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K. Akkouchi, L. Rahmani, R. Lebied

New application of artificial neural network-based direct power control for permanent magnet synchronous generator

Purpose*. This article proposes a new strategy for Direct Power Control (DPC) based on the use of Artificial Neural Networks (ANN-DPC). The proposed ANN-DPC scheme is based on the replacement of PI and hysteresis regulators by neural regulators. Simulation results for a 1 kW system are provided to demonstrate the efficiency and robustness of the proposed control strategy during variations in active and reactive power and in DC bus voltage.* ***Methodology****. Our strategy is based on direct control of instant active and reactive powers. The voltage regulator and hysteresis are replaced by more efficient and robust artificial neuron networks. The proposed control technique strategy is validated using MATLAB / Simulink software to analysis the working performances.* ***Results****. The results obtained clearly show that neuronal regulators have good dynamic performances compared to conventional regulators (minimum response time, without overshoots).* ***Originality****. Regulation of continuous bus voltage and sinusoidal currents on the network side by using artificial neuron networks.* ***Practical value****. The work concerns the comparative study and the application of DPC based on ANN techniques to achieve a good performance control system of the permanent magnet synchronous generator. This article presents a comparative study between the conventional DPC control and the ANN-DPC control. The first strategy based on the use of a PI controller for the control of the continuous bus voltage and hysteresis regulators for the instantaneous powers control. In the second technique, the PI and hysteresis regulators are replaced by more efficient neuronal controllers more robust for the system parameters variation. The study is validated by the simulation results based on MATLAB / Simulink software.* References 26, tables 5, figures 19.

Key words: **artificial neural network, direct power control, permanent magnet synchronous generator, direct power control based on the use of artificial neural networks.**

Мета. *У статті пропонується нова стратегія прямого керування потужністю (DPC), яка базується на використанні штучних нейронних мереж (ANN-DPC). Запропонована схема ANN-DPC заснована на заміні пропорційно-інтегрального (ПІ) та гістерезисного регуляторів на нейронні регулятори. Наведено результати моделювання для системи потужністю 1 кВт для демонстрації ефективності та надійності запропонованої стратегії керування при зміні активної та реактивної потужності, а також напруги на шині постійного струму.* ***Методологія****. Запропонована стратегія базується на прямому керуванні миттєвими активними та реактивними потужностями. Регулятор напруги та гістерезисний регулятор замінені більш ефективними та надійними штучними нейронними мережами. Запропонована методика керування перевірена з використанням програмного забезпечення MATLAB / Simulink для аналізу робочих характеристик.* ***Результати****. Отримані результати показують, що нейронні регулятори мають хороші динамічні характеристики порівняно зі звичайними регуляторами (мінімальний час відгуку, без викидів).* ***Оригінальність****. Регулювання постійної напруги на шині та синусоїдальних струмів на стороні мережі за допомогою штучних нейронних мереж.* ***Практична цінність****. Робота стосується порівняльного дослідження та застосування прямого керування потужністю (DPC) на основі методів штучної нейронної мережі (ANN) для досягнення хороших показників системи керування синхронного генератора з постійними магнітами. У цій статті представлено порівняльне дослідження між звичайним керуванням DPC та керуванням ANN-DPC. Перша стратегія заснована на використанні ПІ-регулятора для керування постійною напругою на шині та гістерезисних регуляторів для керування миттєвою потужністю. У другому методі ПІ- та гістерезисні регулятори замінюються більш ефективними нейронними контролерами, більш стійкими до зміни параметрів системи. Дослідження підтверджено результатами моделювання на основі програмного забезпечення MATLAB / Simulink.* Бібл. 26, табл. 5, рис. 19.

