ISSN: 2251-9246
EISSN: 2345-6221

pp. 157:164

Intelligent Model Based Predicative Controller for DC-DC Converter in Photovoltaic Systems

Amin Rasoulian, Hadi Saghafi*, Mohammadali Abbasian, Majid Delshad

Department of Electrical Engineering, Isfahan (Khorasgan) Branch, Islamic Azad University, Isfahan, Iran, hadisagafi2022@gmail.com

Abstract

The DC-DC converters are one of the most widely used power electronics infrastructure in the modern systems including renewable generations. With development of DC-DC converters, the control system of the DC-DC converters role is becoming more and more. To this end, model predictive control (MPC) is known as one of the potential solutions. Although MPC is an easily implemented control system, it needs a high computational complexity due to the dependency on solving an iterative optimization problem. To overcome this problem, this study develops an artificial intelligence-based on one-dimensional convolutional neural network (1D-CNN) based MPCs. While 1D-CNN benefits from the inherent strong feature extraction/selection capability and lower computational complexity than other deep methods, it still cannot properly track the dynamic changes due to fixed weights during the training process. Thus, this paper integrates the dynamic weighting training process and proposed dynamic weighing 1D-CNN for the implementation of intelligent MPC for the DC-DC converters. The numerical results show an efficient performance of the proposed system and also verifies the superiority of the proposed method in comparison with the conventional MPC and several state-of-the-arts shallow and deep based MPC for the DC-DC converters in terms of the total harmonic distortion (THD).

Keywords: DC-DC converter, one-dimensional convolutional neural network, dynamic weighting training process, model predictive control
Article history: Received 2022-10-13; Revised 2022-11-20; Accepted 2022-12-03, Article Type: Research paper
© 2023 IAUCTB-IJSEE Science. All rights reserved
https://doi.org/10.30495/ijsee.2022.1969247.1232

1. Introduction

Development of DC power source has been quickly increased during the recent years due to the developing of renewable energy such as wind & photovoltaic generations, storage devices, DC power-based technologies, and etc. To connect the DC sources and loads, DC-DC converters is a vital equipment.

The model of PV system consists of PV array, DC-DC converter, inverter, filter, and load, is shown in figure 1. According to the figure 1, DC-DC converter is an inseparable component of photovoltaic system and plays important role. DC-DC converter is used to adjust the voltage for the providing load, and in some cases DC-DC converter is used to change the voltage level [1]. regardless all endeavours in the power electronic devices, there are several challenges still in the implementation of the DC-DC converters. One of the considerable challenges is the control of DC-DC device as an interface system to connect the DC power sources to a set of load/grid. Thus, the design of a progressed control system with desired dynamic response and the ability to adjust the output voltage of the DC-DC converter is a determinative task.

To overcome this problem, different control systems have been presented in the previously presented works. The presented method in the previous literature can be divided in two categories: traditional and advanced. The traditional control system could be mentioned to the linear control systems such as proportional-integral (PI) [2-4] and quadratic control [5], a nonlinear control system such as hysteresis voltage control [6], multi-loop controller [7], repetitive controller [8], deadbeat-based control system [9] and sliding mode-based controller [10]. There are several considerable disadvantages that restricted traditional control systems including i) resonance occurrence due to the variable duty cycle, ii) improper dynamic response due to modulators, iii) sensitivity to the modulator,

iv) feeble performance in presence of interruptions, and v) dependent on the physical model.

To resolve these problems, advanced control systems are widely developed in the last years. Among advanced control systems, model predictive control (MPC) systems are well known as efficient tools to regulate the performance of complex and nonlinear systems considering technical constraints such as constraints of the DC-DC converters. The main features that provide several advantages of the MPC comparing with other traditional/advanced control systems are [11]:

- MPC does not need modulation block
- MPC can include nonlinearities, complexities and even multi-level constructions with an only simple block
- MPC is a flexible control system that is able to adaptively track the input references and abruptions

The key characterization of the MPC is extracting optimal control law based on an iterative optimization process throughout a finite time horizon [12]. Therefore, a cost function is defined and then optimal control law including optimal duty cycle would be provided. MPC has previously used for DC-link capacitor control system [13], rectifier control [14], inverter control of PVs [15], wind power energy conversion system [16], etc. However, the main disadvantage of the MPC that maybe make it improper for the real-time control for the systems such as DC-DC converters, is the computational cost because of solving optimization problem at each time interval. For instance, consider the challenge of optimal duty cycle of the DC-DC converters. In this challenge, the optimal duty cycle of an DC-DC converters should be secured by the control system, while solving a constrained- optimization problem for a mili-second or less time resolution requires expensive solvers, therefore, it is too difficult or highly expensive to implement an MPC to execute in a real-time manner.

