Comparison of long short-term memory and deep neural network optimized neural networks for maximum power tracking of wind turbines

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ABSTRACT

In wind energy conversion systems, maximum power point tracking (MPPT) performance is crucial, as it is directly related to wind speed variability and the characteristics of the equipment used. Maximum power point tracking controllers are essential for optimizing the efficiency of wind power generation. This paper presents the development of three distinct approaches to maximum power point tracking: the classical perturb and observe (P&O) method, and two other techniques based on artificial intelligence, namely long short-term memory (LSTM) networks and deep neural networks (DNNs). Rather than focusing solely on the development of an intelligent neural network-based maximum power point tracking model, our work emphasizes the design of a deep neural network controller with an optimized architecture and a reduced number of layers and neurons per layer, thereby simplifying its implementation in embedded process control units while maintaining high maximum power point tracking performance. The results obtained show that our optimized deep neural network model identifies the point of maximum power more effectively than other techniques, demonstrating remarkable performance in terms of response time, accuracy, and the quality of the generated power.

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1. INTRODUCTION

Renewable energy sources, particularly wind power, are playing a key role in the global transition to sustainable energy [1]. Wind farms generate electricity by harnessing the kinetic energy of the wind, thereby reducing dependence on fossil fuels and cutting greenhouse gas emissions. For wind turbines to operate efficiently, it is necessary to extract as much power as possible despite variations in wind speed. This fluctuation complicates the maximum power point tracking (MPPT) process. For each specific wind speed, there is an optimum operating point that guarantees maximum energy production. This is why MPPT algorithms are essential for continuously adjusting turbine performance to achieve maximum energy production [2], [3].

To increase energy extraction from wind turbines, conversion systems often use permanent magnet synchronous generators (PMSGs), which has given rise to extensive research into optimization strategies [4], [5]. Numerous MPTT methods and converter designs have been proposed to improve efficiency. These methods vary in terms of cost, convergence speed, complexity, sensor requirements and simplicity of implementation [6]. MPPT techniques are generally grouped into classical and artificial intelligence methods [7]–[9]. Traditional approaches such as fractional open-circuit voltage (VOC) and incremental conductance (IC), hill climbing (HC), and perturb and observe (P&O), are simple but can react slowly to rapid wind changes. Solutions based on artificial intelligence, such as neural networks and fuzzy logic, can overcome these limitations and achieve higher performance. These latter make it possible to model the relationships between different system variables in a complex way, and to adapt the control strategy in real time.

Most existing work in the literature of wind turbine maximum power point tracking focuses on improving tracking speed, reducing oscillations, and maximizing extracted power. Our work continues to pursue these objectives while proposing an innovative approach: an optimized MPPT model, designed to minimize computational resources while guaranteeing high-performance tracking. This article presents the application of three maximum power point tracking techniques: one classical technique, that is, perturbation and observation, and two intelligent techniques, which are artificial neural network architectures, long short-term memory (LSTM) and deep neural networks (DNN). In particular, we focus on optimizing the structure of neural networks to reduce their complexity and facilitate their implementation in embedded systems.

This document is divided into four main sections. First, the wind turbine and PMSG generator models are described in detail. Next, the development and validation of the control strategies are presented. The third part discusses the simulation results. Finally, the conclusion summarizes the study and presents prospects for future improvements.

2. THE STUDIED WIND TURBINE SYSTEMS

As shown in Figure 1, the system under study comprises a wind turbine equipped with a permanent magnet synchronous generator. This device transforms the wind's mechanical energy into electrical energy in the form of three-phase alternating current. The electrical energy generated by the PMSG is then rectified into direct current by a diode bridge. This direct current is then boosted in voltage by a boost converter, enabling the maximum power point to be tracked and the voltage level to be adapted to the requirements of the electrical load.

The key element of our system is the maximum power point tracking control techniques. These techniques, such as perturb and observe, long short-term memory networks and deep neural networks, aim to continuously optimize the operation of the wind turbine in order to get the maximum available energy from the wind. By adjusting the generator's operating point, the system's energy efficiency is maximized.

