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Backpropagation Neural Network Adaptive Voltage Control of a High-Gain Transformerless DC/DC Boost Converter for solar applications

Mohcine Byar, Abdelouahed Abounada, Abdenabi Brahmi, Hassan Rayhane
LACEM, Faculty of Sciences and Technology
Sultaln Moulay Slimane University
Beni Mellal, Morocco
Mohcinebyar2013@gmail.com

Abstract— An artificial neural network (ANN) adaptive control method for high-gain transformerless DC-DC boost converter is designed in order to achieve better performance and robustness. An ANN controller have the ability to predict the duty cycle in each moment because it is already trained with a vast number of random values of input, output and reference voltages. In order to minimize the error of obtaining the most convenient duty cycle, a back-propagation algorithm has been used to train the neural network because it has the ability to deal with the weights constantly for the sake of diminishing the loss function which makes the ANN generates the fittest duty cycle. The control scheme has been done for a photovoltaic system and the simulation is done using Matlab/Simulink. Simulation results are given for irradiance, reference voltage and load variations. The results are designated to prove the effectiveness of the proposed control system.

Keywords- Artificial Neural Network; Backpropagation algorithm; High Gain DC/DC boost converter; solar photovoltaic system

I. INTRODUCTION

In today's world, the demand on green energies is increasing significantly due to the paramount issue of global warming caused by fossil fuels [1]. Therefore, solar energy is one of the preferred alternatives because it is considered as an endless and ecological clean source of energy which can prevent the most dangerous issue in the world's agenda [2]. The shifting from fossils fuels to solar energy is rising drastically due to the awareness of individuals and societies of global warming's lasting consequences [3]. Solar generators produce DC voltages which require regulation to become compatible with the load. Thereby, the usage of a solar power plants is always paired with DC-DC converters due to its supreme role as power conditioning units [4]. As a matter of fact, the majority of solar applications require the usage of step-up converters in order to boost low voltage to higher amplitude to supply a specific load or make the connection to grid possible [5]. Furthermore, the main challenge of DC-DC boost converters is pushing towards high gain with taking in consideration decreasing switching loses caused by high duty cycle [6]. For that reason, many papers have been published in the literature seeking to achieve an ultimate scheme of boost converter with high gain and low voltage stress of the switches which provides high efficiency [7-10].

In order to generate and maintain a constant output voltage of the DC-DC boost converter, it is mandatory to use a voltage regulation scheme. Moreover, plethora of controllers are used to regulate the output voltage such as Proportional-Integral-Differential (PID) controller which was widely used in the last decade due to its simplicity [11], but recently the research community is migrating toward artificial intelligence controllers because they are more adequate and have presented promising results in decreasing rise time and overshoot of the output voltage comparing to the classic PID controller [12]. Lately, artificial neural networks (ANN) have been applied to regulate the output voltage of DC-DC boost converter in dynamic condition such as solar applications to get the desired robust control. Further, the awareness of the mathematical model of the system is needless which facilitate the control of complex systems [13] such as the proposed one in this paper.

This contribution aims to obtain the most adequate control of a high-gain transformerless DC-DC boost converter connected to a solar generator by using a back-propagation artificial neural network (BP-ANN) controller which was trained plethora of time in MATLAB to get the adequate duty cycle. Moreover, the proposed control scheme has the agenda of maintaining a stable output voltage, decreasing the overshoot and reducing the stress on switching devices.

Finally, to prove the effectiveness of the proposed ANN controller, the control strategy was tested and simulated in MATLAB/Simulink environment.

II. SYSTEM MODEL

The proposed system model is depicted in Figure 1, it is composed of five main blocks as the following: Photovoltaic panel, High-Gain transformerless DC-DC boost converter, artificial neural networks (ANN) controller, Pulse width modulation (PWM) controller and a resistive load in the output.

