# Performance assessment of a Wind Turbine with variable speed wind using Artificial Neural Network and Neuro-Fuzzy Controllers

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*Abstract*- In this paper we study and compare two control methods for Maximum Power Point Tracking (MPPT) applied to a wind turbine modules system using the Permanent Magnet Synchronous Generators(PMSG) in variable speed atmospheric wind condition. The system with Artificial Neural Network (ANN) and Neuro-Fuzzy controllers are modeled, simulated and analyzed by using MATLAB/SIMULINK (V.R2015a) software.

*Keywords*: Neuro-Fuzzy, ANFIS, variable speed, PMSG, MATLAB/SIMULINK, Wind Turbine, MPPT, Artificial Neural Network.

## I. Introduction

Wind Energy Conversion Systems (WECS) have been attracting wide attention as a renewable energy source due to decreasing fossil fuel reserves and environmental interests as a direct consequence of using fossil fuel and nuclear energy sources [1]. To extract the maximum value of variable speed wind power points we use, generally, the Maximum Power Point Tracking (MPPT).

In general, MPPT methods can be classified into two categories. The first one uses classic methods for example Hill-Climbing (HC), Perturbation and Observation (P&O), and Incremental Conductance (IncCond) and the second uses intelligent methods such as the Fuzzy Logic, Artificial Neural Network (ANN) and the combination between the two previous methods Neuro-Fuzzy.

In the both cases, Artificial Neural Network and Neuro-Fuzzy controllers it is used a proportional-integral (PI) controller to regularize the optimal rotor speed. These algorithms do not require a specific detailed mathematical model or linearization about an operating point and they are independent to system parameter variation. The pitch angle of turbine is synchronized according to the measured wind speed values in neural network and Neuro-Fuzzy controls which are applied to boost the performance.

To get the optimum performance of the wind turbine at variable speed wind, it is necessary to extract the MPPT using different MPPT controllers. The purpose of this paper discusses and compares advantages, efficiency and accuracy for the chosen MPPT techniques in wind conversion system, (Artificial Neural Network (ANN) and Neuro-Fuzzy controllers). Matlab/Simulink is used to design and simulate the wind system turbine and to compare selected MPPT controller's performances.

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This paper is planned on five section: the first section is an introduction which contains a generality of wind turbine system and the purpose of this work. Section II presents the theoretical wind turbine characteristics. Section III describes the MPPT controllers details used in our work. The results and discussions are given in the section IV before the conclusion which is the final part of this paper.

## II. Wind Turbine System

Fig.1 describe The schematic diagram of the variable speed wind energy conversion system studied in this paper. Their principal blocks are wind turbine, PMSG, Rectifier, BOOST

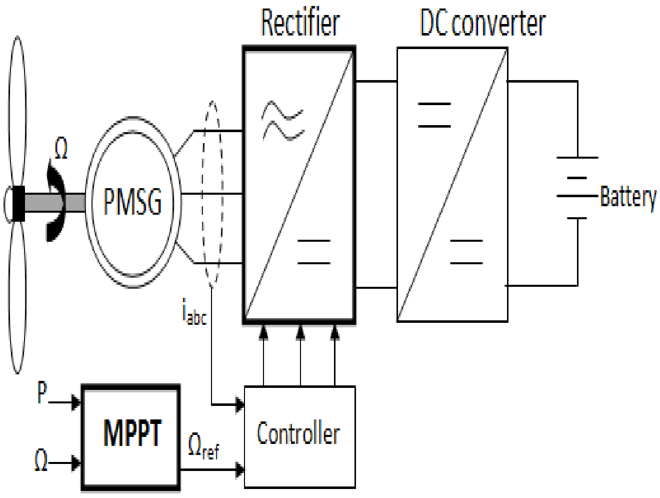


Fig. 1. Variable speed wind energy conversion system.

Converter and Battery.