Ключові слова: **штучна нейронна мережа, пряме керування потужністю, синхронний генератор з постійними магнітами, пряме керування потужністю на основі штучних нейронних мереж.**

Introduction. Electric machines are often known by their windings and their own and complex geometry. In electrical engineering laboratories, the study of synchronous machines with permanent magnet generators is currently a broad research topic. A permanent magnet synchronous generator (PMSG) which obtains energy from mechanical energy for generate an electric current [1]. Synchronous machines with permanent magnets have experienced a great boom in recent years. This is thanks to the improvement of the qualities of permanent magnets more precisely with the help of rare earths, the development of power electronics and the evolution of non-linear control techniques. The advantages of this type of electric machine are numerous, among which we can cite: robustness, low inertia, high mass torque, high efficiency, higher maximum speed and low maintenance cost. In addition, permanent magnets have undeniable advantages: on the one hand, the inducing flux is created without loss of excitation and on the other hand, the use of these materials will make it possible to deviate significantly from the usual sizing constraints. machines and therefore increase the specific power significantly [2]. Several control strategies applied to PMSG, for example vector control [3, 4], direct torque control [5, 6], direct power control (DPC) and sliding mode control [7, 8]. In [9] compared a conventional multi-network, in which the supervision network is replaced by an expert system and a conventional network. They obtained results similar to those of authors in [10]. Their results are more effective when the characteristics are more relevant. In [11] have taken over the multi-networks used in [9] to assess the detection of epileptic transients. The results obtained were compared with those of 4 experts. Even if these results are insufficient to be used in medical practice, they have made it possible to demonstrate that it is possible to detect epileptic transients and that the supervision network eliminates certain bad decisions. In [10] compared several multi-network architectures with a conventional neural network. The neural networks used are error

backpropagation with an input range of 0 to 1. Each neural network is trained 3 times to verify the repetition of the results obtained and to avoid overtraining. The total sum of the squared errors of the test set is used to evaluate the training. The main qualities of neural networks are their capacity for adaptability and self-organization and the possibility of solving non-linear problems with a good approximation [12, 13]. The reason for this trend is the many advantages, which the architectures of artificial neural network (ANN) have over traditional algorithmic methods [14].

Related works. We cite a few articles in this area of research. The article [4] presents a comparative study between voltage oriented control and DPC. It has been shown that best power quality features are given by vector control techniques. On the other hand, direct control offers the better dynamic response. The work [1] assessed the performance of DPC, HYN-DPC (Neural hysteresis DPC) and ANN-DPC. The results obtained confirm that the use of neuron networks improves the total harmonic distortion (THD) and minimizes power ripple. Works [15, 16] proposed the design of sensorless induction motor drive based on DPC technique. An effective sensorless strategy based on ANN is developed to estimate rotor's position and speed of induction motor. Simulation results confirm the performance of ANN based sensorless DPC induction motor drive in various conditions. The article [17] presents a study between HYN-DTC (Neural hysteresis Direct Torque Control) and fuzzy logic PI controller applied to an induction motor. The first method has less THD. The work [18] proposed a new DPC strategy based on a second order sliding mode controller of a doubly fed induction generator (DFIG) integrated in a wind energy conversion system. In the first step it proposed to use a five-level inverter based on the neural space vector pulse width modulation to supply the DFIG rotor side. The results obtained confirm that the use of neural hysteresis controller decrease the THD. The article [19] presents an ANN based DPC of bidirectional 2-level pulse width modulated (PWM) rectifier. Instead of the traditional PI controller, ANN controller is used in this paper to reduce the peak overshoot and ripple in active power. The work [20] a direct power control strategy for a 2.25 kW DFIG is proposed and implemented using a controller based on an ANN with the multilayer perceptron (MLP) structure, which allows the control of the coupled and nonlinear system. All the PI controllers and rotor current estimation block that generated the set of samples for training process were replaced with success by a single MLP controller with twenty hidden neurons. The results have shown that the DPC approach combined with the MLP controller maintain the features of the DPC and adds the inherent characteristic of an ANN controller, more specifically the capability of controlling the coupled and nonlinear system and to generalize the performance to the whole range of operation considered in the training data.

Aim. In this paper a DPC strategy for a PMSG is proposed and implemented using a controller based on an ANN structure. The ANN controller replaces the PI and hysteresis controllers.

Research path followed in this article. The flowchart (Fig. 1) shows the steps followed in this article. The disadvantages of each technique are cited as well as the solutions given in the literature. We always opt for a simple and optimal solution.

