Comparative Study of PID and ANN Controllers for AC Output Voltage Regulation in a Photovoltaic Grid

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ABSTRACT

The coupling system of two different sources has always been an important subject of research in the field of electrical grids of any voltage range. In particular, after the connection of the photovoltaic and the public grids, the voltages cannot be distinguished from each other, because after their coupling there is one voltage across the output load. In this article, we take into account the variation of the current when the load varies in order to establish the relationship between the measured current and the output AC voltage, which can be regulated using only the current. For this purpose, we employ two types of controllers, the Proportional-Integral-Derivative (PID) controller and the Artificial Neural Network (ANN) controller, using Matlab/Simulink. Despite the connection of an inverter, which increases the loss rate and the error, the results are encouraging considering that the error rate obtained for the ANN controller, which is 1.49%, is much lower compared to that of the PID controller, which is 2.4%. Based on the results obtained, it can be concluded that the ANN controller is the best choice to perform this simulation.

Keywords-photovoltaic grid; public grid; PID controller; ANN controller; coupling; connected grids

I. INTRODUCTION

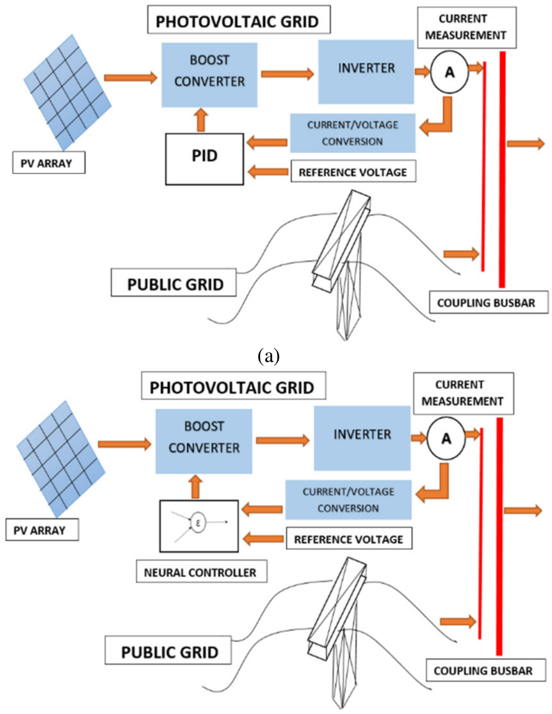
There are several types of networks in buildings that take into account the loads, in particular the active and reactive loads, creating a highly non-linear system. A solution that has been developed to control the load is an intelligent system based on prediction known as Long Short-Term Memory (LSTM) [1]. Connected networks have always been an important subject of research, either in the field of artificial intelligence or even in the study of the impact of different parameters, such as the influence of the network inductance on the quality of the current in a system with a Grid-Connected Inverter (GCI), as well as the intervention of the Proportional-Integral (PI) controller to ensure the correct operation of the loads [2]. Some researchers have opted for conventional methods, away from artificial intelligence, especially in the case of multiple grids connected in parallel, and have based their work only on a single parameter, which is the local stability at the point of connection of these grids, by studying the root causes of the harmonics [3]. Other researchers have a different view regarding connected grids, as they have worked on the performance of the solar power system and improved the DC input voltage variation due to switching by using a closed-loop system [4]. To improve the system from its roots, there are some who have opted for modifying the grid-connected inverter topology by using an improved single-stage topology. The purpose of this process, according to the authors in [5], is to increase the voltage of the photovoltaic generator as well as to convert solar energy into high quality AC current to feed the grid. Researchers who have used artificial intelligence in connected networks have generally relied on a single parameter for improvement, such as in the case of using an intelligent controller which improves active and reactive power [6]. The difference between this controller and other conventional controllers is that it works even when the grid impedance is uncertain. Another work has been carried out to improve the Maximum Power Point Tracking (MPPT) of a photovoltaic system using a combination of a Proportional-