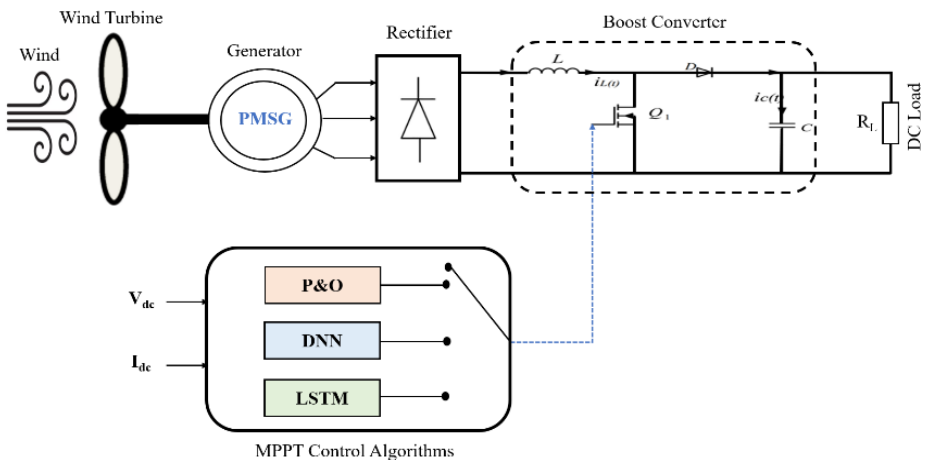


Figure 1. Block diagram of the studied system

2.1. Model of wind turbine

The wind turbine is a device used for converting the wind's energy from kinetic energy into mechanical energy. This conversion process can be described by an equation that relates the mechanical power produced (Pm) to the wind speed [10]–[13].

$$P_m = \frac{1}{2} C_p \rho \pi R_t^2 V_w^2 \quad (1)$$

In permanent operation, this power is proportional to the air density (ρ), the area swept by the blades (determined by the turbine radius R_t), and the cube of the wind speed (V_w). A coefficient of performance (Cp) is also included in this equation, representing the turbine's energy efficiency. This coefficient is strongly influenced by geometric parameters such as the number of blades, their pitch, and their profile, and is theoretically limited by Betz's law. The tip speed ratio (λ) is defined as the relationship between the speed of the blade tips and the wind speed:

$$\lambda = \frac{\Omega R_t}{V_w} \quad (2)$$

The torque produced by the turbine (T_m) is then expressed by (3):

$$T_m = \frac{P_m}{\Omega} = \frac{1}{2\Omega} C_p(\lambda, \beta) \pi \rho R_t^2 V_w^2 \quad (3)$$

When the speed ratio is kept at its optimal value λ_opt, the power coefficient reaches its maximum Cp_max. In this condition, the maximum extractable power from the wind turbine is:

$$P_t^{optimal} = \frac{1}{2} C_{pM} \rho \pi R_t^2 V_w^2 \quad (4)$$

Figure 2 illustrates that for each wind speed. There is an optimal rotor speed that allows the turbine to capture maximum power. This fluctuation in the power point highlights the importance of developing and integrating effective monitoring or tracking methods to ensure wind turbines consistently produce maximum power.

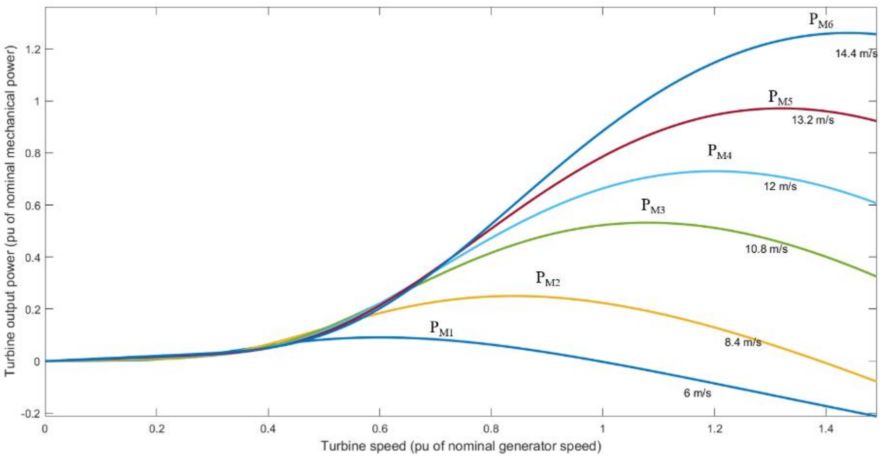


Figure 2. Power curves for a wind turbine at various wind speeds

2.2. Permanent magnet synchronous generator model

PSMGs are commonly employed in wind energy systems and operate on three phases produced by stator field windings. By neglecting the homopolar components of the flux, the model can be simplified using Park transformations [14]–[17]. The simplified mathematical model is described by the system of (5) and (6):