### A. *Wind Turbine Model*

Depending on the aerodynamic characteristics, the wind turbine mechanical Power is given by (1).

$$P = \frac{1}{2}\pi\rho C_p(\lambda,\beta)R^2V_v^2 \quad (1)$$

Where ρ is the air density, $C_p$ is the power coefficient, λ is the tip speed ratio, β is the pitch angle, R is the turbine radius, $V_v$ is the wind speed.
The form of power coefficient $C_p$ equation used is given in (2).

$$C_p(\lambda) = -0.2121\lambda^3 + 0.0856\lambda^2 + 0.2539\lambda \quad (2)$$

It is depended on only one variable is the tip speed ratio λ
Usually, the pitch angle β is the angle between the blades of turbine and its longitudinal axis. In this work β is set to zero.
The tip speed ratio λ is considered as the linear speed form of the rotor to the wind speed. The power value extracted from

the wind turbine system is the utmost when the power coefficient $C_p$ is at its maximum at a defined value of the tip-speed ratio λ.

Accordingly, for each wind speed there is an optimum rotor speed value where maximum power is extracted from the wind. So we can say that $C_p$ is maximal at the particular $\lambda_{opt}$.

The expression of the tip speed ratio λ is presented in (3).

$$\lambda = \frac{\Omega R}{V_v} \tag{3}$$

Where Ω is the turbine angular speed.

The variable speed wind form studied in this work is expressed in (4) and shown in Fig. 2.

$$\begin{aligned} V_v(t) &= 7.5 + 0.2\sin(0.1047t) + 2\sin(0.2665t) \\ &+ \sin(1.2930t) + 0.2\sin(3.6645t) \end{aligned} \tag{4}$$

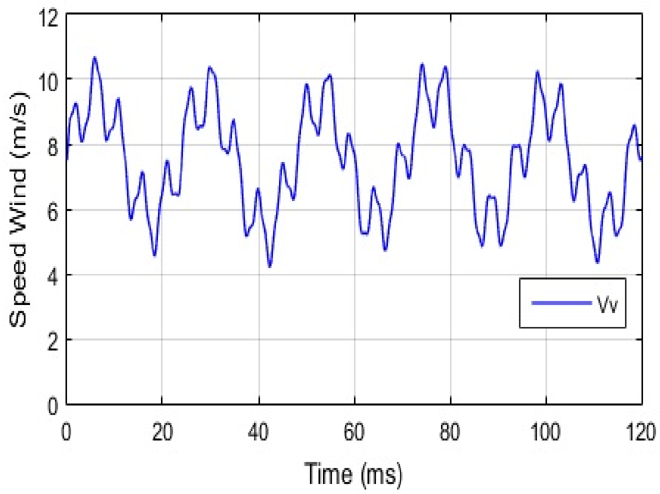


Fig. 2. Allure of the variable speed wind.

### B. Regulation of turbine rotor speed

The adjustment of the wind speed requires the addition of a corrector to optimize the performance of the system. The mechanical system is expressed by (5).

$$J\frac{d\Omega}{dt} = C_m - C_{em} - f\Omega \tag{5}$$

Where:

$J$ is the total inertia (Kg.m$^2$).

$C_m$ is the mechanical torque developed by the turbine(N.m)

$C_{em}$ is the electromagnetic torque (N.m).

$f$ is the viscous friction coefficient (N.m.s.rad$^{-1}$).

We consider a correction Proportional Integral (PI). Their parameters are presented by (6), (7).

$$k_i = J_s.\omega_n^2 \tag{6}$$

$$k_p = 2.\xi\omega_n.J_s - f_s \tag{7}$$

Where:

$Js$ and $f_s$ are respectively the inertia and the viscous friction coefficient of the system.

$\xi$ is the damping coefficient.

$\omega_n$ is the natural frequency.

Inserting the controller will result in the block diagram designed in Fig. 3.

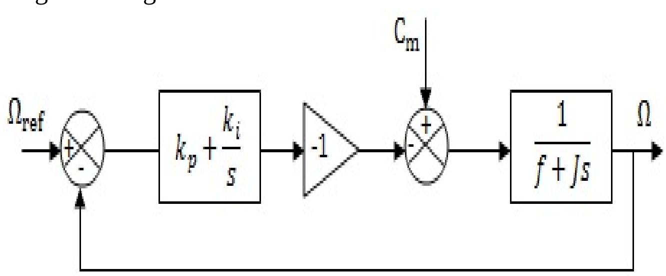


Fig. 3. Block diagram of regulator speed corrector.

