**POWER REGULATION IN PITCH-CONTROLLED VARIABLE-SPEED WIND TURBINE USING A NEURAL NETWORK**

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**Abstract.** *Using a wind turbine for production of electrical energy requires reliable operation. Especially at high wind speeds fluctuations from the wind result in large mechanical loads of the turbine. Therefore an active control system is used to realize a long lifetime of turbine and produce high quality power or increase energy capture.*
*The pitch angle of the wind turbine blades regulates at high wind speeds the torque induced on the rotor. Above rated wind speed, the pitch of the blades is continuously set to the angle of pitch at which rated power is generated. The adjustment of pitch angle is usually made in response to power measurement. Pitch control has so far been the dominating method for power control. Improvement in power quality and alleviation of fatigue damage can be achieved by continuously monitoring the wind turbine and altering the pitch angle of the blades accordingly.*
*The power versus wind characteristics has a highly nonlinear relation for wind turbines. This together with the great variations with time for the wind speeds makes the control design for a wind turbine a non-trivial task . The challenge of wind energy research lies in developing wind turbines that are optimized with respect to both cost and performance. This paper covers the operation of power regulation in a pitch-controlled variable-speed wind turbine generation. A NN architecture was examined. NN provide an extremely powerful information processing tool. They are ideal for control systems due to their nonlinear approximation capabilities, adaptability and computational efficient accredited to their parallel nature. They remove the need to explicitly know the internal structure of a specific task.*
*Since identification and control of nonlinear systems is a major application area for Neural Networks (NNs), a NN Model Predictive Controller (MPC) was implemented to control the pitch angle of the blades of a wind turbine. The overall system was developed using the NN Toolbox of the NN Toolbox for MatLab/Simulink environment.*

## 1 INTRODUCTION

Wind power has the technical potential to meet larger portions of the worlds electricity demand than it does now, but under current market conditions the economic potential is limited. It should be noted that the world demand for electricity is expected to have an annual average growth rate of 3% until 2020. By other side, in 2010, wind power is expected to achieve economic viability (at sites with moderate to high average wind speeds) as a result of technological improvements, economies of scale (resulting from expanding markets), and raised fossil fuel prices (the result of the depletion of fossil fuel resources) [7].

The proliferation of wind turbines as a source of electricity in the future depends upon various economical, political, environmental, social and technical factors. The most important potential barriers for the large-scale development of both onshore and offshore wind energy are the relatively high kilowatt-hour price of wind-generated electricity, the public acceptance (especially in densely populated areas and coastal regions) and the impact on flora, fauna and landscape. On the other hand, the potential of wind power can be enhanced through an increase of the fossil-fuel prices, by means of fiscal instruments, and last but not least by technological advancements aiming at both cost reduction and performance increase [4]. The wind power market is expected to show a continued rapid growth through 2020

For many years most commercial wind-turbines were built using the fixed-speed, stall or pitch regulated concept, to limit the power captured by the wind-turbine at higher wind-speeds. As wind-turbines grew in size to 600 kW and more, the stall-regulated concept became un-economical, mainly because high loads at above-rated wind-speeds resulted in the need for costly strengthening of turbine components. With the introduction of variable-speed wind-turbines, the potential for improvements in power regulation became a reality. The ability of variable-speed wind-turbines to control their rotational speed in response to changing wind conditions greatly reduces the large variations in power experienced with the fixed-speed design and also allows for increased energy capture at low wind-speeds compared with fixed-speed designs [2].

Using a pitch regulated variable-speed wind-turbine for production of electrical energy requires reliable operation. Especially at high wind speeds fluctuations from the wind result in large mechanical loads of the turbine. Therefore an active control system is often used to realize a long lifetime of turbine and produce high quality power or increase energy capture.

In this article, special attention is paid to mathematical modeling and control a wind turbine. A model has been constructed and validated by experimental data obtained from Vestas V-47 660 kW wind turbine [18]. This turbine is chosen were as it represents one of the most popular wind turbines installed in recent years. There is therefore a comparative large amount of data available in the public domain, compared with other available turbines.

As in real world problems of control engineering the nonlinearities are an unavoidable problem that necessitates the development of controllers with special capabilities in solving the nonlinearity problems. NNs have been proved a successful method in identification and control of dynamic systems. In fact [14], control of nonlinear systems is a major application area for NNs. Their approximation capabilities of Multilayer Perceptron (MLP) made them a popular choice for modeling nonlinear systems and for implementing general purpose nonlinear controllers.