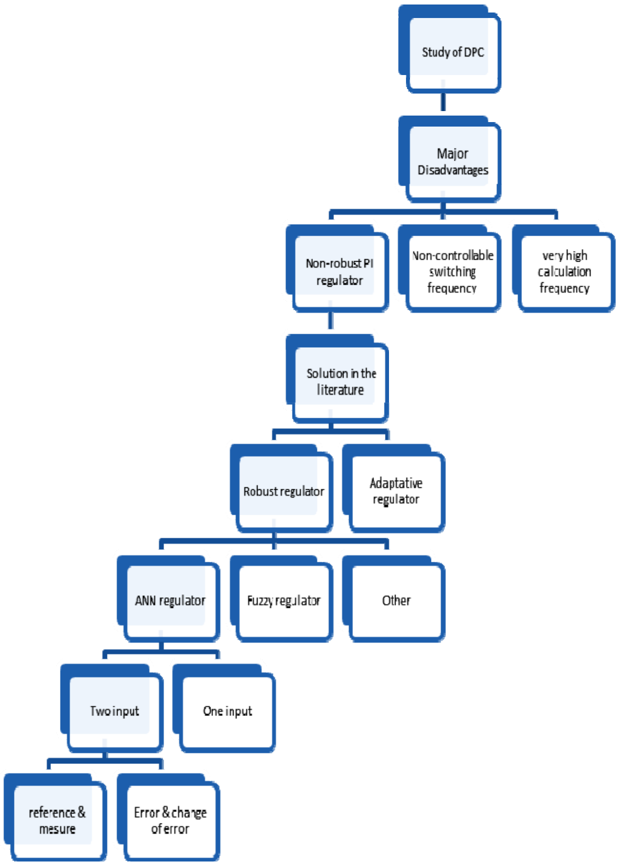

Fig. 1. Flowchart showing the research steps for this article

PMSG modeling. The mathematical model of the PMSG obeys certain essential assumptions simplifying:

- the absence of saturation in the magnetic circuit;
- the sinusoidal distribution of the FMM created by the stator windings;
- hysteresis is neglected with eddy currents and skin effect;
- the notching effect is negligible;
- the resistance of the windings does not vary with temperature.

The structure of the PMSG has a three-phase stator winding. The rotor excitation is created by permanent magnets at the rotor. These magnets are assumed to be rigid and of permeability similar to that of air [21, 22]:

$$U_{ds} = -R_s I_{ds} - L_d \frac{d}{dt} I_{ds} + \omega_r L_{qs} I_{qs} \; ; \quad (1)$$

$$U_{qs} = -R_s I_q - L_q \frac{d}{dt} I_{qs} - \omega_r L_d I_{ds} + \omega_r \varphi_f \, , \quad (2)$$

where U_{ds} and U_{qs} are the stator voltage components; R_s is the stator resistance; L_d and L_q are the components of stator inductances; I_{ds} and I_{qs} are the components of stator current; φ_f is the permanent magnet flux; ω_r is the electric pulsation.

The electrical rotation speed is given by:

$$w_e = p \cdot w, \quad (3)$$

where p is the number of pairs of poles; w is the mechanical speed.

The electromagnetic torque C_e represented by:

$$C_e = \frac{3}{2} \cdot p \cdot \varphi_f \cdot I_{qS} . \qquad (4)$$

The power equations are provided by:

$$P = \frac{3}{2} \cdot (U_{dS} \cdot I_{dS} - U_{qS} \cdot I_{qS}) ; \qquad (5)$$

$$Q = \frac{3}{2} \cdot (U_{qS} \cdot I_{dS} - V_{dS} \cdot I_{qS}) , \qquad (6)$$

where P is the active power; Q is the reactive power.

Uncontrolled rectifier PWM. We have 3 phase line voltages and the fundamental line currents in [22]:

$$U_a = U_m \cos 2\omega t ; \qquad (7)$$

$$U_b = U_m \cos(2\omega t + \frac{2\pi}{3}) ; \qquad (8)$$

$$U_c = U_m \cos(2\omega t - \frac{2\pi}{3}) ; \qquad (9)$$

$$I_a = I_m \cos(2\omega t + \varphi) ; \qquad (10)$$

$$I_b = I_m \cos(2\omega t + \frac{2\pi}{3} + \varphi) ; \qquad (11)$$

$$I_c = I_m \cos(2\omega t - \frac{2\pi}{3} + \varphi) , \qquad (12)$$

where U_m, I_m are the amplitudes of the phase voltage and current respectively; ω is the rotational frequency; φ is the phase difference [23].