## III. The MPPT controllers

### A. The Artificial Neural Network controller

An ANN controller is used to specifically determine the maximum power points values. An Artificial Neural Network is scientifically defined as a complex network composed of interconnected elementary processing units (neurons). Neurons are grouped in layers and can be connected in different ways. The logical topology of connections between neurons decides the network architecture and is depends of the problem to be solved (optimization, non linear regression, classification, etc.). The network comprises parameters which are determined through a learning process. There are many types of ANN. Multi Layer Perceptron (MLP) are feed forward neural networks frequently used to solve nonlinear regression problems. An MLP network is composed of one or more hidden layers fenced by an input layer and an output layer. The neurons of a hidden layer obtain information from the inputs or from the neurons of the preceding hidden layer, and are transferred the result to neurons of the output layer or to the neurons of the next layer. There is no connection between the neurons of the same layer as shown in Fig. 4. The nonlinear function of each input of the network is performed by an output neuron [2].

In Fig. 4 is shown the architecture of a simple neural network.

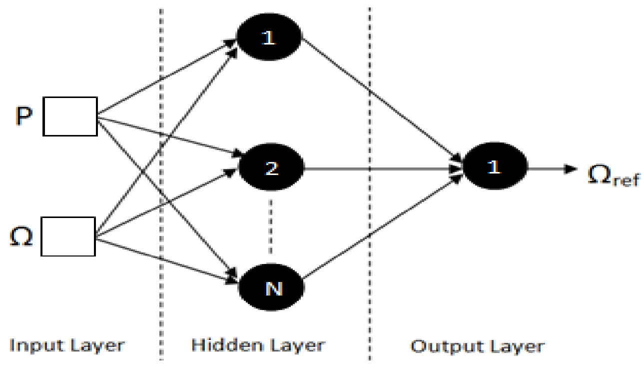


Fig. 4. The general neural network architecture.

The artificial neuron consists of input, activation function and output with respected weight. In the case of simple feed-forward neural network, which contains a single layer of output nodes, the inputs are related directly to the outputs via a series of weights. The weights of the artificial neuron are adjusted and modified usually to obtain the optimized outputs for the specific inputs. The sum of the products of the weights and the inputs is calculated in each hidden node, and we can have two cases:

- If the value is above some threshold (typically 0) the neuron fires and takes the activated value of (typically 1).
- Else it takes the deactivated value (typically -1).

The algorithm used for training of the neural network, in our work, is back-propagation. The back-propagation training algorithm needs only inputs and the preferred output to adjust and adapt the weight. Back-propagation training is referred to as supervised training. The neural network was trained using MATLAB software.

The Fig. 5 shows the model designed, in MATLAB/SIMULINK environment, of the wind energy conversion system with ANN controller.

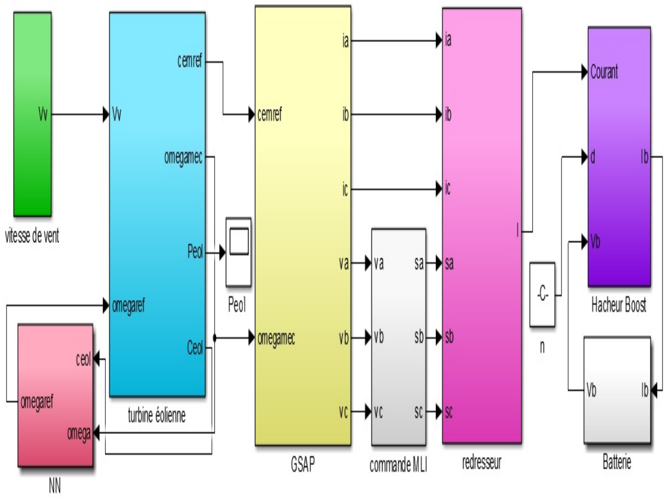


Fig. 5. The model designed for wind energy conversion system with ANN controller in MATLAB/SIMULINK.