The design of an efficient blade pitch controller for a variable-speed wind turbine is crucial if the power smoothing and increased energy capture capabilities are to be fully realized. For this purpose a MatLab/Simulink environment is used for the development of the wind turbine model and a NN MPC is developed to control the pitch angle of the blades. The advanced numerical capabilities built into Simulink, provided an excellent simulation engine for development and control of such a system.

## 2 WIND TURBINES CHARACTERISTICS

A wind turbine is basically a machine which converts the power in the wind into electricity. In modern wind turbines, the actual conversion process uses the basic aerodynamic force of lift to produce a net positive torque on a rotating shaft, resulting first in the production of mechanical power and then in its transformation to electricity in a generator [9]. In fact, in a model point of view, a wind turbine may be seen as a set of four interacting modules (i.e. aerodynamic, mechanical, electrical, and controller) and one module (i.e.

wind)[4] as we can see in Figure 1. Our focus will be in controlling the pitch blades of the turbine, in other words, the aerodynamic part. The essential is given by mathematical expressions that follow.

The power captured by a turbine is given by [6],

$$P_t = \frac{1}{2} p\ r\ C_p(l\,, b) r^2 v_w^3 \tag{1}$$

where $v_w$ is the effective wind velocity through the blades, r is the radius of the wind turbine blades and ? is the air density. The power coefficient $C_p$(?,ß) is a turbine specific function defining the ability of the turbine to convert the kinetic energy of the wind to mechanical energy. $C_p$(?,ß) is a nonlinear function of the pitch angle ß and tip speed ratio ? which is defined by

$$l = \frac{w_t r}{v_w} \tag{2}$$

where $?_t$ is the turbine angular velocity.

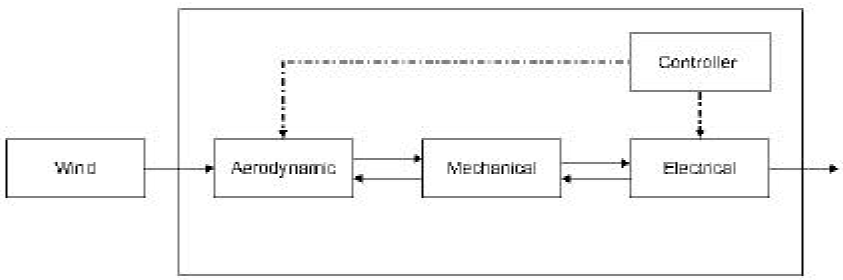


Figure 1: Wind turbine modeled as a set of interacting modules

As we can see in (1) manipulation on the power coefficient using ? and ß will result in manipulation of the power produced by the turbine. $C_p$ surface for Vestas V47-660 is plotted in Figure 2. It has a unique maximum value which is given by an optimal pitch angle and optimal tip speed ratio.

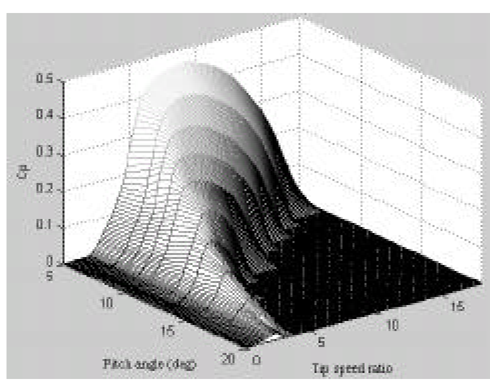


Figure 2: $C_p$ surface for Vestas V47-660

The rotor aerodynamic torque can be achieved by dividing the rotor power by angular velocity of the rotor shaft:

$$T_t = \frac{1}{2w} p\ r\ C_p(l, b) r^2 v_w^3 \tag{3}$$

### 2.1 Turbine control

In a pitch controlled variable speed wind turbine, like Vestas V-47 660 kW, the investigation of control design is divided into below rated operation and above rated operation. Below rated power, the aim of control is to extract maximum energy from the wind. The pitch angle of the blades is fixed at its optimal value and turbine speed is adjusted to follow the changes in wind speed. Above rated power, the control design problem is to limit and smooth the output electrical power.