To overcome the problem, artificial intelligence (AI)-based methods seems to be a potential solution. AI-based method application has quickly enlarged in the power electronics structures due to the high-speed performance, independence of the physical model, flexibility, and operation based on the historical data. AI-based structures can generally be divided into shallow and deep-based networks [17]. It is remarkable that shallow-based methods suffer from a small parameter hypothesis [18], and therefore, cannot capture oscillated and non-stationary signals such as the DC-DC converter outputs. Also, the deep learning-based method as a revolutionary concept in AI can resolve the all abovementioned problems of the shallow-based methods. With addition the hidden layers in the shallow-based structures, new optimization techniques designing in the process of learning, and human development in the technologies, deep neural networks have been attracted attentions and show extended potential in many utilizations such as power transformer, differential protection [19], power quality [20], load consumption [21] and wind speed forecasting [22], power system fault location [23], etc.

Thus, in this paper, the advantages of deep learning structure have been used to improve the operation as well as the computational burden of the MPC in the DC-DC converters. Among different deep structures, convolutional neural networks (CNNs) have been widely used in different applications for inherent strong feature extraction/selection and the requirement to smaller memory space rather than other deep structures [24], [25]. Although two-dimensional (2D-CNN) is used in the different engineering applications, 2D-CNN needs a dataset of labeled 2D data, which makes 2D-CNN improper for real-time utilizations. There are several subjects that make 1D-CNN advantageous and thus superior to 2D-CNN for application in the real-time MPC of DC-DC converters: i) lower computational complexity, ii) easy implementation and training, and iii) lower-cost hardware for the practical implementation. Despite these advantages, the structure of 1D-CNN has been considered fixed, while the control system should be able to track the dynamic changes. To this end, this paper uses a dynamic training process to regulate the learning weights in a dynamic manner and designs a dynamic weighting 1D-CNN structure for the DC-DC converters.

This paper develops an intelligent MPC control system for the DC-DC converters. To achieve the aim, at first, the conventional MPC is used to provide a comprehensive dataset under the full observable conditions. Secondly, a generated dataset is utilized to train a deep structure-based MPC control system. Consequently, the deep-based structure is used to provide optimal control law by providing optimal duty cycle for the DC-DC converters. To this end, a dynamic weighting 1D-CNN structure is designed. Consequently, the dynamic weighting 1D-CNN-based MPC control is applied and prove the superiority of the offered control system through a comparative study with conventional MPC and several state-of-the-arts shallow and deep-based MPCs for the DC-DC converters. Thus, the novelties of the current paper consist of:

An intelligent MPC control system for DC-DC converters based deep neural network is presented

An improved 1D-CNN structure is designed for providing optimal duty cycle of the DC-DC converters

A dynamic weighting training process is proposed for dynamic tracking of the DC-DC converter outputs in a real-time method.

Other part of the paper is organized as follows: Section II represent the dynamic modeling of the DC-DC converters. The description of the conventional MPC for the DC-DC converter is given in Section III. Section IV provides the information of the proposed deep-based MPC for the DC-DC converters in detail. Section V provides the discussion and comparison of the proposed MPC based on the numerical results. The conclusion is provided in Section VI.

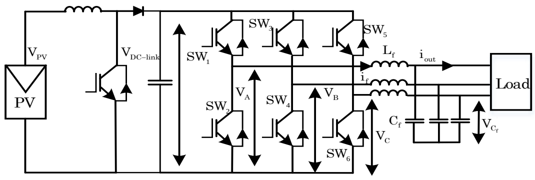

Fig. 1. A schematic of PV System

2. Dynamic Model of DC-DC Converters

The mathematical description of a DC-DC converter is described in this section. The mathematical model is the basis of the proposed deep-based MPC for the DC-DC converters. The output of the DC-DC converter is regulate based on the regulation of the duty cycle of the pulse width modulation (PWM). To prevent the electromagnetic interface (EMI), the switch frequency has been considered fix. Figure 2 shows the model of dc-dc converter.

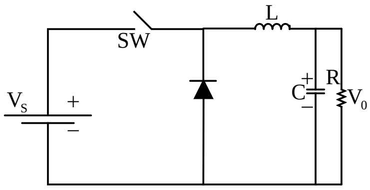

Fig. 2. A schematic of DC-DC converter

The converter can operate in two different modes, i) off-mode, ii) on-mode. The equivalent circuit at off witch mode is shown in Fig 3. In the off-mode condition, the system is described as:

$$\dot{i}_L^t = -\frac{1}{L}V_C^t + \frac{1}{L}V_s \tag{1}$$

$$\dot{V}_C^t = \frac{1}{C}i_L^t - \frac{1}{CR}V_C^t \tag{2}$$

where i_L, V_C, and V_s represent the current of filter inductance, voltage of filter capacitance, and voltage of DC source, respectively.