## B. The Neuro-Fuzzy controller

The Neuro-Fuzzy inference controller with (ANFIS) is a combination of Artificial Neural Network (ANN) and Fuzzy logic. The ANN identifies the patterns and conforms to them to deal with altering environments. On the other hand, the fuzzy inference systems (FIS) combine the human knowledge and carry out the inference and process of decision making [3]. Two frequent fuzzy models, the Mamdani and Takagi-Sugeno (TSK), are defined for FIS in MATLAB/SIMULINK environment.

In this paper, for the MPPT controller with FIS, the inputs are taken as a change in Power (*P*) and mechanical speed rotor ($\Omega_{mec}$) as well. There is a block for calculating the error (E) and the change of the error (dE) at sampling instants' *k* where are expressed by (8) and (9).

$$E(k) = \frac{dP}{dV} = \frac{P(k) - P(k-1)}{\Omega_{mec}(k) - \Omega_{mec}(k-1)} \quad (8)$$

$$dE(k) = E(k) - E(k-1) \quad (9)$$

Where $P(k)$ is the power delivered by wind turbine and $\Omega_{mec}$ is the mechanical speed rotor in instant *k*. Value of the error *E(k)* determines the MPPT controller output according to the sign. For example, if the operating point is located to the left of the MPP of the characteristic $C_p(\lambda)$ the sign of the error *E(k)* is positive, and the reported load resistance to the wind turbine terminal has to be increased. As a effect, the speed rotor reference's has to be decreased.

The Fig. 6 presents the MATLAB/SIMULINK block designed of error and the change of error.

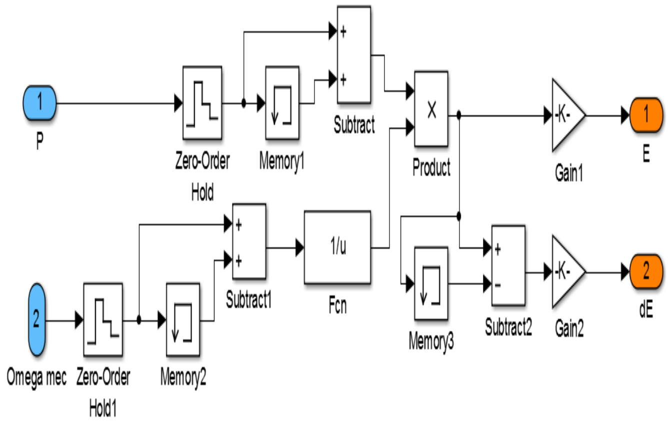


Fig. 6. Block of error and change of error designed in MATLAB/SIMULINK.

In order to avoid the final oscillations approximately the MPP, when the change of the error dE(k) decreases, the speed of convergence to the operating point has to be reduces. As a consequence, the decreasing increment of output has to be reduced. This is the way the MPPT controller ac decide what will be the variation of speed rotor reference ($\Omega_{ref}$) that must be imposed on the wind turbine to approach MPP. Once E(k) and dE(k) are calculated and converted to the linguistic variables, which is the speed rotor reference ($\Omega_{ref}$) of the wind turbine.

The ANFIS is only able to use the TSK fuzzy model owing to its high calculative efficiency, adaptive techniques and built in optimum result in MATLAB/SIMULINK environment. The controller intervene smoothness in convergence step because of the fuzzy TSK inference and to adjust to the prefer result of ANN back propagation algorithm [4]. The structure used of a typical five layer ANFIS system illustrated in Fig. 7

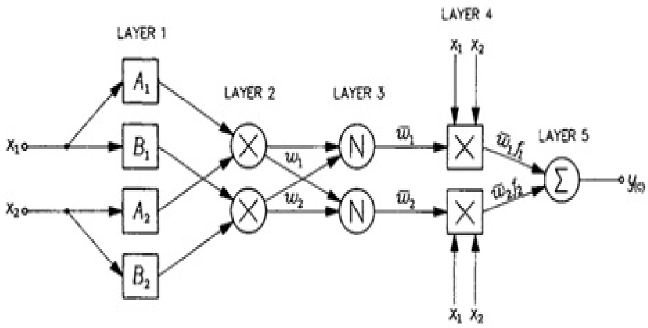


Fig. 7. Structure of typical five layer ANFIS system.

