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A Critical Analysis of The Application of Artificial Neural Network (ANN) in the Field of DC to DC Converters.

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***Abstract*—Because of the fast advancement of renewable energy technologies, the idea of microgrid (MG) is becoming more commonly adopted in power systems. DC MG is gaining popularity due to the benefits of the DC distribution system, including as easier integration of energy storage and lower system loss. The linear controller, such as PI or PID, is established and widely used in the power electronics sector, but its performance degrades as system parameters change. In this paper, an artificial neural network (ANN)-based voltage control technique for a DC- DC boost converter is developed. The model predictive control (MPC) is employed as an expert in this study, providing data to train the suggested ANN. Because ANN is highly adjusted, it is used directly to regulate the step-up DC converter. The key benefit of the ANN is that it reduces the inaccuracy of the system model even with erroneous parameters and has a lower computing overhead than MPC owing to its parallel nature. Extensive MATLAB/Simulink simulations are run to validate the performance of the proposed ANN. The simulation findings reveal that the ANN-based control method outperforms the PI controller under various loading situations. The trained ANN model has an accuracy of roughly 97%, making it acceptable for DC microgrid applications..**

***Index Terms*—ANN, DC Microgrid, DC/DC boost converter, MPC, Primary control.**

I. INTRODUCTION

The depletion of fossil fuels and the consequences of climate change have focused emphasis on alternative energy sources. Therefore, DC/DC converters are becoming increasingly used in several systems [1] - [3] where different voltage levels of loads are connected. This includes energy storage systems, electric vehicles, solar systems, wind turbines, and many others. The DC MG block diagram is shown in Figure 1. DC MG consists mostly of DC loads, energy storage systems (ESS), and renewable energy sources (RES) like solar and wind. Each RES and ESS communicates with the bus via a power electronic interface (PEI). This means that proper management of the PEIs is essential. Proportional-integral (PI) and proportional-integral-derivative (PID) linear controllers, two types of linear controllers that have been widely advocated by the research community [4]-[6], are widely used in the PE industry. Despite its widespread use, the linear controller has a number of shortcomings in real-world applications. These include poor disturbance rejection, the need to tune gains, the drift of the converter's operating point towards instability as a result of alterations to system parameters, and the inability to account for non-linearities in the power system. For these reasons, and in an effort to improve transient behaviour, several different nonlinear control systems have been created. Some examples are fuzzy logic control (FLC), sliding mode control (SMC), and model predictive control (MPC). FLC for DC converter is supplied in [7] for PV-based lighting systems. Using microcontrollers,[8] has studied FLC implementation for DC power converters.FLC primarily utilizes the if-else statement, and its output is determined by predetermined rules that employ this logic. FLC can handle the system's non-linearity and does not require any mathematical system models. Under various circumstances, FLC for DC/DC converter voltage control is also good. Numerous investigations, however, demonstrate that since it lacks rigorous analysis, it is an unreliable controller. Therefore, the literature contains an amalgam of several control strategies to counteract FLC's drawbacks. [9].

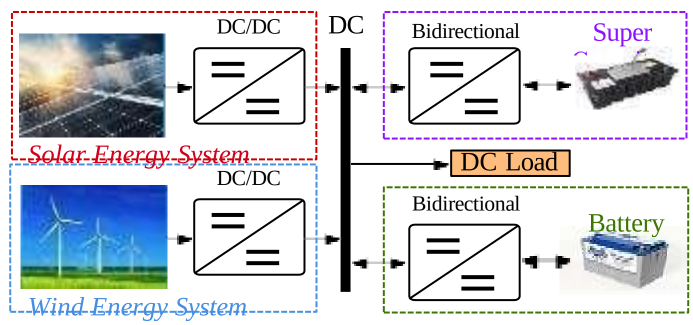

Fig. 1. Possible structure of single bus DC MG, including renewable energy sources such as solar and wind, energy storage systems, and DC load.