Line to line input voltages of PWM rectifier can be described as:

$$U_{sa} = (S_a - S_b) \cdot U_{dc}; \qquad (13)$$

$$U_{sb} = (S_b - S_c) \cdot U_{dc}; \qquad (14)$$

$$U_{sc} = (S_c - S_a) \cdot U_{dc}; \qquad (15)$$

and phase voltages equations give by:

$$U_{sa} = \frac{2S_a - (S_b + S_c)}{3} \cdot U_{dc} ; \qquad (16)$$

$$U_{sb} = \frac{2S_b - (S_a + S_c)}{3} \cdot U_{dc} ; \qquad (17)$$

$$U_{sc} = \frac{2S_c - (S_a + S_b)}{3} \cdot U_{dc} , \qquad (18)$$

where S_a, S_b, S_c are the switching states of the rectifier; U_{dc} is voltage rectifier.

DPC of PMSG. DPC appeared to be competitive with vector control technique. This control method was proposed in [24]. The DPC control is based on the selection of a voltage vector in such a way that the errors between the measured and reference quantities are reduced and maintained between the limits of the bands hysteresis [23, 25]. On the other hand, DPC control is an active and reactive power-based control technique with the advantages of robustness and rapid control (see Fig. 2) it is possible to express that of the reference power by [15]:

$$P_{ref} = U_{dc} \cdot I_{dc}, \qquad (19)$$

where I_{dc} represents the rectifier output current.

Artificial neural network-based DPC. Neural networks have properties of learning, approximation and generalization, so they are of interest for the synthesis of such a command [17, 26]. ANN is a simplified mathematical formulation of biological neurons. They have the capacity of memorization, of generalization and especially of learning which is the most important phenomenon.

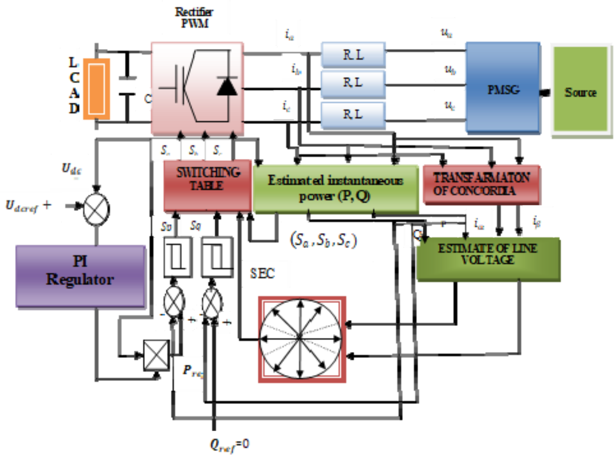

Fig. 2. Block diagram of the DPC

Structure of a neuron. The neuron is the fundamental cell of a network of artificial neurons. By analogy with the biological neuron, the neuron must be able to accomplish the following tasks: collect, process the data coming from the sending neurons and transmit the messages to the other neurons. The relation between the input and the output of the neuron can be given by the following equation:

$$S_i = F(a); \qquad (20)$$

$$S_i = \sum_{j=0}^{N} W(i,j) \cdot x(j), \qquad (21)$$

where the variables N, S_i, F, x and W respectively denote the number of inputs of the neural network, the output vector of the network, the activation function, the vector of the inputs of the neural network and the weight matrix.

We present in Fig. 3 the structure of a simple neuron.

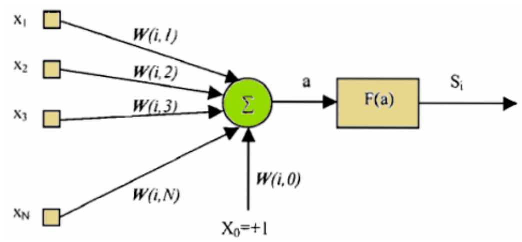

Fig. 3. Structure of a simple neuron

Structure of a single layered neural network. Layered network is a network whose neurons are organized in layers, the simplest form is the single layer network. All input signals are propagated from the input nodes to the output neural layer.

