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Optimization of Wind Power Based on an Intelligent Hybrid Controller

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Abstract
In this paper, the extraction of wind power energy is optimized based on a proportional integral (PI) controller that uses constants gains, which are calculated after applying several tests to a particular simulated wind energy conversion system (WECS). The tool Labview of MATLAB was used for the simulation of the WECS. A neural network (NN) is used for estimating the wind speed based on the measurements of torque load and the turbine rotational speed. Once the wind speed is determined, the optimal angular speed is calculated using a power coefficient (C_p) curve and the controller works in reaching the set point.

Keywords: *Wind Energy Conversion Systems, Energy Optimization, Functional Approximations, Power Point Tracking, Optimization Algorithms*

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I. INTRODUCTION

Wind power technology has developed rapidly in the last two decades, in fact, in 2023, 1 Tw of global wind power was reached and it is expected to present from now on, an increment of more than 100 Gw every year [1]. As the world seeks to transition to a more sustainable energy future, the importance of wind energy and other renewable sources continues to grow [2]. Wind energy conversion systems, have become increasingly important for several reasons: in first place wind is a natural, inexhaustible resource. Unlike fossil fuels, wind energy does not deplete over time, making it a sustainable option for long-term energy production.

Wind energy generation produces no greenhouse gas emissions during operation; this helps mitigate climate change by reducing the reliance on fossil fuels, which are significant contributors to global warming and air pollution. By harnessing wind energy, countries can reduce their dependence on imported fossil fuels, enhancing energy security and reducing vulnerability to energy price fluctuations. Besides, the wind energy sector creates jobs in manufacturing, installation, maintenance, and other related industries. It also stimulates local economies, especially in rural areas where wind farms are often located.

Continuous advancements in wind turbine technology have made wind energy more efficient and cost-effective. Innovations have led to larger, more efficient turbines that can generate more electricity from the same amount of wind. Furthermore, wind energy systems can be deployed on various scales, from small, distributed systems for individual homes or businesses to large-scale wind farms. This flexibility allows for diverse applications and can help integrate renewable energy into existing power grids.

While not without environmental challenges (such as impacts on wildlife and noise), wind energy generally has a lower ecological footprint than other energy sources, especially when considering the entire lifecycle of energy production. Finally, wind energy can contribute to a more decentralized power generation system, reducing the need for large, centralized power plants and enhancing grid resilience [3-5].

Because of its importance, a large number of papers have been published about renewable energy technologies and different approaches. Different tools, such as classical analog and digital control and neural networks, covering arrays, artificial intelligence, diffuse control, meta-heuristics, genetic, and bio-inspired algorithms, have been used for optimization processes, including wind power [6-21].

Working with the C_p curve (which the manufacturer usually provides) is common in WECS; nevertheless, it does not appear as a function, which makes it challenging to handle. There are several representations of C_p, which have been presented in different studies [22-24], some of them are worth to be considered, since they present a reliable option for determining the optimum rotational speed to maximize wind power extraction during the process.

II. DYNAMIC MODELING

Let us consider (1), which defines the C_p relationship between the wind power and the extracted power by the turbine.

$$C_p = \frac{W_p}{T_p} \qquad (1)$$

Where: W_p is the power of the wind and T_p is the power extracted by the turbine. Theoretically speaking, according to Betz limit, the maximum C_p value is $\frac{16}{27} \approx 0.593$, nevertheless, it has been demonstrated that in determined controlled circumstances, this value can be surpassed [25]. In this particular case, the function for C_p is provided by (2), while λ is determined by Eq. (3):

$$C_p(\lambda) = \frac{1.8e^{-0.8(\lambda-4)}}{\left(1+e^{-0.18(\lambda-4)^2}\right)\left(1+e^{-1.26(\lambda-4)}\right)} \qquad (2)$$

$$\lambda = \frac{\omega_r R}{W_s} \qquad (3)$$

Where: ω_r is the rotational angular speed of the turbine (the same than the generator because a direct connection was used), R is the turbine radio, and W_s is the wind speed.