According by [2], to effectively extract wind power while maintaining safe operation, the wind turbine should be controlled according to the three following modes of operation, as can be seen in Figure 3.

- variable speed – optimum ?; (A-B)
- constant speed – variable ?;(B-C)
- constant speed – constant power. (C-D)

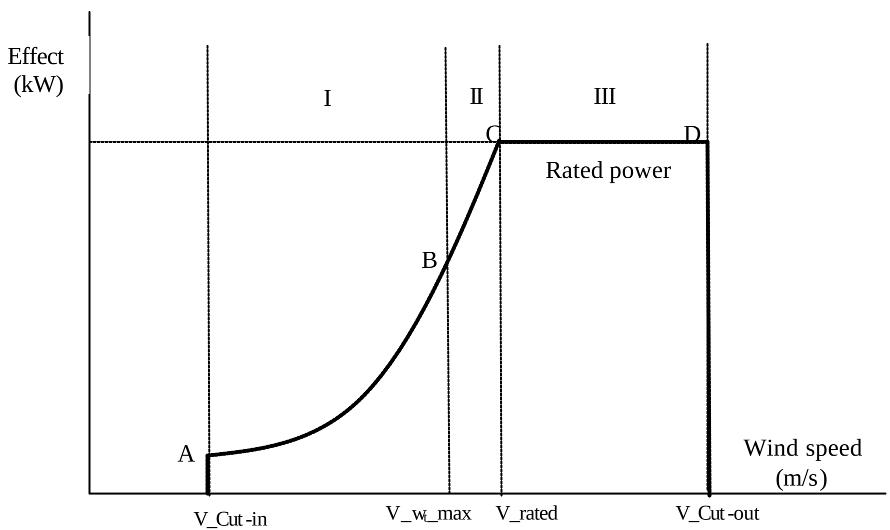


Figure 3: Areas for different control operation

#### 2.1.1 Variable speed – optimum ?

In the first interval, (area I, from point A to B in Figure 3), the low wind seed interval, the operation point of the turbine should be held at the maximum point on the $C_p$ surface. The turbine rotational speed $w_t$, should be adjusted to obtain a constant tip-speed ratio, resulting in maximum turbine efficiency, corresponding to operation at maximum point on the surface in Figure 2.

#### 2.1.2 Constant speed – variable ?

For the second interval, (area II, from point B to C in Figure 3), the middle wind speed interval, the upper rotational speed limitation of the wind turbine ensures that operation at optimal tip-speed ratio is not possible at all wind speeds. The turbine is now not operating on the maximum efficiency point. At point C, the rated turbine power is reached.

### 2.1.3 Constant speed – variable ?

The third interval, (area III, from point C to D in Figure 3), the high wind speed interval, or wind speed above the rated wind speed. From point C to D, the turbine should regulate power at the rated value, this is achieved through the adjustment of the blade pitch angle. The wind turbine should continue to capture power at the rated value, up to the cutoff win speed, corresponding to operation at point D in Figure 3. During this mode of operation the rotational speed should be maintained at the maximum value, determined by the upper limit of the tip-speed ratio.

## 2.2 Pitch block

The pitch actuator consists of a mechanical and hydraulic system which is used to turn the blades of the wind turbine along their longitudinal axis. As we can see from (3), by varying the pitch angle, the aerodynamic torque input to the rotor is altered and hence output power.

Because of the inertia of the blades is large and the actuator should not consume a great deal of power, the actuator has limited capabilities. Its dynamic are nonlinear with saturation limits on both pitch angle and pitch rate [16]. The actuator dynamics as were implemented in Simulink are depicted in Figure 4

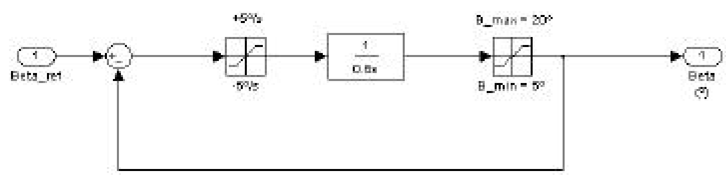


Figure 4: The pitch actuator

were Beta_ref is the “reference” pitch angle and Beta is actuator output (pitch angle).