Model predictive control and slide mode control have been developed, extensively nvestigated, and are now promising options for power electronic converter applications. Variable structure control theory is the foundation of slide mode control. Its fundamental idea is broken down into two phases. The user-defined sliding layer is forcibly inserted into the system state trajectory. The second phase, known as the sliding phase, occurs after the reaching phase. In this phase, state trajectories determined by the user on the basis of application.It performs well, is resistant to parametric changes, and has excellent transient response under various loading circumstances. However, the primary obstacles to its implementation include chattering problems, significant switching losses, and difficult mathematical modelling [11], [12].MPC is a digital control technique that differs from linear control in terms of its fundamentals. It predicts the behaviour for all potential input configurations using the discrete-time model of the converter and its filter. Despite creating a separate loop for each controlled variable and cascading them together, like in the case of linear controllers, one of the inputs with the least (i.e., optimal) value of the predetermined cost function (CF) is chosen and applied to the upcoming sampling instant [13].

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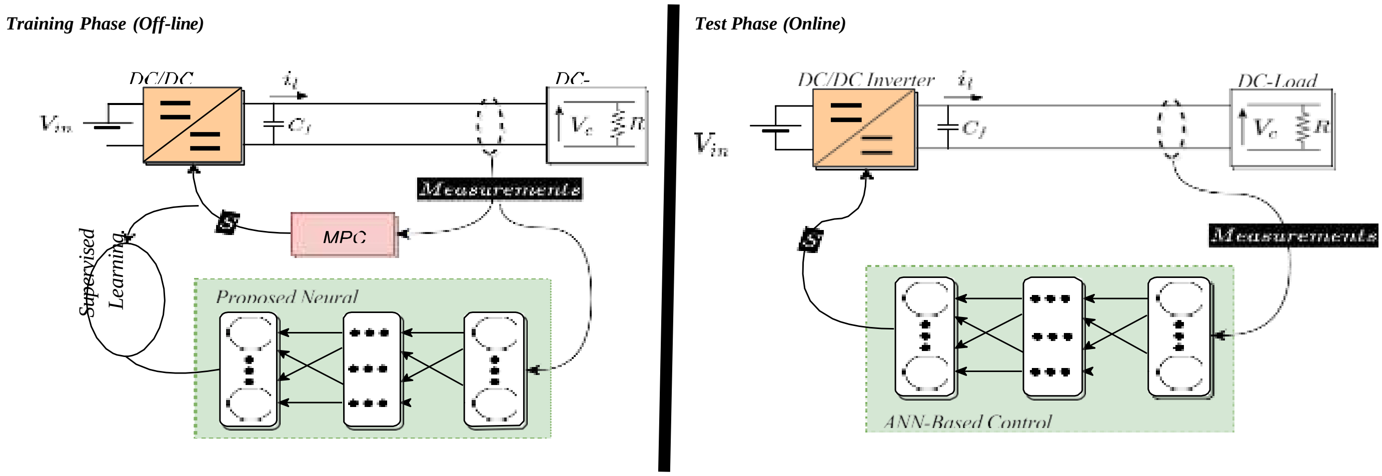

Fig. 2. Overview of the proposed control strategy. During the training phase, the classical MPC is used to control the DC/DC converter and collect the training data. In the test phase, the trained ANN is implemented to control the voltage of the converter instead of MPC [10].

MPC is a digital control technique that differs from linear control in terms of its fundamentals. It predicts the behaviour for all potential input configurations using the discrete-time model of the converter and its filter. Despite creating a separate loop for each controlled variable and cascading them together, like in the case of linear controllers, one of the inputs with the least (i.e., optimal) value of the predetermined cost function (CF) is chosen and applied to the upcoming sampling instant [13]. The Euclidean distance between the controlled and reference signals is essentially squared in the formula for CF. Although it has a high computing cost, variable switching frequency, and performance that depends on the mathematical model of the system, several recent research have proposed a constant switching frequency based MPC for a variety of power electronic applications [12], [14], and [15].