Integral-Derivative (PID) and a Fuzzy Logic Controller (FLC), despite the variable conditions, namely temperature and irradiance, improving the dynamic response, efficiency, and stability of a three-phase inverter connected to the public grid [7]. Authors in [8] conducted a comparative study between a nonlinear controller which is based on the Sliding Mode Control (SMC) approach to establish the control laws of the inverter, using the Lyapunov stability approach to ensure the asymptotic stability of the system, and the well-known FLC. A conventional PI controller was used as the input and an FLC was used to improve the performance. The objective of the two approaches used in this comparison was to control the injected current and to synchronize it with the grid. Authors in [9] considered six fault scenarios including partial shading and open circuit in the photovoltaic array and used Artificial Neural Networks (ANNs) for their diagnosis focusing on the MPPT of the photovoltaic system. Authors in [10] presented an effective integration mechanism with ANN, which produces the best reference signal corresponding to the maximum power location for regulating the MPPT after several variations of PV settings such as temperature and irradiance through a boost converter. Another contribution in the grid area by the authors in [11] is the use of a neural network controller to reduce the current fluctuations in the proton exchange membrane fuel cells with the aim of having a battery with a long lifetime. Authors in [12] compare PID and ANN control methods for a buck-boost converter, where the latter adapts to nonlinearities for improved performance and ultimately provides the best power curve compared to that of the PID. However, their work did not take into account the variation of the load, unlike our work, which consists in controlling the output voltage by changing the load each time, which guarantees the robustness of the regulation. In another work, considered close to ours, the authors studied the performance of a boost converter by regulating its output voltage using the PI control and the ANN control. Both methods were evaluated in terms of accuracy, response speed, and robustness to disturbances, and the PI control proved to be more robust against disturbances. Finally, the simulation is concluded by calculating the efficiency in terms of power. The inverter and the interconnected grids were not considered by the authors, which makes their work partially useful in the field of hybrid grids [12].

Therefore, our work targets an important issue in the field of interconnected grids by performing a simulation of both the solar and the public grid with the purpose of creating a neural controller using Matlab. This controller aims to regulate the AC output voltage of the photovoltaic system after its connection to the public grid. This is achieved by using the current coming from the boost converter, after finding the relationship between this current and the output voltage generated by the inverter, since the direct use of the voltage is not possible because the voltage specific to the PV grid is not known. Using the ANN and PID controllers in Matlab/Simulink allows us to control the AC voltage and compare the results. The reason we chose these types of controllers is that the PID controller has advantages such as simplicity of design, less computational requirements, and stable and robust performance under fixed operating conditions. On the other hand, the ANN controller can adapt to nonlinear dynamics and changing system conditions, provides faster response and better transient performance, and more accurate voltage regulation with minimal steady-state error.

II. PRINCIPLES OF THE SYSTEM

In this study, we use two grids; the first one is an autonomous photovoltaic grid that includes a solar panel, a boost converter and an inverter [12], and the second one is the public grid that directly provides an AC voltage of 220 V at the connection point. As we have already described, the current leaving the boost converter is measured and used to calculate the voltage, the latter being an input of the controller [12]. After correcting the voltage, the inverter provides an AC voltage that is connected to the public grid voltage at the connection point. Figure 1(a) and Figure 1(b) illustrate the general diagrams with a PID and ANN controller, respectively.



(b)

Fig. 1. General diagrams using: (a) a PID controller, and (b) an ANN controller.

A. *Determining the Output Voltage through the Measured Current*

As already mentioned, we measure the current at the output of the boost converter by changing the load, and we also measure the voltage at the output of the inverter. From these measurements (current, resistance, and voltage) we plot the curve that reflects this variation, and the $V(I)$ relation is presented in Table I and Figure 2.

TABLE I. THE $V(I)$ RELATION

R (Ω)	α-duty cycle	V (V)	I (A)
3.0	0.5	244.4	38.50
4.0	0.5	241.2	34.94
5.0	0.5	238.5	31.91
6.0	0.5	235.9	28.89

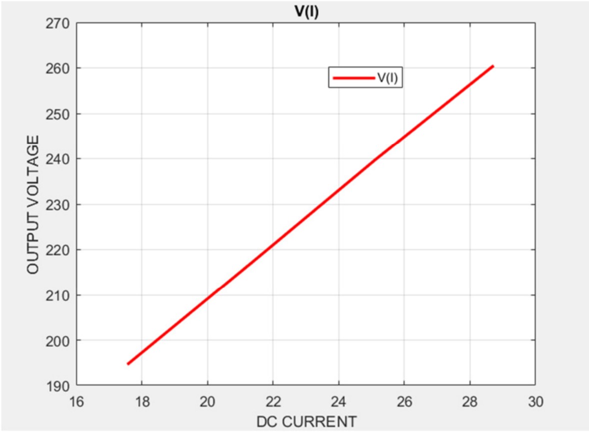


Fig. 2. The $V(I)$ relation.