The number of input (nodes) and output neurons is generally related to the problem to be solved. The inputs will be propagated through the matrix of weights W to then obtain the output response (Fig. 4). The equivalent equation can be written in the form:

$$y_i = \sum_{i=0}^{N} W(i,j) \otimes x(i), \qquad (22)$$

where $x(i)$ is the input vector; $y(i)$ is the output vector; $W(i, j)$ is the weight of the neural network.

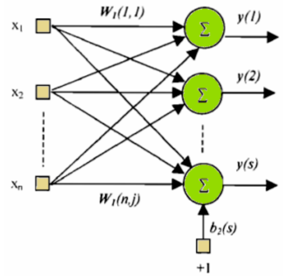

Fig. 4. Structure of a single layered neural network

ANN activation functions. The activation functions used in today's connection models are varied. We can identify three main types of best known functions: *Tansig*, *Logsig* and *Pureline*.

Artificial neural network (ANN) learning modes. Learning can be defined as the ability to store information that can be recalled later. The knowledge of a connection network is stored in the connection weights which will be determined during learning. The goal of learning for a network is to find a set of mimic weights that will error between the output of the network and the desired result.

Learning methods of neural networks.

- learning by backpropagation of the error;
- learning according to a gradient descent;
- learning according to the Quasi-Newton method.

Direct neural power control of PMSG. Figure 5 depicts the construction of the PMSG's direct neural power control (ANN-DPC). The PI voltage regulator and the active and reactive instantaneous power hysteresis regulators are replaced with neural controllers. To generate the ANN controller by MATLAB / Simulink or we have chosen 24 hidden layers for the voltage controller and 5 hidden layers for each hysteresis regulator. Figure 5 gives the block diagram proposed of ANN-DPC.

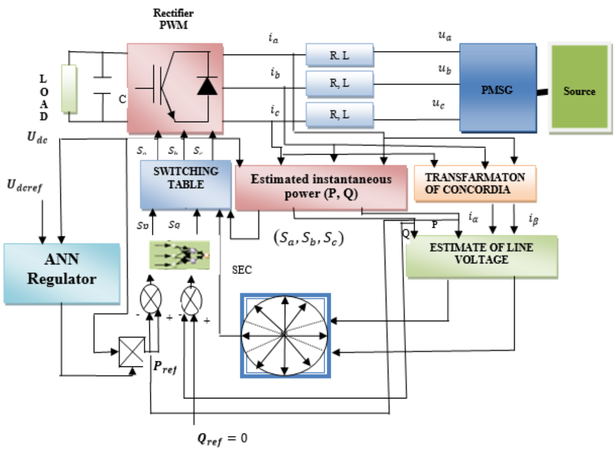

Fig. 5. Block diagram proposed of ANN-DPC

The activation functions are respectively of the «*tansig*» type for the hidden layers and «*pureline*» for the output layers (see Table A.3 in Appendix of this article). An algorithm of carries out the updating of the weights a biases of this network retropropagation called the Levenberg-Marquardt (LM) algorithm.

The representation of the internal structure of the neural voltage controller is shown in Fig. 6.

Figure 7 and 8 illustrates the internal structure of layers 1 and 2 of the neural voltage controller respectively.

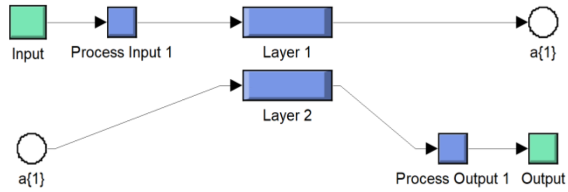

Fig. 6. Internal structure of the neural voltage controller

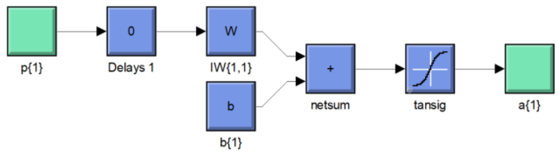

Fig. 7. Internal structure of layer 1

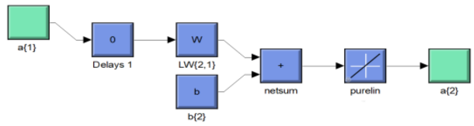

Fig. 8. Internal structure of layer 2

The training performance of ANN-DPC is shown on Fig. 9.

