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FPGA Validated Advanced Learning-Based Voltage Control of DC/DC Converter Feeding CPL in DC Microgrid Applications

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Abstract—The high penetration of renewable energy distribution generations enables the concept of microgrids and is widely accepted for future power systems. In this context, the DC microgrid is preferred due to easy integration, less system losses and offer high reliability and efficiency compared to its counterparts. However, the constant power loads (CPL) are a risk to the stability of the power electronics devices due to their negative impedance characteristics and also effects the voltage quality. To overcome these conditions, this paper proposes advanced artificial intelligence-based control of DC/DC converter to regulate the DC voltage in DC microgrid (MG) applications. At the start, model predictive control is implemented as an expert to control the studied converter to extract the dataset. The extracted dataset is used to train the proposed artificial neural network (ANN). The proposed controller is tested under various operating conditions while feeding the constant power loads. The proposed controller presents a superior transient response compared to conventional model predictive control (MPC). The experimental validation of the proposed scheme is carried out by implementing the controller on the FPGA ZYBO Z7-7020 board. The results are also compared with the conventional PI control. The proposed control technique has less computational burden and mitigates destabilizing effects caused by the CPLs.

Keywords—Artificial Intelligence, Constant Power Load, DC/DC converter, DC Microgrid.

I. INTRODUCTION

The expansion of renewable energy-based distributed generations (DG) systems such as wind, solar, and biomasses becomes more prevalent. Especially the implementation of DGs far away from the main grid. So, to incorporate the DGs in power system systems, DC or AC microgrid is one of the suitable options [1]. The MG is a small-scale independent distribution system with its generation and control. It can also resolve energy issues, improve reliability locally and be operated in islanded or grid-connected mode. The microgrid can be operate as an AC, DC or hybrid system. However, AC MG has disadvantages when compared to DC microgrids, such as skin effect, more complicated control due to the presence of frequency, etc. AC MG also has lower efficiency, high implementation cost and low reliability. In contrast, DC MG are easier to implement due to the absence of reactive power flow, harmonics and voltage unbalances. Additionally, implementation of the DC system lowers the power network weight by 10 tons/MW [2]. The DC MG also acquires attention in different applications such as electric vehicles, naval ships, submarines and telecommunications infrastructure. A basic structural diagram of DC MG is shown

in Fig. 1. Many challenges appear in above mentioned applications of DC, but suitable control approach is one of the critical aspects to be considered when aiming for high stability of the system in challenging operation conditions.

With continuous development in control theory, many new control techniques have been proposed to control the power converters [3]. Linear theory-based controllers such as PID and PR and their combinations are mature and widely used by the power electronics industry. But, gains tuning, parametric uncertainty and inability to handle the power system nonlinearity due to the power converters and constant power loads in DC systems are practical limitations of these controllers [4]. Model-free fuzzy logic-based control for DC/DC converter is discussed in [5]. Slide mode control (SMC) and model predictive control (MPC) have been proposed to overcome the abovementioned issues[6], [7]. SMC is a recently developed popular control method for DC/DC converters and is robust against parametric variations, converges towards the sliding surface and can handle external disturbance. First-order SMC is proposed for DC/DC converters in [8], while second-order SMC for DC MG applications is discussed in [9], implementing the nested voltage and current loop to improve the robustness of the parallel converters. But, the second-order SMC enhanced the performance in terms of transient response but required an extra current sensor, which ultimately increases the cost. In [10], [11], authors proposed the SMC for DC/DC converter in DC MG applications. Overall, the chattering phenomena, high overshoot, variable switching frequency and complex mathematical modelling are potential barriers and make it unsuitable for power converters [12].