In the field of power converters, data-driven or model-free control approaches, and particularly ANN-based systems, are expanding [16]. In order to directly control a three-phase inverter with an output LC filter and obtain improved steady and dynamic performance, an ANN-based control technique has been developed in [10]. A similar control method was put out by authors in [17] for a three-phase flying capacitor multi-level inverter (FCMLI). A neural network predictive-based voltage control for the DC/DC buck converter is suggested in [18]. To train NN, the author used data from PID controllers. The voltage is regulated using neural network predictive control (NNPC) after training. In [19], a NNPC controller for synchronverters linked to the grid is presented.

Generally general, ANN-based controllers are superior because they compared to other controllers due to the following reasons [10], [20]: • They do not require an explicit mathematical model of the system. • Their performance is Following the extraction of the necessary data, several input feature combinations are selected. Finally, the voltage reference, inductor current, and capacitor voltage are selected as input features, while the converter switching state is taken as output feature for the proposed ANN in this study, as illustrated in Fig. 4. The ANN is then trained using these combinations. Once the ANN is trained and has good model accuracy, the ANN model is directly used to generate the optimal switching state for the DC converter. The proposed control strategy's overview is shown in Figure 2: the training phase combines using MPC to anticipate the converter output voltage converter and collection of state variables data under full-state observation. The ANN is trained using the collected data. In the test phase, the trained neural network is employed online to control the converter's output voltage instead of MPC. The suggested control strategy's simulation results are contrasted with those of the conventional PI Controller. The remainder of the essay is structured as follows. The mathematical modeling of the DC/DC boost converter and the basic principle of MPC are explained in Section II. While the proposed ANN and its training procedure are elaborated in Section III. Section IV shows the simulation results for both ANN and PI controllers. Then, future work is discussed in Section V. Finally, Section VI presents the conclusion.

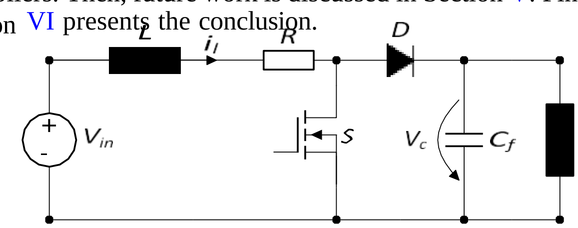

Fig. 3. Circuit diagram of the DC/DC converter.

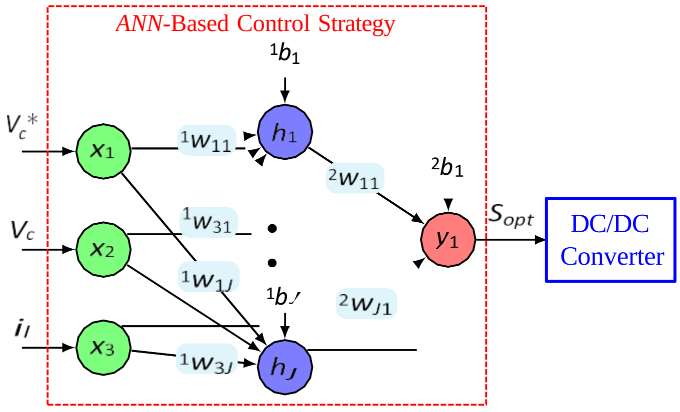

Fig. 4. Block diagram of the proposed ANN-based control scheme for the DC/DC converter. It is trained to map directly from the measured variables, namely, V_c^*, V_c, and i_l, to the *optimum* switching state S_{opt}.

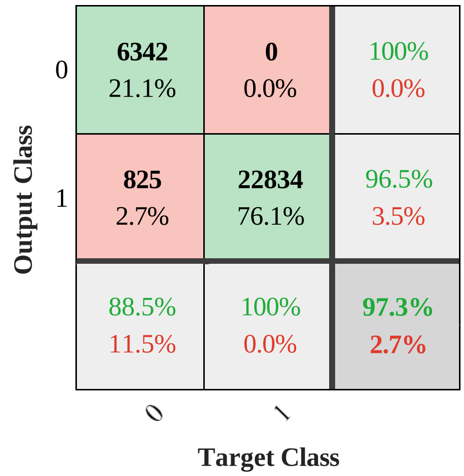

Fig. 5. Confusion matrix of the trained ANN based on the overall training data, where the correct and incorrect observations are highlighted in greenand red, respectively.