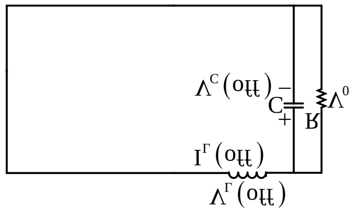

Fig. 3. Equivalent circuit of off-mode condition

In the on-switch mode, the equivalent circuit is shown in Fig 4. In this condition, the system is described as:

$$\dot{i}_L^t = -\frac{1}{L}V_C^t \tag{3}$$

$$\dot{V}_C^t = \frac{1}{C}i_L^t - \frac{1}{CR}V_C^t \tag{4}$$

Considering duty cycle d, the averaging model is:

$$\dot{i}_L^t = -\frac{1}{L}V_C^t \tag{5}$$

$$\dot{V}_C^t = \frac{1}{C}i_L^t - \frac{1}{CR}V_C^t \tag{6}$$

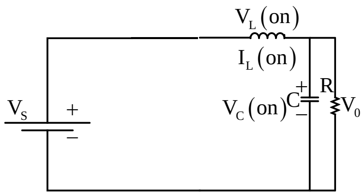

Fig. 4. Equivalent circuit of on-mode condition

In the MPC for DC-DC converter, the principle is prediction the behavior of control parameters to provide optimal control law for duty cycle. To this end, an objective function should be formulated and solved in a specific time horizon (predefine sample number). This paper formulates the objective function based on the predicted output voltage and reference value, as [27]:

$$f^{obj} = \left(i_L^{k+1} - \tilde{i}_L^k\right)^2 + \left(V_C^{k+1} - \tilde{V}_C^k\right)^2 \tag{7}$$

where f^{obj} represents the objective function. $V_C^{k+1}$and i_L^{k+1} show the predicted values, while the reference values of the filter capacitance voltage and filter inductance current are shown by $\tilde{i}_L^k$, and $\tilde{V}_C^k$.

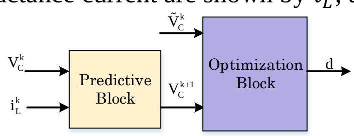

Fig. 5. Two main blocks of MPC for DC-DC converters

Figure 5 depicts the two main blocks of MPC for the DC-DC converters. According to the Fig, the predictive and optimization block should perform in each time horizon. In each time horizon, the following steps should be followed:

- Step 1: Initialize the control system based on reference values

- Step 2: Check the value of the k. If $k = 1$, set $i_L^0 = 0$, $V_C^0 = 0$, $V_{d-C_f}^0 = 0$, and $V_{q-C_f}^0 = 0$. Otherwise, use measured values.
- Step 3: Set $it = 1$ and $\Upsilon = \alpha$ large value
- Step 4: Calculate d
- Step 5: Predict V_C^{k+1}
- Step 6: Calculate f^{obj}.
- Step 7: Compare f^{obj} with Υ. If $f^{obj} < \Upsilon$, set $\Upsilon = f^{obj}$. Otherwise, go to Step 10.
- Step 8: If $f^{obj} < \Upsilon$, save the duty cycle.
- Step 9: Check it. If $it < it_{max}$, $it = it + 1$ and go to step 5; otherwise, go to step 11.
- Step 10: Output the optimal duty cycle.

In the previously presented MPC systems for DC-DC converters, it is necessary to solve the optimization problem in a real-time manner. Since solving optimization problems requires strong and expensive hardware, it is costly to implement the conventional MPC systems. To overcome this problem, this paper proposes dynamic weighting 1D-CNN network-based MPC for the DC-DC converters.

3. Proposed Dynamic Weighting 1D-CNN based MPC for DC-DC converter

The intelligent MPC is constructed based on the teaching and testing procedure. To this end, firstly the structure of dynamic weighting 1D-CNN is introduced. Then, the training process of the designed intelligent MPC for DC-DC converters and the performance of the designed control system are discussed.

A) Dynamic Weighting 1D-CNN

CNN is a strong feature extraction/selection-based structure and can be implemented in a real-time condition, where requires a memory with less space than other conventional deep networks. The 1D-CNN is faster and more convenient than other convolutional methods because it requires simple array operations and has lower computational complexity [26].