Model predictive control is optimal digital control, which solves the optimization problem over a prediction horizon for each sampling time. MPC uses the mathematical model of the converter along with its filter to anticipate future states. The state with the least cost function (CF) value is selected, and its switching state is applied to the next sampling duration. CF is the error value between the reference value and the predicted value of the state variables (voltage, current, frequency or power). It also handles the system's nonlinearities and constraints [13]. Decentralized MPC for DC MG with constant power loads (CPL) is presented in [14]. The proposed technique regulates the bus voltage and ensures power-sharing among the multi-parallel converters. However, the disadvantages of MPC are its high computational burden and inaccurate mathematical modelling that takes the system towards instability [15]. Model-free or data-driven control

techniques have become successful in getting the attention of the research community in the PE domain in recent years [16][17]. So, ANN-based controllers have been proposed for short-term prediction [18], voltage sag classification [19] and problem identification [20]. ANN is the subset of artificial intelligence and machine learning. A total harmonic distortion prediction tool is developed using ANN in [21]. In [22], ANN-aided MPC for DC/DC converter is studied to regulate the DC bus voltage. However, the control is not robust against the voltage change.

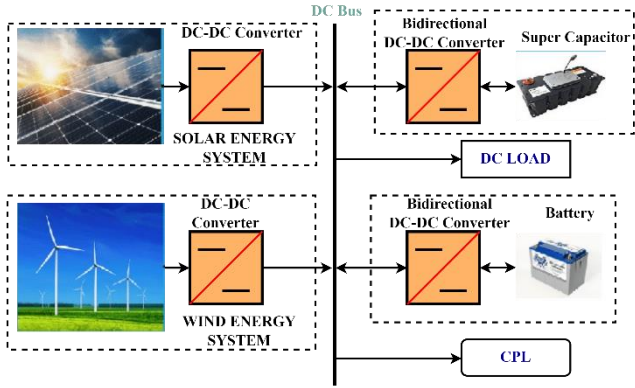


Fig. 1. Typical configuration of DC microgrid.

This paper proposes an artificial neural network-based voltage control strategy for DC-DC converter under constant power loads. In this study, the CPL is the only load connected with the system, which is assumed as the worst-case scenario from a stability point of view. The design of the proposed controller is divided into two stages. Initially, MPC is implemented to regulate the converter voltage and used as an expert for extracting the dataset. In the second stage, the obtained dataset is used to train the proposed ANN. Once the developed ANN has been fine-tuned, the MPC-based controller is replaced with it to test its performance in a closed loop system using MATLAB/SIMULINK. In this study, reference voltage, output voltage, and output current are chosen as input features, and the switching state of the converter is selected as the target. The dataset contains samples from different voltage reference values under different loading conditions, such as step changes in load, changes in input voltages, etc. Moreover, the proposed control is verified by FPGA-in-the-loop (FIL) implementation. The results are also compared with the conventional PI and MPC control.

The rest of the paper is organized as follows: Section II explains constant power loads and its response. The MPC mathematical modelling for DC-DC converter is briefly discussed in section III. The proposed ANN-based control strategy is explained in section IV and the experimental setup and cases are presented in Section V. The last section of the article presents the conclusion.

II. CONSTANT POWER LOADS

Constant power load is the product of voltage and the current of the load [23], [24]. Let's review the basics of the constant power load. It is observed from Fig. 2 that if the voltage across the CPL changes, the load current will also change. This change in the current creates a destabilization effect on the system. The destabilization effect is annihilated

by equalling the source voltage to the CPL voltage, and this point is known as the equilibrium point. The system's operation will become in a steady state at the equilibrium point. The equilibrium point stability of the system is determined from the I-V curves of the load and source. Fig. 3a illustrates the I-V characteristics between CPL and a voltage source. Consider that A is the equilibrium point in the cases of CPL. Further consider that due to a disturbance, the system moves to point A₁, where the load current reduces, and the source voltage is less than the load voltage. Therefore, the current will reduce further, and the operating point will shift further away from point A. The circuit behaves like positive feedback, and current and voltage go to zero and infinity, respectively. In other conditions, if the current increases, then the CPL voltage is less than the source voltage, leading to a further increase in current and moving the equilibrium point further away from point A. Hence, the point A is unstable in the case of CPL.