Proposed methodology

Figure 4 demonstrates the proposed ANN-based control strategy used in this study. The accuracy of MPC depends on the mathematical modeling of the system. However, the proposed control scheme does not need the model of the system, but it requires the training dataset. It maps directly from the raw input features to the desired outputs. Therefore, the performance of the ANN does not depend upon the system model or its parameter. In this work, the reference voltage V_c^*, capacitor voltage V_c and inductor current i_l are chosen as the input features of the trained ANN-based control strategy, while the optimal switching state S_{opt} is considered as its target or output. Initially, the MPC algorithm is simulated to extract the training data, which consists of the input features and the corresponding output, i.e., input-output pairs. Then, the extracted data is used to train the ANN. In our case, the total number of training data samples is 30001. The control- loop of the proposed ANN-based control strategy, at instant k is summarized as follows:

1) Initially, measure i_l and V_c at instant k.
2) Those measured variables, along with the reference value V_c^*, are utilized by our proposed controller todirectly predict the optimal switching state S_{opt}.
3) Then, the optimal switching state is directly applied to the converter without using any modulator.

A grid search tuning method is used for the selection of configuration with 15 neurons. Bayesian regularized technique (BRT) is used to train the ANN and adjust the biases and weights. BRT is more robust than standard propagation meth- ods and can reduce or eliminate the need for lengthy cross- validation [21]. In this research work, 60% of the randominput data is used to train the ANN, while 20% is used for testing and 20% validation. Figure 5 presents the overall confusion matrix, which is used to analyze the accuracy of the trained ANN. The correct classification of the data class is presented in the diagonal entries of the matrix, while other entries show the incorrect classification of the data. The trained ANN that has been used, in this study, has an accuracy of 97%. The trained ANN model is exported to Simulink to test

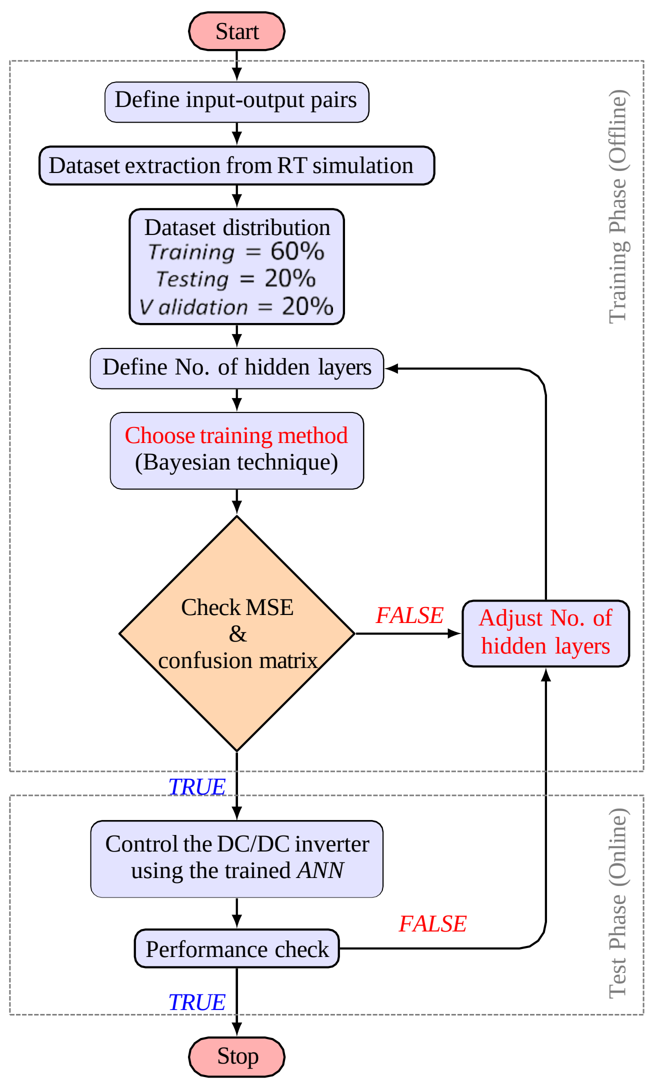

Fig. 6. Main steps of deploying the ANN-based control strategy for the DC/DC converter.