The designed 1D-CNN include three main components, including convolutional layers, pooling layers, and fully-connected (FC) layers. The outputs of convolutional layers are obtained as:

$$X_f^{(\ell)} = f^{ReLU}\left(\sum_{ch=1}^{C} W_k^{(\ell),ch} \otimes X^{(\ell-1),ch} + B_k^{(\ell)}\right) \tag{8}$$

where k, ch, $X^{(\ell-1)}$, $W_k^{(\ell),ch}$, and $B_k^{(\ell)}$represent kernel number, channel number, input set, weight matrix, and bias matrix, respectively. Also, $f^{ReLU}(\bullet)$ shows the rectified linear unit (ReLU).

The pooling layers actually are used to scale and project data from the upper layers to reduce dimensions through overlapping convolution windows and also contribute to capturing features. Also, the FC layers are added to connect all hidden layers in CNN to control the dimension of the 1D-CNN output, and construct the final output map. However, to implement the conventional 1D-CNN, there is a serious obstacle. The structure has been considered fixed, while the control system should be able to track the dynamic changes. To this end, this paper uses a dynamic training process to regulate the learning weights in a dynamic manner. In the training process, the back-propagation process is used to find the learning weights as:

$$\mathcal{G} = \sum_{\alpha\beta} \rho_n^l(\alpha\beta)\,(y_n^{l-1}\omega_{mn}^l) \tag{9}$$

where $\mathcal{G}$ and $\rho_n^l(\alpha\beta)$ indicate the set of gradient weights, and sensitivity of neurons α and β, respectively. Also, ω_{mn}^l represent learning weights where connect the m^{th} feature map of the l^{th} layer to n^{th} feature map of the previous layer, $l-1$.

To find the optimal learning weights, this work in fact offers a dynamic training process to improve the learning weights ω_{mn}^l. To this end, κ and τ are defined:

$$\kappa = \begin{cases} 1 & if\ f^s\,(\mathcal{G}_{mn}^{tr}\mathcal{G}_{mn}^{tr-1}) = 1 \\ -1 & if\ f^s\,(\mathcal{G}_{mn}^{tr}\mathcal{G}_{mn}^{tr-1}) = 0 \end{cases} \tag{10}$$

$$\tau^{tr} = c^{\kappa}\tau^{tr-1} \tag{11}$$

where $\mathcal{G}_{mn}^{tr}$ shows the gradient weights at tr training, while c^{κ} and τ^{tr} are adjustment variables. Furthermore, $f^s(\bullet)$ represents the function to determine the gradients' weights direction. To minimize the loss function in the training process and lead to the optimal learning weights and speed up convergence, κ should be fall into $[0,1]$, therefore, c^{κ} be between the $[0,1]$ or $[1,2]$. In the presented adaptive training process, adding momentum term τ^{tr} prevents slow situation and regulates the learning weights during the training. Thus, the learning weights are improving as follows:

$$\omega_{mn}^{tr} = \omega_{mn}^{tr-1} - \tau^{tr}(1-\zeta)\frac{\partial f_{loss}}{\partial \omega_{mn}^{tr}} - \tau^{tr}\zeta\frac{\partial f_{loss}}{\partial \omega_{mn}^{tr-1}} \tag{12}$$

where ζ shows a regulation parameter between $[0,1]$ and values are dependent on the last two training processes. The characteristics of the designed dynamic weighting 1D-CNN are shown in Table I.

B) Training Deep-based MPC in DC-DC Converter

The proposed intelligent MPC system performs based on the historical dataset. The proposed dynamic weighting 1D-CNN structure is fed by the three measured variables and then convert in the d-q reference frame, while the output is a single array including the number of duty cycle. In the output array, only one element is 1 (shows the optimal duty cycle) and others are zero.

Table.1.
Parameter of dynamic weighting 1D-CNN for MPC in DC-DC converter

Layer	*Filter number*	*Filter size*	*Stride*	*Activation function*
Convolution	48	2*1	2*1	ReLU
Pooling	48	2*1	2*1	-
Convolution	100	2*1	2*1	ReLU
Pooling	100	2*1	2*1	-
FC	500	-	-	ReLU
FC	4	-	-	Linear