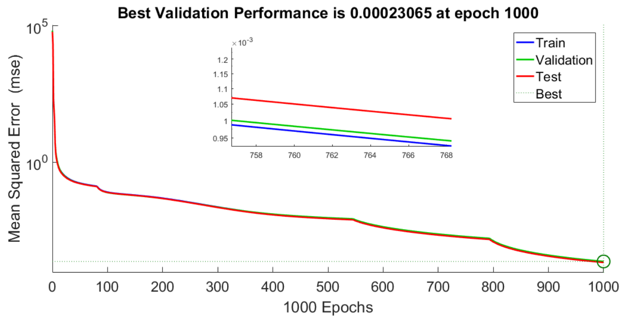

Fig. 9 The training performance of ANN-DPC

The three curves are superimposed. This result is justified in Fig. 10, where the training regression of ANN-DPC also is shown.

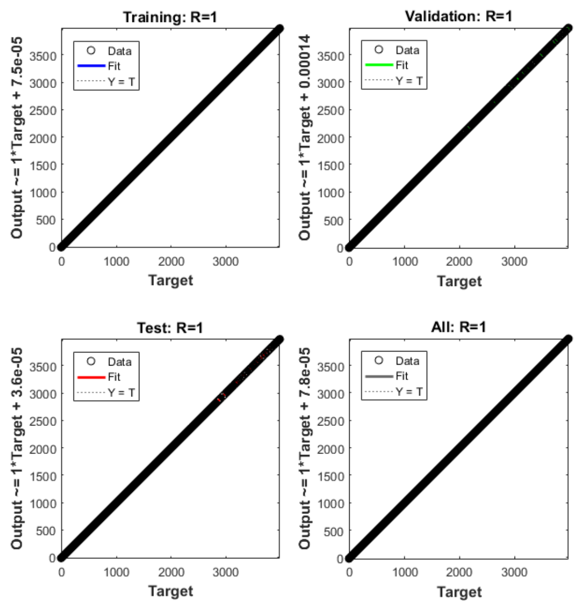

Fig. 10 Training regression of ANN-DPC

Simulation and results of DPC. In Fig. 11 the stator voltage and current of PMSG is shown.

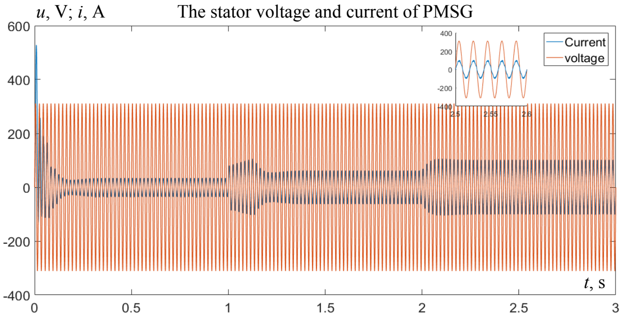

Fig. 11. The stator voltage and current of PMSG

In Fig. 12 the rectified voltage DPC is shown.

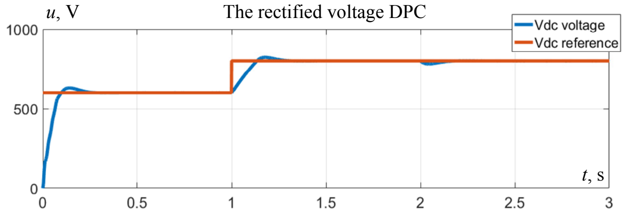

Fig. 12. The rectified voltage DPC

In Fig. 13 the active power DPC is shown.