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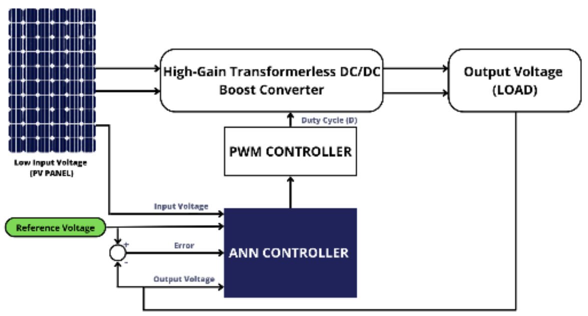


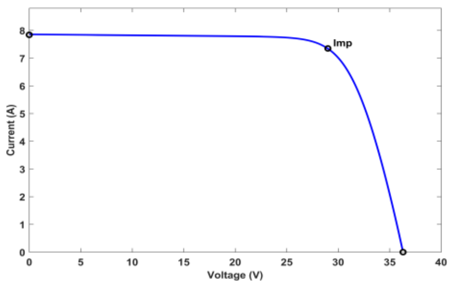
Figure 1: Block diagram of overall system

A. Photovoltaic panel

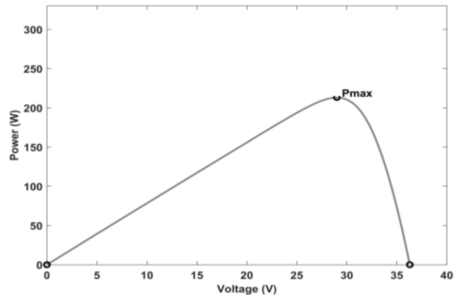
Photovoltaic panels are made up of a number of PV cells which are connected and configured in series and shunt. Moreover, these PV cells are mandatory components of converting incident light (photons) to DC current and DC voltage because of the photovoltaic effect on semiconductors [14]. In addition to that, a photovoltaic panel is considered as a non-linear system because it is characterized by the increasing values of current and voltage (I – V) and it depends heavily on the solar temperature and irradiance [15-16]. In our case we used a SOLTEC 1STH-215-P solar panel with 1 series-connected modules par string and 10 paralleled strings, its parameters are illustrated in Table 1 and the I–V and P–V characteristics are depicted in figure 2.

Table 1: Characteristics of the PV Module SOLTEC 1STH-215-P AT STC (1000 W/m², 25 °C)

Characteristics	***SOLTEC 1STH-215-P***
Maximum Power, P_{max}	*213.5W*
Number of cells	*60*
Open circuit voltage, V_{oc}	*36.3 V*
Short-circuit current, I_{sc}	*7.84 A*
Voltage at P_{max}, V_{mp}	*29 V*
Current at P_{max}, I_{mp}	*7.35 A*
Temperature coefficient of V_{oc}	*-0.36099 %/ °C*
Temperature coefficient of I_{sc}	*0.102 %/ °C*
Light-generated current, I_{ph}	*7.8649 A*
Diode saturation current, I_0	*2.9259e-10 A*
Diode ideality factor	*0.98117*
Shunt resistance, R_{sh}	*313.3991 Ω*
Series resistance, R_s	*0.39383 Ω*



(a)



(b)

Figure 2: (a) I–V and (b) P–V characteristics for PV panel at STC (1000 W/m², 25 °C)

B. High-Gain transformerless DC/DC boost converter

The majority of classical DC-DC boost converters have a limited boosting ability due to because of components perturbations and the gain which is "supposed" ideally infinite. In addition to that, a paramount blocking cause for this type of converter to achieve a higher step-up ratio are magnetic issues which cause energy losses while duty cycle touches higher levels [17-18]. The proposed converter is depicted in Figure 3 and the configuration was well studied in [19], it presents an ability to step up an input voltage of 20~40V to an output voltage of around 400V. Moreover, the gain of converter was already calculated in [19] and it is given by equation (1) and the parameters of the proposed boost converter are given in Table 2.