According to data from the Vestas V47-660 wind turbine [18], the saturation level of the pitch angle is 5º and 20º, and the saturation level of the pitch rate is ± 5º/s. The control problem is quantifying Beta_ref, to provide power smoothing in high winds speeds.

# 3 IDENTIFICATION AND CONTROL USING ANN’S

Due to increasing technological demands and ever increasing complex systems requiring highly sophisticated controllers to ensure that high performance can be achieved and maintained under adverse conditions, there is a demand for an alternative form of control as conventional approaches to control do not meet the requirements of these complex systems. To achieve such highly autonomous behavior for complex systems one can enhance today’s control methods using intelligent control systems and techniques. It is for this reason that NNs are of significant importance in the design and construction of the overall intelligent controller for complex nonlinear systems.

Modern systems are frequently too complex to be modeled by a well known mathematical model. From a given transfer function the system response can be predicted. The reverse of this process, which is, calculating the transfer function from a measured response, is called "system identification". It is essentially a process of sampling the input and output signals of a system, and subsequently using the respective data to generate a mathematical model of the system to be controlled. In fact, system identification enables the real system to be altered without the need to calculate the dynamic equations and remodel the parameters again. Knowledge of the dynamics of the system is useful in the determination of the NN architecture, its inputs, outputs and training process for dynamic model identification purposes.

NNs have several important characteristics that identify them as suitable for the identification and control of nonlinear systems: their ability to learn, their ability for approximation of nonlinear functions and their inherent parallelism. In fact, they have been applied very successfully in the identification and control of dynamic systems. The universal approximation capabilities of the multilayer perceptron make it a popular choice for modeling nonlinear systems and for implementing general-purpose nonlinear controllers [15].

This work consists of the development of a controller that responds for the unit that is responsible for pitching the blades of a wind turbine. The aim is to promote, the maximization of the energy captured, while minimizing the loads of the turbine. This is a typical problem of a complex and nonlinear process. An efficient exploration of the well-known environment MatLab/Simulink for designing and testing a neural MPC was used.

## 4 DEVELOPMENT OF A MODEL PREDICTIVE CONTROLLER

Over the last decade MPC has emerged as the standard for multivariable control in the process industries. Its ability to handle large complex systems involving hundreds of controlled and manipulated variables, dynamic interactions, time delays and constrains make it an attractive tool for many challenging control tasks [10].

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In all NNs architectures used for control two steps are involved: system identification and control design. In the system identification step, a NN model, of the plant under control, is developed, and in the control design step this plant model is used to train the controller, which is a simple rearrangement of the plant model.

### 4.1 System identification

System identification is a technique that permits build mathematical models of dynamic systems based on input-output data.

The first step in NN predictive control is to train a NN to represent the dynamics of the plant. We can represent the output of the dynamical system at time t by y(t) and the input by, u(t). The data set of corresponding inputs and outputs specifies the training set:

$$Z^N = \{[u(t), y(t)], T = 1, \ldots, N\} \tag{4}$$

The objective of training is then determine a mapping from the set of training data to the set of possible weights, so that the NN will produce predictions y(t), witch in some sense are "close" to the true outputs y(t). The prediction error between the plant output and the neural network is used as the NN training signal, see Figure 5.

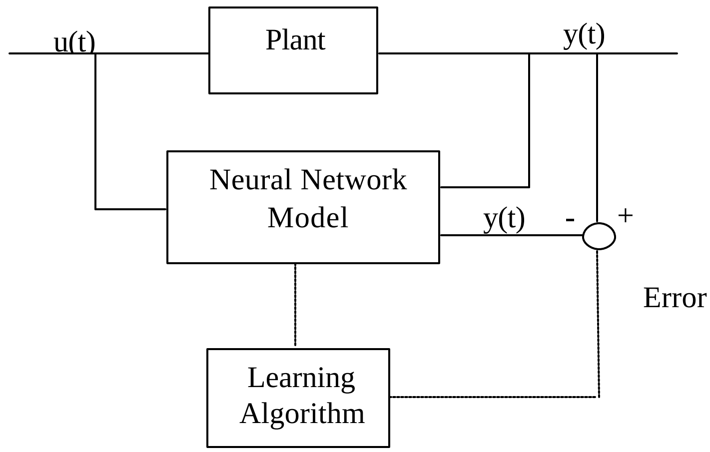



Figure 5: The identification step

### 4.1.1 System identification of the pitch control model

The MLP architecture was chosen and the back-propagation method was used to train the neural network. The training sets were based on sampled data taken from the simulated system of the aerodynamic part of the wind turbine that was implemented in Simulink, see Figure 6 - equations (1) to (3) were applied. Wind speed varies from rated speed (11 m/s) to cut-out speed (25 m/s). Rotational speed was maintained fixed at the maximum value (2.98 rad/s). For u(t) was used the values of Beta that permits obtaining values of $P_t$ near the rated power (660 kW).