We notice that the curve is a line, which can be represented with the well-known equation of a line as:

$$V = aI + b \tag{1}$$

If we take two points from the graph, we can easily calculate the factors a and b, which gives us the final form of the $V(I)$ relation:

$$V = 0.58I + 244 \tag{2}$$

B. The PID Controller

The PID controller is a closed-loop control system for regulating several physical variables such as speed and, in our case, voltage. It is based on three actions: proportional, integral, and derivative, each with its own effect on the regulation, with the general aim of obtaining a precise, fast, and robust system. Although the PID controller is not an intelligent controller, it still gives good results. The three actions in the PID controller are:

- The proportional action (Kp): This action is relative to the required setpoint and increases or decreases it depending on the error value. It is expressed as:

$$u(t) = Kp.e(t) \tag{3}$$

- The integral action (Ki): This action can accelerate the reaching of the desired setpoint and is directly related to the convergence time. It is expressed as:

$$u(t) = Ki.\int e(t)\,dt \tag{4}$$

- The derivative action (Kd): This action helps to reach the setpoint with high precision.

$$u(t) = Kd.\frac{de(t)}{dt} \tag{5}$$

If we add up the three actions, we obtain the PID relation [12]:

$$u[k] = Kp(e + \frac{T}{Ti}\sum_{j=0}^{k} e[j] + \frac{Td}{T}(e[k] - e[k-1]) \tag{6}$$

The use of the PID controller in the system is widely known, its position is just after the photovoltaic system and its role is to regulate the voltage by controlling the boost converter with a Pulse Width Modulation (PWM) signal in its output. We first measure the output current of the boost converter and then calculate the AC output voltage using our previously determined relation. Two inputs are supported in the PID controller, a reference voltage of 220 V and the calculated voltage, which must be close to 220 V, and a PWM control signal is generated at the output that corresponds to the desired voltage. Figure 3 illustrates the position of the PID controller in the system.

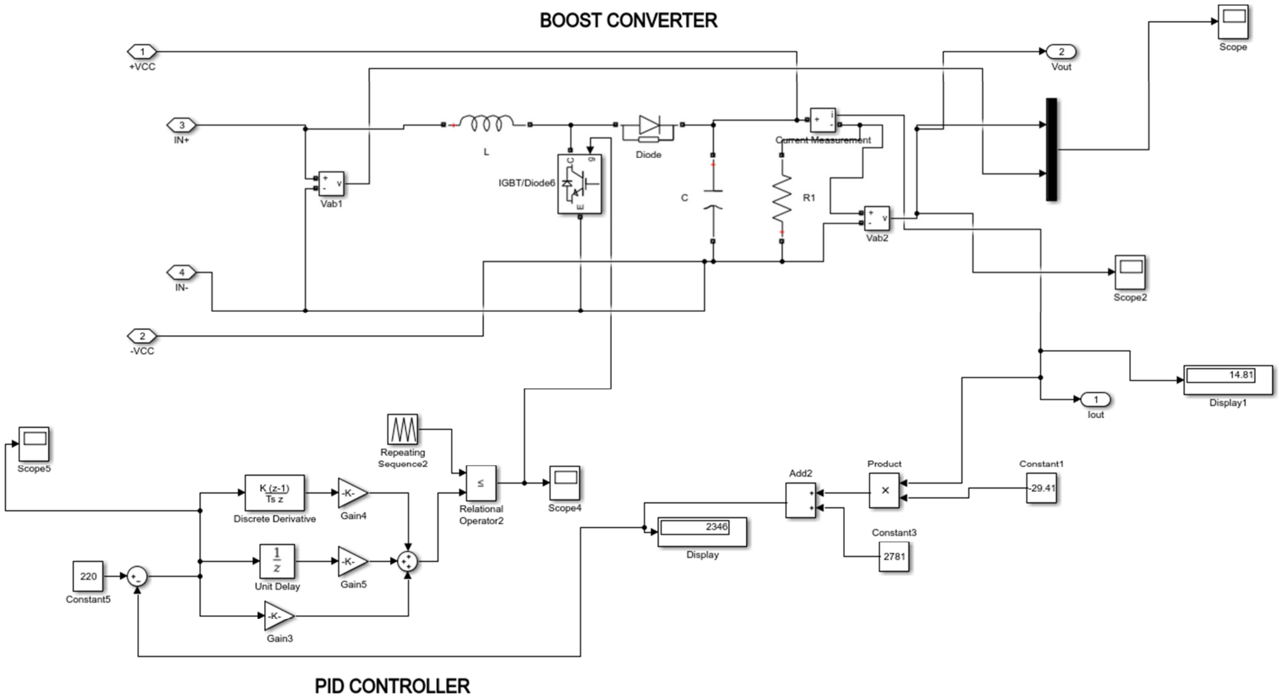


Fig. 3. PID controller position.