C) Deep-based MPC in DC-DC Converter

The intelligent MPC is the basis of the learning process. Firstly, the MPC is used to provide the dataset. The generated dataset by an MPC is used to train the dynamic weighting 1D-CNN in an offline procedure. Then, the designed deep network is used to provide optimal control law. Figure 4 shows the operation of the proposed deep-based control system. from Fig 6(a) it is obviously clear, in the training process, MPC performs to generate the data. In the testing process, only designed dynamic weighting 1D-CNN utilized to secure the optimal duty cycle of the DC-DC converters and shown in Fig 6(b). Figure 6(c) shows the overview of the designed structure of the dynamic weighting 1D-CNN. The trained deep block generates the optimal duty cycle. To this end, firstly, the variables i_L^k, V_C^k, and $i_{out}^k$are measured or computed at the k time interval. Secondly, the dynamic weighting 1D-CNN is applied to provide the optimal output voltage based on measured/estimated values at the $k+1$ time interval. Consequently, based on the optimal output voltage, the duty cycle would send to the DC-DC converters. This process is repeated in a specific time horizon.

4. Numerical Results

This section discusses the proposed control system based on the different operational conditions such as different types of load. To this end, a DC-DC converter (similar to Fig 3) is simulated in MATLAB software. An overview of the proposed deep based MPC is depicted in Fig 6.

To evaluate the proposed intelligent predictive control system, two different cases have been considered in this paper: i) $V_s = 250\ V$, the load varies to 50A at 0.004 s and ii) $V_s = 400\ V$, and load change to 25A. In the last subsection of this section, the superiority of the proposed method is proved according to a comparative study.

A) Dataset

To generate the dataset and train the designed dynamic weighting 1D-CNN, 70 different conditions have been considered based on two different conditions for the load. In the first condition, the load considered as a resistive load, and the data is generated based on the 60 cases dependent on load values (varied from $0.5\ \Omega$ to $34.5\ \Omega$). Furthermore, 10 different cases have been extracted from the nonlinear load model. The nonlinear load is a diode-bridge rectifier. Overall, 245450 samples are generated based on different sampling time, filter parameters, DC-link voltage, the output power of D, and reference values. About 70% of the dataset is devoted to training and 30% of data is considered for the testing process.

B) Discussion on Results: Case I

The output voltage, inductor current, and output current are shown in Figs 6-8, respectively. It is obviously clear in Fig 6, the proposed controller can properly track the reference value, and also the output voltage can be led to the steady-state value with faster response comparing conventional MPC and ANN-based MPC. The inductor current and output current are shown in Figs 7&8 and show similar results including faster dynamic response.

C) Discussion on Results: Case II

The output voltage, inductor current, and output current are shown in Figs 7-9, respectively. As can be seen in Fig 7, the proposed controller can properly track the reference value, and also the output voltage can be led to the steady-state value with faster response comparing conventional MPC and ANN-based MPC. The inductor current and output current are shown in Figs 8&9 and show similar results including faster dynamic response.

Figures 10-12 show the output voltage, inductor current, and throughout the 10ms time period respectively. As can be seen from Fig 10, the output voltage in the proposed control system shows a higher dynamic response. To verify this issue, the behavior of V_0 in the initial conditions can be great proof. The inductor current and output current are shown in Figs. Figures 11&12 show similar results including faster dynamic response.

D) Comparative Study

To prove the superiority of the proposed dynamic weighting 1D-CNN based MPC, this subsection compares the proposed method with:

- Conventional MPC
- Artificial neural network (ANN)-based MPC
- Support vector machine (SVM) based MPC
- 1D-CNN based MPC
- 2D-CNN based MPC

The methods are compared based on total harmonic distortion (THD) of output voltage of voltage.

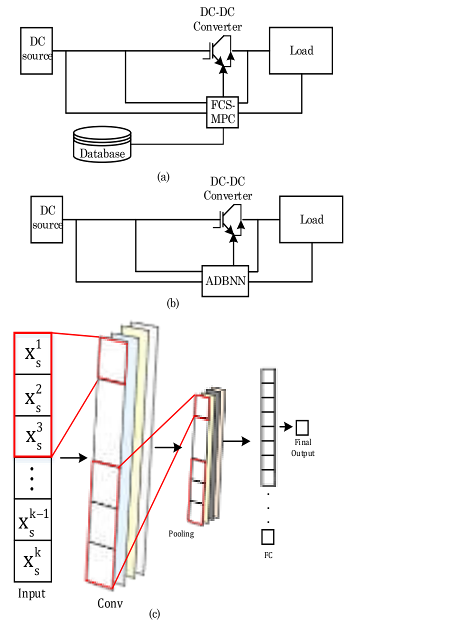

Fig. 6. Overview on of the proposed deep based MPC, (a) Training process, (b) Testing process, (c) structure of dynamic weighting 1D-CNN