In the first layer, Membership Function (MF) will be defined for each of inputs. In the second layer each node via automatic multiplication calculates the firing strength of a rule. The firing strength is normalized in LAYER3. Two regular rules in TSK fuzzy model are defined as

Rule 1: if $x_1$ is $A_1$ and $x_2$ is $A_2$ then $f_1=a_1x_1+b_1x_2+c_1$
Rule 2: if $x_1$ is $B_1$ and $x_2$ is $B_2$ then $f_2=a_2x_1+b_2x_2+c_2$
Where $a_i$, $b_i$ and $c_i$ are the propose parameters defined in the training plant. Also $A_i$ and $B_i$ are the Fuzzy sets input.
To design the wind energy conversion system with Neuro-Fuzzy controller, we use the similar block of system with ANN controller (PMSG, wind turbine, BOOST converter, rectifier and Battery) with addition of the Neuro-Fuzzy controller block.
The designed system with Neuro-Fuzzy controller in MATLAB/SIMULINK environment is shown In Fig. 8.

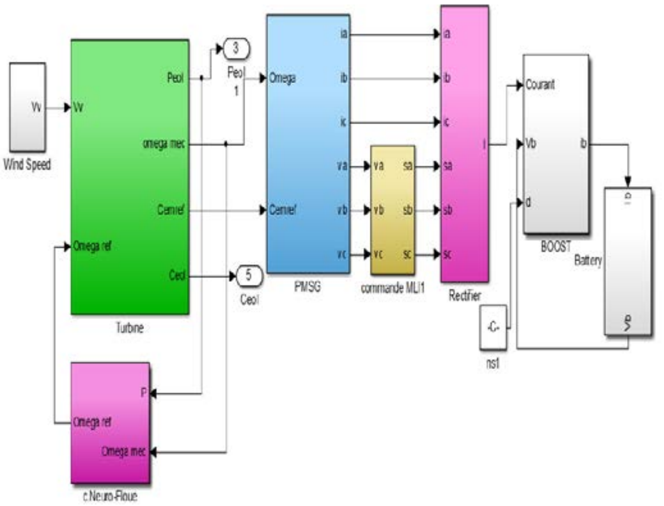


Fig. 8. The system with Neuro-Fuzzy controller designed in MATLAB/SIMULINK environment.

The databases for training the ANFIS inputs are selected and collected from the turbine in fixed speed wind values when the speed wind varies from 5m/s to 15m/s. this database is used for training the network and remaining are used for checking data. The training is done offline using ANFIS toolbox and the target error is set 0.0874%.
Fig. 9 and Fig. 10 shown the proposed respectively the MPPT controller in MATLAB/SIMULINK and the result surface of system.

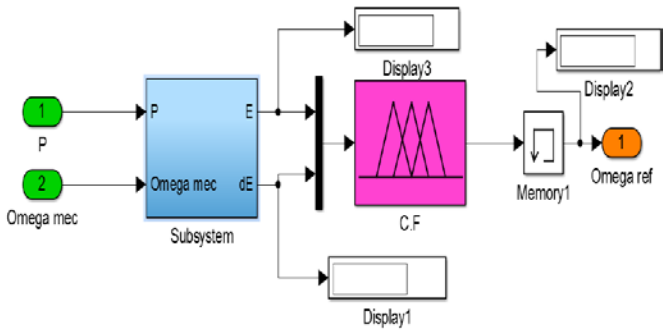


Fig. 9. The proposed Neuro-Fuzzy controller in MATLAB/SIMULINK.

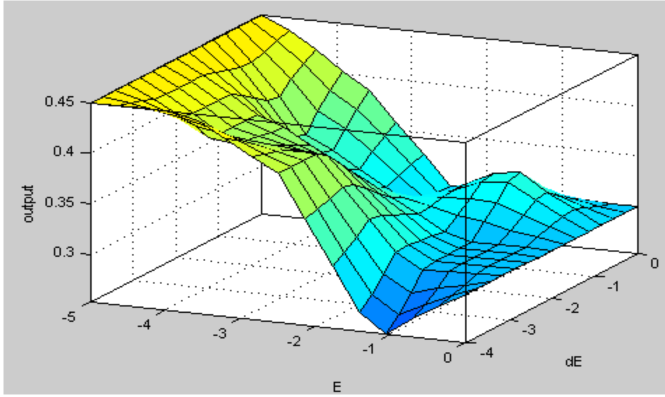


Fig. 10. Three dimensional presentation of Neuro-Fuzzy controller in MATLAB/SIMULINK.