$$\begin{cases} V_d = -R_s I_d - L_d \frac{dI_d}{dt} + \omega L_q I_q \\ V_q = -R_s I_q - L_q \frac{dI_q}{dt} + \omega L_d I_d + \omega \emptyset_f \\ \frac{dI_d}{dt} = -\frac{R_s}{L_d} I_d + \omega \frac{L_q}{L_d} I_q - \frac{1}{L_d} V_d \\ \frac{dI_q}{dt} = -\frac{R_s}{L_q} I_q - \omega \left(\frac{L_d}{L_q} I_d + \frac{1}{L_q} \emptyset_f \right) + \frac{1}{L_q} V_q \end{cases} \quad (5)$$

The electromagnetic torque can then be defined by (6):

$$T_{em} = \frac{3}{2}\left(\frac{P}{2}\right)\left[\left(L_d - L_q\right)I_d I_q + I_q \emptyset_f\right] \tag{6}$$

where P denotes the number of pole pairs and ω is the generator's angular speed. The $\emptyset_f$ refers to the permanent magnet flux. I_d and I_q are the direct and quadrature components of the stator current, respectively. V_d and V_q indicates the direct and quadrature voltages of the stator. L_d and L_q stands for the stator's direct and quadrature inductances, and R_s represents the stator resistance.

3. WIND ENERGY CONVERSION SYSTEM (WECS) CONTROL STRATEGY

Renewable energy sources, such as wind turbines, are characterized by intermittent and fluctuating energy production. To maximize energy capture from these sources, MPPT algorithms are used. By tracking the power of the DC link and dynamically adjusting the system's operating parameters, MPPT techniques enable the system to track the point of maximum power and extract the maximum available power from the wind resource [18]–[20]. To overcome the limitations of conventional MPPT controllers (fixed pitch, oscillations around the MPP, low tracking efficiency, complexity due to a large number of hidden neurons), we propose intelligent MPPT controllers based on an optimized DNN and LSTM neural network.

For MPPT control, neural network training involves pre-processing noisy data, then dividing it into training, validation and test sets. In both DNN and LSTM cases, the controller uses voltage (V_{dc}) and current (I_{dc}) as inputs and aims to optimally adjust the duty cycle of the DC/DC converter. This section will be dedicated to the presentation of the controllers (LSTM and DNN) used and their development stages.

3.1. Long short-term memory (LSTM)

LSTMs are a type of recurrent neural network (RNN) ideal for time series data. They are useful for optimizing energy extraction in wind turbines by implementing MPPT algorithms. In this study, we propose to use an LSTM network to predict the MPP of a wind turbine in real time. In the case of MPPT control, LSTMs are trained to model the non-linear relationship between input variables (voltage, current) and the output variable (duty cycle) used to control the DC/DC inverter. Table 1 illustrates the components of the LSTM controller architecture used in this study. It shows a two-dimensional input sequence processed by a 10-unit LSTM layer, plus a fully connected layer and a regression output layer with a single output.

Figure 3 shows the performance of the LSTM controller. The first curve illustrates the evolution of root mean square error (RMSE). This curve shows a rapid decrease in error at the start of training, then stabilizes at a low value. This indicates that the model is learning efficiently from the training data and is achieving satisfactory performance. The second curve represents the loss function, whose evolution is almost similar to that of the RMSE. The decrease in this loss means that the model is successfully minimizing the difference between its predictions and actual values.