In the Figure 1, the C_p curve correspondent to Eq. (2) is presented. As it can be seen, there is a relationship between the maximum C_p and the correspondent value of λ, this is $(\lambda_{opt}, C_{p_{Max}}) = (4.818, 0.485)$.

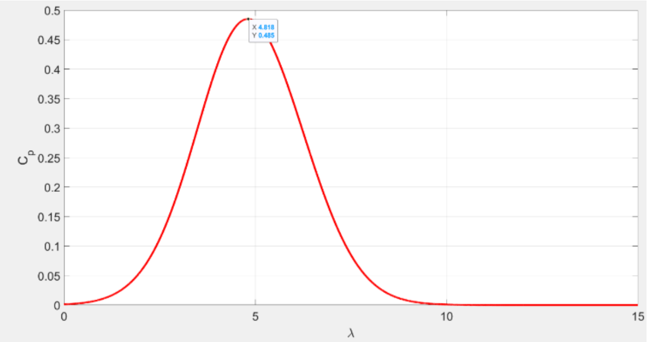

Fig. 1. C_p curve dependent on λ

The C_p curve provided by the manufacturer (shown in Figure 2) of a particular trademark was adjusted to be represented by functional approximations. There are several methods for adjusting curves [26,27], but in this case, polynomial approximation by sections was chosen. On the other hand, a NN trained by around 30 thousand pairs of inputs (T_L, ω_r) was used to estimate the wind speed. Once W_s was determined, the optimum ω_r was calculated using Eq. (4). Figure (3) shows the general diagram of the process.

$$\omega_{r_{opt}} = \frac{\lambda_{opt} W_s}{R} \qquad (4)$$

As it can be seen in Eq. (4), λ_{opt} and the turbine ratio are well known, while the wind speed is calculated by the NN thorough the measurements of T_L, ω_r. The system was simulated in Simulink.

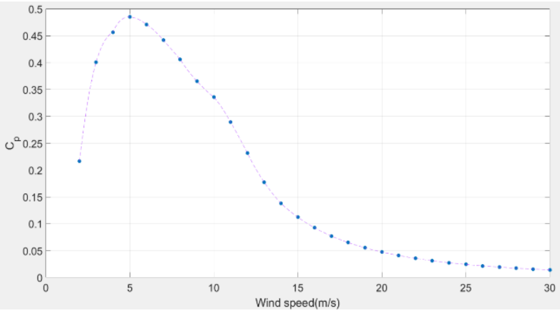

Fig. 2. Turbine's C_p curve generated by sectional polynomial approximation based on the C_p data provided by the manufacturer

The manufacturer's C_p information is dependent on the wind speed; nevertheless, it is more convenient to be presented dependent on λ, so a swept algorithm through the manufacturer's C_p data and Eq. (2) was performed in order to create a manufacturer's C_p curve dependent on λ; then, the T_L *and* ω_r can be calculated to train the NN. Once the weights of the NN were calculated, the pairs T_L, ω_r are the input, and $\omega_{r_{opt}}$ was determined for each pair.