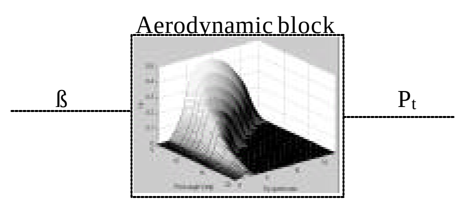



Figure 6: Simulink block used for plant identification

The NN used has 1 hidden layer with 7 neurons, and 2 delayed plant inputs and outputs. The training data used to train the network in the system identification phase is shown in Figure 7.

## 4.2 NN predictive controller

The name predictive control (or model predictive control), steams from the idea of employing an explicit model of the plant to be controlled which is used to predict the future output behavior. This prediction capability allows solving optimal control problems on line, where tracking error, namely the difference between the predicted output and the desired reference, is minimized over a future horizon, possibly subjected to constraints on the manipulated inputs and outputs [1].

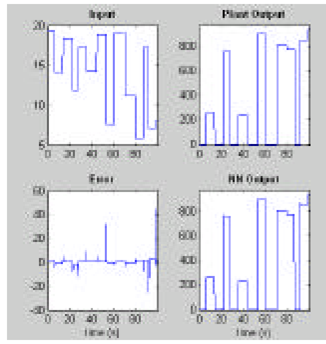



Figure 7: Training data for system identification

The result of the optimization is applied according to a receding horizon philosophy. At time t, only the first input of the optimal command sequence is actually applied to the plant. The remaining optimal inputs are discarded, and a new optimal control problem is solved at time t + 1. The idea is illustrated in Figure 8. As new measurements are collected from the plant at each time t, the receding horizon mechanism provides the controller with the desired feedback characteristics.

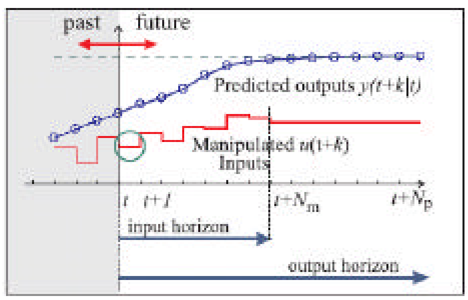



Figure 8: Receding horizon strategy

In the Simulink NN predictive control block, the NN model predicts the plant response over a specific time horizon. The control sign u' is chosen to minimize the quadratic performance criterion

$$J = \sum_{j=N_1}^{N_2} \left( y_r(t+j) - \hat{y}(t+j) \right)^2 + r \sum_{j=1}^{N_u} \left( u'(t+j-1) - u'(t+j-2) \right)^2 \tag{5}$$

where $N_1$, $N_2$ and $N_u$ define the horizons over which the tracking error and the control increments are evaluated. The u' variable is the tentative control signal, $y_r$ is the desired response and y is the network model response. The value of ? determines the contribution that the sum of the squares of the control increments has on the performance index[17].

As Figure 9 shows the controller consists of the NN controller plant and the optimization block. The optimization block determines the values of u' that minimize J, and then the optimal u is input to the plant.

### 4.2.1 NN predictive controller of the pitch angle

The constructed predictive model should be sufficient accurate to catch the main dynamics of the system, but at the same time simple enough to efficiently compute predictions.