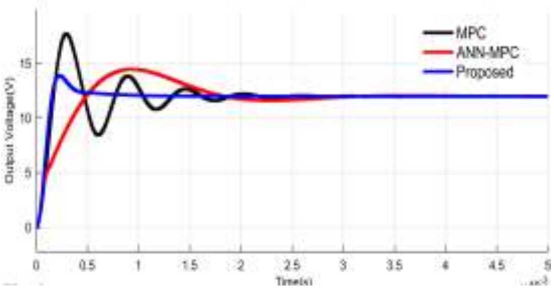

Fig. 7. Output voltage: case I

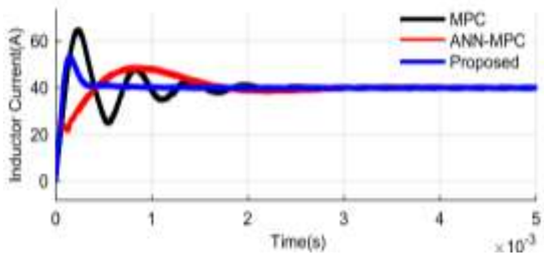

Fig. 8. Inductor current: case I

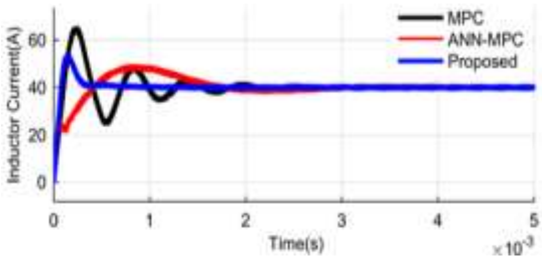

Fig. 9. Output current: case I

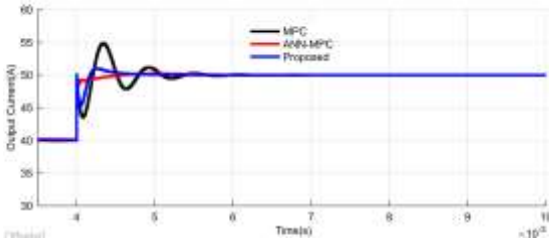

Fig. 10. Output voltage: case II

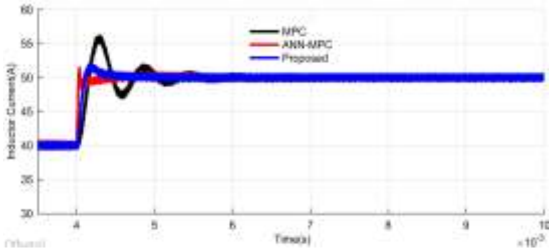

Fig. 11. Inductor current: case II

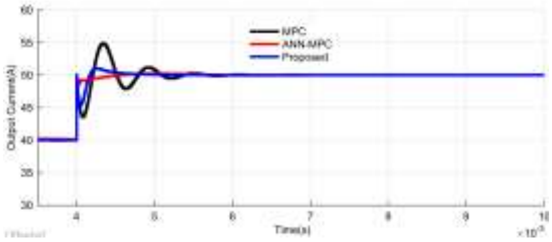

Fig. 12. Output current: case II

For this purpose, the conventional and intelligent MPCs are compared for 10 different samples in cases I & II. The results are given for two cases in Fig 13. As can be seen from this Figure, the proposed method shows the lowest level of voltage THD in two samples and cases. For instance, considering case II and sample #2, the proposed method reduces the THD obtained by the conventional MPC by about 78.47% and improves the THD obtained by shallow-based MPCs, i.e. ANN-based MPC and SVM-based MPC respectively 55.56% and 54.01%. Furthermore, in comparison with state-of-the-art deep-based MPCs, the proposed method significantly improves THD approximately 48.84% rather than 1D-CNN and 49.43% rather than 2D-CNN. The lowest values of THD are obtained by the proposed dynamic weighting 1D-CNN, therefore, the superiority of the proposed dynamic deep network is obvious in terms of THD.