its performance under the original scenario. To sum up, the complete procedure of the learning-based control strategy is illustrated in Fig. 6, highlighting the main steps of the training and test phases.

II. Simulation Results

The trained ANN model is exported into the Simulink model of the DC/DC converter to validate and verify theperformance of the proposed control strategy. Extensive MATLAB/Simulink simulation is carried out. The performance of the boost converter with the proposed control scheme is investigated under normal load and step change of load. The simulation parameters of the converter are given in Table II.

Table II
Simulation Parameters.

Parameter	Value
DC Input V_{in}	70 [V]
Inductor value L	10×10^{-3} [H]
Resistance Value R	80×10^{-3} [Ω]
Capacitor C_f	100 [mF]
Load P	0–1500 [W]
PI Parameter K_p, K_i	0.054, 8.86
Switching Frequency	20 [kHz]

Figure 7 illustrates the performance of our proposed control strategy, considering normal load conditions. The simulation starts at $t = 0$ s, where a resistive load of 20 Ω is connected with the system. The reference voltage is set to 95 V. Initially, the system takes around 20 ms to reach the reference value. After a transient period, the output voltage and current wave forms remain stable and do not show distortion. Figure 8

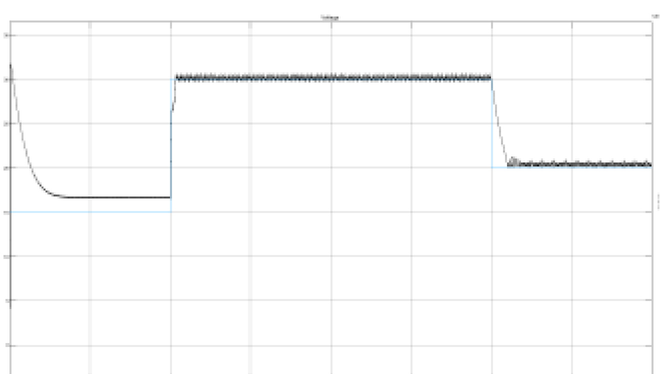

Fig. 7. Simulation results of the output voltage and current of the DC boost onverter under normal load conditions

Shows the performance of the proposed controller from full load to no-load condition and vice versa. At $t = 0.4$ s, the load is disconnected from the system; i.e., the converter is under no-load condition. It is observed that the voltage remains stable, and the current becomes zero. While at $t = 0.5$ s, the load is again connected to the system. The voltage remains stable, while the current is increased to 4.9 A. However, there is no transient observed in the simulation. After the interval of 0.6 s, further loads are added into the system to investigate the response of the proposed controller. It is observed from Fig. 8 that with increasing the load, the voltage remains stable while keeping track of the reference value with un-noticeable distortion, demonstrating the superior performance of the proposed ANN-based control scheme under different loading and transient conditions. Figure 9 presents the simulation