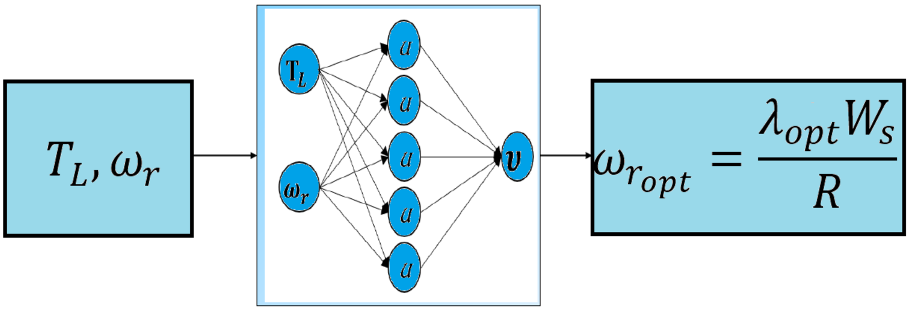

Fig. 3. Diagram for calculating optimum ω_r

III. NEURAL NETWORK

The NN utilized one input, one output, and a hidden layer. The data divisions were random, the training used was Levenberg-Marquardt, and the performance was mean squared error (MSE). 1000 iterations were executed to obtain the best validation epoch, which was $6.058x10^{-7}$ and was reached at epoch 1000, as shown in Figure 4. On the other hand, Figure 5 shows the Gradient, Mu, and validation checks in everyone of the 1000 epochs.

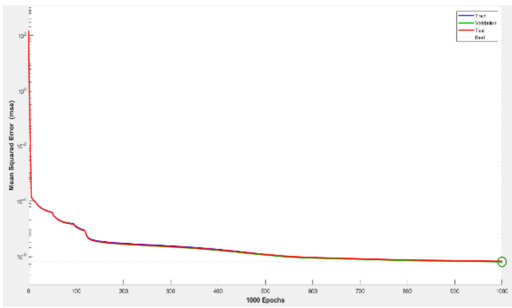

Fig. 4. Epoch validation performance

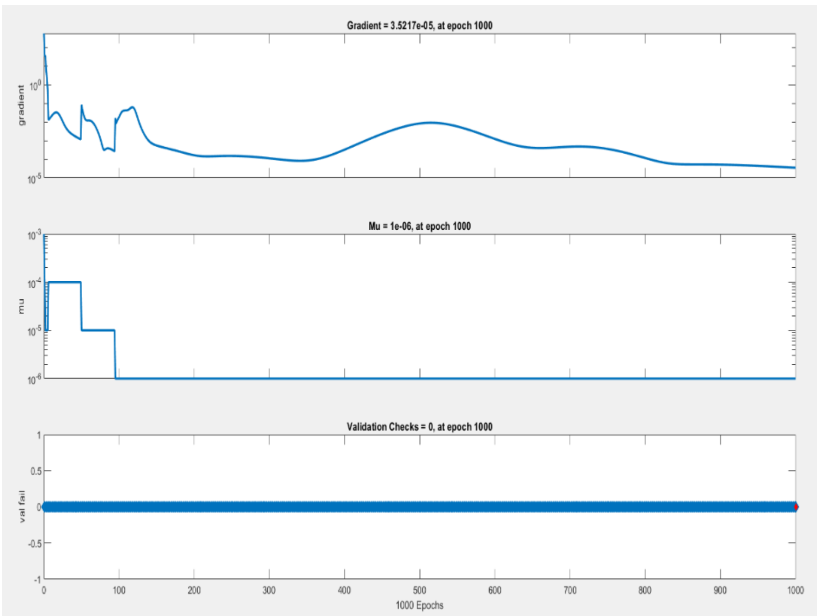

Fig. 5. Epoch validation performance

Finally, Figure 6 presents the NN training regression, with epoch 1000 being the maximum epoch reached. Training, test, validation, and the whole performance elements are presented respectively in every quadrant of the figure.