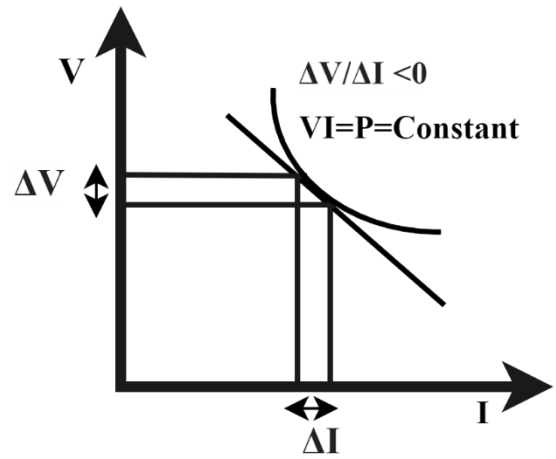


Fig. 2. Negative impedance properties of CPLs.

Fig. 3b represents the V-I curve for the resistive load and voltage source. Let's assume that B is the steady state equilibrium point and the current increase occurs due to the disturbance and the operating point moving to B₁. So, the load voltage is more than the source voltage. The load voltage becomes negative, and the current will decrease. As a result, the operating point will shift back to point B. In the second condition, the current reduces. As a result, the load voltage is less than the source voltage. The load voltage becomes positive, and in response to this behavior, the current will increase and shift the operating point back to equilibrium point B. In fact, the resistive load has positive incremental resistance, while CPL has negative incremental resistance properties which is obvious basing on CPLs mathematical representation:

$$i_{cpl}(t) = \frac{P}{V_{cpl}(t)}; \forall v_{cpl}(t) > \varepsilon \quad (1)$$

where P , i_{cpl} , and v_{cpl} are the rated power, current, and voltage of the load respectively. v_{cpl} is equal to the converter's output voltage, and ε is a small positive value. To sum up the above discussion, the equilibrium point will be stable when the positive change in current causes the load voltage to be greater

than the source, and a negative change in current originates the load voltage to become less than the source voltage.

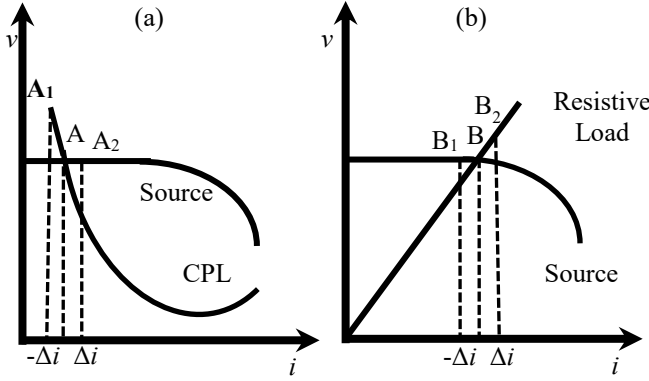


Fig. 3. Voltage-current characteristics of a CPL, resistive load and voltage source.

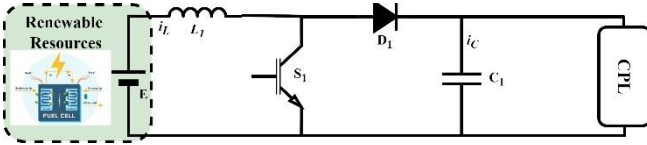


Fig. 4. Circuit diagram of DC/DC converter feeding CPL.

III. MATHEMATICAL MODELLING OF MPC

In order to implement the MPC, it is necessary to develop the discrete-time model of the DC converter. Fig. 4 illustrates the circuit diagram of the DC/DC step-up converter feeding CPL. The output voltage of the step-up DC converter is controlled by varying the duty cycle of the pulse width modulation (PWM) signal. But in the case of MPC, the pulse for the switch is directly generated by the MPC algorithm. In Fig. 4, S_1 is a controllable switch, R_1 is the damping resistance, and current through inductor L is i_L , and the voltage across the capacitor C_1 is V_{c1} . V_{in} represents the input voltage of the DC source. Equation (2) explains the inductive nature while (3) presents the capacitive behavior of the dc converter:

$$\frac{di_{L1}(t)}{dt} = -\frac{R_1}{L_1}i_{L1}(t) - \frac{V_{c1}(t)}{L_1} + \frac{V_{c1}(t)}{L_1}u(t) + \frac{V_{in}}{L_1} \quad (2)$$

$$\frac{dV_{c1}(t)}{dt} = \frac{1}{C_1}i_{L1}(t) - \frac{1}{C_1}i_{L1}(t)u(t) - \frac{1}{R_1C_1}V_{c1}(t) \quad (3)$$