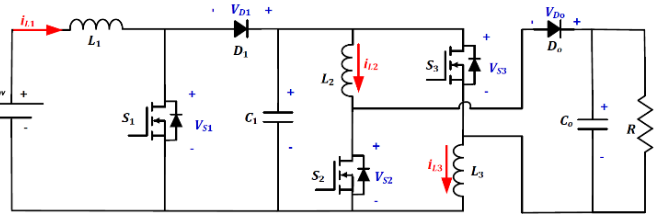


Figure 3: High-Gain Transformerless DC/DC Boost Converter [19]

$$\frac{V_{out}}{V_{pv}} = \frac{(1+D)}{(1-D)^2} \quad (1)$$

Table 2: Specifications of the converter's parameters

Component	***Specification***
Photovoltaic input voltage, V_{pv}	*35 V*
Input inductors, L_1, L_2, L_3	*40 mH*
capacitors, C_{in}, C_1, C_0	*1000 μF*
Switching frequency, F_s	*30 KHz*

C. ANN Controller

The proposed ANN controller is based on a single layer perceptron [20], which is fundamentally uses one layer in the input connected to four neurons. The first is photovoltaic voltage V_{pv}, the second is output voltage V_o, the third is the error which is the difference between the desired voltage and output voltage (e = V_{ref} - V_o) and the fourth is reference voltage V_{ref} which is the bias and it is defined externally, the structure is depicted in figure 4. Moreover, a feed forward network with back propagation algorithm is used to train the network and minimize the error of obtaining the most adequate duty cycle.

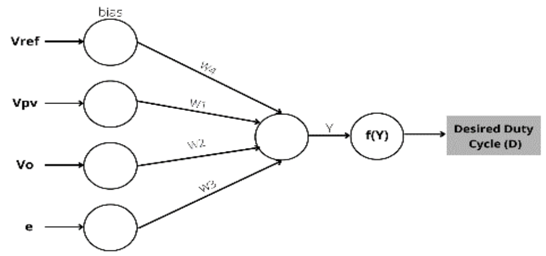


Figure 4: Structure of the BP-ANN Controller

Basing on the literature and the previous explanations of backpropagation algorithm in training ANN [21-23] and in order to get the most adequate value of the desired duty cycle, the error minimization is done by calculating the equation Y using (2) where k is the sampling time and the weights are randomly initialized. In addition to that, the calculated duty cycle is obtained using equation (3) of the logarithmic sigmoid and finally the error between desired duty cycle D_d and calculated duty cycle D_{Calc} is calculated in equation (4).

$$Y = V_{pv} w_{1_k} + V_o w_{2_k} + e w_{3_k} + V_{ref} w_{4_k} \tag{2}$$

$$D_{Calc} = \frac{1}{1 + e^{-Y}} \tag{3}$$

$$error = D_d - D_{Calc} \tag{4}$$

Further calculations and algorithm demonstration are already done in [24]. To illuminate the way of how the ANN and the training has done in our case, 100000 random values of each of reference voltage, input voltage, output voltage and error was introduced to the network and the duty cycle was calculated plethora of time in order to get the right one for each random case, the Mean Squared Error (mse) of getting the fittest duty cycle was small and it is illustrated in figure 5.