C. The ANN Controller

The objective is to determine the duty cycle that will give us a voltage close to V_{IN}, in our case V_{IN}=220 V, which represents one of the ANN controller inputs. Once the input V_{OUT}, which represents the voltage calculated by the $V(I)$ relation, is input, the controller tries to bring it closer to V_{IN} by changing the duty output or the duty cycle, which controls the boost converter [13-19]. Figure 4 shows the structure of the ANN controller, which has two inputs V_{IN}, V_{OUT} and a duty output, and consists of 2 hidden layers and 10 neurons in each layer.

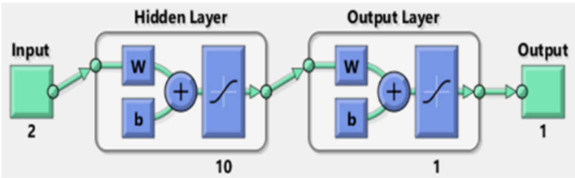


Fig. 4. ANN controller tool.

The Deep Learning Toolbox, which provides functions and applications for designing, training, and simulating ANNs, is used for a two-layer feed-forward network with sigmoid hidden in the neurons' inputs and outputs, that is trained with the Levenberg-Marquardt backpropagation algorithm (trainlm). Like the PID controller, the ANN controller also receives two inputs, V_{IN}=220 V, which represents the reference voltage, and V_{OUT}, which represents the voltage calculated by (2), to provide a PWM signal at the output that alternatively adjusts the voltage to 220 V [20-27]. Figure 5 shows the ANN controller training sheet, and Figure 6 shows the position of the ANN controller relative to the boost converter. The ANN controller performed 1000 epochs to minimize the error, knowing that the V_{OUT} input is varying.

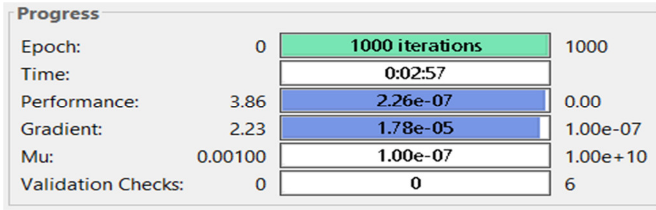


Fig. 5. ANN controller training sheet.

Figure 7(a) illustrates the curves between the training, validation and test, and shows how successful the training is. It can be seen that there is a small gap between the curves, indicating a very good result. The regression plots in Figure 7(b) indicate that there is a total convergence between the desired values and the recorded values, providing a perfect result of training, testing, and validation close to 1, with the best validation performance close to 3.35×10^{-7} [28-35].