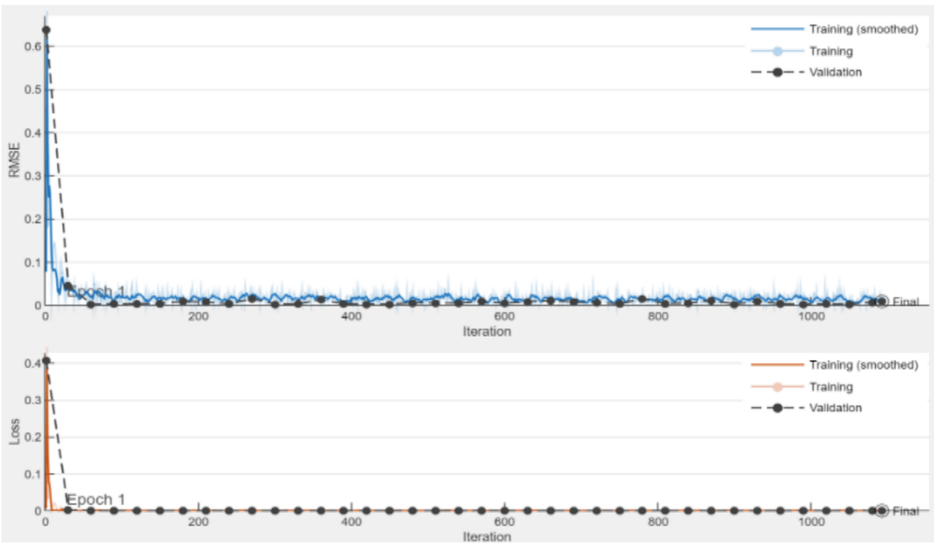


Figure 3. LSTM controller training performances

Table 1. The used LSTM controller architecture

	Name	Type	Activations
1	Sequence input with 2 dimensions	Sequence input	2
2	LSTM with 10 hidden units	LSTM	10
3	Fully Connected	fully connected layer	1
4	R-mean-squared-error	Regression output	1

3.2. Optimized deep neural networks

ANNs are information processing systems inspired by the human brain. They have been the subject of intense research and the extraction of pertinent information from complex data. Their flexible architecture enables ANNs to learn patterns, make predictions and aid decision-making in many areas, such as MPPT for wind turbines, which is their application objective in our case. Figure 4 shows the architecture of an ANN conceived for tracking the point of maximum power. The neural network uses voltage and current as inputs. It is trained to predict the optimal duty cycle to apply to the DC/DC converter, with the aim of extracting maximum power from the wind turbine.

The design of neural networks poses challenges of computational complexity, as the number of layers in the network can lead to excessive computation times. It is crucial to find a balance between model complexity and capacity for generalization. This study aims to optimize the architecture of a deep neural network to reduce computational costs while maximizing performance. To achieve this, we carried out several series of experiments. We varied parameters such as the number of hidden and output layers (HL and HO), activation functions, number of neurons per layer, number of learning iterations and optimization algorithms. The detailed results of these experiments are presented in Table 2.

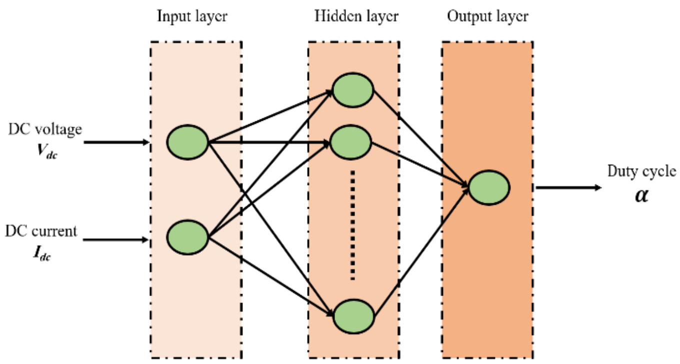
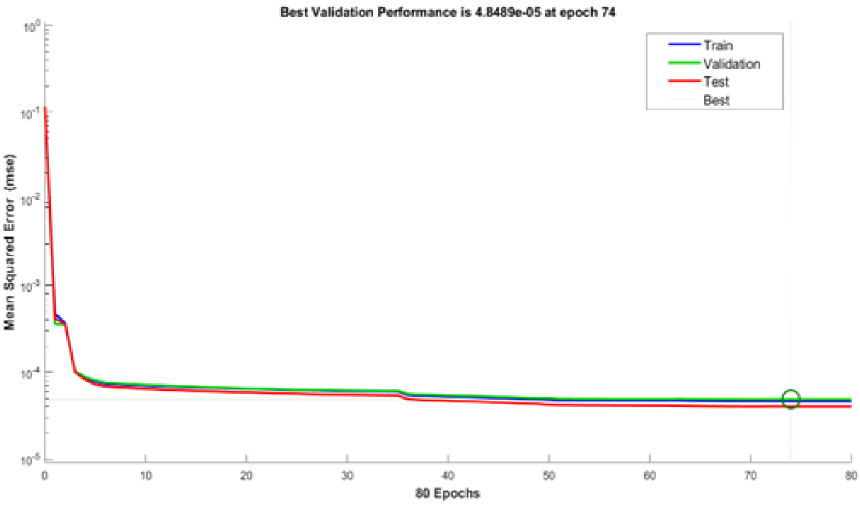