Switch states (S_1) are defined by function $u(t)$, as shown in (4). If $S_1 = 1$, switch S_1 is in the ON state; if switch $S_1 = 0$, switch S_1 is in the OFF state.

$$u(t) = \begin{cases} 1 & S_1 = 1 \\ 0 & S_1 = 0 \end{cases} \quad (4)$$

The discrete-time model of the DC converter is expressed in (5-6). These equations are used to anticipate the future response of voltage and current.

$$i_L(k+1) = \left(\frac{TR_1}{L_1} - 1\right)i_L(k) + (u(k) - 1)\frac{T}{L_1}V_{c1}(k) + \frac{T}{L_1}V_{in} \quad (5)$$

$$V_{c1}(k+1) = \frac{T}{C_1}i_{L1}(k) + \left(1 - \frac{T}{C_1R}\right)V_{c1}(k) - \frac{T}{C_1}i_{L1}(k) * u(k) \quad (6)$$

Where $(k+1)$ represents the future or next (coming) instant. T is the sampling time.

The formulation of the cost function (CF) is an essential part of the development of MPC. CF is the positive error value between the reference and actual state parameter value. In this case the positive value is ensured by squaring the error. The CF chosen in this study is illustrated in (7).

$$J_{DV}(k) = (V_c^*(k+1) - V_c(k+1))^2 \quad (7)$$

The execution of the MPC algorithm is as follows:

- At the start of the switching instant, the voltage and current of the converter are measured using sensors.
- Equation (5-6) is used to predict the current and voltage at the coming instant for all possible switching states, and then CF is evaluated using (7) for all possible states. In this study, N is taken as one. So, there are only two possible switching states.
- The state at which CF has a minimum value is chosen. This state is given to the converter switch for the coming instant.

IV. PROPOSED ANN CONTROL STRATEGY

The artificial neural network is a subset of machine learning. It creates the mathematical relation based on gains between the inputs and outputs. ANN consists of a set of nodes known as neurons. These neurons create the layers, which are parallelly connected. The output of the single neuron is mathematically expressed as:

$$n_{out} = Act(b + \sum_{o=1}^m x_o \cdot w_o) \quad (8)$$

The general equation used to compute the output of multilayers FF-ANN is as follows:

$$n_{ij} = Act_j^i(b_j^i + \sum_{o=1}^{m_{i-1}} n_{(i-1)o} \cdot w_{oj}^i) \quad (9)$$

Where i is the number of hidden layers, j represents the number of neurons, and n_{ij} is the neuron's output at the j^{th} layer. It is necessary to have data to implement ANN. So, it requires to have a closed-loop simulation of the plant. In this study, a model predictive voltage control is implemented to extract the data of input features and output (targets). The reference voltage, actual voltage and output current are chosen as ANN's input features, switching pulses are selected as an output or target. The development of ANN is divided into three steps: offline training, testing and validation. The extracted data from simulations is used to train the ANN. After the training, fine-tuned ANN is tested in real-time simulation. The overall principle of the proposed ANN based controller is shown in Fig. 5.

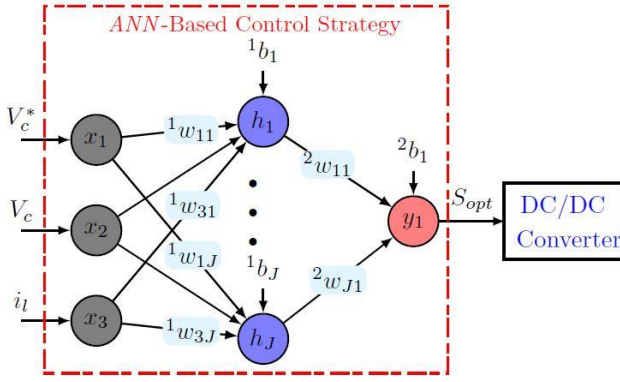


Fig. 5. The principle of the proposed ANN controller.

