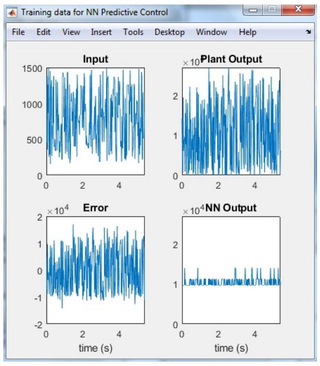

Fig. 7. Training data of the NNPC

C. *Simulation results*

After establishing the NNPC structure and parameters, the response of the model in steady state conditions and subsequent two sudden changes of wind speed, one increasing from 8 m/s to 12 m/s and one decreasing between same values, was analyzed. The variation was considered to occur at t=5 s.

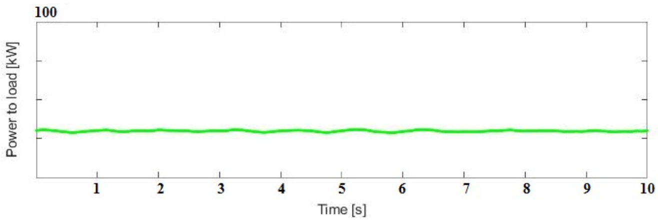

Fig. 8. Plant response under constant wind speed

As pictured in Fig. 8 and Fig. 9, plant output under constant reference and uniform or variable wind speed has very similar evolution trend, highlighting controller's capacity to adapt and ensure load supply.

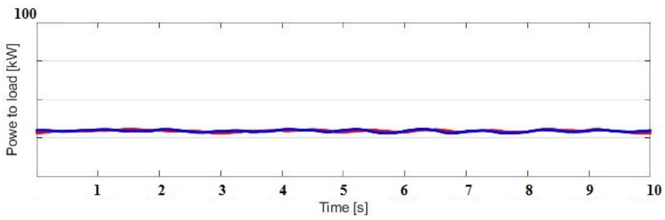

Fig. 9. Plant response in dynamic conditions

It can be noticed that the behavior of the system in dynamic conditions stabilizes.

V. CONCLUSIONS

NNPC represents a control strategy that can overcome the issues related to highly variable renewable sources, such as wind energy. Simulation results presented for a NNPC providing the torque reference for the PMSG in WECS show good performances in different conditions, steady and transient determined by wind speed variation. The proposed configuration allows achieving control objectives without using an integral component for regulation, which makes the system more stable.

Control strategies relying on NNPC show a promising perspective regarding implementation in renewable energy systems, and further in hybrid power configurations. Selecting convenient input-output pair is particular to each application and strongly depends on the objective pursued. Simulations on this subject are therefore of major interest and shall be developed in following research.

ACKNOWLEDGMENT

This work was supported by a grant of the Romanian Ministry of Research and Innovation, CCCDI – UEFISCDI, project number PN-III-P1-1.2-PCCDI-2017-0404 / 31PCCDI/2018 and 37BMPNIII-P3-199/2016-I05.16.01, within PNCDI III.

REFERENCES

[1] C. Zhao, U. Topcu, N. Li, "Design and stability of load-side primary frequency control in power systems", IEEE Transactions on Automatic Control, vol. 59, no. 5, pp. 1177-1189, 2014.

[2] S. M. Tripathi, A. N. Tiwari, D. Singh, "Grid-integrated permanent magnet synchronous generator energy conversion systems: A technology review", Renewable and Sustainable Energy Reviews, vol. 51, pp. 1288-1305, 2015.

[3] D.A. Ciupăgeanu, G. Lăzăroiu, M. Tîrşu, "Carbon dioxide emissions reduction by renewable energy employment in Romania", Proceedings of 2017 International Conference on Electromechanical and Power Systems (SIELMEN 2017), 11-13 October, Iaşi, Romania, pp. 281-285, 2017.