Figure 4. MPPT artificial neural network architecture

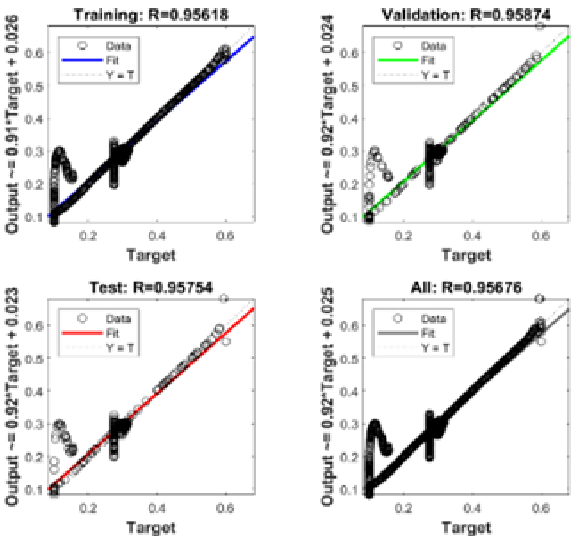
Table 2. Summary of best training results

Algorithm	MLP model structure	HL and OL	R square	MSE (x10-4)	N° of Epoch
Variable learning rate gradient descent	[2-10-1]	Logsig - Purelin	0.937	3.3409	321
	[2-4-1]	Tansig - Purelin	0.926	1.02598	428
	[2-6-1]	Purelin - Purelin	0.942	4.32863	197
Gradient descent with momentum	[2-3-1]	Logsig - Purelin	0.947	1.32985	386
	[2-4-1]	Tansig - Purelin	0.926	2.29044	484
	[2-7-1]	Purelin - Purelin	0.932	3.32875	783
The resilient backpropagation algorithm	[2-5-1]	Logsig - Purelin	0.923	0.70639	101
	[2-9-1]	Tansig - Purelin	0.956	0.90728	94
	[2-12-1]	Purelin - Purelin	0.942	1.42508	75
	[2-5-1]	Logsig - Purelin	0.956	0.48489	74
Levenberg-Marquardt	[2-7-1]	Tansig - Purelin	0.956	0.89862	93
	[2-9-1]	Purelin - Purelin	0.937	0.97868	52

Table 2 shows that, when using the Levenberg-Marquardt algorithm as the training optimization approach with a [2-5-1] architecture and using the Logsig-Pulin activation functions as the hidden layer and output layer activation functions, respectively, we achieved satisfactory results in terms of MSE and correlation coefficient at epoch 74. These improved results are shown in Figures 5(a) and 5(b). Analysis of the performance curve reveals two distinct phases in model learning. From the first few epochs we observe a rapid decrease in the mean square error, reflecting effective mapping of relationships in the data and a correctly adjusted learning rate. This initial phase shows a progressive convergence towards a remarkable minimum value of 4,8489×10^{-5} reached at 74 epochs. The final stabilization of the error at this extremely low level (of the order of 10^{-5}), with no noticeable fluctuation, confirms not only the model's ability to perfectly minimize the gap between predictions and target values, but also the absence of overlearning. Moreover, the correlation coefficient shown in Figure 5(b) is very close to 1, shows the strong correlation between the optimized DNN model outputs and desired outputs.