In this study, A feed-forward neural network is trained on the extracted data. The data set chosen for the offline training of ANN contains random samples of selected variables on different reference voltage values, such as 90V, 95V, 100V and 105V. Furthermore, the data set is randomly divided into three sets: Training set, validation and testing set with the ratio of 60%, 20% and 20%, respectively. The hidden number of neurons in the network is 15, and Bayesian regularized technique “trainbr function” is used as a training function. There are many methods to evaluate the performance of trained ANN but we applied two methods in this study. The first one is the confusion matrix, which evaluates the performance on the basis of output. In our case, the output of the ANN is 0 or 1 (pulse for the switch S_1). So, 78.8% of samples in the dataset belong to output class 1 while 21.2 % of samples are part of the output class 0. The total number of samples in the dataset is 180006. The proposed controller correctly predicts the output class of the random sample by overall accuracy of 97.2%, as shown in Fig. 6. Fig. 7 demonstrates the mean square error (MSE) during the network training. The performance of the trained network is good when the value of MSE is close to zero or zero. In our case, the value of MSE is 0.02143, which is attained during the offline training of the network.

Confusion Matrix			
Output Class	0	38190 21.2%	0 0.0%
	1	4991 2.8%	136825 76.0%
		88.4% 11.6%	100% 0.0%
			97.2% 2.8%

Fig. 6. The confusion matrix presents the accuracy of the trained ANN.

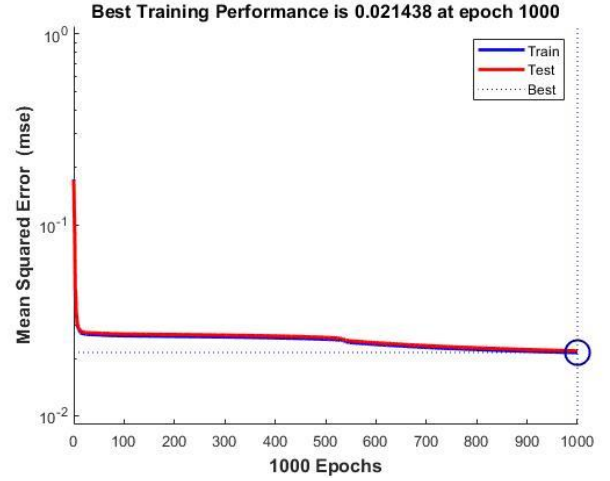


Fig. 7. Mean square error value of the proposed network during the training up to the 1000 epoch size.

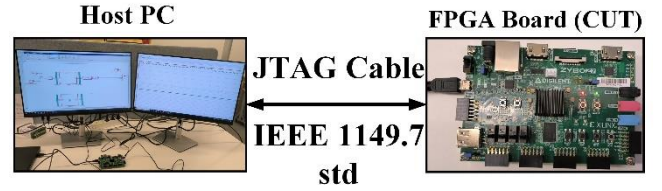


Fig. 8. Experimental setup to validate the proposed control technique.

TABLE I. SIMULATION SYSTEM PARAMETERS.

Parameters	Values
Inductor L	1mH
Capacitor C	1000 μ F
V_{ref}	85-115 V
Rated CPL Power	500-1000 W
DC input V_{in}	65-90V
PI Parameter	$K_p=0.054$; $K_i= 8.86$
FPGA Board	Zybo z7-7020

V. EXPERIMENTAL RESULTS

To validate the proposed approach's performance, effectiveness and transient response, the controller FPGA-in-loop-based validation is carried out. The test set is shown in Fig. 8. The system parameters are presented in Table 1. The ANN-based controller runs on the FPGA board, and DC/DC converter and load are simulated in the MATLAB/Simulink environment. The FPGA-in-the-loop (FIL) wizard provides the capability to use MATLAB/SIMULINK for testing controllers in real hardware conditions. The FIL wizard generates the code in VHSIC hardware descriptive language (VHDL). Then the generated VHDL code of the controller under test (CUT) is burned on the selected FPGA board. The communication between the board and MATLAB /SIMULINK is carried out through a JTAG cable. In this study, ZYBO Z7 (ZYNQ-7020 development board) is used. The ZYBO Z7 is driven by 125 MHz oscillators and supports the JTAG mode. It has 13300 Logic slices, 106,4000 flip flops and 630 KB embedded RAM.