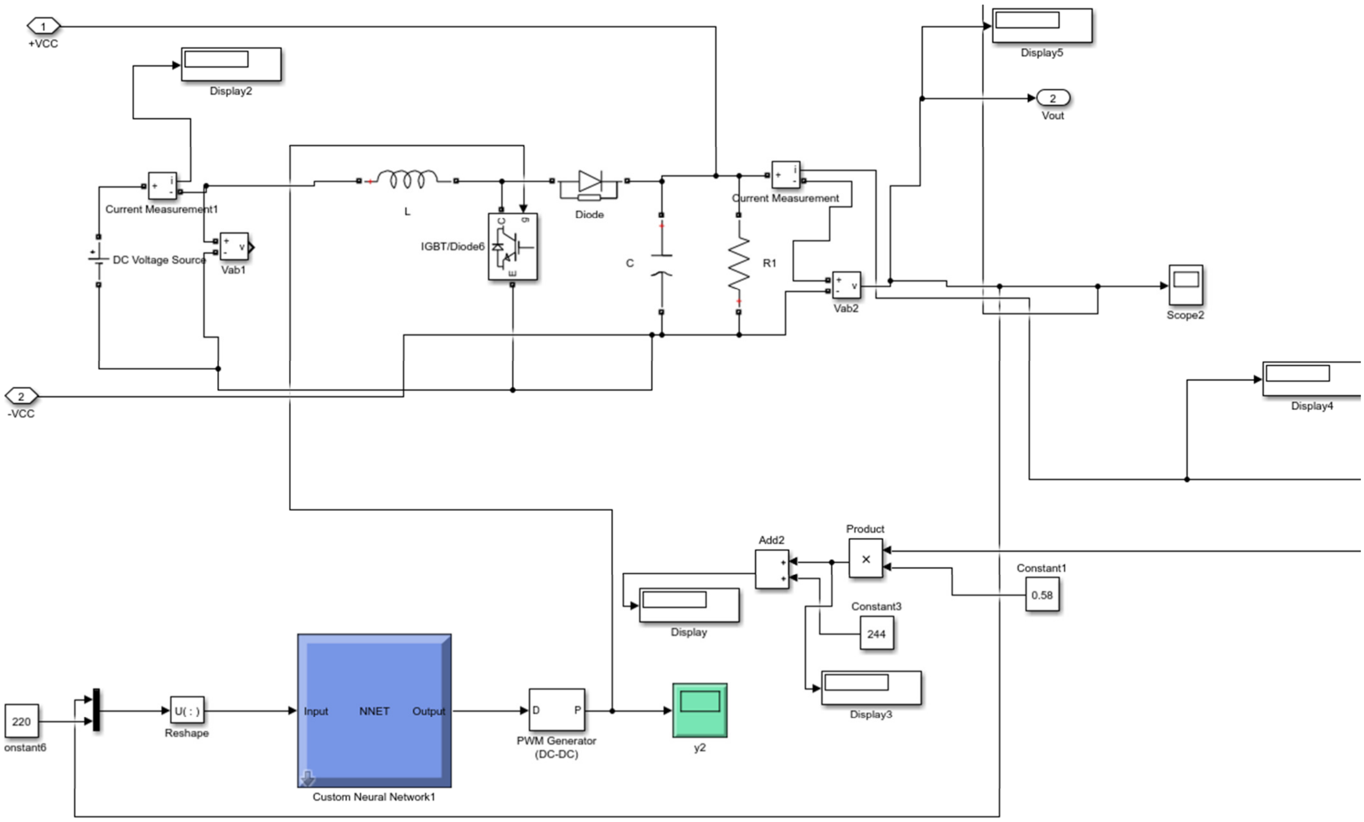
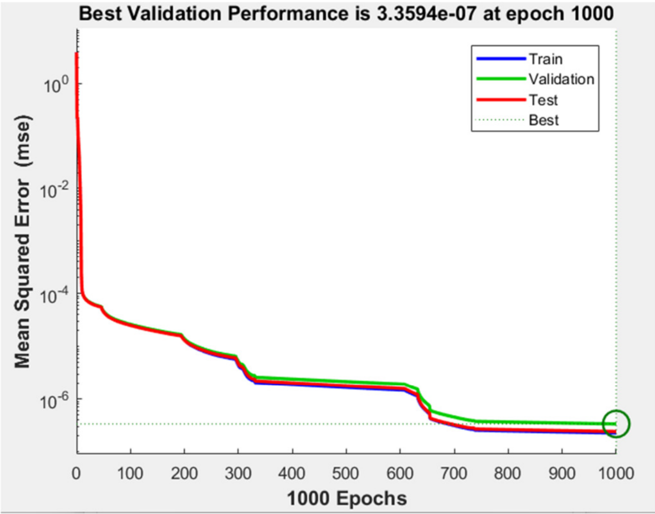
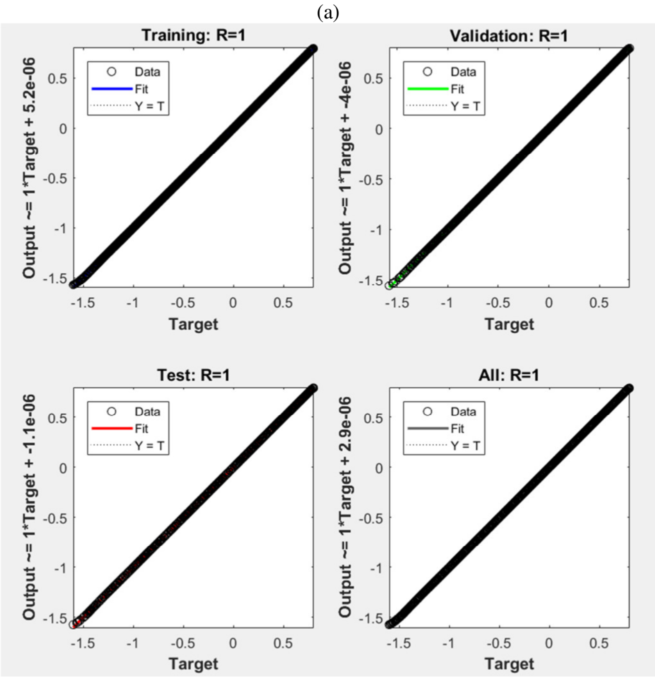


Fig. 6. ANN controller position.