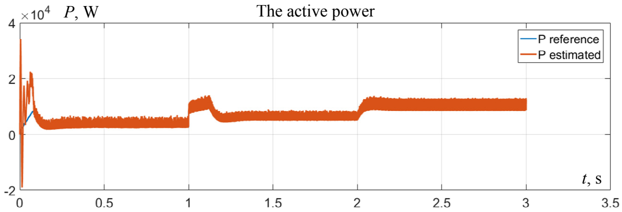

Fig. 13. The active power DPC

The results obtained when changing the DC bus reference voltage for the twelve sector control are shown in the next figures. Figure 14 shows a clear improvement in THD (7.3 %) compared to conventional DPC (12.71 %).

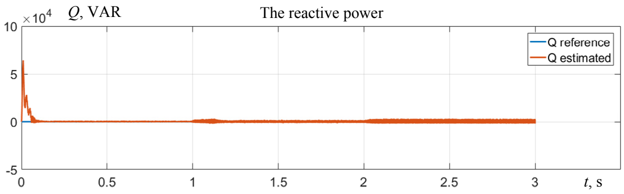

Fig. 14. The reactive power DPC

In Fig. 15 the line current i_b and its harmonic spectrum are shown.

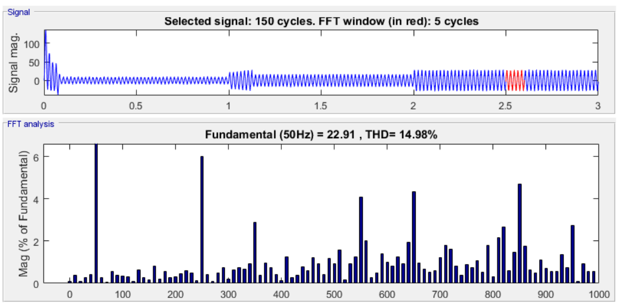

Fig. 15. The line current i_b and its harmonic spectrum

Simulation and results for ANN-DPC. Figure 16 shows that the DC bus voltage follows its reference without overshoot with minimal retraining time and allowable static error.

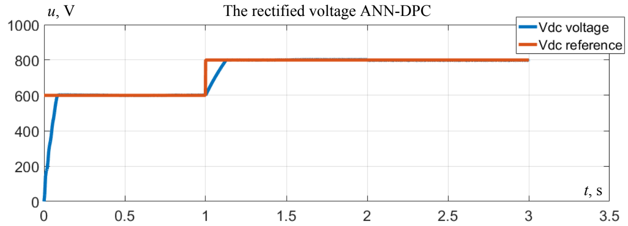

Fig. 16. Rectified voltage ANN-DPC

Figure 17 shows that the active energy follows its reference with the existence of peaks.

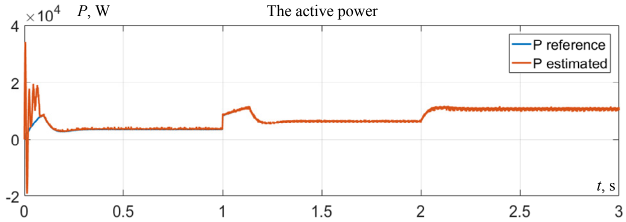

Fig. 17. The active power ANN-DPC

Figure 18 shows that reactive energy follows its reference with a peak passage at start-up.

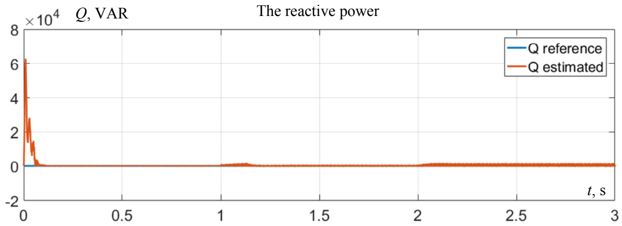

Fig. 18. The reactive power ANN-DPC

Figure 19 shows that the current is sinusoidal with a start peak passage.