## IV. Results and Discussions

The numerical values of the wind turbine and PMSG characteristics used in our system are given in table I and table II.

TABLE I. Wind Turbine specifications

| | |
|---|---|
| Air density " $\rho$ " | 1.2 kg/m$^3$ |
| Turbine radius " R" | 0.5 m |
| Turbine height "H" | 2m |
| Inertia constant "J" | 16Kg/m$^2$ |
| Friction factor "f" | 0,01Kg.m/rad |
| Maximum coefficient of power "$C_{pmax}$" | 0,15 |
| Optimal tip speed ration "$\lambda_{opt}$" | 0,78 |

TABLE II. PMSG specifications

| | |
|---|---|
| Number of Rotor pole pairs | 2 |
| Stator phase resistance | 0,137 Ω |
| Stator phase inductance | 0,0027 H |
| Inertia constant | 0,1Kg.m$^2$ |
| Friction factor | 0,06Kg.m/rad |

To compare and analyze the different results of the MPPT controller's structures, we have analyzed many cases of artificial neural networks with two fixed hidden layers. To obtain the optimum controllers we have used different activation function and neuron numbers in these two layers. The artificial neural networks ANN structures proposed are given in table III.

TABLE III. The Structures of Analyzed ANN Controllers

| Controller Type | ANN structure | 1st layer | 2nd layer | 3rd layer |
|---|---|---|---|---|
| 1 | Neuron numbers | 1 | 1 | - |
| | Activation function | sigmoid | sigmoid | - |
| 2 | Neuron numbers | 2 | 1 | - |
| | Activation function | sigmoid | linear | - |
| 3 | Neuron numbers | 10 | 1 | - |
| | Activation function | sigmoid | sigmoid | - |
| 4 | Neuron numbers | 10 | 1 | - |
| | Activation function | sigmoid | linear | - |
| 5 | Neuron numbers | 1 | 1 | 1 |

| | | | | |
|---|---|---|---|---|
| | Activation function | sigmoid | sigmoid | sigmoid |
| 6 | Neuron numbers | 1 | 1 | 1 |
| | Activation function | sigmoid | linear | linear |

### *A. First ANN structure*

In Fig. 11 is shown the comparison between power versus time evolution obtained with MPPT controller with the first ANN and Neuro-Fuzzy controllers. The first analyzed ANN structure has the first and the second hidden layer with a single neuron and a sigmoid activation function. As one can see, the maximum power value is obtained more quickly with the Neuro-Fuzzy controller.

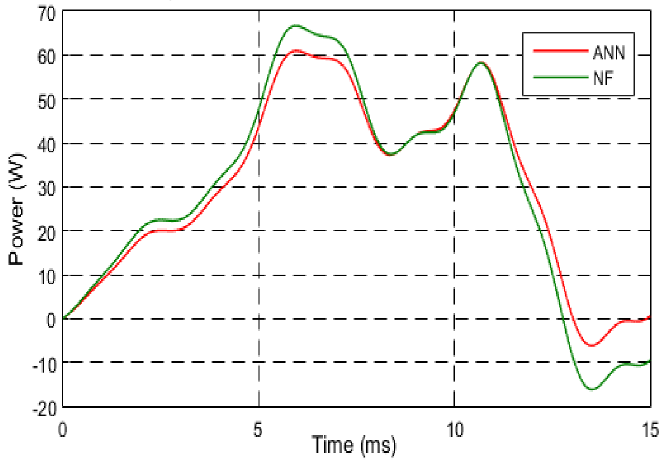


Fig. 11 Comparison between power-time dependence obtained with structure 1 of ANN controller and Neuro-Fuzzy controller

### *B. Second ANN structure*

The second analyzed ANN structure has the first hidden layer with two neurons and a sigmoid activation function, and the second hidden layer with a single neuron and linear activation function. The comparison of power-time dependence realized with the dependence obtained with ANN and Neuro-Fuzzy algorithms is shown in Fig. 12. As we see the maximum value of power is obtained more quickly in the case of the Neuro-Fuzzy controller.