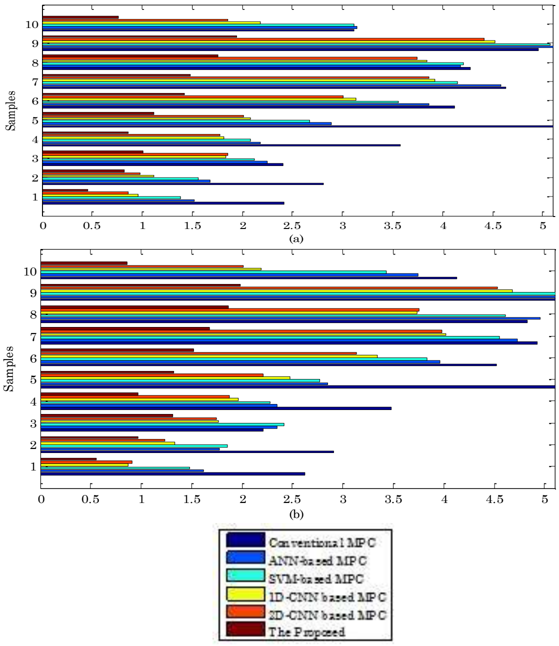

Fig. 13. Comparison between the proposed method with conventional MPC, ANN-based MPC, SVM-based MPC, 1D-CNN-based MPC, and 2D-CNN-based MPC, (a) case I, (b) case II

5. Conclusion

This paper develops a new dynamic weighing 1D-CNN structure to resolve the computational complexity problem of the MPC for the DC-DC converters. To evaluate the performance, three different conditions have been considered to demonstrate the performance of the proposed intelligent MPC. Besides, the proposed method is compared with conventional MPC and several shallow-based MPCs including ANN-based MPC and SVM-based MPC and several deep-based MPCs including 1D-CNN-based MPC and 2D-CNN-based MPC in terms of THD. The results show at least a 45% improvement in comparison with conventional MPC and state-of-the-art MPCs and validate the superiority and performance of the proposed intelligent MPC for the DC-DC converters.

References

[1]. M. Z. Hossain, N. A. Rahim, and J. a. l. Selvaraj, "Recent progress and development on power DC-DC converter topology, control, design and applications: A review," *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 205-230, 2018/01/01/ 2018.

[2]. U. Manandhar, B. Wang, X. Zhang, G. H. Beng, Y. Liu, and A. Ukil, "Joint Control of Three-Level DC–DC Converter Interfaced Hybrid Energy Storage System in DC Microgrids," *IEEE Transactions on Energy Conversion*, vol. 34, no. 4, pp. 2248-2257, 2019.

[3]. N. Hou, Y. Li, Z. Quan, Y. W. Li, and A. Zhou, "Unified Fast-Dynamic Direct-Current Control Scheme for Intermediary Inductive AC-Link Isolated DC-DC Converters," *IEEE Open Journal of Power Electronics*, vol. 2, pp. 383-400, 2021.

[4]. K. Sharma and D. K. Palwalia, "Design of digital PID controller for voltage mode control of DC-DC converters," in *2017 International conference on Microelectronic Devices, Circuits and Systems (ICMDCS)*, 2017, pp. 1-6.

[5]. C. Jaen, J. Pou, R. Pindado, V. Sala, and J. Zaragoza, "A Linear-Quadratic Regulator with Integral Action Applied to PWM DC-DC Converters," in *IECON 2006 - 32nd Annual Conference on IEEE Industrial Electronics*, 2006, pp. 2280-2285.

[6]. L. Corradini, E. Orietti, P. Mattavelli, and S. Saggini, "Digital Hysteretic Voltage-Mode Control for DC–DC Converters Based on Asynchronous Sampling," *IEEE Transactions on Power Electronics*, vol. 24, no. 1, pp. 201-211, 2009.

[7]. F. Kurokawa, S. Sukita, and J. Sakemi, "A New Multi-Loop Digital Control DC-DC Converter," in *4th International Telecommunication - Energy special conference*, 2009, pp. 1-5.

[8]. E. Tedeschi, P. Mattavelli, D. Trevisan, and L. Corradini, "Repetitive Ripple Estimation in Multi-sampling Digitally Controlled dc-dc Converters," in *IECON 2006 - 32nd Annual Conference on IEEE Industrial Electronics*, 2006, pp. 1685-1690.

[9]. B. Wang, X. Zhang, J. Ye, and H. B. Gooi, "Deadbeat Control for a Single-Inductor Multiple-Input Multiple-Output DC–DC Converter," *IEEE Transactions on Power Electronics*, vol. 34, no. 2, pp. 1914-1924, 2019.

[10]. Y. M. Alsmadi, V. Utkin, M. A. Haj-ahmed, and L. Xu, "Sliding mode control of power converters: DC/DC converters," *International Journal of Control*, vol. 91, no. 11, pp. 2472-2493, 2018/11/02 2018.

[11]. M. M. Mardani, M. H. Khooban, A. Masoudian, and T. Dragičević, "Model Predictive Control of DC–DC Converters to Mitigate the Effects of Pulsed Power Loads in Naval DC Microgrids," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 7, pp. 5676-5685, 2019.