[4] IRENA (2018), "Renewable power generation costs in 2017", International Renewable Energy Agency, Abu Dhabi

[5] D.A. Ciupăgeanu, G. Lăzăroiu, O. Zachia, "The influence of wind turbine generators on power systems dynamic behavior", Proceedings of 18th Symposium on Thermal Science and Engineering of Serbia, 17-20 October, Sokobanja, Serbia, pp. 541-551, 2017.

[6] Y. Xia, K. H. Ahmed, B. W. Williams, "A new maximum power point traking technique for a permanent magnet synchronous genrator based wind energy conversion system", IEEE Transactions on Power Electronics, vol. 26, no. 12, pp. 3609-3620, 2011.

[7] A. Rolán, A. Luna, G. Vásquez, D. Aguilar, G. Azevedo, "Modeling of a variable speed wind turbine with a permanent magnet synchronous generator", IEEE Iternational Symposium on Industrial Electronics ISIE 2009, 5-8 July, Seoul, Korea, pp. 734-739, 2009.

[8] X. Liu, X. Kong, "Nonlinear model predictive control for DFIG-based wind power generation", IEEE Transactions on Automation Science and Engineering, vol. 11, no. 4, pp. 1046-1055, 2014.

[9] M. Chinchilla, S. Arnaltes, J. C. Burgos, "Control of permanent-magnet generators applied to variable-speed wind-energy systems connected to the grid", IEEE Transactions on Energy Conversion, vol. 21, no. 1, pp. 130-135, 2006.

[10] M. E. Haque, M. Negnevitsky, K. M. Muttaqi, "A novel control strategy for a variable speed wind turbine with a permanent magnet synchronous generator", IEEE Transactions on Industry Applications, vol. 46, no. 1, pp. 331-339, 2010.

[11] M. A. Rahman, D. M. Vilathgamuwa, M. N. Uddin, K.-J. Tseng, "Nonlinear control of interior permanent-magnet synchronous motor", IEEE Transactions on Industry Applications, vol. 39, no. 2, pp. 408-416, 2003.

[12] K. Amei, Y. Takayasu, T. Ohji, M. Sakui, "A maximum power control of wind turbine generator system using a permanent magnet synchronous generator and a boost chopper circuit", Proceedings of the Power Conversion Conference, 2-5 April, Osaka, Japan, vol. 3, pp. 1447-1452, 2002.

[13] T. Senjyu, R. Sakamoto, N. Urasaki, T. Funabashi, H. Fujita, H. Sekine, "Output power leveling of wind turbine generator for all operating regions by pitch angle control", IEEE Transactions on Energy Conversion, vol. 21, no. 2, pp. 467-475, 2006.

[14] www.mathworks.com

[15] D. Kumar, K. Chatterjee, "A review of conventional and advanced MPPT algorithms for wind energy systems", Renewable and sustainable energy reviews, no. 55, pp. 957-970, 2016.

[16] A. Medjber, A. Guessoum, H. Belmili, A. Mellit, "New neural network and fuzzy logic controllers to monitor maximum power for wind energy conversion systems", Energy, no. 106, pp. 137-146, 2016.

[17] S. J. Underwood, "On-line parameter estimation and adaptive control of permanent magnet synchronous machines", PhD Thesis, University of Akron, Akron, Ohio, USA, 2006.

[18] R. Ata, "Artificial neural network applications in wind energy systems: a review", Renewable and sustainable energy reviews, no. 49, pp. 534-562, 2015.

[19] M. J. Corley, R. D. Lorentz, "Rotor position and velocity estimation for a salient-pole permanent magnet synchronous machine at standstill and high speeds", IEEE Transactions on Industry Applications, vol. 34, no. 4, pp. 784-789, 1998.

[20] M. Linke, R. Kennel, J. Holtz, "Sensorless position control of permanent magnet synchronous machines without limitation at zero speed", IEEE 28th Annual Conference on the Industrial Electronics Society IECON02, 5-8 November, Sevilla, Spain, pp. 674-679, 2002.