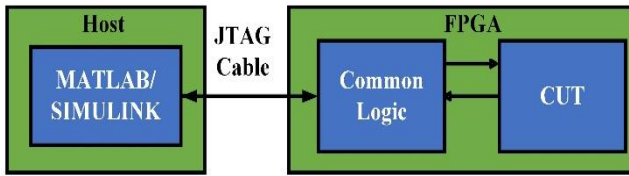


Fig. 9. The working principle of FPGA-in-loop simulation environment.

Fig. 9 illustrates the working of the FIL implementation in MATLAB/SIMULINK. The CUT is burned on the FPGA board while the remaining DC/DC converter model runs on the MATLAB/SIMULINK environment. The interactive communication is done through a JTAG cable. FIL Implementation is performed in the following steps:

1. The controller under test is specified using a Simulink subsystem. Then inputs and outputs of the subsystem are defined as fixed data types (This operation can be performed using SIMULINK Fixed Point Tool).
2. After defining data types, select the CUT subsystem, open the HDL workflow, and run all tasks.
3. After running all tasks successfully, MATLAB will generate the VHDL code of CUT and write it up on the FPGA board.

Furthermore, The PI and MPC results are simulated in MATLAB/SIMULINK environment. In this study, the PI controller was tuned only manually to have adequate performance, but possibly somewhat better tuning could have been possible with some optimal tuning methods. At the same time, the Proposed controller is implemented on the FPGA. The results are split into three cases, and only CPL is connected with the system, which is one of the worst cases from the stability point of view.

A. Reference voltage tracking

In this scenario, the transient response of the DC converter is examined with the change of reference voltage. In the beginning, the reference voltage is set to 100V. As depicted in Fig. 10, the output voltage tracks the reference voltage and output current becomes stable at 0.002 s. There is no disturbance observed in output voltage and output current. In the second scenario, at $t=0$ s, the CPL load of 500 W is connected with the system and voltage and load current becomes stable in no time. It is observed from the zoomed-in graph of Fig. 11 that the transient response of the proposed controller is slightly better and has less overshoot than conventional MPC. At $t=0.4$ s, the voltage reference is decreased to 85 V to observe the effect of change in voltage reference and also verify the controller response. However, both controllers track the reference voltage and remain stable without disturbance. Due to the decrease in the voltage, the current escalates to keep the power constant. Again, at $t=0.6$ sec, the reference voltage suddenly increases to 115 V. Both controllers track the new reference without any distortion, as demonstrated in Fig. 11.

B. Robustness to unknown changes in load

To validate the controller response to the unknown load variations. The constant power load of 500 W is initially connected at the point of common coupling (PCC). At $t=0.4$ s, the load connected at PCC is increased to 1000 W, and at $t=0.6$ s, the connected load is decreased to 500 W, as shown in

Fig. 12. It can be seen from Fig. 12 that the performance of the proposed controller is better than the conventional PI controller. There is no variation observed in the proposed controller's case, while the PI controller cannot handle the increase in load and has more voltage deviation with steady-state error. Thus, the proposed controller is robust against load variations.

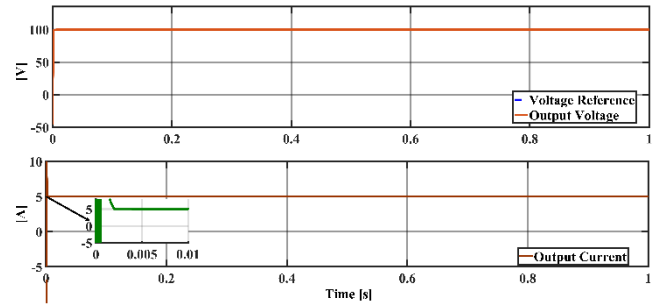


Fig. 10. Start-up response of the proposed controller.