[12]. S. Vazquez *et al.*, "Model Predictive Control: A Review of Its Applications in Power Electronics," *IEEE Industrial Electronics Magazine*, vol. 8, no. 1, pp. 16-31, 2014.

[13]. S. Vazquez, P. Acuna, R. P. Aguilera, J. Pou, J. I. Leon, and L. G. Franquelo, "DC-Link Voltage-Balancing Strategy Based on Optimal Switching Sequence Model Predictive Control for Single-Phase H-NPC Converters," *IEEE Transactions on Industrial Electronics*, vol. 67, no. 9, pp. 7410-7420, 2020.

[14]. X. Xiao, Y. Zhang, J. Wang, and H. Du, "An Improved Model Predictive Control Scheme for the PWM Rectifier-Inverter System Based on Power-Balancing Mechanism," *IEEE Transactions on Industrial Electronics*, vol. 63, no. 8, pp. 5197-5208, 2016.

[15]. J. Hu, J. Zhu, and D. G. Dorrell, "Model Predictive Control of Grid-Connected Inverters for PV Systems With Flexible Power Regulation and Switching Frequency Reduction," *IEEE Transactions on Industry Applications*, vol. 51, no. 1, pp. 587-594, 2015.

[16]. D. Song, J. Yang, M. Dong, and Y. H. Joo, "Model predictive control with finite control set for variable-speed wind turbines," *Energy*, vol. 126, pp. 564-572, 2017/05/01/ 2017.

[17]. S. Afrasiabi, M. Afrasiabi, B. Parang, M. Mohammadi, S. Kahourzade, and A. Mahmoudi, "Two-Stage Deep Learning-based Wind Turbine Condition Monitoring Using SCADA Data," in 2020 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES), 2020, pp. 1-6.

[18]. S. Afrasiabi, M. Afrasiabi, B. Parang, and M. Mohammadi, "Integration of Accelerated Deep Neural Network Into Power Transformer Differential Protection," IEEE Transactions on Industrial Informatics, vol. 16, no. 2, pp. 865-876, 2020.

[19]. M. Afrasiabi, S. Afrasiabi, B. Parang, and M. Mohammadi, "Power transformers internal fault diagnosis based on deep

convolutional neural networks," Journal of Intelligent & Fuzzy Systems, vol. 37, pp. 1165-1179, 2019.

[20]. M. Mohammadi, M. Afrasiabi, S. Afrasiabi, and B. Parang, "Detection and Classification of Multiple Power Quality Disturbances based on Temporal Deep Learning," in 2019 IEEE International Conference on Environment and Electrical Engineering and 2019 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), 2019, pp. 1-5.

[21]. M. Afrasiabi, M. Mohammadi, M. Rastegar, L. Stankovic, S. Afrasiabi, and M. Khazaei, "Deep-Based Conditional Probability Density Function Forecasting of Residential Loads," IEEE Transactions on Smart Grid, vol. 11, no. 4, pp. 3646-3657, 2020.

[22]. M. Afrasiabi, M. Mohammadi, M. Rastegar, and S. Afrasiabi, "Advanced Deep Learning Approach for Probabilistic Wind Speed Forecasting," IEEE Transactions on Industrial Informatics, vol. 17, no. 1, pp. 720-727, 2021.

[23]. S. Afrasiabi, M. Afrasiabi, M. Mohammadi, and B. Parang, "Fault localisation and diagnosis in transmission networks based on robust deep Gabor convolutional neural network and PMU measurements," IET Generation, Transmission & Distribution, vol. 14, no. 26, pp. 6484-6492.

[24]. S. Afrasiabi, M. Mohammadi, M. Afrasiabi, and B. Parang, "Modulated Gabor filter based deep convolutional network for electrical motor bearing fault classification and diagnosis," IET Science, Measurement & Technology, vol. 15, no. 2, pp. 154-162, 2021.

[25]. S. Afrasiabi, M. Afrasiabi, B. Parang, and M. Mohammadi, "Designing a composite deep learning based differential protection scheme of power transformers," Applied Soft Computing, vol. 87, p. 105975, 2020.

[26]. D. Neupane and J. Seok, "Bearing Fault Detection and Diagnosis Using Case Western Reserve University Dataset With Deep Learning Approaches: A Review," IEEE Access, vol. 8, pp. 93155-93178, 2020.

[27]. Kouro S, Cortes P, Vargas R, Ammann U, Rodriguez J. 2009. Model predictive control-a simple and powerful method to control power converters. IEEE Transaction on Industrial Electronics. June 2009. vol.56, no.6.