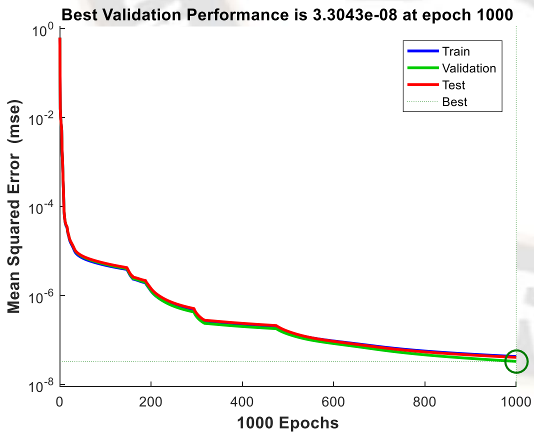


Figure 5: Mean Squared Error of ANN training

III. SIMULATION AND RESULTS

To study and verify the performance of the proposed controller, a simulation in MATLAB/Simulink was done. The diagram of the simulated system is depicted in figure 6. As it is already mentioned, the input parameters of the BP-ANN controller are respectively V_{pv}, V_o, V_{ref} and e to find out the duty cycle. Furthermore, the PWM modulator is fundamental to the convert because it converts duty cycle into a control signal of the DC-DC boost converter's switches. For simplification reasons, all the components are considered ideal in the simulation and the parameters are presented in Tables 1&2.

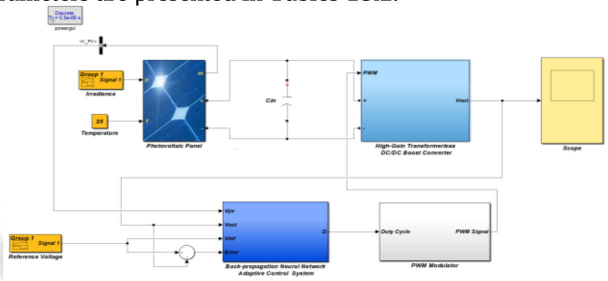


Figure 6: Block diagram of the whole system in MATLAB/Simulink

In order to test the robustness of the proposed control scheme, three simulation scenarios were done. The first scenario is where the load is constant, the PV panel is under STC and reference voltage is variable, the second one is fixing the reference voltage and the PV panel under STC but this time a variation of load was done, and finally the third scenario is varying the PV panel's irradiance.

A. *First scenario: V_{ref} variation*

In this scenario, the load was fixed in R=160Ω and the PV panel was simulated under STC which allows it to generate a voltage of around $V_{pv} = 35V$. Firstly, reference voltage was settled in 200V and the output voltage is depicted in figure 7. Secondly, figure 8 shows the output voltage when $V_{ref} = 230V$ and finally reference voltage was fixed in 250V and output voltage of the boost converter is shown in figure 9.

It is evident from figures 7-9 that the BP-ANN controller shows robust and adequate results in tracking three various reference voltages with the same boost converter's parameters and the same input voltage. The BP algorithm adjust regularly the weights of the ANN in order to get the most convenient duty cycle for the desired output voltage and table 3 shows that whenever reference voltage increases, rise time also rises but output voltage becomes more stable because overshoot diminishes.

Table 3: Simulation results for reference voltage variation

	V_o*(Median)*	*Rise time*	*Overshoot*
$V_{ref} = 200V$	*199.4 V*	*43.63 ms*	*3.67 %*
$V_{ref} = 230V$	*234 V*	*70 ms*	*0.504 %*
$V_{ref} = 250V$	*251.8 V*	*87 ms*	*0.505 %*

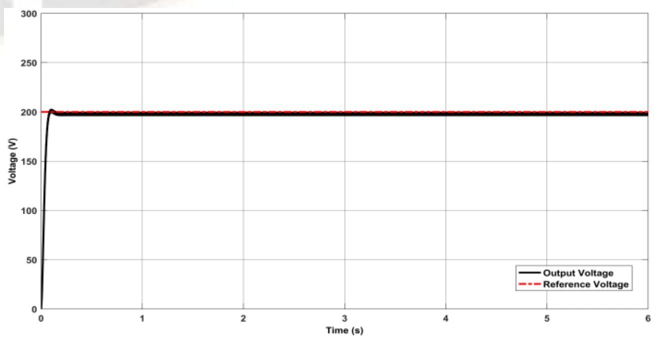


Figure 7: Output voltage of the boost converter under BP-ANN control with $V_{ref} = 200V$