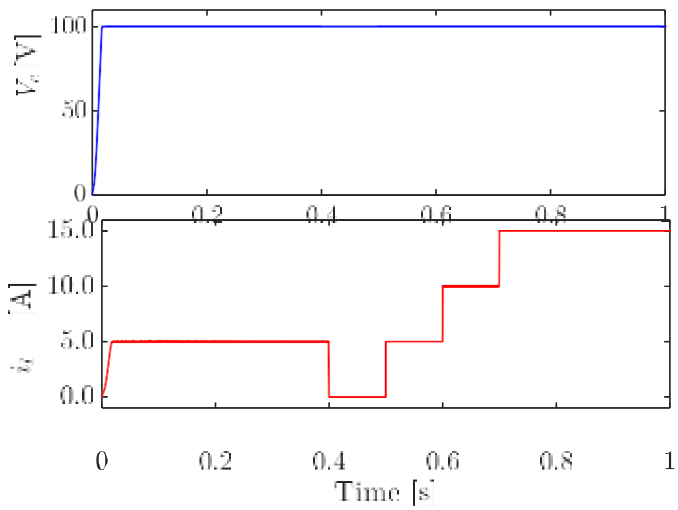

Fig. 8. Simulation results of the output voltage and current of the DC boost converter under full load to no-load test.

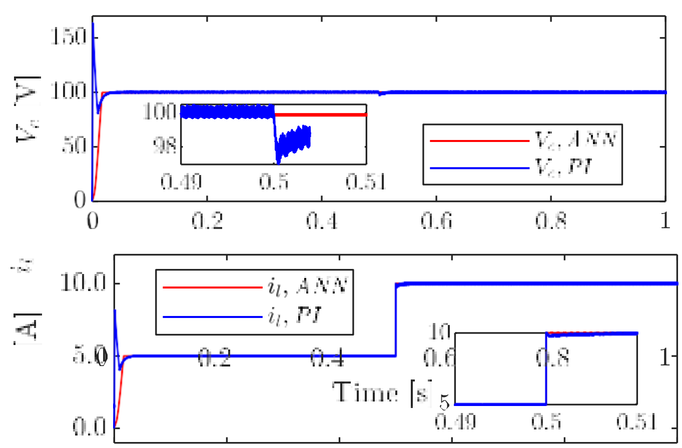

Fig. 9. Simulation results of the output voltage and current of the DC boost converter using PI and ANN-based controllers under step change of load.

outcomes of our suggested controller with a step change in load. At time t = 0.5 seconds, the DC load doubles. We can see that while the current increases as the load increases, the voltage does not change and remains consistent. However, the current waveform barely has any transient duration before becoming steady. Additionally, a comparison with the PI controller is shown in Figure 9. A overshoot is visible in the PI controller outside of the transient period.

Consequently, a high rating semiconductor switch is needed, which raises the cost of the converter and poses a risk to the DC/DC converter's switch in terms of voltage and current. In comparison to the PI controller, the ANN-based control strategy offers superior wave quality and less distortion. Additionally, the PI-based controlled converter's output current is distorted, but the ANN controller's current wave is consistent, steady, and has less loss.

III. Discussion and Future Work

In this work, the suggested control method is evaluated on the same reference value under various loading situations after being trained on the same reference value (Vc = 95 V). The suggested ANN model will be trained in subsequent work, and its performance will be assessed against several reference values. It will also be educated on different factors like filter settings, switching frequencies, etc., suggesting a more general control approach. Additionally, we have noted that the performance of our suggested controller is comparable to that of the MPC that was employed to extract the training data. This is why the PI controller is used to do the comparison. However, the ANN-based controller outperforms the MPC since it has a consistent switching frequency and a lighter computational load..

IV. Conclusion

In this study, we suggested a voltage control method for the DC/DC step-up converter based on feed-forward artificial neural networks. To retrieve the training data, model predictive control is utilised. The data is then used to train the ANN offline. Once the ANN has been correctly trained, the MPC is removed, and the trained ANN successfully regulates the DC/DC converter's voltage in accordance with the reference voltage. The ANN is trained, and its biases and weights are modified, using the bayesian regularised approach. In order to illustrate the effectiveness of the suggested controller, several tests were also carried out throughout the simulation, such as step changes in load and the shifting of load from full load to no load and vice versa. Through the use of simulation findings, it has been shown that the suggested control system performs more effectively overall than the traditional linear controllers. When used in DC microgrid applications, where the DC boost converters need high precision for fine-tuning controller settings, the suggested approach will be beneficial.

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