(a)



(b)

Fig. 7. ANN controller: (a) training, validation, and test curves, and (b) the regression parameters.

III. SIMULATION RESULTS

The results obtained are values of the output voltages at the inverter for two cases: the voltages measured with the PID controller and the voltages measured with the ANN controller. The objective for both cases is that the output voltages do not exceed the minimum threshold, which is 198 V, and the maximum threshold, which is 242 V. Tables II and III present some measured values for the two cases, and Figure 8 shows the graphs of the two cases.

The boost converter with these characteristics was able to keep the output voltage close to 220 V. However, from the second load value, which is 3 Ω, the voltage dropped below 220 V and reached a minimum value of 212V. Nine voltage values (212.9 V, 212.7 V, 212.6 V, 212.5 V, 212.4 V, 212.4 V, 212.3 V, 212.2 V, 212.0 V) were around 212 V which increased the error value. In the case of the ANN controller, it's from the fourth load value, which is 5 Ω, that the voltage decreased and became less than 220 V, and the minimum value reached was 213.4 V. In addition, there were only three voltage values around 213 V (213.9 V, 213.7 V, 212.4 V), which decreased the error value.

TABLE II. OUTPUT VOLTAGE AND LOAD CURRENT USING THE PID CONTROLLER

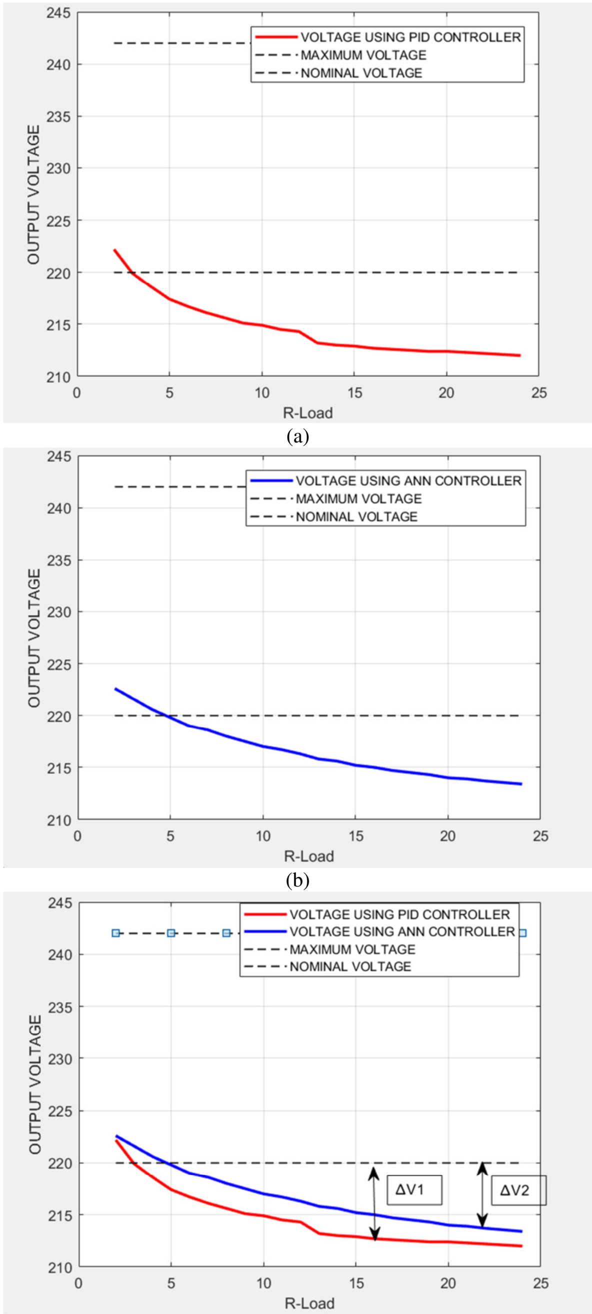
R (Ω)	*V* (V)	*I* (A)
2	222.2	15.80
3	219.9	11.33
4	218.6	09.42
5	217.4	07.84
6	216.7	07.01
7	216.1	06.32
8	215.6	05.79
9	215.1	05.33
10	214.9	05.04
11	214.5	04.68
12	214.3	04.47
13	213.2	02.94
14	213.0	02.82
15	212.9	02.72
16	212.7	02.53
17	212.6	02.47
18	212.5	02.38
19	212.4	02.30
20	212.4	02.23
21	212.3	02.16
22	212.2	02.11
24	212.0	01.95