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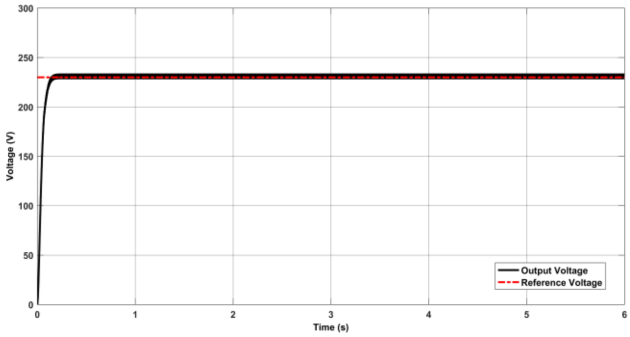

Figure 8: Output voltage of the Boost converter under BP-ANN control with $V_{ref} = 230V$

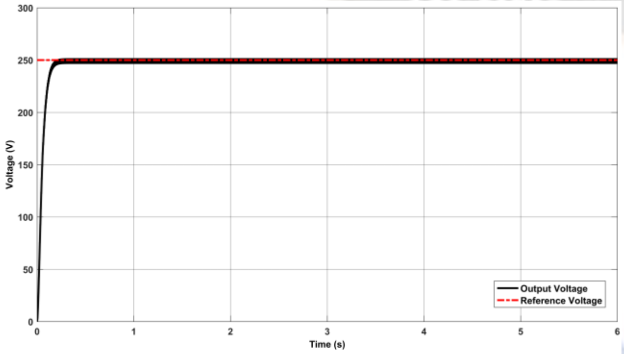

Figure 9: Output voltage of the boost converter under BP-ANN control with $V_{ref} = 250V$

B. Second scenario: Irradiance variation

In order to study the robustness of the proposed control scheme and because it is designated to perform in photovoltaic applications, a simulation under abrupt variation of irradiance was done. Furthermore, the load was fixed in R=160Ω and a constant reference voltage was also applied to the converter $V_{ref} = 200V$. Irradiance's variation values are shown in figure 10 and its output voltage response is depicted in figure 11.

Figure 10 depicts abrupt changes in irradiance which causes changes in photovoltaic voltage. It is shown in figure 11 that in the moment of 1s when the irradiance reduced suddenly from 1000 W·m−2 to 500 W·m−2, output voltage normally tents to reduce but the controller tracked reference voltage in almost 0.1s which is fast. Otherwise, the controller does the same thing when the irradiance increases and for that reason it is concluded that BP-ANN controller is robust against changes in PV panel's irradiance.

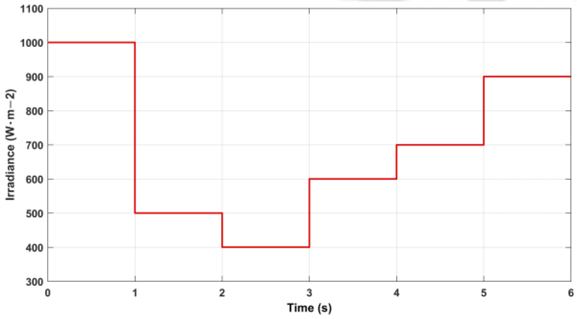

Figure 10: Irradiance variation of the PV panel

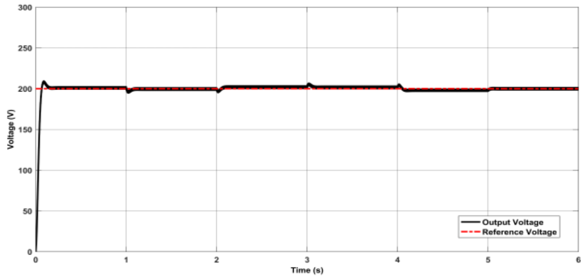

Figure 11: Output voltage of the boost converter under BP-ANN control with variable irradiance

C. Third scenario: Load variation

In this last scenario, a testing of the controller against load variation was done, three values of load were connected to the output of the boost converter, load values are 150Ω, 200Ω and 250Ω, reference voltage was fixed in 200V and the PV panel is under constant irradiance and temperature (STC). The output respond voltages are illustrated respectively in figures 12-14.