(a)



(b)

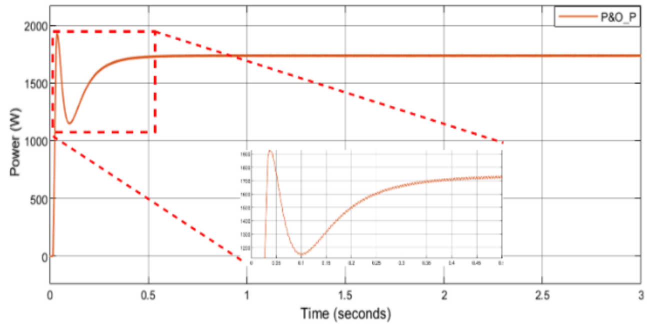
Figure 5. DNN model performance: training, validation and testing (a) DNN training performance and (b) regression analysis of the DNN model

4. RESULTS AND DISCUSSION

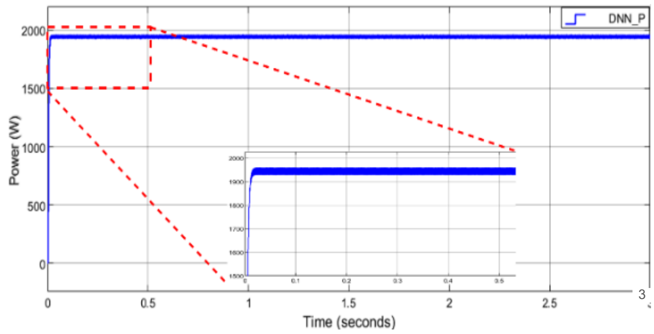
The objective of this section is to present, analyze, and compare the results of maximum power point tracking provided by the LSTM and DNN models, as well as by the classic P&O method. To validate the robustness of the models we have developed, we will test them under two distinct operational conditions. The first will involve tracking the maximum power point in an environment of constant wind speed, while the second will assess their ability to adapt to variations in wind speed.

Scenario 1: Constant wind speed

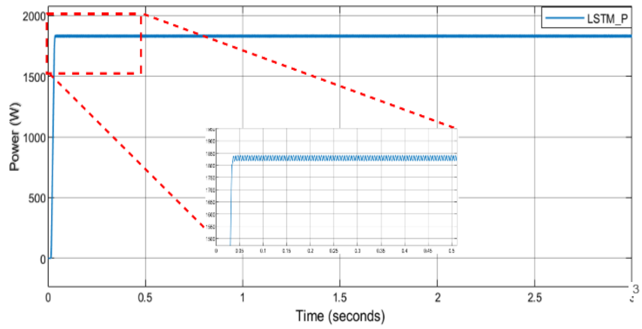
In this case, the wind turbine was given a constant wind speed (12 m/s). Figures 6(a), 6(b), and 6(c) illustrate the maximum power produced using different methods: respectively, the method based on the perturbation-observation technique (P&O_P), the proposed method based on the LSTM model (LSTM_P), and the method based on the proposed optimized DNN model (DNN_P). Figure 6(d) shows a comparison between the power extracted by the three techniques and the theoretical maximum power (Theoretical_P). It is clear that the three methods are very close in terms of maximum power, but a significant difference is observed when using the proposed DNN model. In fact, the use of the optimized DNN model offers higher performance, with an efficiency of 98.7% and a remarkable tracking speed. The optimized DNN model succeeds in locating the point of maximum power in 0.032 seconds.



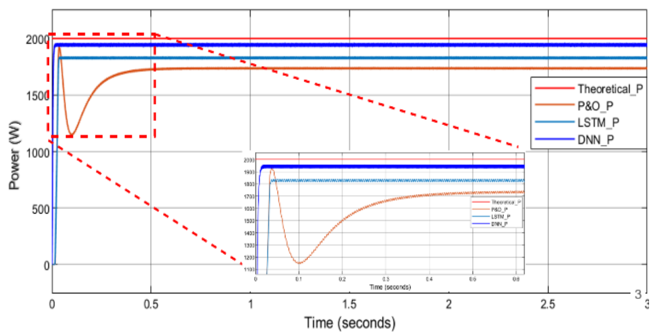
(a)



(b)



(c)



(d)

Figure 6. The maximum power extracted (constant wind speed) using (a) P&O_P, (b) LSTM_P, (c) DNN_P, and (d) Theoretical_P

Scenario 2: variable wind speed

To validate the robustness of the tracking system in a dynamic environment, we simulated rapid variations in wind speed (5 m/s, 7 m/s, 10 m/s and 12 m/s). The results presented in Figure 7 shows that the optimized DNN model stands out for its ability to efficiently track the point of maximum power, even in the presence of suddenly varying wind speeds. In fact, it is characterized by its reduced oscillations, high efficiency, and very short response time compared to existing work in the field of MPPT tracking improvement for wind power systems [21]–[25].