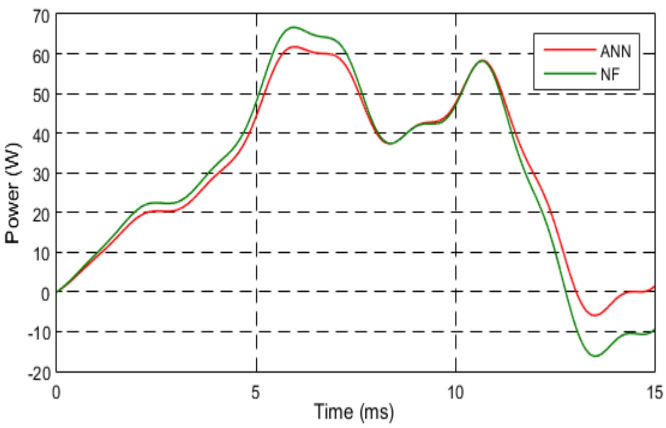


Fig. 12 Comparison between power-time dependence obtained with structure 2 of ANN controller and Neuro-Fuzzy controller

### *C. Third ANN structure*

In Fig. 13 is shown the comparison between power versus time evolution obtained with MPPT controllers with the third ANN and Neuro-Fuzzy controllers. The third analyzed ANN structure has 10 neurons in the first hidden layer and sigmoid activation functions. Although the maximum value of power obtained with the third ANN controller is quickly but it is inferior to the maximum value of power obtained with the first and the second ANN structures. The maximum value of power obtained with Neuro-Fuzzy controller is more important.

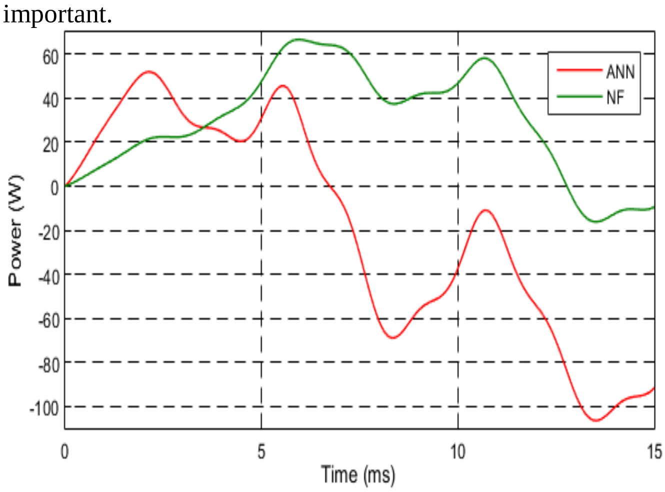


Fig. 13 Comparison between power-time dependence obtained with structure 3 of ANN controller and Neuro-Fuzzy controller

### *D. Fourth ANN structure*

The fourth analyzed ANN structure has the first hidden layer with 10 neurons and a sigmoid activation function, and the second hidden layer with a single neuron and linear activation function. The comparison of power-time dependence realized with the dependence obtained with ANN and Neuro-Fuzzy algorithms is shown in Fig. 14.In this case, the maximum value of power obtained with ANN controller is more quickly and more important.