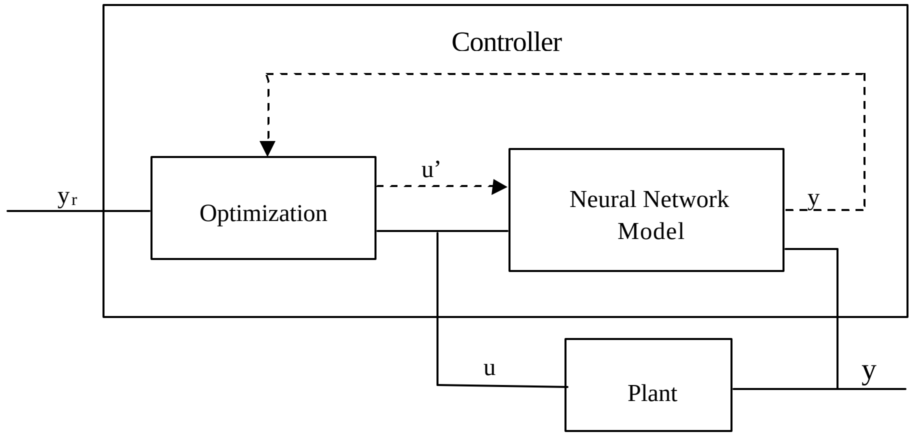



Figure 9: Implementation of the controller block in Simulink

The overall system with the NN model reference controller is realized with MatLab/Simulink software and is shown in Figure 10.

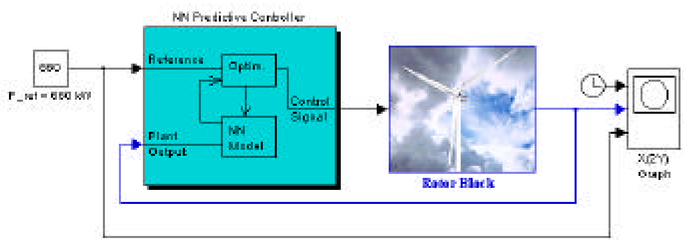
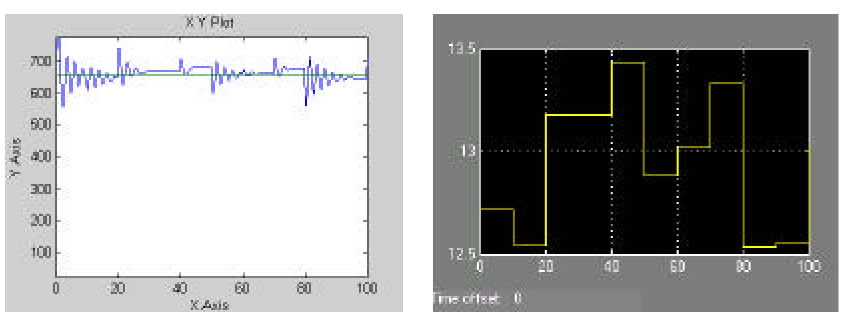



Figure 10: Block diagram of model reference controller of the pitch angle ß

The controller horizons $N_1$, $N_2$ and $N_u$ were fixed in 1, 3 and 2 respectively. The control weighting factor ?, is fixed in 0.5. The obtained results are presented now.

The desired power versus the response of the system is shown in Figure 11-a), with a wind speed signal about 13/s (above rated speed), Figure 11-b).




a) b)

Figure 11: a) Rated power versus output signal of the system b) wind speed signal

Basically the main idea is that, blade pitch can be changed to provide power smoothing in high wind speeds. Nevertheless, what the figures shows is what [9] says, in practice, power is only controlled in the average and some power fluctuations still exist.

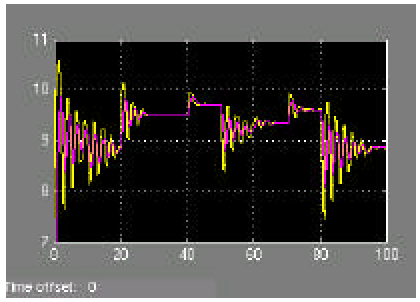



**Figure 12:** Control signal (Beta_ref) and actuator output (pitch angle)

Analyzing Figure 12, we can see the control signal produced by the NN MPC, with the real actuator output, the pitch angle of the blades. The faster the pitch mechanism responds to gusts, the smoother the power in high winds will be. However, blade rotation velocities are limited by the strength of the pitching mechanism and blade inertia.

## 5 CONCLUSIONS

A suitable NN MPC was designed and tested using simulation software, for smoothing the power produced by a wind turbine. Matlab NN Toolbox has proved a very powerful tool for building the purposed architecture and perhaps extended to build a more complex model. Nevertheless, more experimental work will be needed to validate that the controller would be a practical alternative to actual existing controllers in wind turbines. A comparison must be made between real results and the results of the simulation model.

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