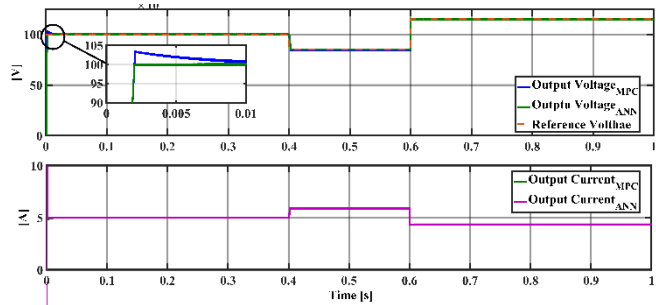


Fig. 11. Voltage reference tracking response of proposed controller compared to conventional MPC.

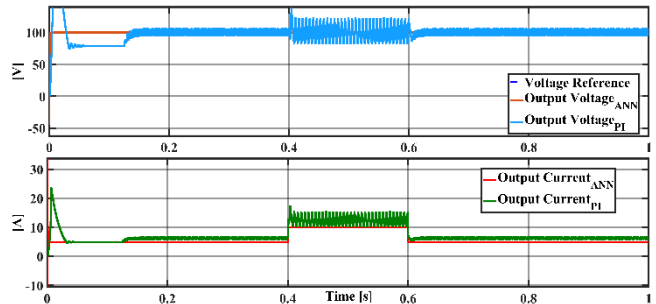


Fig. 12. Performance comparison between proposed ANN and PI controller under a change in load.

C. Robustness against the change of input voltage

In this case, the performance of the proposed controller is evaluated against the variation and noise input voltage. The case represents the PV solar sources and also the diode-based rectifier output. The input voltage of the DC converter is 80 V as shown in the Fig. 13. The $\pm 5\%$ of the voltage fluctuation at the frequency of 50 Hz is added into the nominal input voltage as exhibited in Fig. 13. At $t=0.4$ s, the input voltage is increased to the 95 V, and at $t=0.6$ s, the input voltage is decreased to the 75 V to examine the effect of input voltage change and voltage noise on the performance of the proposed controller. The results show that the proposed controller rejects the disturbances and fluctuations and presents better transient performance. Accordingly, the proposed controller is robust against input voltage variations and fluctuations.

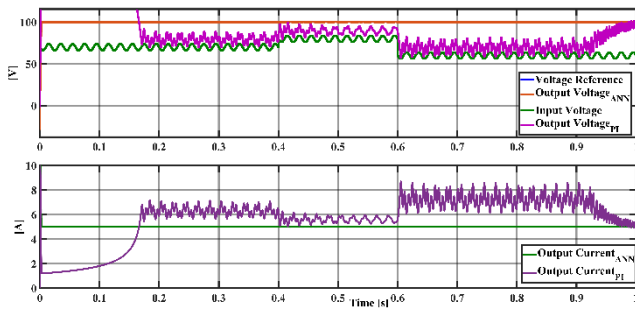


Fig. 13. Proof of proposed controller robustness against the input voltage fluctuations and variations and comparison with the PI controller.

VI. CONCLUSION

This paper introduces an ANN-based voltage control approach for DC/DC boost converter under constant power loads (one of the worst cases). Initially, MPC is implemented to extract the dataset, which is used to train the ANN. The Bayesian regularized technique is used to train the ANN and adjust the biases and weights of the ANN. The proposed ANN control's overall performance is better in terms of transient response compared to MPC and conventional PI control strategies and robust against uncertainties, input variations and system nonlinearities. To validate the performance of the proposed control technique, FPGA-in-loop testing is also conducted using ZYBO Z7-7020 FPGA board. The implementation of the proposed technique would be useful in DC microgrid and critical applications, where it requires high robust performance under variations.

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