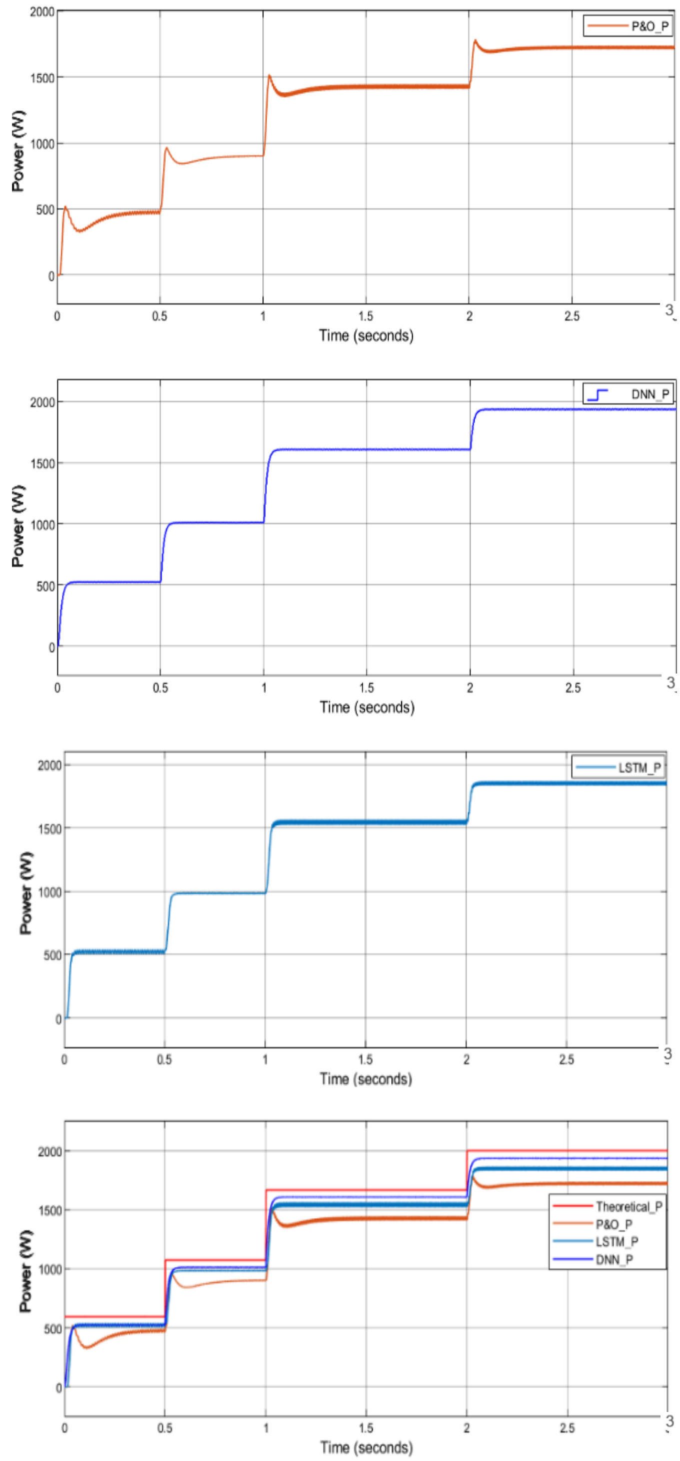


Figure 7. The maximum power extracted (variable wind speed)

5. CONCLUSION

This paper presents an approach to MPTT in wind power systems, a crucial challenge for optimizing energy production and making wind power installations efficient. Our comparative study shows that this solution outperforms both the conventional (P&O) method and the LSTM network-based approach, offering remarkable performance on several levels such as oscillation rate and maximum power point localization speed. The main objective of this research was to design an intelligent controller capable not only of adapting in real time to rapid and unpredictable fluctuations in wind speed, but also of maximizing energy extraction while maintaining optimum operational stability and with optimized neural architecture. Our optimized DNN model has some remarkable features that make it particularly suitable for real-time applications: a reduced oscillation rate around the MPP, a very fast convergence speed, and a very compact neural architecture. These exceptional performances in terms of stability, speed and efficiency make our approach particularly interesting for real-time implementation.

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