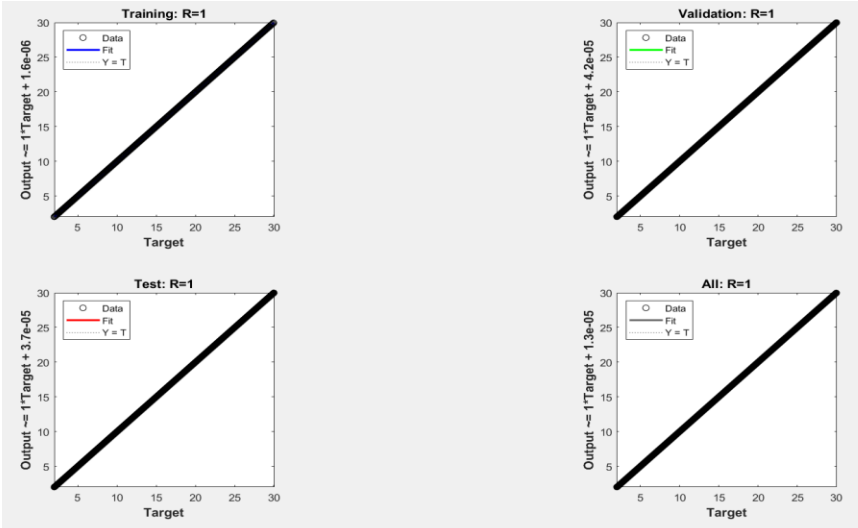

Fig. 5. Neural network training regression

IV. BLOCKS DIAGRAM

Figure 5 represents the general block diagram for maximizing the wind power extraction. The wind turbine and the permanent magnet synchronous generator (PMSG) are in a direct drive connection. A multilevel boost converter (MBC) extracts the energy from the PMSG by commuting the power transistors. The proportional integral (PI) controller (which gains were determined thorough different dynamic tests applied to the simulated system in Simulink), is responsible for sending the appropriate duty cycle to the MBC to reach the optimum turbine angular speed calculated by the NN for every pair T_L, ω_r. Finally, a pure resistive load in star connection is placed at the final stage of the WECS.

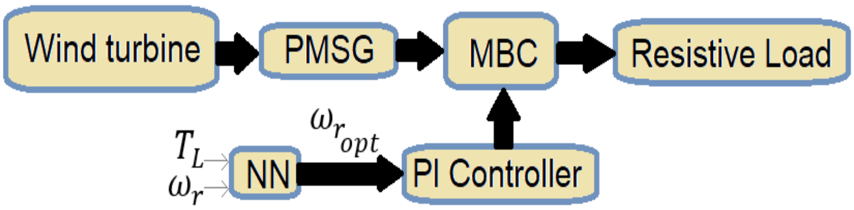

Fig. 5. General block diagram

The structure for the PI digital controller is shown in Eq. (5), where x_I, x, u, r are the state variable of the integrator, state variable of angular speed, the duty cycle input, and the negative feedback of the angular speed respectively. C, G and H are matrices of dimension $1x1$.

$$\begin{bmatrix} x_I(k+1) \\ x(k+1) \end{bmatrix} = \begin{bmatrix} 1 & C \\ 0 & G \end{bmatrix} \begin{bmatrix} x_I(k) \\ x(k) \end{bmatrix} + \begin{bmatrix} 0 \\ H \end{bmatrix} u(k) - \begin{bmatrix} 1 \\ 0 \end{bmatrix} r(k) \qquad (5)$$

V. RESULTS

In order to verify the performance of the simulated WECS, 20 different wind speeds were estimated by the NN and then sent to the PI controller. Every 18 seconds wind speed variations were programmed for the tests. As can be seen in Figure 6, the optimum angular speed was reached approximately in five seconds in every interval. In Figure 7, the PI controller performance can be verified regarding the maximum theoretical wind power extracted. The purple lines represent optimum theoretical values, while the orange lines represent the dynamic changes of the variables ω_r and wind power extracted. Table 1 shows the different wind speeds estimated by the NN to test the PI controller.