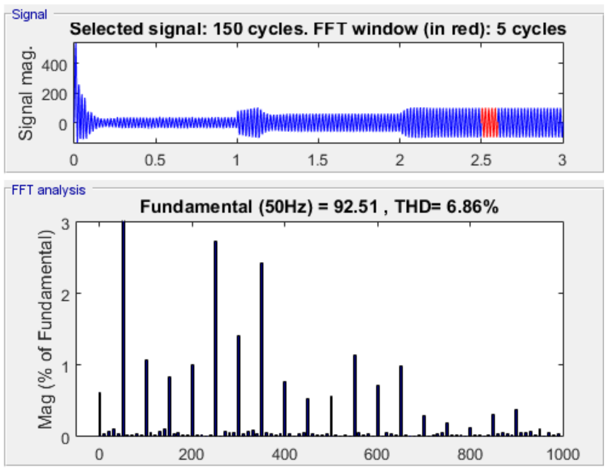

Fig. 19. The line current i_a and its harmonic spectrum ANN-DPC

Study comparative between DPC and ANN-DPC is shown on Table 1.

Table 1

Study comparative between DPC and ANN-DPC

		THD	Active power ripple	Reactive power ripple
Reference test	Classical DPC	12.71	bad	very good
	ANN-DPC	7.3	very good	good
Robustness test	Classical DPC	9.34	bad	bad
	ANN-DPC	6.86	very good	very good

As an example a comparative study with published results are shown on Table 2.

Table 2

A comparative study with published results

Method	THD, %	Ripple of power
1. ANN-DPC (ANN replaces PI controller) [19]	6.52	bad
2. HYN-DPC (ANN replaces Hysteresis controller) [1]	37.25	good
3. ANN-DPC (ANN replaces switching table) [1]	31.95	very good
4. Proposed method – ANN-DPC (combination of methods 1 and 2)	6.86	very good

Conclusions.

In this paper, a direct power control (DPC) is proposed for controlling the PWM rectifier supplied by a PMSG in terms of rapid control of active and reactive power. Decoupled active and reactive power control is achieved without the use of a decoupling system or a change in coordinates. DC voltage is controlled to a consistent incentive in all conditions. The application of a new scheme by replacing the PI and hysteresis regulators has been applied in order to minimize the THD and a better control of the instantaneous powers in terms of speed and ripple rate. The simulation results confirm the effectiveness of the applied technique:

- the sinusoidal form of the line current;
- the current must be in phase with the voltage;
- reactive energy compensation
- a low THD;
- ripple rate of powers;
- time response of DC voltage.

Finally, we prove that the method (ANN-DPC) is the best compared to the classic DPC control.

APPENDIX

Table A.1

PMSG parameters

Parameter	Value
Direct stator inductance L_d, H	0.012
Stator quadrature inductance L_q, H	0.0211
Permanent magnet flux φ_f, Wb	0.9
Stator resistance R_s, Ω	0.895
Inertia J, kg·m^2	0.00141
Number of poles n_p	3
Friction force F, N·m/rad·s	0

Table A.2

Rectifier parameter

Parameter	Value
Line resistance R_l, Ω	0.2
Line inductance L, H	0.011
Filtering capacity C, F	0.0047
DC voltage reference U_{ldcref}, V	600-800

Table A.3

Parameters of Levenberg-Marquardt (LM) algorithm

LM parameters	V_{dc} controller	H_p, H_q*
Number of hidden layers	24	5
Learning rate	0.002	0.002
Number of iterations (epochs)	1000	200
Convergence acceleration rate	0.9	0.9
Goal	0	0
Activation function	*tansig*	*tansig*

*H_p, H_q are respectively hysteresis active and reactive power controllers.

Conflict of interest. The authors declare that they have no conflicts of interest.

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Kamel Akkouchi [1], PhD,
Lazhar Rahmani [2], Professor of Electrical Engineering,
Ryma Lebied [3], PhD,
[1] Electrical Engineering Laboratory of Constantine (LGEC),
Department of Electrical Engineering,
University of Constantine 1,
25000 Constantine, Algeria.
[2] Automatic Laboratory of Setif (LAS),
University of Ferhat Abbes Setif,
19000 Setif, Algeria
[3] Electrotechnical Laboratory Skikda (LES),
University 20 August 1955,
26 Road El Hadaiek 21000, Skikda, Algeria.
e-mail: akkouchi.kamel@umc.edu.dz (Corresponding author),
lazhar-rah@univ-setif.dz,
r.lebied@univ-skikda.dz