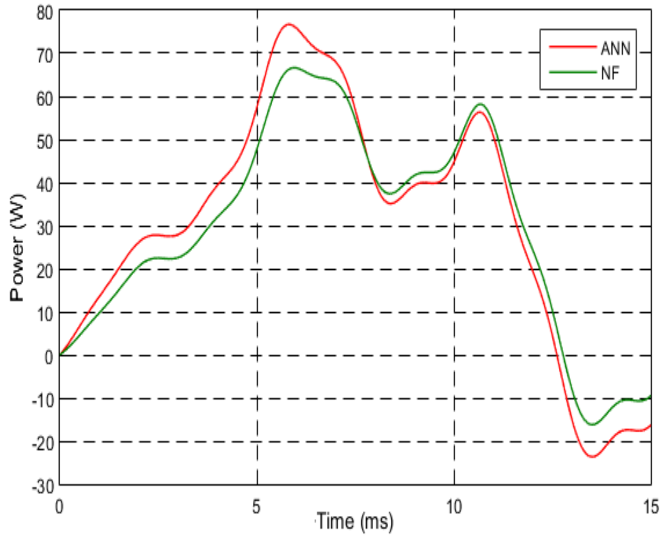


Fig. 14 Comparison between power-time dependence obtained with structure 4 of ANN controller and Neuro-Fuzzy controller

### E. *Fifth ANN structure*

The fifth analyzed structure has three hidden layers and sigmoid activation functions. The comparison of power-time dependence realized in this case with the dependence obtained with ANN and Neuro-Fuzzy algorithms is shown in Fig. 15. In this case, the maximum value of power and curves obtained with the ANN and Neuro-Fuzzy controllers are practically the same.

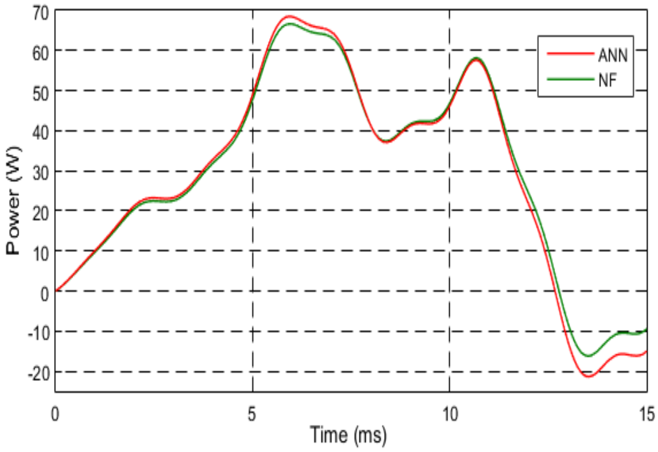


Fig. 15 Comparison between power-time dependence obtained with structure 5 of ANN controller and Neuro-Fuzzy controller

### F. *Sixth ANN structure*

In Fig. 16 is shown the comparison between power versus time evolution obtained with MPPT controller with the last ANN and Neuro-Fuzzy controllers. As one can see, the maximum power value is obtained more quickly with the Neuro-Fuzzy controller.

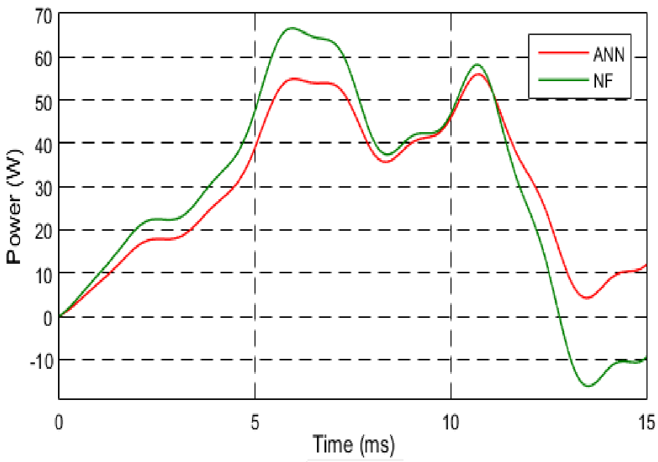


Fig. 16 Comparison between power-time dependence obtained with structure 6 of ANN controller and Neuro-Fuzzy controller

## V. Conclusion

In general, the MPP achieving time of ANN controller and Neuro-Fuzzy controller is practically the same. For the analyzed cases it is about 6ms.

When the ANN controller is used, the MPP achieving time is faster it is about 2,5ms in third case.

The maximum power value of system with Neuro-Fuzzy controller is more important than the system with ANN controller in the first, second, third and sixth cases.

The maximum power value of system with Neuro-Fuzzy controller is less inferior to the system with ANN controller in two cases (fourth and fifth cases).

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