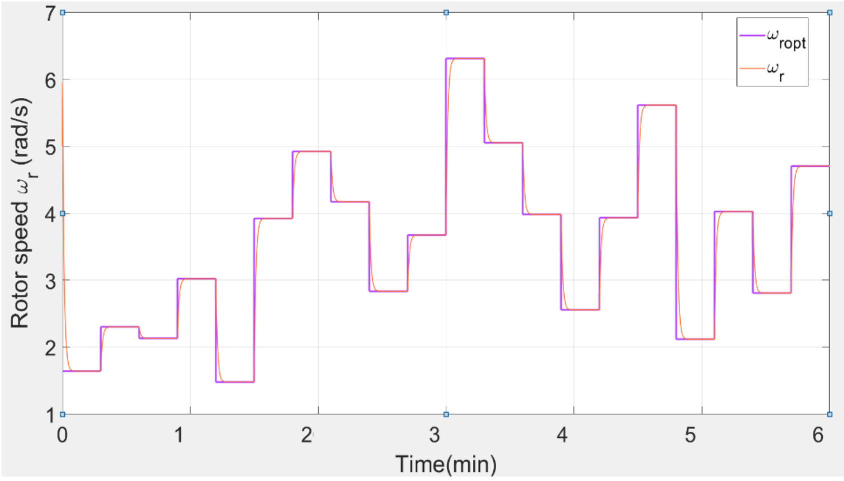

Fig. 6. Rotor speed behavior

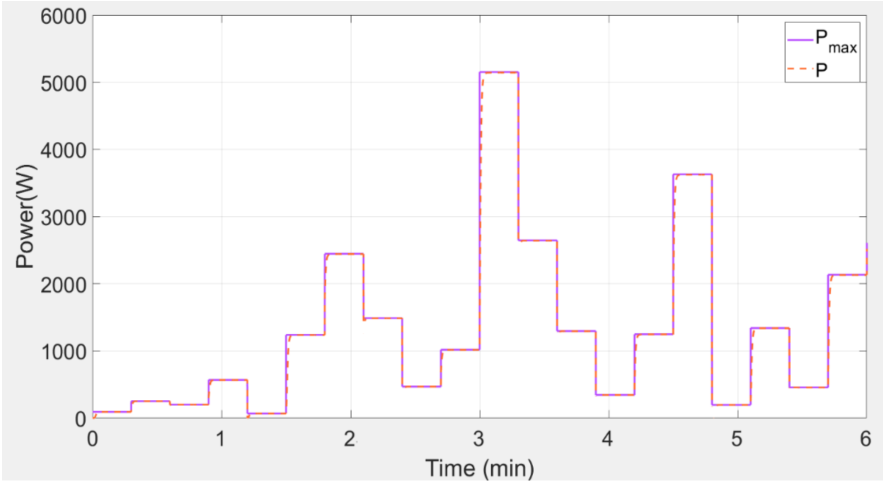

Fig. 7. Wind power extracted behavior

Table 1. Wind speeds estimated by the NN for verifying the PI controller performance

Interval(s)	Wind speed m/s	Interval(s)	Wind speed m/s	Interval(s)	Wind speed m/s	Interval(s)	Wind speed m/s
0-18	5.03	90-108	12.01	180-198	19.32	270-288	17.19
18-36	7.05	108-126	15.07	198-216	15.47	288-306	6.49
36-54	6.53	126-144	12.77	216-234	12.19	306-324	12.33
54-72	9.26	144-162	8.68	234-252	7.83	324-342	8.6
72-90	4.53	162-180	11.25	252-270	12.04	342-360	14.4

VI. FINDINGS AND COMMENTS

The neural network was able to appropriately obtain the different wind speeds for every pair T_L, ω_r, while the constant gains obtained by different dynamic tests in the simulated WECS in Simulink allowed the system to present a remarkable performance in reaching the optimum rotational speed and, consequently, maximum wind power extraction.

VII. CONCLUSION

This work used a hybrid PI controller to optimize the wind power extraction. On the one hand, the different tests applied to the simulated WECS allowed the linearization of the system without losing dynamic enrichment. The results confirmed the controller's reliability. On the other hand, it isn't easy to measure accurately the wind velocity. Nevertheless, the NN presented an excellent performance for estimating the wind speed through the pair T_L, ω_r, which are variables more straightforward to measure. Finally, Eq. (2) allowed us to build a correspondence between the manufacturer's C_p values and the tip speed ratio λ, hence, it is easy to calculate the pair T_L, ω_r to train the NN.

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