TABLE III. OUTPUT VOLTAGE AND LOAD CURRENT USING THE ANN CONTROLLER

R (Ω)	*V* (V)	*I* (A)
2	222.6	14.02
3	221.6	13.12
4	220.6	12.21
5	219.8	11.43
6	219.0	10.70
7	218.6	10.19
8	218.0	09.58
9	217.5	09.10
10	217.0	08.54
11	216.7	08.24
12	216.3	07.82
13	215.8	07.40
14	215.6	07.10
15	215.2	06.78
16	215.0	06.55
17	214.7	06.26
18	214.5	06.01
19	214.3	05.77
20	214.0	05.54
21	213.9	05.36
22	213.7	05.17
24	213.4	04.82

Figure 8(c) contains three curves, the output voltages with the PID controller and the ANN controller, and the nominal voltage, which is 220 V. The ΔV1 error represents a percentage of 2.4%, whereas the ΔV2 error represents a percentage of

1.49%. In Figure 8(a), we notice that for the PID controller, the output voltage has crossed the nominal voltage and reached the value of 212 V, which allows us to say that the PID controller has not proved its capacity and robustness in this progressive variation of the voltage. On the other hand, in Figure 8(b), we observe that the ANN controller was able to keep the voltage close to the nominal voltage, especially when we observe in Figure 8(c) that ΔV2 < ΔV1, which indicates that the ANN controller is the right choice for our work.



(a) (b) (c)

Fig. 8. Output voltage using: (a) the PID controller, (b) the ANN controller, and (c) a comparison between the two controllers.

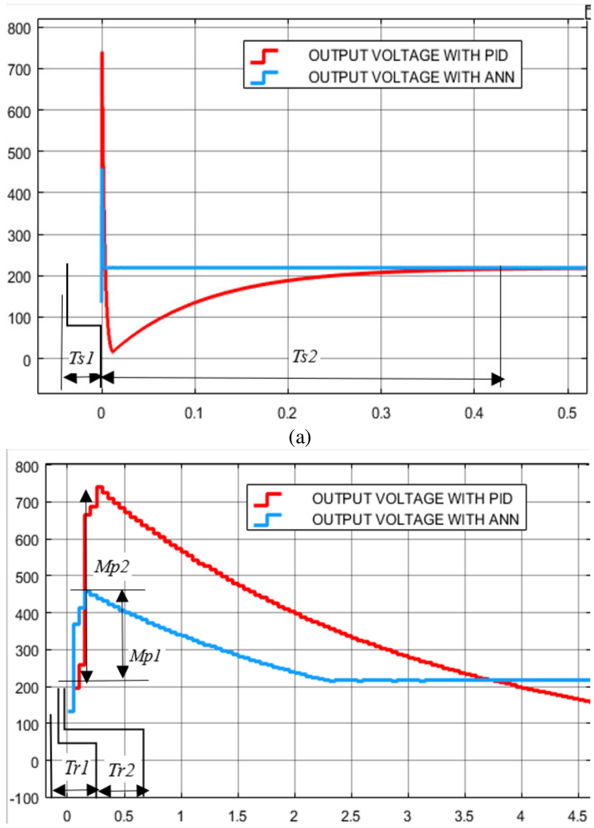
Figures 9(a) and 9(b) show the output of the boost converter so as to compare the parameters of the two curves as follows:

Tr1<Tr2, Ts1<Ts2, Mp1<Mp2

where *Tr1, Tr2* are the rise times, *Ts1, Ts2* are the settling times, and *Mp1, Mp2* are the peak overshoots of the ANN and PID controllers, respectively. It can be observed that the ANN controller has the fastest rise time, fastest response time, good stability, and low steady-state error that indicates high control accuracy. In addition, all the parameters mentioned in Table IV prove the superiority of the ANN controller over the PID controller.