From figures 12-14 and results in table 4, it is obviously noticeable that whenever load value increases, that causes an increase in overshoot ratio and output voltage value because load's current decreases which forces the voltage to increases abruptly to maintain the stability of output rated power. Meanwhile, BP-ANN controller takes just around 40ms to deliver the desired output voltage in the cases of load variation.

Table 4: Simulation results for load variation

	V_o(Median)	***Rise time***	***Overshoot***
R = 150Ω	*199.4 V*	*43.63 ms*	*3.67 %*
R = 200Ω	*202.2 V*	*37.09 ms*	*9.34 %*
R = 250Ω	*209.3 V*	*34.09 ms*	*13.07 %*

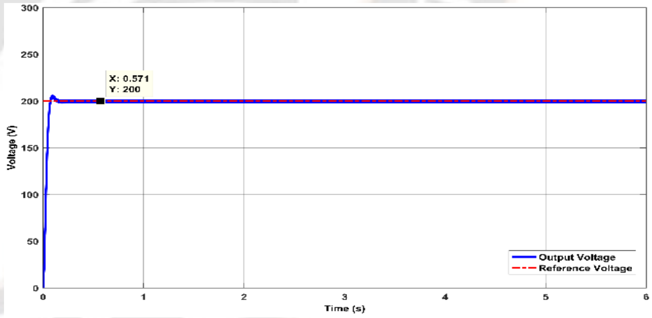

Figure 12: Output voltage of the boost converter under BP-ANN control with R=150Ω

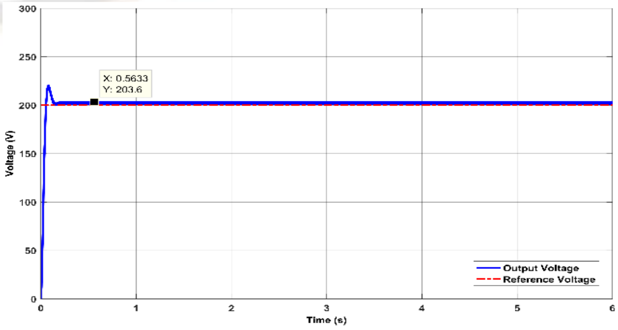

Figure 13: Output voltage of the boost converter under BP-ANN control with R=200Ω

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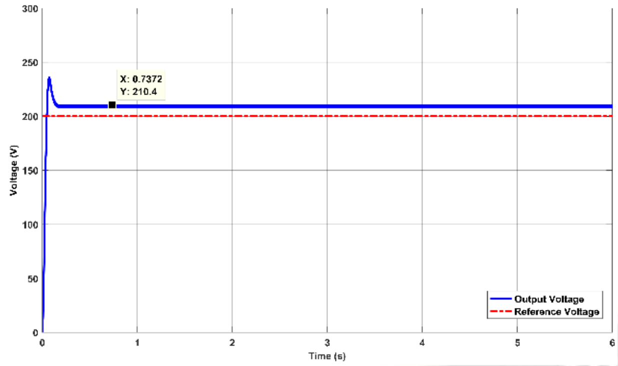

Figure 14: Output voltage of the boost converter under BP-ANN control with R=250Ω

IV. Conclusions

In this paper, an artificial neural network controller using back-propagation learning algorithm has been presented for voltage regulation of a high-gain transformerless DC-DC boost converter used for photovoltaic applications. The back-propagation learning algorithm has been explained briefly. To get accurate results input, output and reference voltages has been considered as an input of the controller. Moreover, the advantage of the proposed control scheme is that it does not superfluous any information about the controlled system and it is easily tunable. Simulation results proved the robustness and stability of the BP-ANN controller against numerous abrupt internal and external disturbances. Furthermore, three case studies have been considered in simulations and the results shows that the controller always succeeds to stand against these disturbances and regulate the voltage with small tolerance. Finally, the controller showed promising results and can be implemented in practical applications.

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