TABLE IV. COMPARISON OF ANN AND PID CONTROLLERS

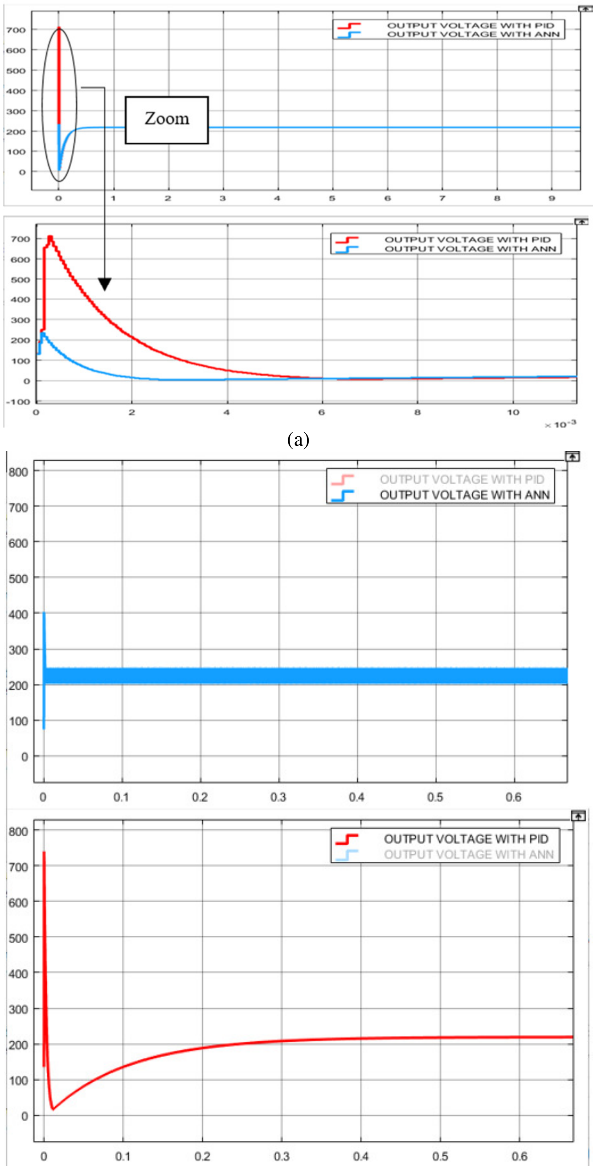
Parameters	PID controller	ANN controller
Average voltage (V)	216.7	217.4
Voltage error rate (%)	2.4	1.49
Average current (A)	4.98	08.25
Average power (W)	1079.16	1793.55



(a) (b)

Fig. 9. (a) Output voltage using the ANN and PID controllers, and (b) comparison of peak overshoot and rise time for the two controllers.

Figure 10(a) shows the added disturbances for each system, where it is evident that the boost controlled by the ANN controller gave the best result, demonstrating its robustness to the disturbances. Figure 10(b) shows the load variation by changing the load every 1 s, and this time it is the PID controller that gave the best result with a more stable signal.



(a)

(b)

Fig. 10. Responses of the PID and ANN controllers: (a) by adding disturbances, and (b) by instantaneously changing the load.

IV. CONCLUSION

In this paper, we used the Artificial Neural Network (ANN) controller technique, which proved to be effective for our work compared to the Proportional-Integral-Derivative (PID) controller and showed the best simulation results. The ANN controller was able to control the output voltage by applying the technique of converting current into voltage and using the latter to control the output voltage to limit it between the minimum and maximum thresholds. The first test showed the ability of the ANN controller to keep the AC voltage close to the reference voltage. The second test showed the stability and response speed of the ANN controller. Finally, the robustness was tested by adding disturbances to the system, which also showed the superiority of the ANN controller. The only test that favored the PID controller was the fast load switching test.

The closest work to ours is that of the authors in [12], because they compared the efficiency of the boost converter using the PI converter and the ANN converter. They found that the boost converter controlled by the ANN controller has a better efficiency, which is equal to 98%, 97%, 97%, 97%, 96%, and 95% for increasing loads. When we calculate the efficiency with respect to the output voltage, we take the first six values of the voltage and find 98.81%, 99.27%, 99.72%, 99.90%, 99.54%, which indicates that the efficiency of our ANN controller is better. Possible future research can include the use of ANN controller with adaptive algorithms or the neuro-fuzzy controller to improve the performance of the boost converter.

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